THREE PIECES OF APPLIED RESEARCH ON FINANCIAL MARKET COMOVEMENTS

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The dramatic development of the financial system and instruments and the phenomenon that is generally described as the globalization trend seem to lead to more integrated global financial markets. On the one hand, this is considered an essential component of improving both the operational and informational efficiency of financial markets. On the other hand, however, local shocks may well end up having far-reaching consequences especially when they generated in a major financial market. These two effects are at the heart of this work.

In the mainstream literature, financial market integration is often captured through the price comovements. The first chapter of this Thesis specifies correlations conditionally on a dynamic structure that also involves breaks based on which it examines the comovements between the foreign exchange and stock exchange markets by making the distinction between developing and developed economies. Based on a comprehensive and long sample of both developed and developing stock and foreign exchange markets, it reports findings that suggest the presence of large negative comovements between the two markets across the globe and particularly amongst the markets of the developed economies during the recent financial turmoil.

A relevant albeit very recent strand of the literature looks at financial market integration in terms of connectedness. The second chapter of this Thesis expands the notion to capture volatility connectedness amongst a comprehensive and long sample of stock markets using well-established measures of network analysis based on which it examines whether instead of a growing degree of integration there is actually a natural level of connectedness. The findings suggest that during the episode of interruptive events such as financial crisis, political events and terrorist attacks, the connectedness intensifies; but only for the stock market of developed economies and, most importantly, for only a short period of time.

Finally, the third chapter of this Thesis investigates the impact of stock market volatility on foreign exchange returns. It was found that volatility changes were significant factors and the risk premium tended to be positive.

Keywords: correlations, volatility, stock markets, currency markets, network analysis.

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Chapter 1

Introduction

The phenomenon of financial market comovements has long been established as an important factor of asset pricing and risk management. In the recent decades, a large amount of empirical findings such as Longin and Solnik (1995), Berben and Jansen (2005) and Bartram, Taylor, and Wang (2007) have shown an increase in financial market comovements during the so called "tranquil" period. This phenomenon leads to the concerns of the level of financial market integration and the benefit of international and cross-market diversification.

At the same time, recent economic shocks have ended up with far-reaching consequences, giving rise to historical economic events such as the Global financial crisis. Therefore, it is hardly surprising that exploring the mechanism through which such shocks propagate and magnify within the existing financial system has been a topic that has attracted so much attention from both academia and the finance industry.

However, the commonly discussed comovement of market returns has focused on the dependence within the equity assets, while the research on the cross-sectional market linkages is relatively modest. In particular, the linkages of equity and foreign exchange market are noteworthy, because equity markets are typically viewed as mirroring the overall state of the underlying economy, and the foreign exchange markets are thought of as reflecting the state of the global financial system. This work investigates the comovements between stock and foreign exchange markets by answering two of the remaining issues the literature: the dichotomy between the developed and developing financial markets and the potential bias that the respective empirical work might have due to the presence of structural changes for which there is no provision. Hence, we applied break test of Karoglou (2010) and Killick and Eckley (2014) to estimate the break points, and used the Dynamic Conditional Correlation (DCC) model of R. Engle (2002) to investigate the daily dynamics of cross-market linkages between stock and foreign exchange markets.

Based on a comprehensive and long sample of both developed and developing stock and foreign exchange markets, the comovements demonstrate very rich dynamics. Extensive comovements are likely to be triggered during the episode of financial turmoil. Particularly in the 2007/8 Global Financial Crisis and the ensuing sovereign debt crisis, there were presence of large negative comovements between the two markets across the globe and particularly amongst the markets of the developed economies. On the other hand, the emerging markets were inevitably involved in the crisis, but the magnitude of comovement was not comparable to the one within advanced markets. This may indicate the decoupling effects between the advanced and emerging markets.

Further on the impact of major economic events, we are interested in whether there is an underlying natural level of market connectedness, on which the impact of interruptive events is rather temporary. The connectedness is described by the dependence of stock market volatility, as it captures key information, such as public sentiment and market uncertainty. By investigating the topological structure and evolution of this dynamic graph, we can reveal a much deeper understanding about how it has been affected by substantial economic events. To this aim, we followed the idea of correlation-based network (initially established by Mantegna, 1999) and brought together the DCC model and a broad set of intraday range-based volatility to build up a dynamic graph which presents topological properties of the global financial system. And then we selected the commonly used measures, diameter and minimum spanning tree, as well as the not-so-often used centrality measure and community detection, to show different aspects of this dynamic graph.

Generally, our findings are different to the literature that claims a substantial volatility integration. By monitoring the graphic features of the equity network, we found that what led to increased connectedness was the degree of economic shocks, particularly from developed countries. Whereas, the connectedness recovers to a natural level after a short period of time. In addition, the extrema of the connectedness did not involve the emerging market. On the contrary, volatility changes of emerging market tend to be more heterogeneous during shocks.

Lastly, since the exchange rate arrangements became more flexible following the breakup of Bretton Woods Agreement, the possible risk factors to be involved in the determination of the foreign exchange rates increased, among which the impact of stock market volatility is the focus in our work. To this aim, we used DCC model to capture the pairwise dependency of stock market volatility changes and foreign exchange returns. Then, by building upon a principal component analysis (Jolliffe, 1986), we proxy the effect of the risk transmission channel between stock and foreign exchange market.

Empirically, volatility changes of major stock composites are significant factors in the determination of the foreign exchange returns. In other words, the risk premium tended to be positive. Particularly, such effect is commonly seen in the currencies of developed countries but relatively limited for those of developing countries.

Chapter 2

Financial market comovement between equity and foreign exchange, 1996-2017

2.1 Introduction

The interest of the research community on financial market comovements emerged as the growing development and openness of the global financial transactions increased the importance of cross-market linkages in determining the state of each individual market. These linkages are directly related not only to practices of international portfolio management but also to a much broader set of issues such as regional market integration, risk spillovers and so forth. Due to the recent economic events, even policy makers became highly interested in the comovements between financial markets, because it was essential for the stability of the global financial system. By the time of constructing this study, there has been a lot of research on equity market comovements. And yet, research on cross-sectional market linkages is surprisingly modest.

Particularly noteworthy are the linkages between equity and foreign exchange markets. Equity markets are typically viewed as mirroring the overall state of the underlying economy. The foreign exchange market however, ever since the breakdown of the Bretton Woods Agreement, has also been invariably thought of as reflecting the state of the global financial system. In fact, the mutual effect between stock price and foreign exchange rates was incorporated in the flow-oriented model of Dornbusch and Fischer (1980) and the stock-oriented model by Branson (1981) and Frankel (1992).

In general, changes in the foreign exchange rates are expected to affect the asset market in several ways since they constitute a major determinant of a country's international competitiveness and hence the future cash flows of firms; and consequently they are expected to have an impact on stock market prices. In the same spirit, the performance of international portfolios is expected to be hinged on the foreign exchange rate risk that its constituent assets bear. The reverse relationship however in practice has proved much more forceful since there are plentiful examples of, say, a blooming stock market that has led to substantial rises in money demand which were translated, not always into higher interest rates but very often into substantial capital inflows (e.g. due to positions of large hedge funds firms). Consequently, the linkages of these two markets is very likely to be affected by risk and liquidity shocks.

Most importantly, due to the continuously growing intertwining structure of the global financial system, any fallout in one (major) asset or one market is likely to end up being a disruptive event in another asset or market. This partly explains why situations like banking crises, stock market crashes, bursting of speculative bubbles, currency crises and sovereign defaults, appear to be more and more frequent since late 20th century. Therefore, it is only natural that the impact of economic shocks on cross-section dependence has grown and become lately an inherently vital issue for risk management practices and the preparation of monetary policy.

Important though it is, there are two issues of the linkages between stock and foreign exchange markets that the underlying literature has not addressed. The first issue is about the very important dichotomy between the developed and developing financial markets. The second issue is about the bias of the respective empirical work that might exist due to the presence of structural changes for which there is no provision. The purpose of this work is to address both of these issues together.

In terms of the dichotomy between the developed and developing financial markets, the main question is whether the global market reacts to disruptive events in a homogeneous manner. For instance, the 2007 subprime bubble burst in the U.S. led to a recession across globe and triggered the Eurozone debt crisis. However, although this has been characterised as the Global Financial Crisis, it is not clear as to whether markets outside the Eurozone or even outside the EU have been affected by it. Economies which are not deeply integrated with the global financial system may have experienced very little the effect of this crisis. On the other hand, the high risk of government bond in the monetary union which caused a liquidity shock to market participants, has inevitably driven to a selloff of certain asset classes; and that could provide the way that the crisis could be channeled into them. What exactly has happened has not been examined yet.

In terms of the bias of the respective empirical work that might exist due to the presence of structural changes for which there is no provision, the question is whether the evolution of the linkages between stock and foreign exchange returns is much richer than what is presumed by the existing empirical literature. This issue is not new, as the potentially changing market structure attracted a great interest as early as 1960s due to the buying structure of commodity shifted from a circular competitive relationship among firms to a dominant firm situation. The change in the market structure urged the idea of adding breaks into economic model. Evidences of regime change were found in many key economic and financial series, such as exchange rate (Alogoskoufis and Smith, 1991), interest rate (Garcia and Tsafack, 2011; Ang and Bekaert, 2002) and equity premium (Pástor and Stambaugh, 2001). Moreover, structural changes are not only found in levels. For example, Andreou and Ghysels (2002) discussed the dynamic evolution of financial market volatility, and demonstrated the presence of multiple breakpoints in the volatility dynamics. However, nothing has been done to incorporate this established facts into the empirical investigations about the linkages between stock and foreign exchange markets.

This work aims to address these two issues. Specifically, it investigates the daily dynamics of cross-market linkages between stock and foreign exchange market, during 1996-2017. Data are collected from the benchmark markets of 26 stock indices and 18 foreign exchange rates. Based on the break tests of Karoglou (2010) and Killick and Eckley (2014) and the Dynamic Conditional Correlations (DCC) model of R. Engle (2002), it shows that the comovements demonstrate very rich dynamics and there is a dramatic difference between the developed and developing economies.

The remainder of the chapter is structured as follows. Section 2.2 contains a review of the literature. Section 2.3 presents the methodology and Section 2.4 describes the data. Section 2.5 presents and discusses the empirical results. Finally, Section 2.6 concludes.

2.2 Research context

There are three general strands of the literature that this work relates to. The first one is the literature on financial market comovements; the second one is the literature on the linkages between stock and foreign exchange markets; and the third one is the literature on the detection of structural changes in financial market returns. This part overviews briefly the very long first strand in Section 2.2.1 and explains the dichotomy between developing and developed financial markets in Section 2.2.2. Then, it presents the short existing literature of the second strand, which is directly linked to this work, in Section 2.2.3. Finally, it overviews primary employed econometric methods that have been used for examining the cross-market dependence in Section 2.2.4; and concludes with a discussion on the econometrics of structural change in Section 2.2.5.

2.2.1 Financial market comovement

The time when market comovements firstly drew a lot of attention from the research community was primarily after the occurrence of "Black Monday" in 1987, when the prices of all major stock markets made similar spectacular drops. Shiller (1989) studied the resemblance between the US and UK market in price and dividend series and found that market averages, as well as expected rates of return on market averages in these two countries moved together. Analysis at hourly frequencies by King and Wadhwani (1990) found that the correlation went up as volatility increased. They concluded that the uniform fall in global stock markets might be due to the "self-reinforcing" increase in volatility, and then the price changes were less closely tied together when volatility decreased.

A primary issue that ever since then was pondered upon was "Do different financial markets crash jointly, or is a fall of one a gain for another?"(quoted from Hartmann, Straetmans, and Vries, 2004). From the experiences of a series of financial crises, it appeared that a joint crash was more likely. For example, equity markets respond to bad news more strongly than other financial markets; and moreover the (broader) regional correlation seem to increase dramatically during a financial crisis. Forbes and Rigobon (2002) examined the market dependence in the period of 1987 U.S. market crash, 1994 Mexican Peso Crisis and 1997 East Asian Crisis. They found that the conditional correlations of the centre of each crisis and OECD countries increase by 30% to 40%. Carrieri, Errunza, and Majerbi (2006) argued that apart from the interdependence in developed financial markets, there was some also regional contagion during the 1997 East Asian Crisis. More recently, after the Lehman Brothers' collapse, Kotkatvuori-Örnberg, Nikkinen, and Äijö (2013) found significant increases in the correlations globally (see dynamic regional correlations with the U.S. in Figure 2.1).

In fact, a strong market interdependence was also observed in the so called 'tranquil period'. Early empirical work of Longin and Solnik (1995) pointed out that conditional correlations were not constant, and they increased when volatility was high especially for some industrialized economies. Among many others, a sectoral view of cross-country equity

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Figure 2.1: Dynamic regional correlations with the U.S. (Kotkatvuori-Örnberg, et al., 2013).

correlations in Berben and Jansen (2005) suggested a structural increase in the correlations among the stock markets of US, UK and Germany in period 1980-2000, whereas the correlations with Japan had remained the same (see kernel-smoothed estimates of correlations in Figure 2.2). A notable market dependence within the Euro area was also found by Bartram et al. (2007) according to whom the large equity markets had increasing market dependence after the introduction of the common currency.

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Figure 2.2: Kernel smoothed estimates of correlations between market index returns (Berben and Jansen, 2005).

A direct consequence of the above is that the high comovements during tranquil and turmoil periods directly affect the benefits of international portfolios. The design of a well-diversified portfolio crucially depends on the correct understanding of how closely stock returns are correlated. Some early studies presented a good chance of effective diversification. For example, it was suggested by Solnik (1974) that US investors could diversify their risk domestically to approximately 27% of the average risk of a typical US stock but they could lower their diversification limit to as little as 11% by expanding the population of stocks internationally. Similarly, Heston and Rouwenhorst (1994) suggested that due to country-specific sources of return variation, diversification across different countries within an industry was a much more effective tool for risk reduction than industry diversification within a country. And most importantly, De Santis and Gerard (1997) claimed that the expected gains from international diversification for a U.S. investor have not significantly declined before and after the 1987 crash.

However, due to the increasing comovements across national stock markets since the mid-1990s this seems to no longer be the case. Empirically, Longin and Solnik (2001) found that the correlation of large returns did not necessarily follow the assumption of multivariate normality with constant correlation. In particular, correlation of negative returns did not converge to zero, which meant that the correlation would be more likely to increase in bear markets, but not in bull markets. And Christoffersen, Errunza, Jacobs, and Jin (2014), by extending the dynamic correlation to a time-varying measure of diversification benefits, reported that the overall diversification benefits decreased both in developed and emerging markets (see Figure 2.3). However, it appears that there is still a good chance of reaping diversification benefits in emerging market.

Figure 2.3: Conditional diversification benefits (CDB) using the DCC model: developed, emerging and all markets (Christoffersen, et al., 2014).

2.2.2 Why the developed and developing financial markets dichotomy matters

Within the context of financial market comovements, the research community has not paid much attention to the dichotomy of developed and developing financial markets, although there are several reasons why the stories should differ. In the last quarter of the 20th century, many of the developing markets went through extensive moves towards an open market, maybe following what was suggested by scholars, namely that the economic openness of the country is a reliable predictor of economic growth. In this spirit, many emerging markets increased their external liabilities and international reserves. However, until the burst of the subprime crisis, financial integration in emerging and developing markets was significantly less than the integration level amongst industrial countries, see Figure 2.4 (Lane and Milesi-Ferretti, 2007). Unsurprisingly, financial markets that were isolated by capital controls seemed less responsive to overseas influences. In contrast market liberalization links the expected returns of local markets to the covariance of the global market.

In the episode of financial turmoil, developing markets were inevitably involved in the joint crash. In the 2007 subprime crisis, emerging market asset prices were largely insulated or decoupled from the crisis for some months, but fell even harder than prices for U.S. assets later on (Dooley and Hutchison, 2009). US stock had its predominant influence, without exception in developing markets. According to Chudik and Fratzscher (2011), Asia was more severely affected by U.S. liquidity shocks while Latin America faced larger negative effects from risk shocks. The U.S.-specific shocks adversely affected the advanced economies on the financing conditions and affected developing countries on the real side of the economy. Reinhart and Rogoff (2009) explained that capital movement to emerging markets was considered to be procyclical, which in turn, leaded to procyclical macroeconomic policies in these countries.

2.2.3 Cross-asset dependence: equity and foreign exchange

The strand of literature that looks at the comovements across different types of financial markets (cross-sector) is rather modest. The most discussed cross-sector dependence appears to involve the stock market and bond market pair, most likely because of the general impression of the flight-to-quality phenomenon. However, Hartmann et al. (2004), Garcia and Tsafack (2011) seemed to establish that dependence between stock and bond prices is rather weak, and definitely much smaller in magnitude to the inter-sector dependence. Strong international transmission tended to happen within the same asset class (Ehrmann, Fratzscher, and Rigobon, 2011).

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(a) International financial integration, 1970-2004: ratio of sum of foreign assets and liabilities to GDP.

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(b) International financial integration, 1970-2004: ratio of sum of foreign assets and liabilities to GDP.

Figure 2.4: Financial integration (Lane, 2007)

The other important cross-sector linkages that have been studied, and are directly relevant to this work, is between equity and foreign exchange markets. The former class is thought of as cash-based that quickly responds to any disturbance in the state of the domestic economy, and the latter class is the largest market in the world and traded 24-hours a day. The primary focus of this literature has been the cross-dependence of stock market prices and foreign exchange rates. Based on the well-known flow-oriented model of Dornbusch and Fischer (1980), stock prices are affected by the risk of foreign exchanges. In particular, currency movements affect international competitiveness and the balance of trade position, which in turn affects current and future cash flows of companies and their stock prices. The reverse, the impact of equity prices on exchange rates, was initially documented in the pioneer studies of Branson (1981) and Frankel (1992). Following the theory that capital mobility determines exchange rates, the causal effect stemming from stock market prices to the foreign exchange rates was demonstrated and named as the "stock-oriented effect".

A tangent empirical literature looks at the exchange risk premium. Among others, Dumas and Solnik (1995) pointed out that assets not only contained the traditional premium based on the covariance with the market portfolio, but also some exchange risk premium, which was negative on average. In other words, stocks that are sensitive to foreign exchange risk seem to have lower returns than others. Some of the results from Carrieri et al. (2006) is shown in Table 2.1. The conditional currency risk premia from emerging market were significant in both developed and developing countries. Lagged exchange rate movements also had significant impact on stock returns for the majority of the developed countries (Inci and Lee, 2014).

The reverse relationship, however, seem much more complicated. This may be due to the fact that there can be several channels that this direction of the relationship may occur. Overall, there seems to exist two primary approaches to examine it, namely the monetary approach and the portfolio-balance approach. According to the monetary approach, the price of currencies should be only affected by the underlying economic activity or the adopted monetary policy. For example, Solnik (1987) took stock prices as proxies of economic activity and found that with the increase of international equity flows, the demand of currency which equity prices were denominated was higher. According to the portfolio-balance approach, the exchange rates are determined by asset market equilibrium in the short run and by real disturbance in the current account in the long run, and monetary disturbance generally does

Table 2.1: Estimated risk premia (RP) in 1995-2001 (Carrieri, et al., 2006).

	Base Specification				Crisis Specification			
	World RP	Major Currency RP	EM Currency RP	EM-Specific RP	World RP	Major Currency RP	EM Currency RP	EM-Specific RP
Panel A. Developed Markets Assets								
G7								
All sample	57.6%	25.1%	8.8%	8.6%	49.8%	28.6%	10.7%	10.8%
1995–2001	56.2	22.6	10.5	10.7	52.7	27.5	7.2	12.6
Canada	53.9	16.3	11.4	18.5	50.2	22.2	6.6	21.0
France	54.6	28.6	11.1	5.8	54.3	31.4	6.5	7.8
Germany	60.1	21.6	10.5	7.7	45.0	28.1	10.1	16.8
Italy	48.5	21.8	12.9	16.9	50.0	25.2	8.5	16.4
Japan	53.5	30.5	8.0	8.0	50.4	35.7	5.6	8.4
U.K.	54.9	29.5	9.4	6.1	51.6	35.9	5.6	6.9
U.S.	68.0	10.2	10.1	11.7	67.4	13.9	7.4	11.3
Other Developed Markets								
All sample	42.4	17.1	18.5	22.0	36.2	25.3	18.0	20.5
1995–2001	26.8	20.3	25.3	27.7	36.4	23.0	14.9	25.7
Greece	36.8	17.8	23.2	22.2	36.7	22.7	14.8	25.8
Hong Kong	19.7	22.9	26.3	31.1	36.7	23.8	13.5	26.0
Singapore	23.8	20.1	26.3	29.8	35.9	22.7	16.3	25.1
Panel B. Emerging Markets Assets								
All sample	23.7	19.4	21.0	35.8	22.4	21.4	19.9	36.3
1995–2001	21.9	15.5	22.4	40.3	22.7	19.9	17.0	40.4
Argentina	13.2	3.3	13.5	70.0	15.6	7.7	14.6	62.1
Brazil	36.5	8.8	17.3	37.3	37.6	10.8	11.8	39.8
Chile	27.1	0.6	23.4	48.9	28.3	0.3	18.7	52.7
Colombia	0.0	28.5	42.1	29.5	14.5	39.3	17.5	28.6
Mexico	44.5	7.7	14.2	33.7	35.1	13.4	12.4	39.1
Venezuela	12.0	48.2	17.4	22.4	9.8	56.8	15.1	18.3
India	11.6	12.1	26.7	49.6	14.4	15.7	18.1	51.8
Korea	36.2	12.6	20.5	30.6	40.0	9.6	17.3	33.1
Malaysia	16.7	16.8	30.6	35.9	15.1	23.7	21.6	39.6
Philippines	20.9	17.3	22.5	39.3	24.2	19.5	20.7	35.5
Taiwan	16.2	15.4	20.9	47.6	8.0	25.5	22.6	44.0
Thailand	27.6	14.6	19.3	38.4	30.0	16.0	13.5	40.5

not change the equilibrium real exchange rate (Branson, 1981). The recent study of Gabaix and Maggiori (2015) emphasized the connection of financial forces, balance sheet risks and risk-bearing capacity of financiers, by attributing it to the fact that most financial markets are imperfect and exchange rates are sensitive to imbalances in the other financial markets.

2.2.4 Econometric methods for cross-market dependence

With regards to the recent literature on the econometric methods that have been adopted for cross-market dependence, it is primarily built upon the GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) family of models which has been expanded to capture a time-varying covariance. The distribution of a fitted multivariate GARCH is generally treated as the implied distribution of a portfolio. It was first conceptualised by R. F. Engle (1982) to capture the effect of changing volatility in a time series (ARCH model) and later generalised by his student, Bollerslev (1986) to allow the conditional variance to be a function of its own lagged values. This model proved parsimonious enough to name the whole class of related and exotic models. Modeling the covolatilities demanded a multivariate extension of the GARCH model and Bollerslev, Engle, and Wooldridge, 1988 provided the basic framework for a multivariate-GARCH, known as the diagonal VECH model.

$$h_{ijt} = \omega_t^* + \alpha_{ij} \sum_{i=1}^{t} \beta_{ij}^{t-1} (R_{i,t-i} - \mu_{i,t-i})(R_{j,t-i} - \mu_{j,t-i}) \tag{2.1}$$

where h_{ijt} is the unconditional covariance between returns i and j. This model captures the covariance as a geometrically declining weighted average of past cross products of unexpected returns. The VECH-type models are more feasible for large-scale problems (see for instance Ledoit, Santa-Clara, and Wolf, 2003), but in practice they are quite restrictive for capturing the cross-dynamics. R. F. Engle and Kroner (1995) proposed a different parametrization of the conditional covariance, known as the BEKK model. It models the conditional covariance matrix with a vector of past shocks. However, the BEKK model lacks any computational advantage, as it generates a large number of parameters.

There are a few methods that are built on these covariance model and provide information of the coherence of multi-variables. Bollerslev (1990) constructed the equation of conditional correlation (CCC) to measure the coherence of two variable. The simplified optimization makes CCC widely used in empirical research. Tse and Tsui (2002) followed the VECH-representation form and introduce a varying-correlation approach. Christodoulakis and Satchell (2002) suggested a time-dependent conditional correlation matrix using the Fisher transformation. However, it was R. Engle (2002) who extended the CCC model parsimoniously to a time-varying setting in a variant that he named Dynamic Conditional Correlation (DCC). This is the model we adopt here and is described in detail in the Methodology section.

2.2.5 Non-normality decomposition

The last strand of literature that is relevant to this work is the literature on the econometrics of structural change because its possible presence has typically been a major concern for time series modelling. Breaks in economic and financial series could come up due to instability in the system, such as innovation, specialization, shifts in economic policy, large volatile in main commodity markets, a surge of trading volume and unanticipated events. Traditionally, a shock was treated as temporary effect which barely changes the system. However, Nelson and Plosser (1982) firstly pointed out that in most macroeconomic and financial aggregates, current shocks might have a permanent effect on the long-run level.

The typical break tests identify abrupt change in the structure of a system. Then, by segmenting the data series at the estimated breakpoints, and undertaking any form of analysis separately for each segment, one would obtain results that might be heterogeneous overall but still homogeneous within each segment. Consequently, the possible bias in the analysis that would result from not taking into account the impact of the underlying structural changes would be alleviated. Because of the nature of structural changes is not known ex ante, it has proved quite challenging to develop break test methods with general applicability. This is explains why the earliest method, Chow's test (1960) is still applied to examine whether the pre-break data and post-break data exhibit significantly different statistic properties. After the dramatic improvements in computational power of the 80's and 90's a substantial literature emerged focusing on detecting the existence of structural breaks and estimating the location of breaks.

From a certain perspective, the existing break tests can be roughly grouped into two types: the break identification methods based on asymptotic theory and the Bayesian approaches. Methods based on asymptotic theory are originated from quality control (Page, 1955) and conducted by hypothesis testing procedures. The cumulative sum (CUSUM) and the likelihood ratio statistics have proved to be the most widely applied methods. Methods based on Bayesian approaches generally start with specifying the break process and then go on to make finite-sample inference. The major subdivision of this approach assumes the predictability of breakpoint, which also contributes to break forecasting. A more detailed review of the existing break test approaches is included in AppendixA.

At this point it is worth noting that structural breaks are easily confused with other statistical phenomena. For example, when we analyse the long-run economic activity and its relation to short-run fluctuations, it is actually quite difficult to distinguish between structural changes and unit roots. The debate on unit root or structural change began with Nelson and Plosser (1982) that they could not reject the hypothesis of a unit autoregressive root in 13 of 14 U.S. variables. Conventional viewpoint was that economic dips are followed by recovery (trend-stationary), while the other view was that economic downturns result in permanently lower economic growth levels in the long run. Perron (1989) suggested that much of the persistence of time series was due to infrequent permanent shocks, which also affected the results of unit root test. In this particular case, it proved possible to devise some statistical procedure to separate breaks in level from random walks and also from shifts from a stationary to a random walk behaviour involves several statistics (a systematic review and subsequent research can be found in Diebold, Nerlove, et al., 1988, and Stock, 1994).

In other cases, devising such a procedure has not been possible yet. For example, Diebold and Inoue (2001) performed Monte Carlo experiments to show that a mixture model with appropriately time-varying mixture weight can explain long-range dependence. However, there was not enough evidence to support the causality of structural breaks and long memory. Hence, it is easy to be confused between structural breaks and fractional integration. In a very similar spirit, Granger and Hyung (2004) found that time series with occasional level shifts in mean perhaps showed long memory. The more breaks, the higher value of sample autocorrelation. Disentangling breaks from long memory is one of those cases that actually proved quite difficult especially as the number of breaks increase.

2.3 Methodology

The primary vehicle through which we capture the linkages across stock and foreign exchange markets is the respective price changes that take place in each over time and how closely these evolve over time. To do so, we look at the time-varying correlations of stock market (price) returns with foreign exchange rate returns. Given that the particular focus of this work in capture as accurately as possible the comovements between these series, we bring together two different set of methods. The first is a model that captures the time-varying nature of correlations; and the second is a procedure that captures the possible presence of structural changes. Given that the latter is applied prior to fitting the former, the discussion will first be about detecting breaks and then about the model to capture the time-varying correlations.

With respect to finding the possible structural changes in each market, this seem to be a key point, that has not been considered in the existing literature although surprisingly it is generally viewed as self-evident that there are plenty of factors that are quite likely to affect the dynamics of each series in an abrupt and permanent way. Following Andrews (1993) and Andrews and Ploberger (1994), there have been several break tests that have been developed to find the number and timing of the change points. Appendix A briefly covers the most popular break tests. In this work, we chose break tests that do not make a distinction between breaks in the mean and/or variance dynamics.

With respect to capturing the time-varying correlations between stock and foreign exchange rate returns we adopt two approaches. The first approach is based on the detected breakpoints and the segmentation of the samples. Using the typical non-parametric sample correlation coefficient estimated for each segment effectively captures one form of time-variation, even if that seems piecewise. The second approach is based on the dynamic conditional correlation model (DCC) of R. Engle (2002) which is able to model the dynamics of market comovements, based on multivariate volatility specification. An alternative options would be the DCC of Tse and Tsui (2002), but given the segmentation of the samples due to the existence of breaks the former model, which is computationally simpler (the conditional correlation is not formulated as a weighted sum of past correlations), is more appropriate. Given the similarity of the specification however, it is hardly likely that the results would be any different. The remainder of this part provides more details about the two aspects of the adopted modeling approach.

2.3.1 Break test

To identify the number and timing of breaks in regression models, a variety of approaches are available. The typical paradigm is to adopt one popular break test and apply it each series. More recently however, some procedures allow the combination of the outcomes of several break tests, producing a more robust set of results. In this work, we follow both of these approaches, the latter based upon the Nominating-Awarding procedure of Karoglou (2010) and the former based on the pruned exact linear time (PELT) of Killick and Eckley (2014).

With respect to the break detection method of Karoglou (2010), this is a two-stage procedure in which the so-called nominating stage is followed by the so-called awarding stage. In the nominating stage, a list of CUSUM-type tests statistics is applied correspondingly in an iterative scheme that identifies the breakpoints in ascending and descending time order. The underlying CUSUM-type tests have been shown to perform satisfactorily under the most common ARCH-type processes (see for example Andreou and Ghysels, 2002). Appendix A describes each in detail. As for the iterative scheme, the algorithm[1] is as follows:

1. Calculate the test statistic under consideration using the available data.
2. If the statistic is above the critical value split, the particular sample into two parts at the date at which the value of a test statistic is maximized.
3. Repeat steps 1 and 2 for the first segment until no more (earlier) change points are found.
4. Mark this point as an estimated change point of the whole series.
5. Remove the observations that precede this point (i.e. those that constitute the first segment).
6. Consider the remaining observations as the new sample and repeat steps 1-5 until no more change points are found.

The same procedure is repeated on the residuals from the best GARCH model. The nominated break dates for each series are simply all those have been detected. The awarding stage compares statistically the means and variances and whole distributions of each pair

[1]There are several advantages of adopting this iterative scheme in comparison to the simple binary-division one that is typically adopted. For example, the latter is likely to produce more breaks when transitional periods exist. Also, the time-ordering search for finding breaks can also avoid potentially existing masking effects especially when it is combined with the ascending and descending time-ordering.

of contiguous segments. If the means, variances or distributions of a pair of contiguous segments are different, the break date is awarded.

Among the various parametric methods, penalised likelihood approaches are widely used. In this work, we apply the pruned exact linear time (PELT) method of Killick and Eckley (2014). This procedure is based on the optimal partitioning approach and involves a pruning step with dynamic programming. The idea is that for a given changepoint, if the cost, C reduces, the best segmentation includes this change point. The candidate changepoints satisfying this condition are noted and removed from the next iteration. More formally, the iterative scheme is,

1. Calculate $C(y_{t^*+1:T}) = \min_{t \in R_{t^*}} [C(y_{t+1:T}) + C(y_{t+1:t^*}) + K]$.
2. Let $t^1 = \arg\{\min[C(y_{t+1:T}) + C(y_{t+1:t^*}) + K]\}$.
3. Set changepoint $cp(t^*) = [cp(t^1), t^1]$.
4. Set $R_{t^*+1} = \{t^* \cap R_{t^*} : C(y_{t+1:T}) + C(y_{t+1:t^*}) + K < C(y_{t^*+1:T})\}$.

The cost function is based on minus the maximum log-likelihood:

$$C(y_{t+1:t^*}) = -\max_{\theta} \sum_{i=1+t}^{t^*} \log f(y_i|\theta). \tag{2.2}$$

For a single point t_θ, the maximum log-likelihood statistic is

$$\lambda = 2[\max_{t_0} ML(t_0) - \log p(y_{1:n}|\hat{\theta})], \tag{2.3}$$

where $\hat{\theta}$ is the maximum likelihood estimate of the parameters. If there are m changepoints, we can extend the statistic to multiple breaks estimation by summing the likelihood of $m+1$ segments,

$$\sum_{i=1} m + 1[C(y_{t^*+1:t_i})] + \beta f(m), \tag{2.4}$$

where $\beta f(m)$ is the threshold. For the change in variance, the cost of a segment is

$$C(y_{t(i-1)+1:t_i}) = (t_i - t_{i-1}) \left[\log(2\phi) + \log\left(\frac{\sum_{j=t_{i-1}+1}^{t_i} (y_j - \mu)^2}{t_i - t_{i-1}} \right) + 1 \right]. \tag{2.5}$$

PELT is designed to identify changes in mean and variance, which makes it plausible to estimate the stationary segments in the volatility of a financial time series. The algorithm has a linear computational cost, which is smaller than binary segmentation. The exactness of the resulting segmentation is not affected that the global optimal segments are yielded.

The simplest way to examine the evolving correlations is by making use of the segmentation of the samples that the detected breaks identify. In particular, after breaks are detected for each series, it is possible to put them together and segment the samples of every pair of stock market returns and foreign exchange rate returns. For each of these jointly-segmented samples, one can simply estimate the typical non-parametric sample correlation coefficient. The time-varying nature of the correlations of each pair of series can then be captured by the corresponding set of these piecewise correlation estimates.

The results are almost averaging those of the Dynamic Conditional Correlation model. This proved particularly useful in building upon them not only a visual but also a statistical comparison of their evolution with other series using the Fisher z-transformation (i.e. inverse hyperbolic tangent function), to deal with the fact that the timing and magnitude of change in correlation may differ in each pair, and through that to perform the typical Z-test for testing the equality of the cross-sectional relationships. Consequently, we would be able to more explicitly test the impact of the dichotomy between developed and developing countries on the evolution of correlations.

2.3.2 Dynamic conditional correlation

As explained above, here we employ the dynamic conditional correlation specification, proposed by R. Engle (2002). The VAR-GARCH DCC is shown as followed,

$$r_t = \gamma_0 + \sum_{i=1}^{m} \gamma_i r_{t-a} + \varepsilon_t \tag{2.6}$$

$$\varepsilon_t = diag\{\sqrt{h_{i,r}}\} \cdot \mu_t, \quad \mu_t \sim i.i.d \tag{2.7}$$

$$h_t = \omega + \sum_{i=1}^{p} \kappa_i h_{t-i} + \sum_{i=1}^{q} \lambda_i (\varepsilon_{t-i} \varepsilon'_{t-i}) \tag{2.8}$$

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha(\mu_{t-1}\mu'_{t-1}) + \beta Q_{t-1} \tag{2.9}$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}. \tag{2.10}$$

$r_t = (r_{s,t}, r_{f,t})'$vector of daily log-returns of stock index and foreign exchange rate; $\varepsilon_t = (\varepsilon_{s,t}, \varepsilon_{f,t})'$ is the residuals from VAR model, $h_t = (h_{s,t}, h_{f,t})'$ is the conditional variance and $\mu_t = (\mu_{s,t}, \mu_{f,t})'$ is the standardized residuals of GARCH model. γ, ω and λ are coefficients.

In the step of DCC, $\bar{Q} = E[\mu_t, \mu_t']$ is the unconditional variance matrix of μ_t; $Q_t = (q_{ij,t})$ is a symmetric positive definite matrix. R_t contains conditional correlations,

$$\rho_{sf,t} = \frac{(1-\alpha-\beta)\bar{q}_s f + \alpha\mu_{f,t-1} + q_{sf,t-1}}{\left((1-\alpha-\beta)\bar{q}_s s + \alpha\mu^2_{s,t-1} + q_{ss,t-q}\right)^{1/2}\left((1-\alpha-\beta)\bar{q}_f f + \alpha\mu^2_{f,t-1} + q_{ff,t-q}\right)^{1/2}} \tag{2.11}$$

The DCC model can be estimated with a two-stage approach to maximize the log-likelihood function.

$$L(\theta, \phi) = L_V(\theta) + L_C(\theta, \phi) \tag{2.12}$$

where $L_V(\theta)$ is volatility term that sums individual GARCH likelihoods, and $L_C(\theta, \phi)$ is used to estimate the correlation parameters.

To fit each pair of data segments the best DCC-GARCH model, we set the lag, m of VAR (m) and the lag, p and q to be in the range of 1 to 6. Firstly, each pair of series is processed through the mean model iteratively with respect to $m \in [1, 6]$. The best-fit one is picked up according to AIC. Respectively the residuals ε_t are further modeled by DCC-GARCH in the same iterative scheme with $p, q \in [1, 6]$. Accordingly, the best fit ones are chosen by the minimum value of BIC.

2.4 Data

Data comprises of 22-years daily close-to-close country stock market indices and foreign exchange rates. In this work, foreign exchange rates are nominal exchange rates, which daily spot price against the U.S. dollar (USD). Selection of the currencies is to cover different levels of economic development and different regions. The sample set is narrowed down to 18, because many countries do not have legal tender of their own, or the exchange rate was pegged for the most time. For the selection of 18 currencies, the ones of Brazil, India, Indonesia, South Africa, South Korea, Thailand and Turkey are under managed float regime;

Danish krone and Hong Kong dollar are fixed price; Chinese yuan and Swiss franc are under Crawl-like arrangement; and the others are free floating. The data spans from the 1st of January 1996 to the 31st of December 2017 and consequently there are 5740 number of data points in each series. This time span covers periods of many financial market events, such as the 1997 Asian crisis, the introduction of euro, the dot-com bubble, the 2007 subprime crisis and the ensuing sovereign debt crisis. Data were obtained from DataStream.

Following customary practice, we model the daily returns i.e. the first-order difference of the natural logarithm of the closing prices, given as:

$$r_t = \ln p_t - \ln p_{t-1} \tag{2.13}$$

Table 2.2 and Table 2.3 provide a statistical overview of all the return series by reporting the sample arithmetic mean, standard deviation, skewness and excess kurtosis. Overall, stock markets tend to be generally more volatile than foreign exchanges. All equity indices have leptokurtic distributions and the overwhelming majority of them are negatively skewed. In contrast, currencies tend to have positive skewness although they all have also leptokurtic distributions.

Table 2.4 presents the simple correlations of each pair of assets. Large correlation appears in many data pairs. Among 18 currencies, Brazilian real, Canadian dollar, Indian rupee, Japanese yen, Mexican peso and South African rand tend to have stronger correlations with some of the benchmark indices.

Table 2.2: Descriptive statistics of the daily log-returns of 18 benchmark foreign exchanges.

Country	Index	Number of observation	Mean	Standard deviation	Skewness	Kurtosis
Brazil	BRL	5740	2.14E-04	0.0099	0.4794	16.7385
Canada	CAD	5740	-1.48E-05	0.0054	-0.1097	5.9366
China	CNY	5740	-4.26E-05	0.0010	-0.6946	68.9859
Denmark	DKK	5740	1.96E-05	0.0061	0.0689	2.7218
Eurozone	EUR	5740	1.80E-05	0.0060	-0.1725	2.5093
Hong Kong	HKD	5740	1.91E-06	0.0003	-2.5398	60.1470
India	INR	5740	1.04E-04	0.0037	0.3577	9.2336
Indonesia	IDR	5740	3.10E-04	0.0137	2.0417	82.4253
Japan	JPY	5740	1.53E-05	0.0067	-0.4806	5.1162
Mexico	MXN	5740	1.62E-04	0.0066	0.7614	12.2307
Russia	RUB	5740	4.36E-04	0.0156	5.4163	337.3219
South Africa	ZAR	5740	2.13E-04	0.0100	0.2734	5.8987
South Korea	KRW	5740	5.61E-05	0.0088	-0.7254	99.4361
Sweden	SEK	5740	3.68E-05	0.0071	-0.1821	3.5786
Switzerland	CHF	5740	-2.90E-05	0.0067	-0.8168	21.9843
Thailand	THB	5740	4.49E-05	0.0054	0.9013	54.8741
Turkey	TRY	5740	7.23E-04	0.0096	7.5428	274.8002
UK	GBP	5740	2.40E-05	0.0057	0.5626	11.5582

Table 2.3: Descriptive statistics of the daily log-returns of 26 benchmark stock indices.

Country	Index	Number of observation	Mean	Standard deviation	Skewness	Kurtosis
Australia	ASX300	5740	1.80E-04	0.0095	-0.5064	6.1591
Belgium	BEL20	5740	1.63E-04	0.0120	-0.0363	5.9839
Brazil	IBOV	5740	5.01E-04	0.0198	0.2894	14.1798
Canada	TSX60	5740	2.15E-04	0.0106	-0.7095	9.9569
China	SSEC	5740	3.13E-04	0.0164	-0.3877	5.7908
Chile	IGPA	5740	2.76E-04	0.0075	-0.0331	10.1997
Denmark	OMXC20	5740	3.70E-04	0.0106	-0.4165	5.9086
France	CAC40	5740	1.82E-04	0.0141	-0.0636	4.8417
Germany	DAX30	5740	3.04E-04	0.0147	-0.1469	4.4525
Greece	ATHEX	5740	-2.89E-05	0.0187	-0.3004	6.0386
India	NIFTY500	5740	4.68E-04	0.0148	-0.4350	7.3607
Indonesia	IDX	5740	4.38E-04	0.0150	-0.2235	8.9491
Ireland	ISEQ	5740	2.00E-04	0.0131	-0.6711	8.9169
Italy	MIB	5217	-2.11E-05	0.0154	-0.1993	4.7400
Japan	NIKKEI	5740	2.37E-05	0.0147	-0.3173	6.1841
Mexico	MEXBOL	5740	5.01E-04	0.0138	0.0371	8.3215
Netherlands	AEX	5740	1.58E-04	0.0140	-0.1476	6.0343
Portland	WIG30	5740	1.98E-04	0.0159	-0.1830	3.1289
South Korea	KOSPI	5740	1.79E-04	0.0170	-0.2204	6.0816
Spain	IBEX35	5740	1.77E-04	0.0146	-0.1512	5.7964
Sweden	OMXS30	5740	2.68E-04	0.0146	0.0395	4.1387
Switzerland	SMI	5740	1.82E-04	0.0117	-0.1867	6.4333
Thailand	SET	5740	5.48E-05	0.0150	0.0466	8.6329
Turkey	XU100	5740	9.87E-04	0.0232	-0.0330	6.8957
UK	FTSE	5740	2.86E-04	0.0097	-0.5152	5.9259
US	S&P500	5740	2.56E-04	0.0117	-0.2488	8.5784

Table 2.4: Pearson correlation of the daily returns of foreign exchange and national stock indices.

	BRL	CAD	CNY	DKK	EUR	HKD	INR	IDR	JPY
ASX300	-0.2027	-0.2318	-0.0583	-0.0458	-0.0664	-0.0798	-0.2216	-0.1048	0.1112
BEL20	**-0.3058**	-0.2936	-0.0357	-0.0151	-0.0110	-0.0680	-0.2240	-0.0556	**0.2536**
IBOV	-0.2427	-0.1950	-0.0361	-0.0599	-0.0514	-0.0394	-0.1427	-0.0643	0.0931
TSX60	**-0.2524**	-0.2314	-0.0312	-0.0699	-0.0668	-0.0689	-0.1618	-0.0586	0.1280
SSEC	-0.0690	-0.0640	-0.0365	-0.0587	-0.0362	-0.0300	-0.1185	-0.0277	0.0407
IGPA	**-0.2592**	-0.2322	-0.0203	-0.0533	-0.0491	-0.0735	-0.1997	-0.0668	0.1475
OMXC20	**-0.3088**	**-0.3090**	-0.0240	-0.0043	-0.0103	-0.0731	-0.2233	-0.0737	0.2463
CAC40	**-0.3265**	**-0.3258**	-0.0380	-0.0030	0.0216	-0.0700	-0.2096	-0.0652	**0.2722**
DAX30	**-0.3016**	**-0.2871**	-0.0399	0.0133	0.0400	-0.0533	-0.1881	-0.0646	0.2394
ATHEX	-0.1913	-0.2062	-0.0321	-0.0861	-0.0724	-0.0569	-0.1828	-0.0550	0.1358
NIFTY500	-0.1506	-0.1492	-0.0400	-0.0486	-0.0394	-0.0514	**-0.3083**	-0.0636	0.1055
IDX	-0.1526	-0.1459	-0.0713	-0.0388	-0.0286	-0.0589	-0.2049	-0.2346	0.0603
ISEQ	**-0.2672**	**-0.2603**	-0.0123	0.0111	0.0198	-0.0444	-0.2045	-0.0470	**0.2532**
MIB	**-0.3149**	**-0.3257**	-0.0430	-0.0683	-0.0535	-0.0779	-0.2294	-0.0695	**0.2647**
NIKKEI	-0.1594	-0.1721	-0.0174	-0.0023	-0.0275	-0.0744	-0.1463	-0.0860	0.1549
MEXBOL	-0.2221	-0.1993	-0.0277	-0.0508	-0.0378	-0.0400	-0.1475	-0.0740	0.1058
AEX	**-0.3136**	**-0.3103**	-0.0378	0.0278	0.0602	-0.0553	-0.1973	-0.0628	0.2700
WIG30	-0.2218	**-0.2693**	-0.0307	-0.0400	-0.0636	-0.0490	-0.1864	-0.0982	0.1297
KOSPI	-0.1529	-0.1491	-0.0415	-0.0160	-0.0168	-0.0580	-0.1666	-0.0866	0.0639
IBEX35	**-0.3197**	**-0.3155**	-0.0482	-0.0569	-0.0334	-0.0707	-0.2186	-0.0706	0.2438
OMXS30	**-0.3034**	**-0.2898**	-0.0347	-0.0082	0.0136	-0.0600	-0.1829	-0.0585	0.2170
SMI	**-0.2791**	**-0.2601**	-0.0205	0.0410	0.0707	-0.0410	-0.1686	-0.0564	**0.2571**
SET	-0.1416	-0.1728	-0.0466	-0.0566	-0.0351	-0.0579	-0.1862	-0.1545	0.0489
XU100	-0.2012	-0.1869	-0.0151	-0.0283	-0.0444	-0.0437	-0.1495	-0.0182	0.0937
FTSE	**-0.3519**	**-0.3621**	-0.0548	-0.0665	-0.0826	-0.0782	**-0.2781**	-0.0702	0.2415
SP500	-0.1946	-0.2051	-0.0164	-0.0452	-0.0233	-0.0437	-0.1370	-0.0329	0.1561

Continued on the next page.

Table 2.4 Continued from the previous page.

	MXN	RUB	ZAR	KRW	SEK	CHF	THB	TRY	GBP
ASX300	**-0.2584**	-0.0700	-0.2022	**-0.2529**	-0.1505	0.0258	-0.0860	**-0.2522**	-0.1135
BEL20	**-0.4176**	-0.0898	**-0.2944**	-0.1568	-0.1778	0.1185	-0.0435	-0.1677	-0.1095
IBOV	**-0.3077**	-0.0954	-0.2462	-0.1234	-0.1336	0.0388	-0.0830	-0.1095	-0.0944
TSX60	**-0.3007**	-0.0963	**-0.2532**	-0.1024	-0.1806	0.0271	-0.0637	-0.1308	-0.1331
SSEC	-0.0620	-0.0496	-0.0766	-0.1092	-0.0703	-0.0155	-0.0479	-0.0922	-0.0496
IGPA	**-0.3200**	-0.0951	-0.2373	-0.1357	-0.1453	0.0492	-0.0831	-0.1480	-0.0901
OMXC20	**-0.4087**	-0.1170	**-0.2777**	-0.1686	-0.1899	0.1168	-0.0674	-0.2147	-0.1211
CAC40	**-0.4529**	-0.1194	**-0.3107**	-0.1446	-0.1712	0.1558	-0.0587	-0.1593	-0.0907
DAX30	**-0.4136**	-0.1058	**-0.2775**	-0.1166	-0.1384	0.1580	-0.0544	-0.1571	-0.0714
ATHEX	**-0.2504**	-0.1208	-0.1956	-0.1286	-0.1535	0.0414	-0.0780	-0.1631	-0.1133
NIFTY500	-0.1855	-0.0543	-0.1420	-0.1389	-0.1089	0.0283	-0.0708	-0.1812	-0.0776
IDX	-0.1810	-0.0738	-0.1515	-0.1901	-0.1011	0.0257	-0.1564	-0.1785	-0.0781
ISEQ	**-0.3756**	-0.1060	**-0.2650**	-0.1383	-0.1419	0.1283	-0.0397	-0.1594	-0.1250
MIB	**-0.4453**	-0.1247	**-0.3158**	-0.1759	-0.2137	0.0948	-0.0649	-0.1608	-0.1507
NIKKEI	-0.2090	-0.0575	-0.1585	-0.2066	-0.1043	0.0568	-0.0738	-0.2029	-0.0929
MEXBOL	**-0.3058**	-0.0562	-0.2265	-0.1320	-0.1391	0.0553	-0.0646	-0.1312	-0.0799
AEX	**-0.4350**	-0.1135	**-0.2823**	-0.1402	-0.1395	0.1809	-0.0499	-0.1539	-0.0840
WIG30	**-0.3138**	-0.1034	-0.2465	-0.1515	-0.1896	0.0466	-0.1022	-0.1685	-0.1095
KOSPI	-0.1803	-0.0357	-0.1329	-0.3428	-0.0875	0.0491	-0.1096	-0.1736	-0.0549
IBEX35	**-0.4424**	-0.1131	**-0.3006**	-0.1427	-0.1843	0.1159	-0.0712	-0.1719	-0.1341
OMXS30	**-0.4106**	-0.1115	**-0.2700**	-0.1483	-0.1604	0.1321	-0.0714	-0.1653	-0.0710
SMI	**-0.3991**	-0.0955	**-0.2518**	-0.1152	-0.1138	**0.2630**	-0.0370	-0.1346	-0.0457
SET	-0.1859	-0.0380	-0.1381	-0.1902	-0.1088	0.0352	-0.2172	-0.1572	-0.0743
XU100	**-0.2684**	-0.0873	-0.2176	-0.1057	-0.1304	0.0393	-0.0610	-0.2226	-0.0724
FTSE	**-0.4424**	-0.1300	**-0.3465**	-0.1877	-0.2483	0.0702	-0.0722	-0.2397	-0.1507
SP500	**-0.2669**	-0.0691	-0.1979	-0.0753	-0.1273	0.0822	-0.0278	-0.1040	-0.0861

Note: Correlations that are larger than 0.25 are presented in bold.

2.5 Empirical results

Following the discussion of the Methodology, the empirical results are presented effectively in three sections and discussed a separate final section. In particular, the first section (Section 2.5.1) presents the results from applying the break tests; the second section (Section 2.5.2), which as noted in the Methodology effectively builds upon the results of the previous one, presents the results from estimating the non-parametric correlation coefficient for each jointly segmented pair of series; and the third section (Section 2.5.3) does the same but for the estimates based upon the best-fit DCC model. The last section (Section 2.5.4) provides an overall discussion of the results.

2.5.1 Breakpoints

Both break detection approaches have identified several breakpoints. The number of breakpoints produced by the Nominating-Awarding procedure range from one to eleven, which suggests that the average duration of a regime lies between two to eleven years. The respective break dates listed in Table 2.5 and Table 2.6. In the same vein, the number of breakpoints produced by the PELT procedure under the penalty value 10^{-7}, is quite similar to the Nominating-Awarding procedure, ranging from two to thirteen. However, the threshold of the penalty is still an ongoing research (Killick and Eckley, 2014), so there is lack of theoretical evidence of a best penalty method. As the penalty value is the theoretical type I error, we set the penalty value to be at most 10^{-6}. The number of changepoint changes slightly with respect to the penalty value after 10^{-6}, as exemplified in Figure 2.5.The respective break dates presented in Table 2.7 and Table 2.8 are also quite similar.

One of the most interesting features of the detected break dates is that most of these dates match both the timing of some extraordinary events that took place in the past two decades and the timing of major influential events that took place within each market or regionally. For example, the detected breaks that are found in the currency markets of east and south Asia in mid-1997, such as China, Indonesia, South Korea and Thailand, are consistent with what is generally agreed as the overall date of Asian crisis. Similarly, breaks are found in the Russian ruble during 1998 and 2014 match the dates of Russian crises. Breaks are also detected in the major equity markets in 2001/2, which can be attributed to

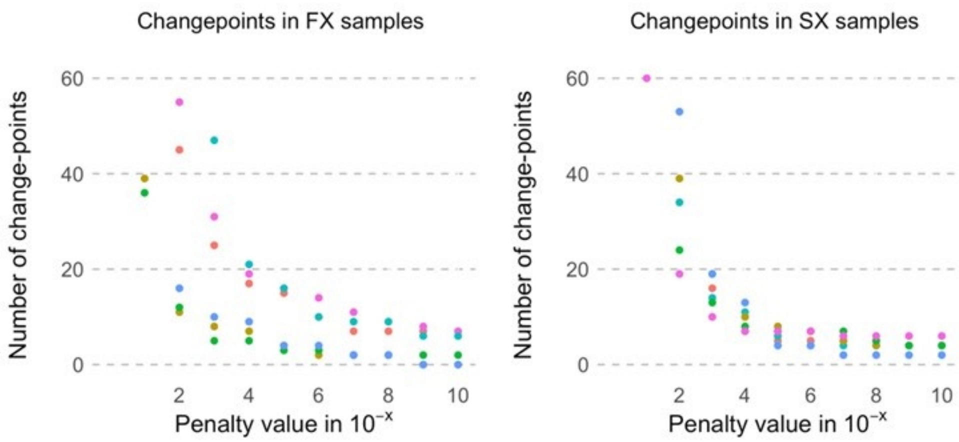

Figure 2.5: Number of change point of SX and FX daily returns with respect to penalty value.

Table 2.5: Dates of breakpoints in foreign exchange returns, detected by Nominating-Awarding method.

BRL	CAD	CNY	DKK	EUR	HKD	INR
18 Jan 1999	24 Aug 1998	21 Feb 2014	19 Aug 2004	19 Aug 2004	21 Sep 1998	28 Aug 1998
10 Jun 2003	14 Sep 2007		13 Aug 2008	13 Aug 2008	25 Sep 2003	02 May 2008
09 Sep 2008	14 Sep 2010		21 Nov 2011	21 Nov 2011	24 Nov 2003	09 Oct 2013
30 Jun 2009	23 Jan 2015		20 Jan 2015	20 Jan 2015	13 Jan 2016	
08 Oct 2014	25 Jan 2016		02 Sep 2015	02 Sep 2015	16 Feb 2016	
					30 Mar 2016	
IDR	**TRY**	**MXN**	**RUB**	**KRW**	**SEK**	**GBP**
01 Oct 1997	27 Feb 2001	27 May 2009	28 Aug 1998	20 Nov 1997	02 Sep 1998	01 Jul 2002
27 Oct 1999	27 Nov 2001	13 Aug 2012	12 Jan 1999	12 Aug 1998	13 Aug 2008	18 Jun 2010
22 Oct 2002	05 May 2009	11 Mar 2015	04 Nov 2014	18 Mar 2008	19 Dec 2011	17 Jan 2012
24 Jun 2009	17 Dec 2014	12 Jan 2016	19 Jan 2015	20 May 2009		07 Jan 2015
20 Aug 2013				28 Dec 2011		15 Jan 2016
				04 Nov 2014		

the dot-com bubble burst at that time. Finally, it is worth noting that in most stock market returns and almost half foreign exchange rate returns, structural breaks appeared in mid-2007. On the side, it is interesting to mention that even the June 2016 Brexit referendum can be associated with a detected break in the markets of the UK and of some EU countries.

Table 2.6: Dates of breakpoints in stock market returns, detected by Nominating-Awarding method.

ASX300	BEL20	TSX60	IGPA	OMXC20	CAC40	DAX30
30 Oct 2001	05 Aug 1997	30 Oct 1997	12 Jun 1998	15 Jul 1997	06 Aug 1998	24 Jul 1997
30 Jul 2007	27 Jul 2007	24 Aug 2009	19 May 2000	13 Aug 2007	16 Apr 2003	20 Jun 2003
22 Jul 2009	18 Jan 2008	09 Jan 2012	06 Dec 2011	03 Jul 2009	18 Jan 2008	18 Jan 2008
11 Jan 2012	27 May 2009	24 Sep 2014	05 Jun 2013	31 Mar 2015	19 May 2009	21 Jul 2009
03 Dec 2014	07 Oct 2014	24 Aug 2015	20 Feb 2014		09 Aug 2012	09 Aug 2012
01 Jul 2015		23 Feb 2016	06 Jul 2015		26 Sep 2014	15 Oct 2014
09 Oct 2015					25 Jun 2015	
					09 Oct 2015	

ATHEX	ISEQ	MIB	NIKKEI	KOSPI	MEXBOL	AEX
28 Sep 2001	27 Jul 2007	11 Apr 2003	09 Jan 2008	05 May 2003	28 Oct 1997	21 Jul 1997
26 Jun 2008	14 Jul 2010	09 Sep 2008	25 May 2009	24 Jul 2009	10 Jan 2001	11 Jul 2003
17 Oct 2014	12 Jun 2012	27 May 2009	26 Aug 2015	20 Sep 2012	19 Oct 2001	18 Jan 2008
31 Aug 2015	07 Oct 2014	13 Aug 2012		02 Jul 2015	29 Jul 2009	21 Jul 2009
		26 Sep 2014		24 Feb 2016	07 Dec 2009	26 Dec 2011
		02 Jul 2015			24 Jan 2012	06 Oct 2014
					18 Mar 2013	25 Jun 2015
					21 Oct 2013	09 Oct 2015
					03 Dec 2014	07 Mar 2016
					18 Feb 2015	
					27 Jul 2015	

WIG30	IBEX35	OMXS30	SMI	XU100	FTSE	SP500
11 Feb 2002	13 Apr 2004	29 Oct 1998	09 Jul 1998	02 Nov 1998	20 Jul 1999	01 Apr 1998
01 Jun 2010	20 Jan 2009	14 Apr 2004	29 Jun 2004	20 Apr 2004	22 Jul 2010	22 Oct 1998
15 Aug 2012	13 Sep 2013	29 Jul 2008	30 Jul 2008	27 May 2010	20 Dec 2012	22 Jul 2010
22 Jun 2015		09 Jul 2010	12 Apr 2010		16 Jul 2014	26 Dec 2012
		08 Jul 2013	06 Dec 2012		28 Sep 2015	
		07 Oct 2015	08 Oct 2015			

Table 2.7: Dates of breakpoints in foreign exchange returns, detected by PELT method.

BRL	CAD	CNY	DKK	EUR	HKD	INR	IDR	JPY
11 Jan 1999	23 Oct 1997	28 Mar 1996	06 Aug 2008	09 Sep 2008	09 Dec 1996	14 May 1996	14 Jul 1997	02 May 1997
09 Mar 1999	28 Apr 2003	25 Jun 1997	12 Jun 2009	01 Apr 2009	14 Sep 1998	01 Jan 1997	12 Nov 1998	02 Apr 1999
23 Jul 2002	26 Sep 2008	27 Jun 1997			12 Dec 2000	18 Aug 1997	09 Nov 2001	
15 Nov 2002	18 Mar 2009	03 Aug 1998			18 Sep 2003	21 Aug 1998	19 Jul 2006	
03 Sep 2008	29 Nov 2011	05 Aug 1998			17 Nov 2003	11 Oct 1999	02 Oct 2008	
10 Dec 2008		27 Aug 2001			09 Sep 2005	05 May 2000	30 Jan 2009	
01 Oct 2014		19 Jul 2005			22 Sep 2006	02 Nov 2000	18 Jun 2010	
		21 Jul 2005			19 Mar 2009	15 Sep 2003	08 Sep 2011	
		03 Mar 2006			10 Dec 2009	25 Apr 2008	15 Jun 2012	
		03 Feb 2009			08 Mar 2012	13 Dec 2013	19 Jul 2013	
		15 Jun 2010			06 Jan 2016		14 Dec 2016	
		03 Jul 2015			03 Mar 2016			
		07 Aug 2015						
MXN	RUB	ZAR	KRW	SEK	CHF	THB	TRY	GBP
22 Oct 1997	04 Jun 1998	16 May 1996	16 Oct 1997	09 Sep 2008	25 Feb 2008	07 May 1997	20 Feb 2001	10 Sep 2008
05 Nov 1997	16 Jul 1998	21 May 1998	20 Mar 1998	01 Jul 2009	25 Jan 2012	01 Sep 1998	23 Feb 2001	01 Apr 2009
11 Feb 2004	10 Mar 1999	08 Feb 1999	07 Jan 1999	15 Mar 2012	13 Jan 2015	15 Jan 2001	17 Sep 2001	15 Jun 2016
08 Sep 2008	11 Feb 2000	24 Sep 2001	05 Mar 2008		23 Jan 2015	14 Dec 2006	01 Oct 2008	05 Jul 2016
01 May 2009	20 Nov 2001	08 Sep 2008	28 Aug 2008			22 Mar 2007	06 May 2009	
	03 Dec 2002	01 Apr 2009	29 Apr 2009					
	16 Sep 2004		21 Dec 2011					
	28 May 2008							
	11 Jun 2009							
	22 Aug 2014							
	06 Nov 2014							
	13 Apr 2016							
	24 Oct 2017							

Table 2.8: Dates of breakpoints in stock market returns, detected by PELT method.

ASX300	BEL20	IBOV	TSX60	SSEC	IGPA	OMXC20
01 May 2003	14 Jul 1997	09 Jul 1997	21 Oct 1997	22 Jan 1998	21 Oct 1997	08 Jul 1997
18 Mar 2005	10 Jun 2002	12 Mar 1999	17 Dec 2002	05 Feb 1998	13 Jun 2000	01 Sep 2008
23 Jul 2007	20 May 2003	02 Sep 2008	10 Jul 2007	06 Dec 2006	29 Jan 2007	05 May 2009
15 Jul 2009	20 Jul 2007	01 Apr 2009	29 Aug 2008	27 Nov 2009	22 Jun 2009	07 Nov 2016
	20 May 2009		14 Aug 2009	28 Nov 2014	22 Jul 2011	
	11 Jul 2016		11 Jul 2016	06 May 2016	29 Nov 2011	
					15 Nov 2017	
CAC40	**DAX30**	**ATHEX**	**NIFTY500**	**IDX**	**ISEQ**	**MIB**
10 Mar 1997	08 Jul 1997	31 Dec 1996	16 Jan 2008	04 Aug 1997	24 Oct 1997	04 Jul 2001
31 May 2002	12 Jun 2002	02 Nov 2001	21 Aug 2009	28 Oct 1999	28 Mar 2003	18 Jul 2005
16 May 2003	13 Jun 2003	07 Jan 2008		25 Jul 2007	20 Jul 2007	01 Sep 2006
11 Jan 2008	02 Sep 2008	25 Jun 2015		19 Aug 2009	23 Aug 2010	02 Apr 2007
01 Apr 2009	01 Apr 2009	30 Jul 2015		28 Dec 2016	08 Jun 2016	15 Dec 2014
11 Jul 2016	08 Aug 2016	27 Jun 2016			08 Jul 2016	29 Dec 2015

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Table 2.8 Continued from the previous page.

NIKKEI	MEXBOL	AEX	WIG30	KOSPI	IBEX35
12 Sep 2008	21 Oct 1997	21 Feb 1997	04 Feb 2002	18 Sep 1997	11 Jul 1997
08 Apr 2009	04 Jan 2001	10 Jun 2002	03 Sep 2008	28 Apr 2003	10 Jul 2003
11 Nov 2016	11 Sep 2008	17 Jul 2003	20 Nov 2009	28 Aug 2008	11 Jan 2008
	22 Jul 2009	24 Jul 2007		08 Apr 2009	25 Sep 2012
		11 Sep 2008		13 Sep 2012	
		01 Apr 2009			
		11 Jul 2016			

OMXS30	SMI	SET	XU100	FTSE	SP500
15 Oct 1997	03 Aug 1998	13 Jun 1997	11 Apr 2003	24 Sep 1997	25 Mar 1997
14 Apr 2003	12 Jan 1999	05 Jun 2000	25 May 2010	20 Jul 2007	24 Jul 2003
10 May 2006	30 Aug 2001	26 Oct 2004		20 May 2009	18 Jul 2007
02 Sep 2008	04 Jul 2003	15 Dec 2006		03 Aug 2012	02 Sep 2008
28 Apr 2009	01 Jan 2008	19 Dec 2006		08 Jun 2016	20 Apr 2009
25 Jul 2012	02 Apr 2009	11 Sep 2008		08 Jul 2016	19 Dec 2011
18 Jun 2015	08 Jul 2016	15 Jan 2009			08 Nov 2016
08 Jul 2016		27 Jan 2014			
		11 Nov 2016			

Having obtained all these breaks, it is possible to provide a visual overview of their timing and effect simply by noting them on the graph of each return series. Given the similarities between the two approaches the breakdates depicted will be based on PELT break test. As it can be seen in Figure 2.7 and Figure 2.6, the detected breaks are either at the start of a phase or the end of it. For instance, daily returns become larger around 2007/2008 for equity and currency markets of a large number of countries.

Interestingly, most of the developed markets share several characteristics such as: (i) the 'tranquil' (lowest volatility period) happens in between 2004-2007; (ii) the extremely large returns appear in between late 2007 and early 2010, which has the highest level in the time span of the sample series; (iii) a significant drop of market volatility appears in early 2013.

Another interesting observation seems to be that the Eurozone appears clearly as the most affected area by the recent financial turmoil. By the time of this writing, the impact of the crisis seems to be residing, judging from the level of volatility regime that the breaktest detected. In the largest stock markets in Euro area, the extremely large returns start from 2008 and end in April 2009. After that, the daily returns remain substantially large, at least in comparison to their historical levels, until 2016. However, in the GIPSI[2] countries, the spell of high volatility returns varies in each country, lasting until August 2010 in ISEQ, January 2009 in IBEX35, July 2009 in MIB and July 2015 in ATHEX. Thereafter, and until the end of our sample, the volatility is still higher than what was during the tranquil period of 2004-2008. The rest of the global market seems to have reacted typically much milder to the Eurozone crisis although in various degrees. The level of high volatility returns is hardly ever larger than what it has been during a more local crisis.

In contrast, the results of exchange rate returns in emerging markets tell different stories. China moved to managed floating exchange rate in 2005, and the band is extending throughout recent years. This could partially explain why the influence of the 2007/8 crisis is greater on CNY than the impact of the 1997 Asian crisis. For BRL and ZAR, the influence of 2007 crisis is not as durable as it in INR, which lasts until 2013. A break point in 2008 is also detected in RUB, but the volatility level after that break is rather small comparing

[2]GIPSI is one of the acronyms that have been used in the popular press to refer to the economies of Greece, Italy, Portugal, Spain and Ireland but also Iceland.

to the one that is associated with the 2014 Russia financial crisis.

Figure 2.6: Daily log-returns of stock indices.

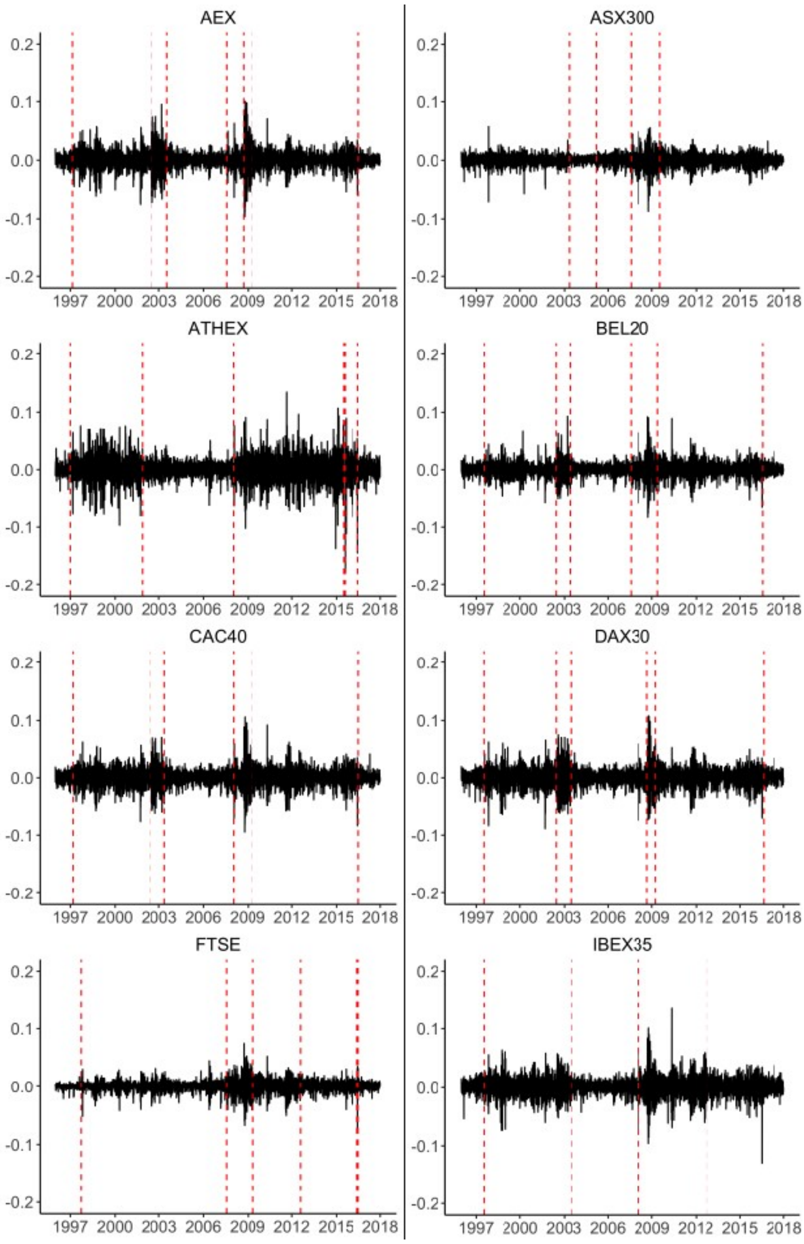

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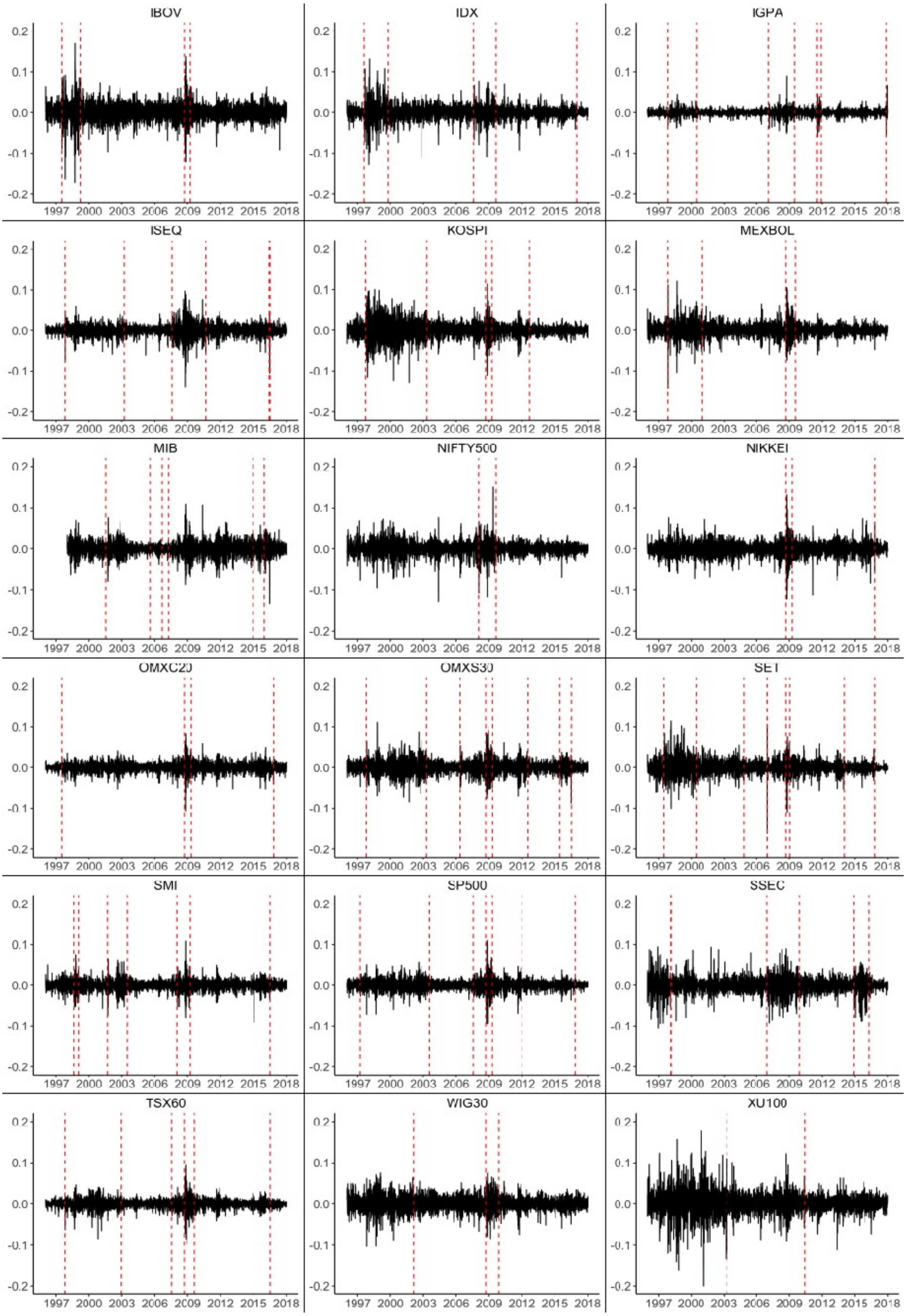
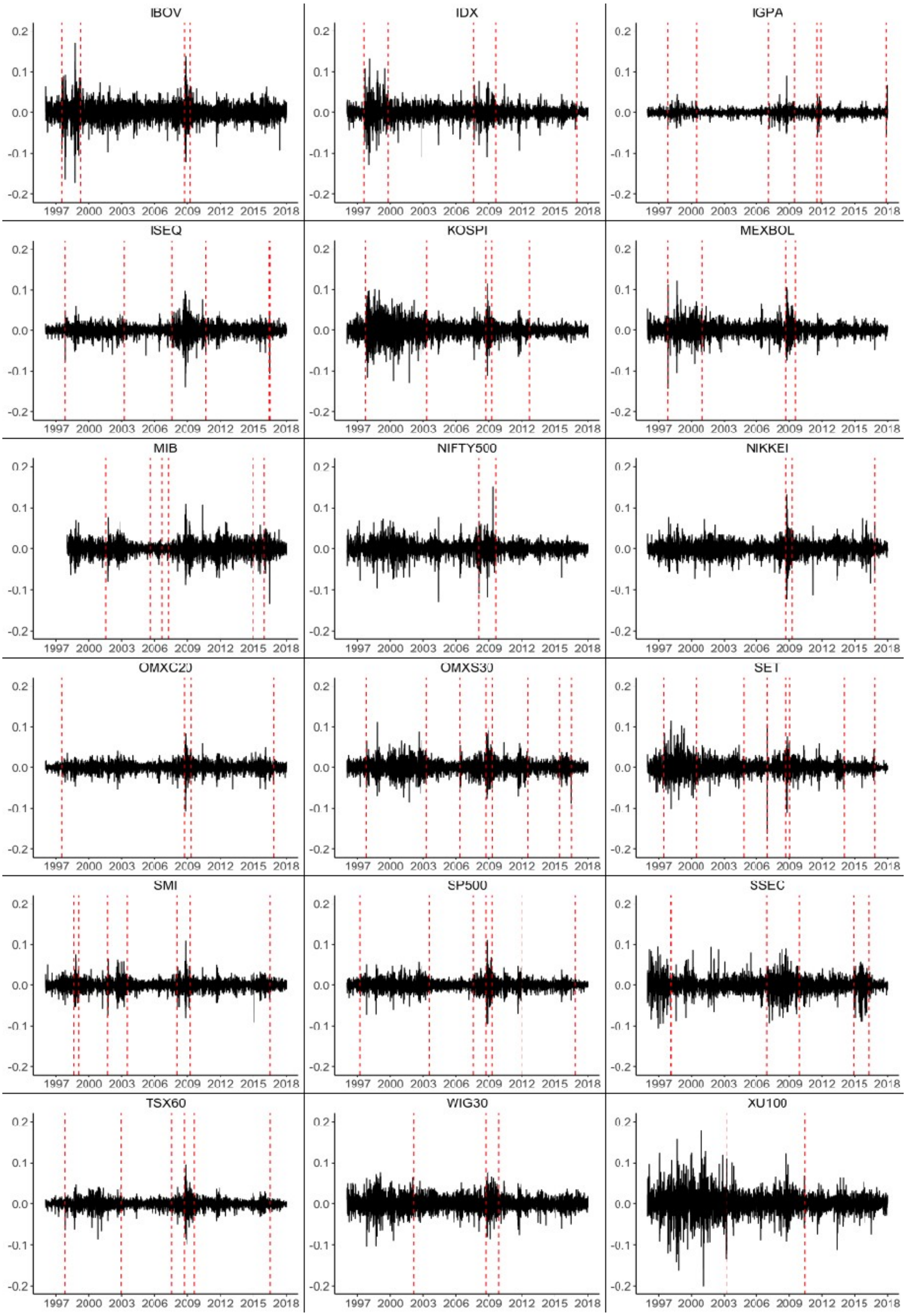
Figure 2.6 Continued from the previous page.



Note: The potential beaks detected by PELT method are marked in red dash.

Figure 2.7: Daily log-returns of foreign exchange and their potential breaks detected by PELT method.



Note: The potential beaks detected by PELT method are marked in red dash.

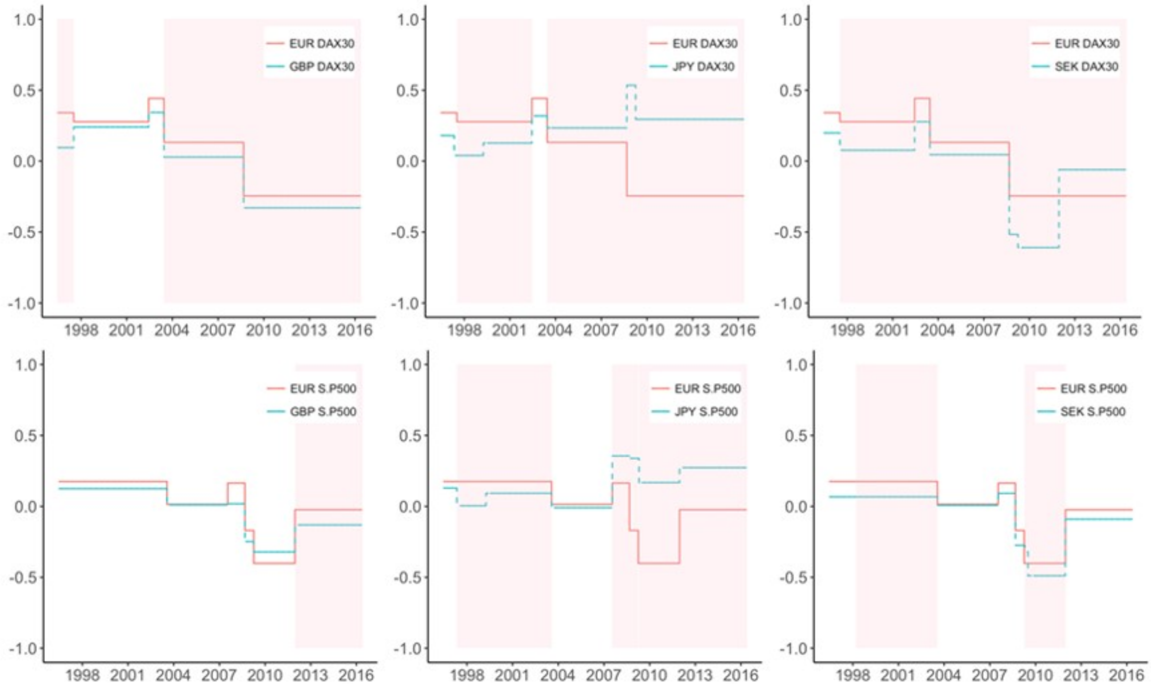
2.5.2 Unconditional segmented correlations

Following the results from break test, in this section we construct a segmented correlation series for each pair of stock market returns and foreign exchange rate returns. Shown in Figure 2.8, shading areas are results of Z-test, which indicate significant difference between correlations according to the respective time span.

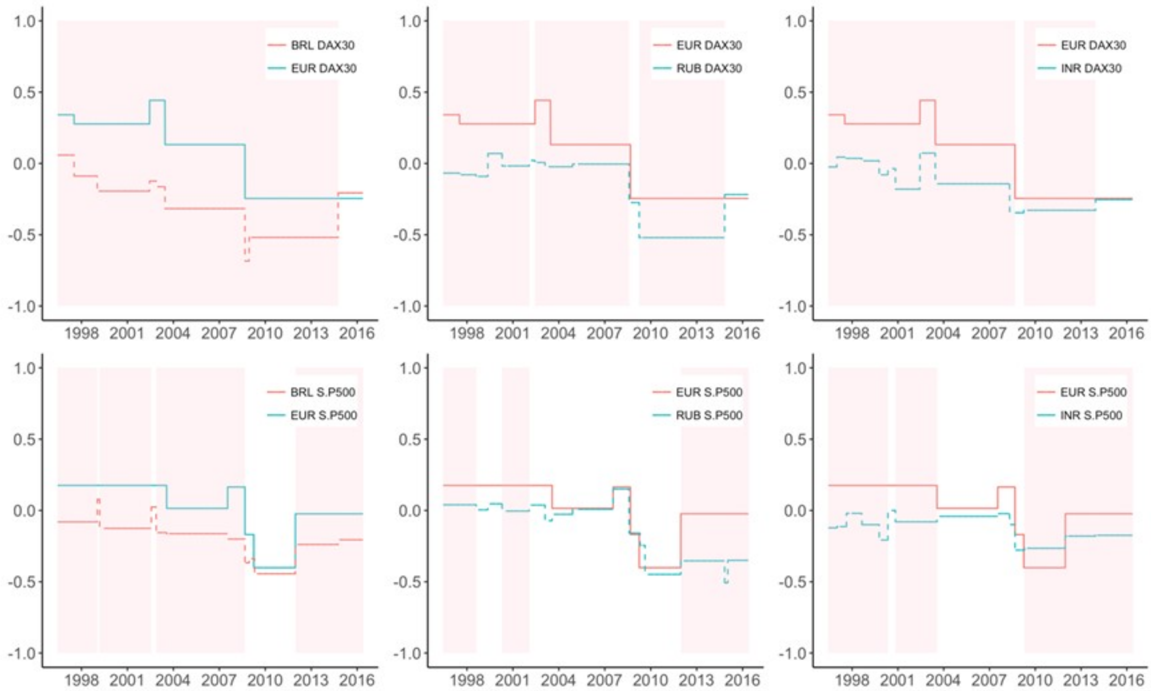
We focus on the comparison between euro and other currencies' connection with two emblematic equity indices, DAX30 and SP500. For a group of currencies there has been no significant difference in the association with SP500. As shown in Figure 2.8, EUR, GBP, SEK, RUB and SGD almost have the same sectional unconditional correlations with SP500, with the value dropping to near -0.5 in 2009-2012. The only exception is JPY, the correlation of which with DAX30 and SP500 is much less volatile than that of the other pairs.

In terms of the major developing markets, the BRICS, we can see that apart from CNY, which fluctuates in a very small range, all the other four currencies are largely affected by the debt crisis. The statistical significance in the difference of correlations of BRICS and euro suggests that the debt crisis has had a major effect on the structure of cross-market correlations. For instance, although the Indian rupee shows relatively week association with Germany, the correlation jumps to around -40% (as the level of euro-Germany) during crisis period.

Figure 2.8: Sectional unconditional correlations of foreign exchange returns and major stock market returns.



(a) Main currencies' correlation with DAX30 (upper row) and SP500 (bottom row).



(b) BRIC country currencies' correlation with DAX30 and SP500.

Note: The time periods are shaded if the correlations are significantly different with Z-test.

2.5.3 Dynamic conditional correlation of stock price and exchange rate

The results from examining all the pairs of stock market returns and foreign exchange returns are plentiful (468 pairwise correlations graphs) and therefore they are included in Appendix A, along with the normality fit of the original series and the standardized residuals.[3] For the robustness, each GARCH model is fit in an iterative fashion from GARCH(1,1), GARCH(2,1) to GARCH(6,6). Accordingly, the best fit ones are chosen by the minimum value of BIC.

Overall they suggest that the conditional correlations between stock market returns (henceforth SX) and foreign exchange rate returns (henceforth FX) decrease at the time of the major economic shocks. The level of correlation changes largely in the period of 2007-2009 for most of the asset pairs. Furthermore, the dichotomy between developing and developed markets has proved to be essential, because developing markets have been much less affected than developed ones by the Global Financial Crisis and the ensuing sovereign debt crisis.

The remainder of this section depicts some significant results based on some major markets. The selection of representative markets are in three aspects. First angle is the cross-market relation among the poles of the world economy, the US, EU and Japan. Majority of the literature on cross-market dependence focused on these three states. This work contributing on this discussion by providing a long-term and dynamic relation analysis. The second angle is to compare developed and developing markets, so more countries are included for this purpose. There are many emerging countries that collectively account for more and more global growth. Particularly, Brazil, China, India, Indonesia, South Korea, South Africa and Russia are rendered as BRIC or BRIICS, because their economic potential are considered to be dominant in the near future. Last but not lease, with respect to the Eurozone crisis, the country group with were at the centre of the storm are quite selected, and the comparison with dominant Eurozone market is informative on the dynamic of global market dependence during large events.

It is worth noting here that Figures 2.9- 2.13 that present the results are also highlighting the generally accepted time of five extraordinary events, namely the 2nd of July 1997

[3] The parameter estimates are excessively voluminous to be presented even in a Thesis and for that reason they have been inevitably omitted. However, they can be made available upon request.

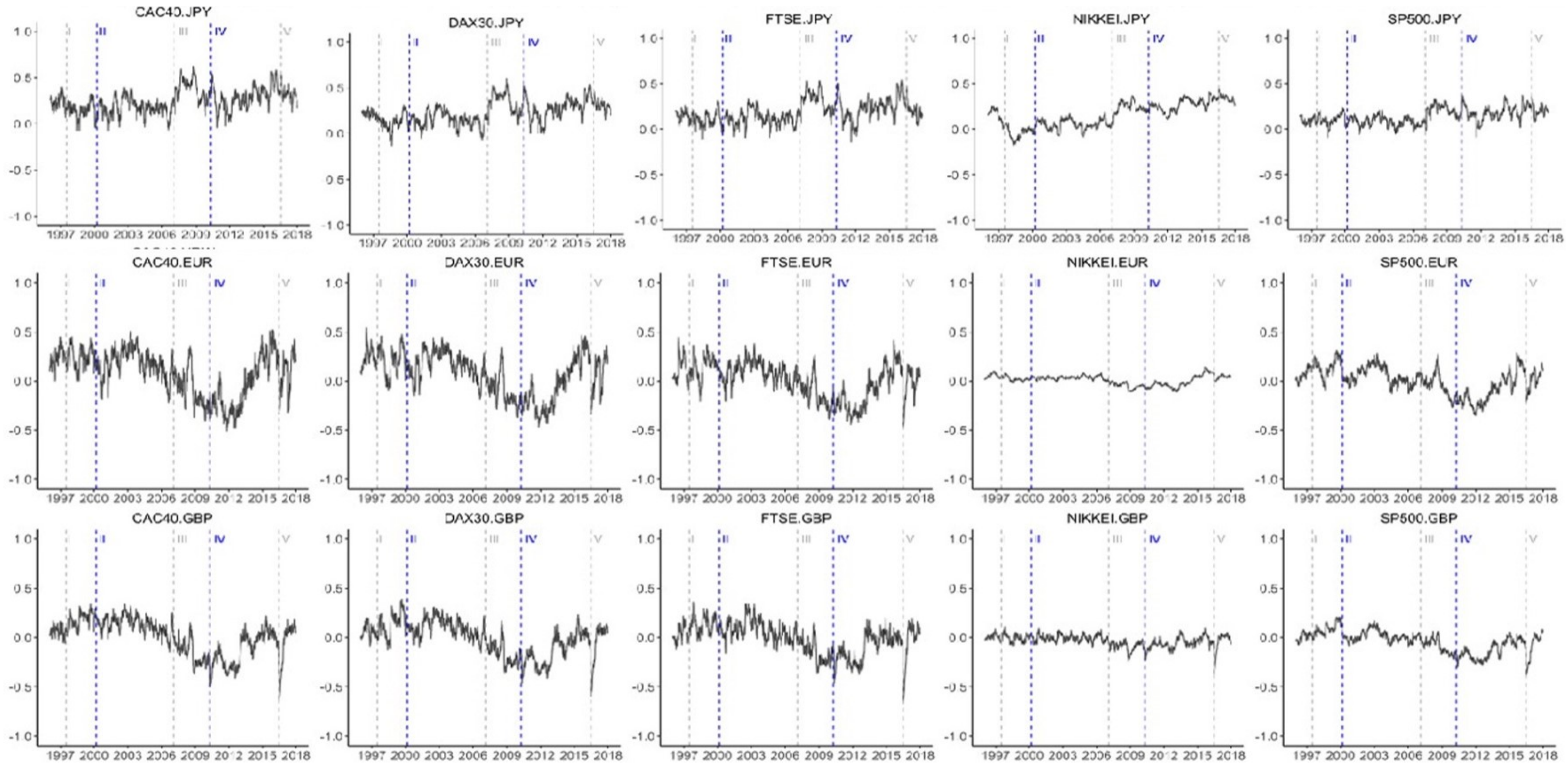
Asia crisis, the 10th of March 2000 dot-com bubble burst, the 29th of January 2007, when the largest subprime lenders started to file for protection or bankruptcy, the 11th April 2010, when the first bailout plan was agreed by EMU leaders to GIPSI, and the another recent one namely the 24th of June 2016 Brexit referendum.

Cross-market dependence in major economies

The cross-market dependence in the financial markets of developed economies shows a lot of heterogeneity. With respect to the three pole of the world economy, shown in Figure 2.9, the strongest dependence appeared within the major EU countries, i.e. France, Germany and the UK. Catalyzed by Eurozone crisis and recent Brexit, comovement of stock composite and foreign exchange had been intensified. Similarly, the comovement of the US stock composite and EU currencies became stronger since the 2008 financial crisis, of which the correlation is slightly milder than it of EU market. On the other side, Japan had the least effect from the other two major states. Japanese yen is positively correlated with the benchmark stock indices, i.e. CAC40, DAX30, NIKKEI, FTSE and SP500 throughout the 22 years. Their correlations increased with the start of 2007/8 financial crisis. Furthermore, NIKKEI was only mildly affected by British pound and euro.

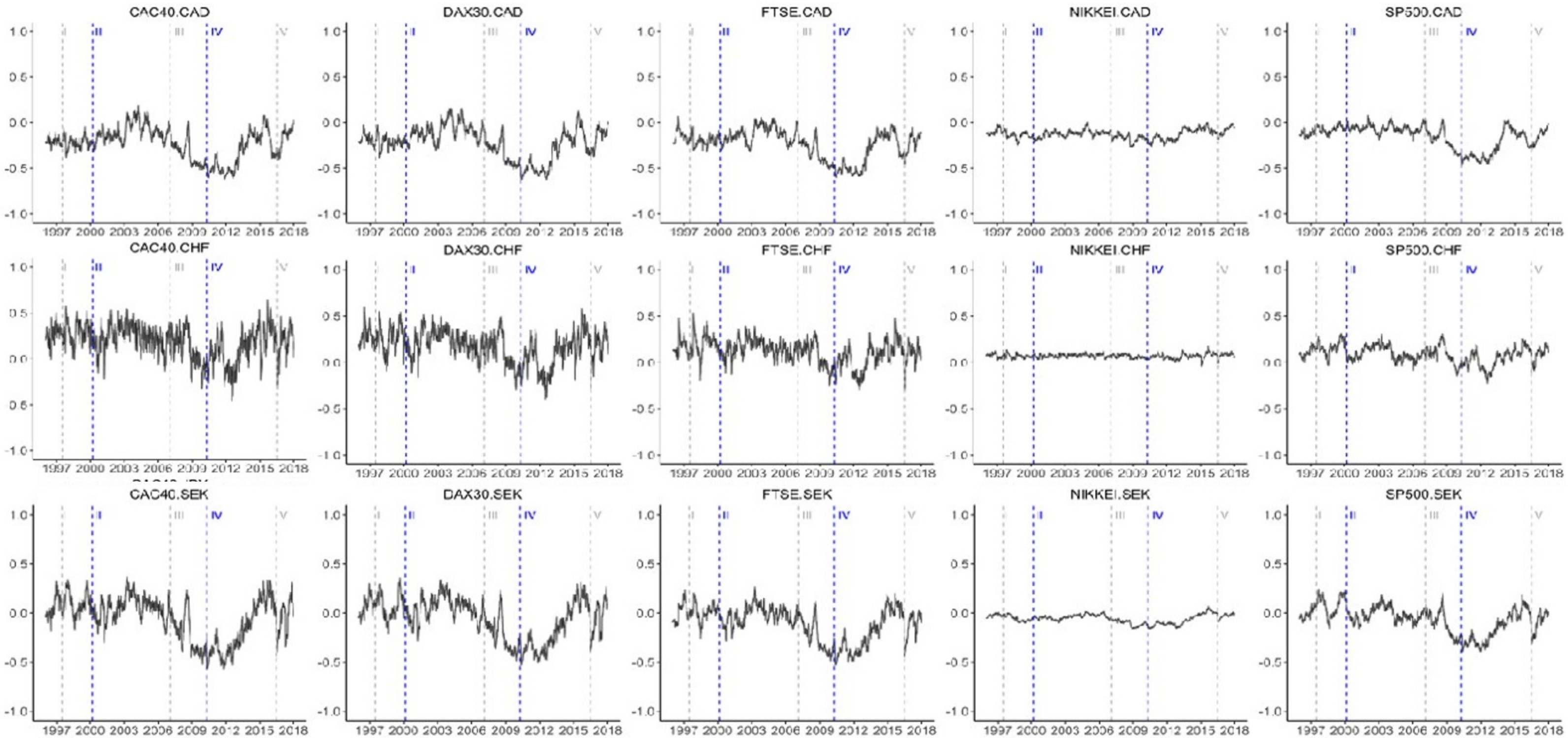
As for the other major currencies, shown in Figure 2.10, Swiss franc, Canadian dollar and Swedish krona are similar to euro, which had positive albeit mild correlations with most of the major stock composite, during the recent financial turmoil reversed into a substantial negative level. The only exception is NIKKEI. Again there was hardly large association between NIKKEI and foreign currencies.

Figure 2.9: Dynamical conditional correlations of major stock composite indices and the world major payment currencies, Japanese yen, British pound and euro.



Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum.

Figure 2.10: Dynamical conditional correlations of Canadian dollar, Swiss franc, Swedish krona and the major stock composite indices.



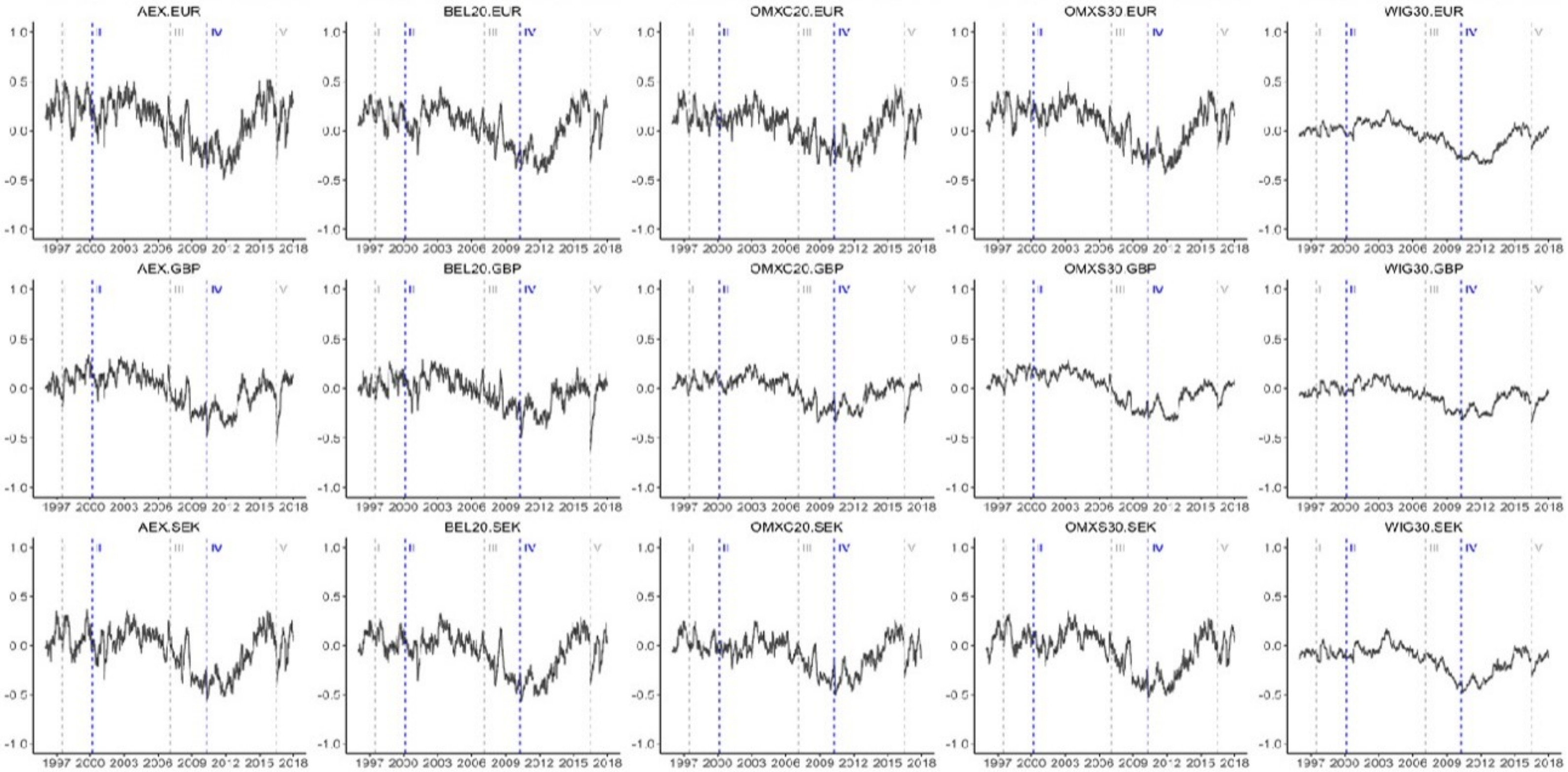
Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum

Cross-market dependence in the European Union

In the European Union, the currencies have homogeneous pattern of the time-varying correlation (Figure 2.11). CAC40, DAX30, FTSE, AEX and BEL20 had almost the same dependence with currency markets. OMXC20 and OMXS30 also shared many similarities. With EU stock markets, the correlations evolved from positive to extreme negative levels since 2007/08 crisis, and recovered to pre-crisis level around 2015. Such fluctuation also happened to correlations of EU currencies, WIG30 and SP500 in a milder way, and followed by NIKKEI, which seemed less affected than the EU currencies. Then, during the time of Brexit referendum, June 2016, the correlations dropped again. In particular, the extreme correlations of UK and EU markets after Brexit are either equal to or even lower than the local minima during the Eurozone crisis.

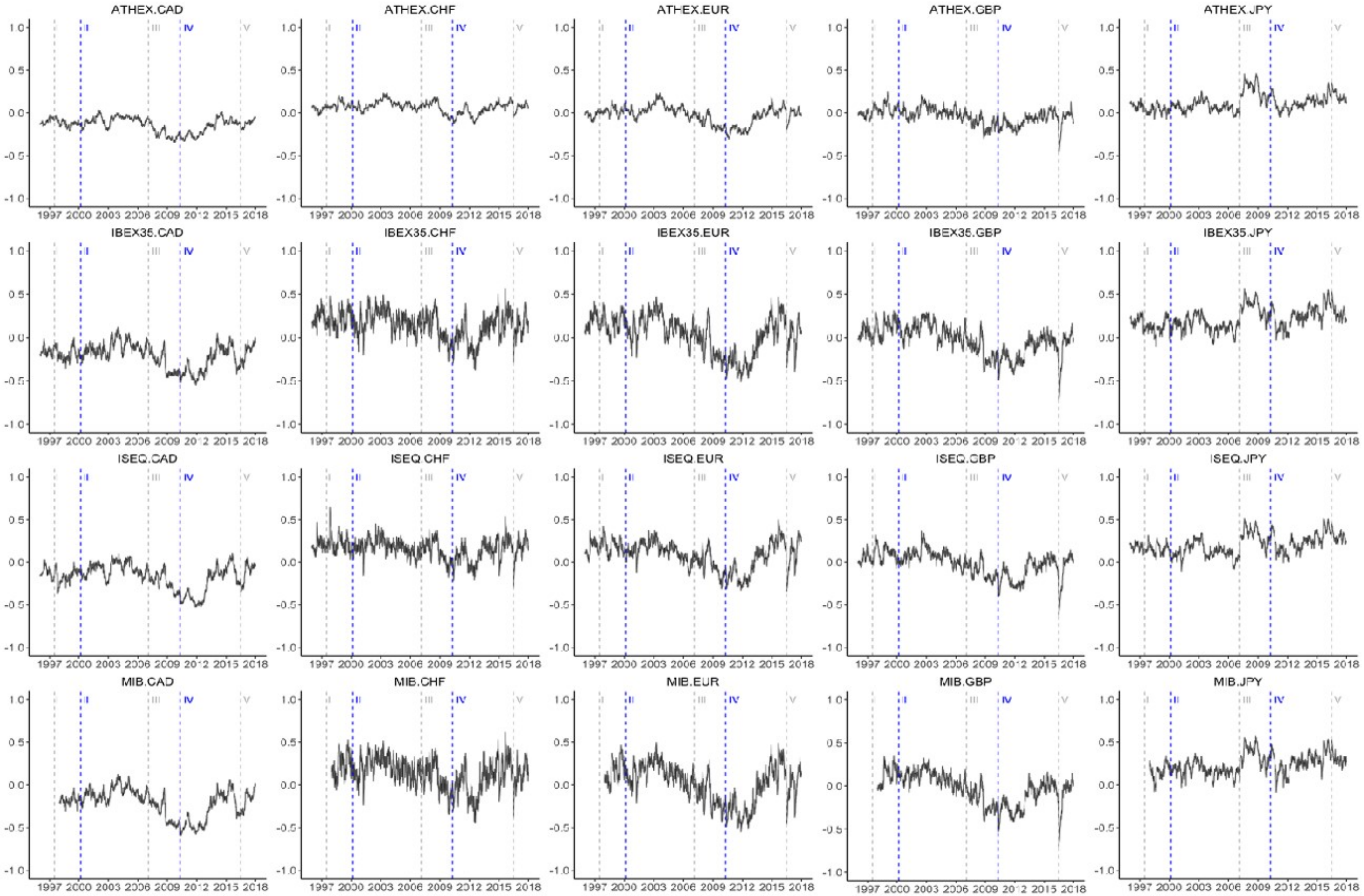
The pattern of cross-market correlations between the stock market returns of the GIPSI economies and the major currencies seem to be homogeneous. As can be seen in Figure 2.12, before the debt crisis, there was around 30% correlation of euro and GIPSI. During the Eurozone debt crisis, the correlation dropped to around -50%. A large level of correlation (around 50%) between JPY and GIPSI markets lasted until 2010, the time of the first bailout package. In fact, there was a gradual erosion in the level of correlation before our choice of subprime crisis date. Recovery of the extreme level of correlations was expected after the announcement of bailout plan, when the correlations bounced but dropped again after April 2010. The actual recovery started in late 2011 for the major markets, and then in early 2012 for GIPSI markets.

Figure 2.11: Dynamical conditional correlations of EU stock market and currencies.



Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum

Figure 2.12: Dynamical conditional correlations of major currencies and GIPSI equities.



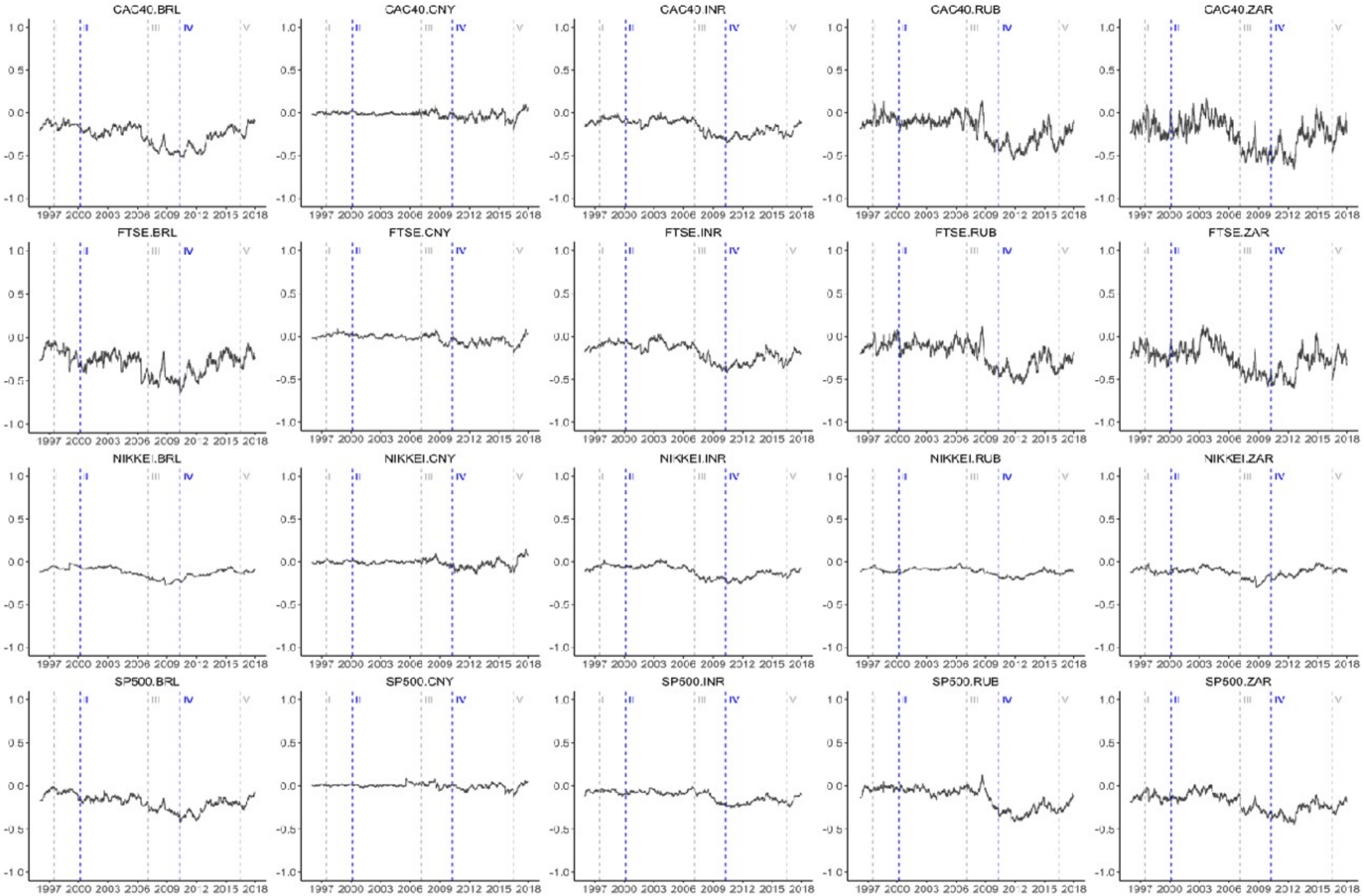
Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum

Cross-market dependence between developed and developing economies

In general, currencies of developing countries are less correlated with the benchmark stock indices. As shown in Figure 2.13, Chinese yuan was pegged with USD until July 2005, and that is why the correlations are stable during 1996-2004. It still has very limited exposure to international shocks, and its correlations with major financial markets change very mildly. The other currencies are relatively flexible and are all involved in the strengthening of the correlation trend in various degrees. The Indian rupee had the mildest dependence with the four largest stock indices while the Russian rouble was involved in the increasing market dependence relatively late, around 2009. The Brazilian real and the South African rand are more correlated with CAC40 and FTSE than with NIKKEI and SP500.

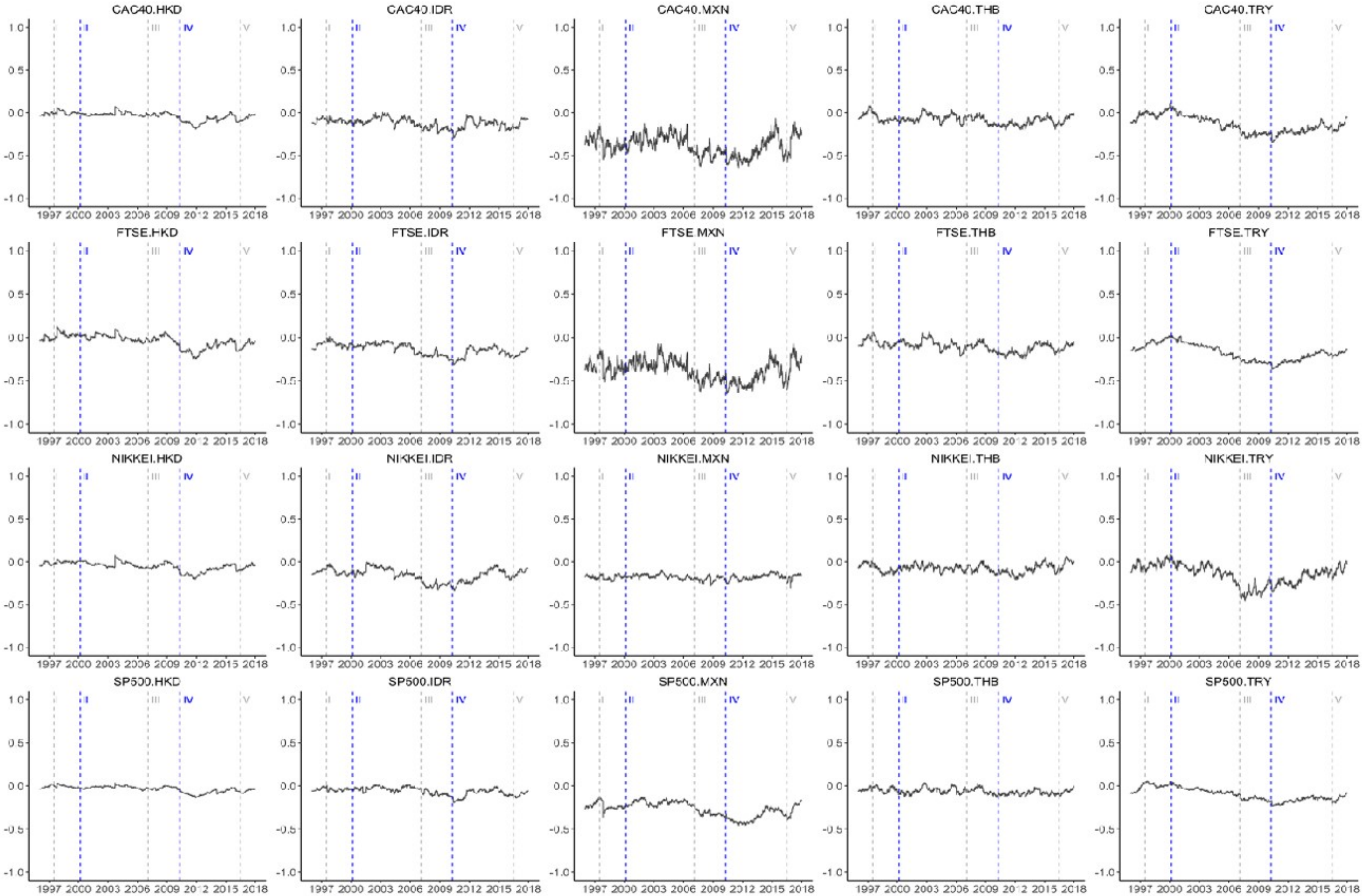
As for the other developing markets, shown in Figure 2.14, the largest change in dynamic conditional correlations started after 2007/08 financial crisis for most of the market pairs but they are hardly comparable to those of the developed economies. The extreme strong market dependence appeared on MXN-CAC40, MXN-FTSE and TRY-NIKKEI. The conditional correlations recovered from 2012 and became strong again during the time of Brexit referendum.

Figure 2.13: Dynamical conditional correlations of major stock composite indices and BRICS currencies.



Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum

Figure 2.14: Dynamical conditional correlations of major composite indices and currencies of emerging markets.



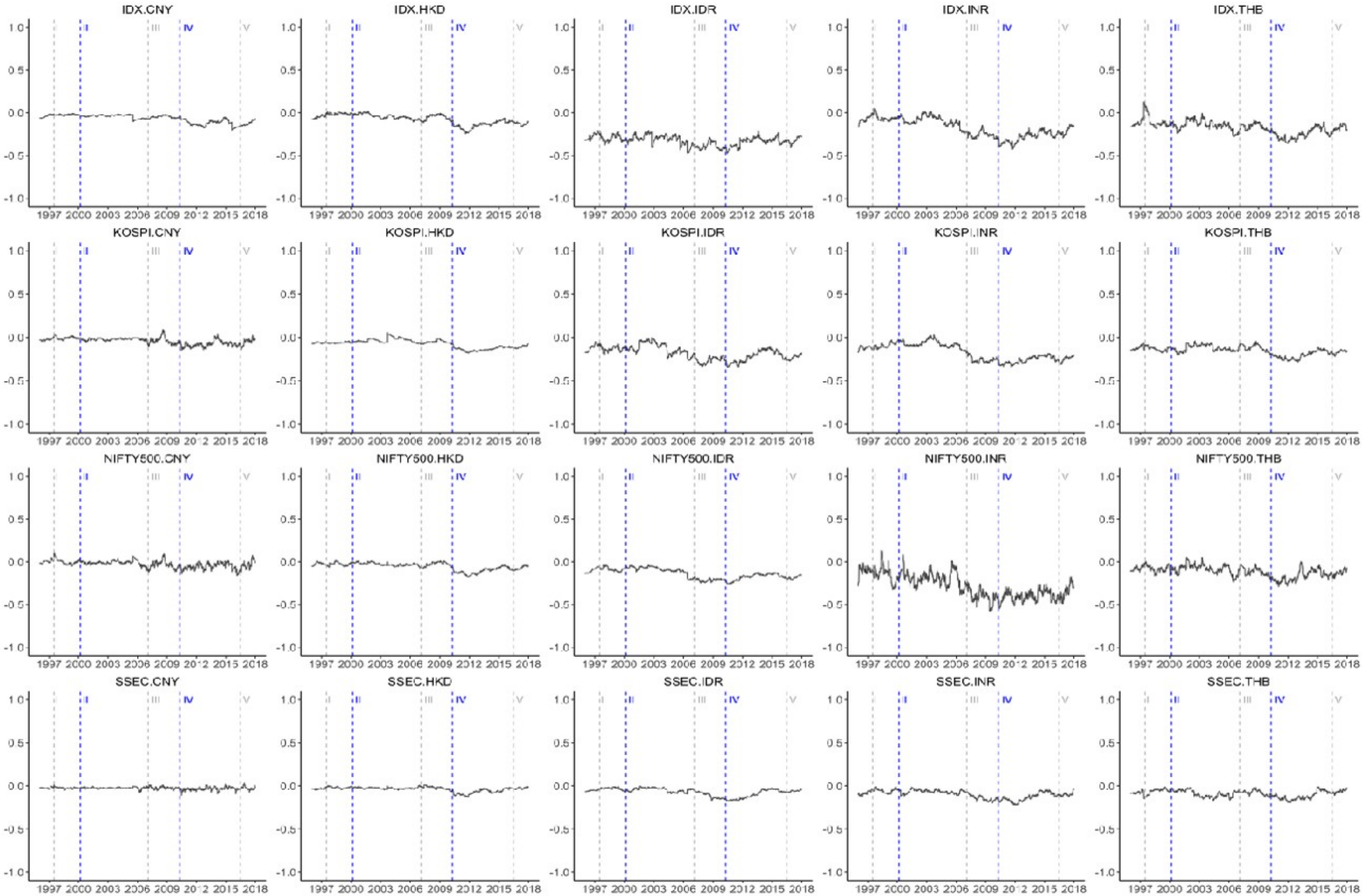
Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum

Cross-market dependence in developing economies

In developing Asia, cross-markets dependence is relatively mild, comparing to such relation with developed market. Among the countries that were selected in this study, South Korea, India, Indonesia and Thailand are more correlated with one another. The foreign exchange policy of these markets are more open, which appeared to share more comovemnent with the neighbour countries. Moreover, their joint market dependence seem to be more sensitive to the disruptive events we are focusing on. As it can be seen from Figure 2.15, the 1997 Asia financial storm was accompanied by increasing dependence of market returns. The 2007/8 financial turmoil had even larger impact on the conditional correlations of Asian markets.

On the other hand, currency that has more conservative foreign exchange policy, such as Hong Kong dollar and Chinese yuan, barely showed correlations with neighbour countries. Though Chinese market was inevitably involved in the events of 2007/8 crisis, and the correlation with South Korea and India peaked around 2008. The level of association is milder than the correlations with world major countries,probably due to the increasingly tighter trade links.

Figure 2.15: Dynamical conditional correlations of emerging Asia stock market and currencies



Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum

2.5.4 Discussion of the results

Findings in this work fill the gaps in the literature in three aspects, (i) the up-to-date dynamic cross-market comovements between FX and SX returns; (ii) empirical evidences of the dichotomy between the developed and developing financial markets during the recent global financial crisis; (iii) and the incorporation of break points with the analysis of market dynamics.

First of all, the results contain rich information of the comovement between forex and equity markets. In general, when volatilities are high, the price changes, at least in the major markets, tend to become highly correlated with the exchange rate changes. These findings are in line with King and Wadhwani (1990) and Pindyck and Rotemberg (1993) according to whom the prices of different assets move together only in response to common changes in the macroeconomic variables. The large level change of correlation is accompanied by extreme market volatility, which appears to have been 'self-reinforcing'. However, the comovements of price changes exhibited much more persistence than the high market volatility. In other words, the recovery period of multivariate comovement is significantly longer than the univariate volatility.

Different to the existing literature in the same topic which focused on particular country groups, this work aims to include as many markets as possible, in order to reveal the possible interactions of the two sectors across regions and levels of development. Hence, this work makes supplement to many papers. For instance, Phylaktis and Ravazzolo (2005) found that real exchange rate and domestic stock market were positively correlated. However, in our results, this statement is proved true for advanced market during the tranquil period only, while such market relation in emerging markets such as India and Indonesia tended to be negative. In addition, Caporale, Hunter, and Ali (2014) stated that market dependence of six major advanced markets increased during the recent crisis, which implied limited benefit of diversification. Whereas, in this work, the dependence indeed became stronger in general, but towards the negative side. Although this could be attributed to some extent to the time asynchronicity of the data, all stock markets close at some point while foreign exchanges operate globally 24 hours a day which means that the timing of the reported closing prices and the reported foreign exchange rates may well not coincide and therefore pointing to overlapping albeit somewhat different information sets.

Secondly, the global market is often differentiated to developing and developed world, which is roughly the case in our results, while the developed country group cannot be described uniformly. The results are against the hypothesis of globalization, but recognizing market integration in certain country group and strong comovements during the episode of global financial crisis. The conditional correlations appeared to be much highly associated amongst the European markets which is quite reasonable given the extensive market integration that they are involved in. Literature on the EU region tended to support the market integration. For instance, Bartram et al. (2007) showed that market dependence of large eurozone countries increased after the introduction of common currency. Even the UK and Sweden were involved in the regional integration. This statement remains true until now from our results. On the other hand, it is also very interesting to observe various phenomena such as that JPY against the USD is affected by the crisis while the NIKKEI stock market index has remained relatively stable. Our results seem to contradict Berben and Jansen (2005) and Morana and Beltratti (2008) with regards to the JPY but not after 2007/8 financial crisis. Inverse comovement between exchange rate and stock returns was found in advanced economies during the crisis. Such strong comovements vanished immediately for the connections with NIKKEI, but appeared to be sticky for the other large stock markets.

In addition, the results indicate decoupling between the advanced and EMEs. Although we found that the comovement between exchange rates and stock prices becomes stronger during the crisis, the magnitude is not comparable to the one within advanced markets. Some other research that investigated the fundamentals such as Lin (2012) suggested that such market dependence was mainly driven by capital flow rather than trade.

In terms of the structural changes, the detected break dates proved very closely associate with major economic events corresponding to local economy turning points, monetary policy changes and the global financial market turmoil. The uncanny association seem to provide a more intuitive plausible explanation than long memory as suggested in Diebold et al. (1988)[4]. This should not be surprising given that even from a graphical inspection it

[4]See also the correlogram of every data series in Appendix B

proved that financial markets reacted to recent financial crisis in a similar manner, prompting typically large volatilities.

Finally, the by-product of this work is to date the end of the recent financial turmoil. Market dependence in the period of series crisis, 1996-2001, and the period of recent turmoil, 2007-2009 are larger than the tranquil period. Authors who argue that markets have become increasingly integrated confuse a transitory with a permanent increase in correlations. Our results of sectional conditional correlation generally contain a recovery phase, where the level of correlation is approximately the same to the level in global growth period, 2002-2006 or sometimes called tranquil period in this work. See also the start time points of large correlations and the recovery period in Table 2.9.

Table 2.9: Start time points of the strong correlations and the recovery period.

Currency	Increase of comovement starts (Season, Year)	Correlated Stock Index	Decrease of comovement starts (Season, Year)	Correlated Stock Index
GBP	4th 2006	All Stock Indexes	4th 2011	Greece, Italy, Spain
			2nd2012	Germany, UK, US
EUR	1st 2006	Greece, Spain, Germany, UK, US	2nd 2012	All Stock Indexes
	1st 2007	Italy		
JPY	4th 2006	All Stock Indexes	2nd 2010	All Stock Indexes
CAD	4th 2006	All Stock Indexes	2nd 2010	Greece
			4th 2011	Spain
			2nd 2012	Germany, UK, US, Italy
BRL	1st 2006	All Stock Indexes	1st 2010	All Stock Indexes
RUB	4th 2007	Germany, US, Greece	3rd 2010	Greece
	4th 2008	Italy, Spain, UK	4th 2011	Italy, Spain
			4th 2012	Germany, UK, US
INR	1st 2007	All Stock Indexes	1st 2010	All Stock Indexes
			2nd 2012	Germany, UK, US, Italy, Spain

2.6 Conclusions

This work focuses on the cross-sector dependence between stock price and foreign exchange rate. By applying a set of break tests and modeling the dynamic conditional correlation we were able to reveal the market structural and time-varying cross-market dependence. Many structural changes were detected, which were align with the occurrence of large economic events. Particularly, the 2007/08 subprime crisis and the ensuing financial turmoil clearly had the largest impact on the underlying global structure. Overall, the cross-market dependence rose to the highest levels although it was followed by a somewhat 'recovery' period after 4-5 years, which may imply the ending of the crisis episode. Nevertheless, the 2007 crisis did not reduce the benefit of international and cross-market diversification and the emerging markets were less correlated and affected by it than the developed markets. In particular, the Asian markets and the BRICS country group were only mildly involved in the increasing market comovement trend.

Chapter 3

Is there a natural level of volatility connectedness across stock markets? Evidence from a volatility network analysis

3.1 Introduction

Stock markets are linked through various channels and these linkages by extension are often thought of as defining a network with a certain degree of connectedness. The most prominent vehicle of information that captures, for instance, public sentiment and market uncertainty, is typically thought of to be stock market volatility. which also explains the voluminous literature and avid interest of the research community, practitioners, regulators and policy makers on the directly relevant issues such as volatility transmission and spillover effects. This view has led recently into the often explicit suggestion that volatilities across the stock markets of the world has become continuously more integrated especially during major economic events. In this work, we test this assumption against the possibility that instead what exists is an underlying natural level of connectedness which only temporarily may be affected by major economic events.

To this aim, we examine stock markets around the globe through the prism of a complex network key properties of which can be captured by the tools of network analysis. Given that each of the stock markets is also thought of as mirroring the state of the underlying economy, it is no wonder that, once the improvements in computational power has made it possible, the research community has become more actively engaged into using network analysis to examine the properties of this network. In this spirit, the entire global system can be conceptualised as a dynamic graph; by capturing its topological structure and through its evolution we can reveal a much deeper understanding about its connectedness and how it has been affected by substantial economic events. This approach can have significant repercussions on portfolio management and financial stability assessment.

A major issue that these endeavours brings up involved a definite measure of this connectedness. Canonical work such as Mantegna (1999) and Onnela, Chakraborti, Kaski, Kertesz, and Kanto (2003) constructed the network with correlations and extracted the core structure of the network by generalising the notion of the minimum spanning tree that they adopt from network analysis. A more recent measure of volatility connectedness by Diebold and Yılmaz (2014) was based upon the coefficients of the generalised variance decomposition.

In this work, we propose a different avenue to examine volatility spillovers using network analysis that brings together the Dynamic Conditional Correlations (DCC) model of R. Engle (2002) and a broad set of intraday range-based volatility measures to build up a dynamic graph which presents topological properties of the global financial system. Based on these we can then adopt three well-established measures of network analysis including the eigencentrality measure, which surprisingly has been so far ignored in the literature despite being quite popular in network analysis. In this way we can access several tools to examine volatility spillovers. For example, when we look at the average correlations of the volatility changes over time, we observe that they increase substantially, peaking at the 2006-09, residing a bit later and rising again in 2016-17. But when we look at the day-by-day measures of connectedness of the volatility changes network we can very clearly identify many substantial financial and economic events and how they have affected the overall level of connectedness. This allows us to classify the impact of each of these events which can in turn directly be used for predictive analysis of potential future events, although not pursued in this work. Of particular mention is the event of the so-called Global financial crisis, which we find it proves quite distinctive and involves almost all developed markets, but interestingly, leaves the developing markets almost unscathed.

The remainder of this chapter is as follows. Section 3.2 reviews literature on volatility transmission and Section 3.3 explains our approach, presents the volatility estimators, and how we undertake network analysis. Section 3.4 describes the data. Section 3.5 shows and discusses the results, followed by concluding remarks in Section 3.7.

3.2 Literature review

There are three strands of the literature associated with this work. The first strand is about volatility proxies. This is the foundational measure upon which we build our empirical work. It is briefly discussed in the Section 3.2.1. The second strand is about the structure of cross-market linkages. A great number of literature can be found on this topic, which, interestingly, seems to come in waves each following some major financial turmoil. It has been well established that when financial markets are 'down' (i.e. they reach low values in comparison to their historical long-term trend), there is often an increase of their comovements of their market returns. The vast majority of the respective papers in this literature is effectively about asset price comovements. However, the interest has relatively recently shifted on volatility comovements which is what the focus of this work, reviewed in Section 3.2.2. Lastly, the third strand of the literature, that this work is directly associated with, is about the network approach and specifically how it has been applied upon financial data. This literature emerged timidly since the early 2000s due to its heavy demands of computational power and it is briefly mentioned Section 3.2.3. There, we overview the development of the research that effectively studies the topological properties of the financial system.

3.2.1 Volatility proxies

With respect to the measure of volatility we have to note that it has always been considered a key research area because it makes possible to quantify the degree of uncertainty or risk that one needs to bear in financial markets. The volatility measure based on returns (return-based volatility) is the mostly widely adopted, and is overwhelmingly the basis of GARCH-type and historical volatility models. However, its minimal requirements on data is inherently attached to its well-documented potential informational inefficiency of return-based volatility.

Another option of volatility estimation is to use the implied volatility of options pricing models. The primary issue with this approach is that is it heavily based on additional assumptions about the stochastic properties of option prices that have already been found unfounded in many empirical investigations. Moreover, data limitations make such an approach infeasible in practice for a wide variety of studies since, for example, they do not exist for all national indices over a sufficiently long time period.

The third option is to construct non-parametric volatility estimator by standard time series techniques. Specifically, realized variance seems to be preferred for the so-called ultra-high-frequency data; and range-based measures are preferred for lower (e.g. daily) frequency data whenever such data are available. Comparison studies (see Alizadeh, Brandt, and Diebold, 2002, Brandt and Jones, 2006 and Christensen and Podolskij, 2007 for instance) suggested that the range-based volatility offers a more precise estimation that is also more robust to microstructure noise, and performs better in terms of forecasting. This is why we adopt this approach in this empirical work.

There are a few range-based volatility measures, which are sensitive to the outliers. Assuming the log-price process is driftlessly, Parkinson (1980) was the first to include intraday extreme value to estimate the diffusion constant, of which the measurement errors were found far less than ones based on returns,

$$\hat{\sigma}_p^2 = \frac{1}{4\ln 2}(\ln H_t - \ln L_t)^2 \tag{3.1}$$

where H_t and L_t are the highest and lowest prices of the day. Garman and Klass (1980) proposed similar estimators based on the commonly available information of securities. The Garman-Klass method tends to improve the estimator by including opening and closing price, which adjust with respect to the implicit drift.The volatility can be presented as

$$\hat{\sigma}_{GK}^2 = 0.5[\ln(H_t/L_t)]^2 - (2\ln 2 - 1)[\ln(C_t/O_t)], \tag{3.2}$$

where O_t and C_t are the open and close prices of the day.

The Parkinson and Garman-Klass volatility estimators are proved to provide more accurate estimation than the traditional method (difference of closing prices). There are two other extension on the above mentioned method. Rogers and Satchell (1991) extended the Garman-Klass estimator by adding a drift term,

$$\hat{\sigma}_{RS}^2 = \frac{1}{N}\sum_{n=t-N}^{t} \ln(H_n/O_n)[\ln(H_n/O_n) - \ln(C_n/O_n)] + \ln(L_n/O_n)[\ln(L_n/O_n) - \ln(C_n/O_n)], \tag{3.3}$$

where N is the assumed number of steps taken by the random walk. This adds a correction to the original estimator in Garman-Klass approach.

A further refinement to this method by Yang and Zhang (2000), which adds in the sum of estimated overnight variance and the estimated opening market variance, is given by

$$\begin{aligned}\hat{\sigma}_{YZ}^2 = {} & \frac{1}{(N-1)}\sum_{n=t-N}^{t}\left[\ln(O_n/C_{n-1}) = \ln(O_n\bar{/}C_{n-1})\right] \\ & + \frac{k}{N-1}\sum_{n=t-N}^{t}\left[\ln(O_n/C_{n-1}) = \ln(O_n\bar{/}C_{n-1})\right] + (1-k)\hat{\sigma}_{RS}^2,\end{aligned} \tag{3.4}$$

where $k = \frac{0.34}{1.34+(N+1)/(N-1)}$.

The performance of the aforementioned four volatility estimators is not always ascending chronologically. Bali and Weinbaum (2005) and Todorova (2012) found that the adjustment in the Rogers-Satchell estimator did not contribute to notable increase in accuracy and it was in fact the least robust estimator under financial turbulence. Whereas, the Parkinson estimator is often the best estimator, and followed by the Garman-Klass, because the drift-driven upward bias is removed by the download bias which is potentially caused by discreteness. Akay, Griffiths, and Winters (2010) also found that Parkinson estimator is the most efficient at high volatility levels.

3.2.2 Volatility transmission

With respect to the literature on volatility transmission, on has to note that it has grown substantially over the last two decades. Initially, this issue was discussed in King and Wadhwani (1990), who found that an increase in volatility results in an increase in the correlation between market returns, or in other words, what they call, the contagion effect. Later, Koutmos and Booth (1995) confirmed the growth of interdependence among several major equity markets, with respect to market volatility. More recently, there have been many more empirical papers which provide evidences that support volatility integration across emerging and developed markets or, at least, through episodes of tranquil and turmoil in the largest countries (see for example Caporale, Pittis, and Spagnolo, 2006, Corradi, Distaso, and Fernandes, 2012 and Beirne, Caporale, Schulze-Ghattas, and Spagnolo, 2009).

Some other most extant evidences of changes in volatility transmission are found during episodes of financial turmoil as in volatility spillovers. The earliest studies which verified volatility spillovers in financial market is believed to be carried out by Hamao, Masulis, and Ng (1990). In the recent series of financial crisis, Chiang and Wang (2011) found structural changes in G7 countries' market volatility, and an increase in tail dependence between volatility series, which indicated a contagion effect caused by subprime crisis. Kenourgios (2014) also found contagion effect in cross-market volatility across the phases of subprime and Eurozone crises, which might be caused by homogeneous expectation on market future direction of practitioners.

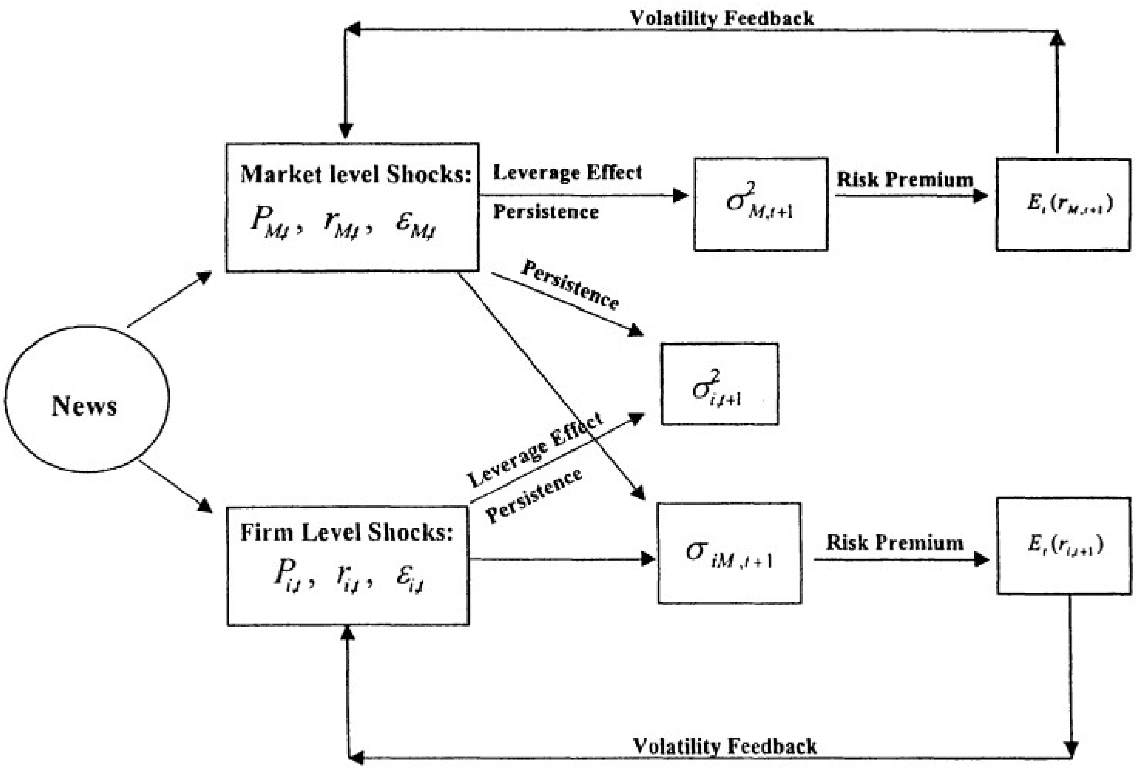
Such comovement of market volatility was explained by illiquidity spirals in Brunnermeier and Pedersen (2009). Losses lead to cut in long positions; consequently prices of the fundamentals decline. This could result in further losses in the existing long positions and higher margins would be demanded. Both consequences reinforce the funding problems for speculators; inevitably, the loss spiral and margin spiral emerge. These two spirals enhance one and another, which have stronger impact than the simple sum of the two effects.

On the other hand, some form of decoupling effect across countries is also reasonable to be expected during a financial crisis, because investors tend to adjust their portfolio to weight more on safe assets. There are evidences of heterogeneity in market dependence in the literature supporting this decoupling hypothesis. Ehrmann and Fratzscher (2009) found that the less integrated countries, in terms of the real economy and financial development, tended to have a lower degree of comovement. Some local equity markets like those of China, India and Malaysia seem to barely react to monetary policy shocks from the US. A similar phenomenon was found in European markets by MacDonald, Sogiakas, and Tsopanakis (2018) for the European Debt crisis. They verified the decoupling effect by clearly differentiating the interconnections between core and peripheral countries.

Furthermore, it appears that when there is a major policy change or economic shocks, the disruptive event in one market could affect volatility of another. In fact, markets tend to be sensitive to information generated in the other markets. Bilateral economic factors but also cultural factors, such as macroeconomic announcements, market capitalization, trade, common language and geographical locations have been considered to have significant impact upon equity market integration (Bali and Weinbaum, 2005). Among the many potential factors that have been examined, macroeconomic information, especially from a major developed country is clearly the most discussed factor that can potentially lead to large volatility comovement. For instance, Ehrmann and Fratzscher (2009) argue that the announcement of US monetary policy has led to strong volatility transmission in countries that were in the similar level of real economy and financial development.

Finally, it is worth noting that generally speaking, financial markets seem to react to good news and bad news asymmetrically in terms of volatility changes (see for example the discussion and findings of Koutmos and Booth, 1995). Bad news in one market may well cause higher volatility in the next market to trade. This volatility feedback, as it was called, was described by Bekaert and Wu, 2000 in a flow chart, shown in Figure 3.1. Because the good (bad) news cause an increase in conditional volatility, the prices increase (decrease) results in lower (higher) expected returns. On the other hand, conditional volatility may decrease due to positive return shocks. The impact of good news on volatility transmission is particularly complicated.

Figure 3.1: News impact at the market level and the firm level (Bekaert and Wu, 2000).



3.2.3 Network analysis on financial data

With respect to the literature of network analysis that has been applied upon financial data, we have to note that it is still at its infancy, although it has timidly emerged since the early 2000s. At this stage, it appears that there are two approaches for analysing them.

The first approach is to build such a network upon the correlation between the constituent components (mainly assets). The typical method, as demonstrated in Mantegna (1999) and Onnela et al. (2003), is to transform some correlation estimates into ultrametric distances so as for them to provide the weights of the links of the components in the graph. Then based on that they produce a tree description from which the minimum spanning tree is used to present the core links in the network.

The second approach, is to focus on another relevant feature of network which is community. This is essentially about compartmentalising the components of the system that is captured by the network. Its advantage lies in the fact that community detection has already attracted extensive interest from the research in sociology, biology and computer science. However, its application onto financial markets is, to the best of our knowledge, so far limited to Fenn et al. (2012), who focus on foreign exchange returns with the purpose of tracking the time-varying persistence of the detected communities in the underlying dynamic network.

3.3 Methodology

Our analysis is primarily based upon examining how the volatility connectedness of the stock exchange markets across the world changes over time. To this aim we measure the level of connectedness of a network that comprise of time-evolving correlations of volatility proxies across the benchmark stock market indices of a wide selection of countries. Consequently, we formulate a procedure of three steps. First, we determine how to measure volatility in each stock market index. Then, we use dynamical conditional correlation to measure the correlations of our volatility proxies across all pairs of indices all while taking into account possible clustering that they might exhibit. Finally, we construct the respective network of these correlations and use different network analysis measures to summarise the connectedness at each point in time.

A key feature of our analysis is that, unlike most of the existing literature, it is based upon the percentage changes in stock market volatility, not its level. This modeling decision facilitates not only the derivation of the necessary daily correlations, since our series are not bounded to the positive region, but also the use of a much simpler estimate of volatility changes namely the log-difference of the intraday range which we use for our illustrations, although the results are quite similar when we use the other volatility proxies. Equally important however is the fact that it addresses parsimoniously several issues of volatility modeling that have been raised in numerous empirical and theoretical studies. For example, the very well documented high persistence in volatility dynamics, which motivates the use of variance models such as the Integrated-GARCH or RiskMetrics^{TM}, suggests explicitly that the volatility process has a unit root. Alternatively, the presence of structural changes in volatility dynamics, which has also been used as an explanation of the high volatility persistence (see for example Hillebrand, 2005), suggests that overdifferencing the volatility series is a good method to deal with the bias that a certain class of breaks induce (see for example Clements, Hendry, et al., 1997).

The remainder of this section explains each step in details. In particular, the first part of this section discusses the volatility proxy we adopt here. The second part discusses the network analysis measures we use to capture the connectedness over time.

3.3.1 GARCH–DCC model

$$\varepsilon_t = diag\{\sqrt{h_{i,r}}\} \cdot \mu_t, \quad \mu_t \sim i.i.d \tag{3.5}$$

$$h_t = \omega + \sum_{i=1}^{p} \kappa_i h_{t-i} + \sum_{i=1}^{q} \lambda_i (\varepsilon_{t-i}\varepsilon'_{t-i}) \tag{3.6}$$

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha(\mu_{t-1}\mu'_{t-1}) + \beta Q_{t-1} \tag{3.7}$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}. \tag{3.8}$$

where $\varepsilon_t = (\varepsilon_{s,t}, \varepsilon_{f,t})'$ is the range-based volatility. The volatility proxy ε_t are modeled in the iterative scheme with $p, q \in [1, 6]$. Accordingly, the best fit ones are chosen by the minimum value of BIC.

3.3.2 Volatility proxy

The first step is to determine how to measure volatility in each stock market index. There are several methods to proxy stock market volatility requiring different types of data. Given that our focus involves the dynamics of international markets over a long time period, the data readily available are primarily range based volatility measures. Alizadeh et al. (2002) highly suggested the use of log-range, because it is efficient and close to Gaussian distribution. Practically, it also allows wide choices of samples of volatility and relatively long window, comparing to the implied volatility index.

The range-based volatility estimator is given by,

$$\hat{\sigma}_t^2 = \frac{1}{4\ln 2}(\ln H_t - \ln L_t)^2, \Delta\hat{\sigma}_t^2 = \hat{\sigma}_t^2 - \hat{\sigma}_{t-1}^2 \tag{3.9}$$

where H_t and L_t are the highest and lowest prices in a trading day, and $\Delta\hat{\sigma}_t^2$ is the change in volatility that is applied in the rest of the model. Because volatilities: (i) are asymmetrically distributed, (ii) exhibit in practice a very large degree of serial correlation, to the point that empirically the coefficient estimates of GARCH-type models sum to unity or very close to unity suggesting that volatility contains a unit root; and (iii) are likely to contain breaks, the over-differencing method is not only a convenient econometric trick but actually necessary. This is also in line with Hillebrand (2005) and Kim and Kon (1999) who show that high persistence may also be a manifestation of ignored breaks in the volatility of financial time series and therefore are likely to lead to substantial modeling errors. The differencing operation has been used extensively to address this issue, and an early application can be seen in Clements et al. (1997), who demonstrate explicitly that overdifferencing eliminates the impact of seasonal unit roots.

3.3.3 Network approach based on dynamic conditional correlations

Next, we construct the respective network of the dynamical conditional correlations and the respective measures that summarise the network connectedness at each point in time. Following the previous step, we consider the dynamic conditional correlation of each pair of the 25 markets as the time-evolving weighted links in a dynamic network, denoted as $G(V, E)$ where V is a set of 25 vertices (nodes) and E the set of all edges (links). The weights of edges are transferred from the value of DCCs. Such a graph can be described with an adjacency matrix (here A). Once such a graph is defined, we can use network analysis measures to reveal the connectedness of this graph. Therefore, such measures would collectively reveal the evolution of the volatility transmission across the different markets.

Eigencentrality

Different centrality measures are developed and applied to suitable area. We adopt eigenvector centrality in this work, as it measures relative importance of all vertices. Based on the idea that a node has higher score if its neighbour is more important, Bonacich (1972) proposed a measure which use eigenvector of the adjacency matrix to indicate the centrality. Let A be the adjacency matrix such that $a_{ij} = 1$ if node i is connected to node j and $a_{ij} = 0$ if not. Then, eigenvector centrality for node i is given by

$$\lambda x_i = \sum_{j-1}^{n} a_{ij} x_j, \quad i = 1, 2, \ldots, n. \tag{3.10}$$

There are other widely used centrality measures, such as degree centrality and betweenness centrality. However, the former measure is based on the number of links, which is not adapted to our results of volatility DCC in part of the period. A vertex could have large degree, but the high degree does not take the level of influence into account, which does not necessarily suggest the vertex is in the centre of the graph. Betweenness centrality focuses on the shortest path, which is not in line with our question on volatility transitivity. Eigen-centrality is known by its famous variant, the PageRank algorithm, which is designed by Google to rank webpages. Because eigenvector centrality counts only important links, time complexity is $O(m^2)$ for all vertices, which is more economical than closeness centrality and betweenness centrality.

Diameter

The other commonly used measurement is the diameter, which tells the longest route between every pair of vertices in the graph, i.e. the largest eccentricity of all vertex v. Diameter is given by,

$$d = \max_{v \in V} \epsilon(v), \tag{3.11}$$

where $\epsilon(v)$ is the geodesic distance between v and any other vertex.

Community detection

Communities in a graph are more closely-related. One string of community detection seeks to maximize the modularity,

$$Q(C) = \frac{1}{2w} \sum_{i,j} \left[A_{i,j} - \frac{\sum_i A_{ij} \cdot \sum_j A_{ij}}{2w} \right] \delta(c_i, c_j), \tag{3.12}$$

where w is the sum of all edge weights in G, c_i is the community that contains v_i, and $\delta(c_i, c_j)$ is the Kronecker delta which is 1 when v_i and v_j are in the same community and 0 if not. A few algorithms are available to find the partition C that maximizes Q. In our work, we apply the spin-glass (or Potts) method in Reichardt and Bornholdt (2006).

Minimum spanning tree (MST)

MST is best known for selecting the most relevant market linkages in network analysis. It is widely used because of its simplification of a complex graph. For a graph with m elements, the MST obtains $m-1$ most important links out of the total $m(m-1)/2$ links without constructing a loop. A transformation from correlation to ultrametric distance is given by Mantegna (1999),

$$d_{ij} = \sqrt{2(1-\rho_{ij})}, \quad d_{ij} \in [0, 2]. \tag{3.13}$$

More correlated vertices v_i and v_j have smaller distance. Prim's algorithm Prim (1957) allows weights for the undirected links, which has two steps, i) initialising a tree with an arbitrarily selected vertex; ii) iteratively adding in a vertex (outside the set) which has the minimum distance to the tree.

Then we adopt the integration measure which was provided by Onnela et al. (2003) for MST.

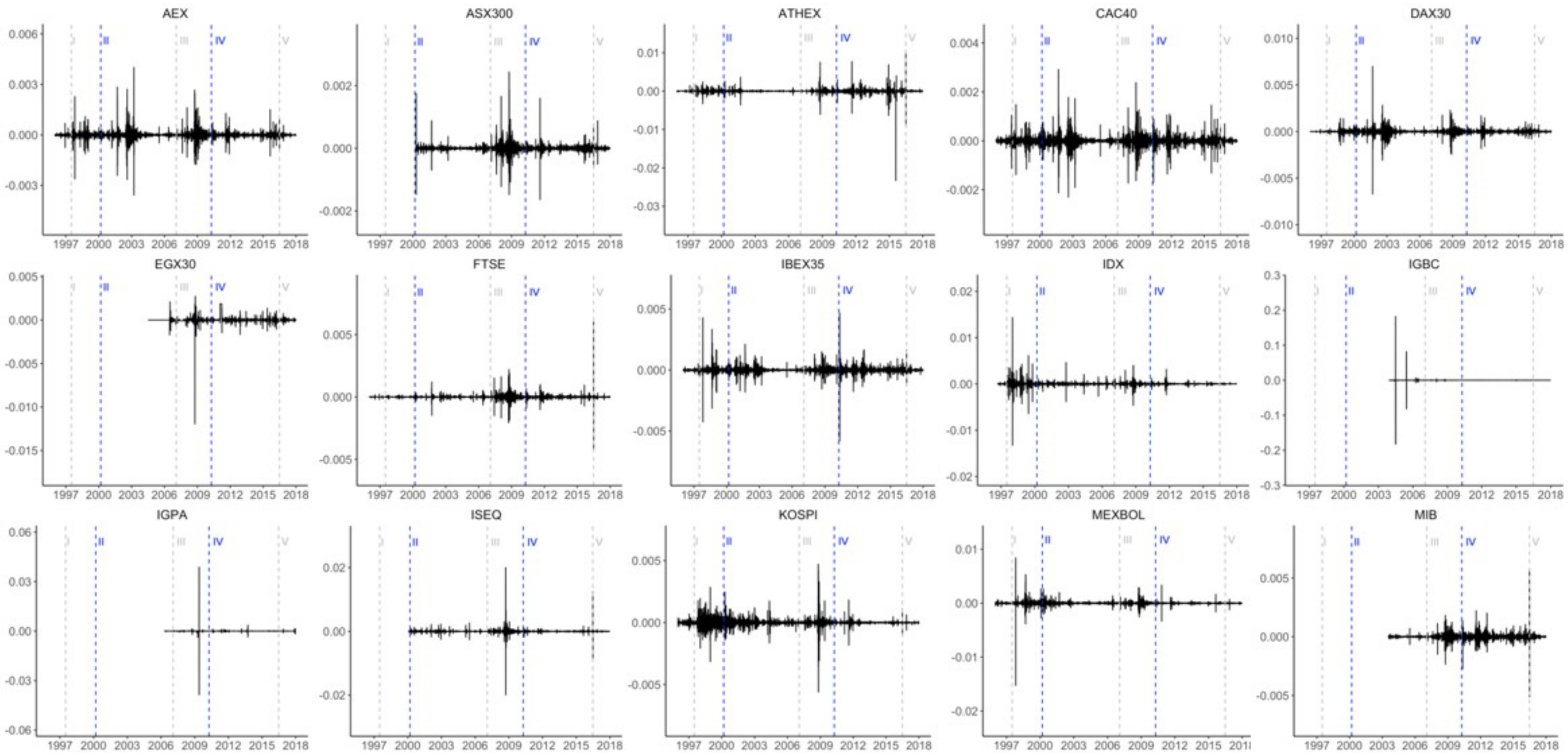
$$L(t) = \frac{1}{n-1} \sum_{d_{i,j} \in MST} d_{ij}^t, \tag{3.14}$$

where n is the number of vertex. Small $L(t)$ suggest large level of integration.

3.4 Data

Our dataset comprises of the intraday highest and lowest prices of 25 national indices from DataStream. It is composed by 16 industrialized countries and 9 emerging countries and spans the period from 01/01/1996 to 31/12/2017. The period covers many episodes of extraordinary events which are suspected to have impacted upon the structure of the global financial system. Indicative examples include the 1997 Asian crisis, the dot-com bubble collapse of 2000, the 2007 subprime crisis, the ensuing European sovereign debt crisis and the Brexit referendum. The first difference of Parkinson volatility is shown in Figure 3.2. There are large changes of volatility that follows the occurrence of some or all these events in every index. Table 3.1 overviews some basic statistical properties of the growth series we are using.

Figure 3.2: First difference of Parkinson volatility.



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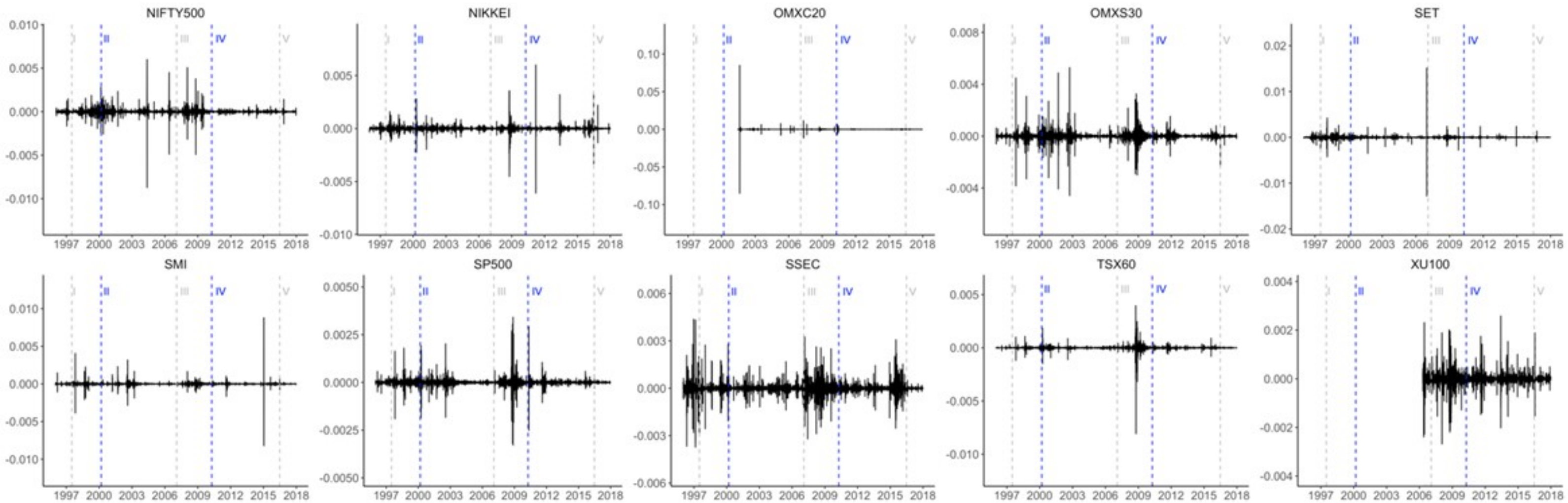


Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum

Table 3.1: Overview of the statistical properties of the first difference of Parkinson volatility of the 25 national stock indices.

Country	Index	Number of observation	Mean	Standard deviation	Skewness	Kurtosis
Australia	ASX300	4629	-5.62E-07	1.20E-04	2.6182	105.5556
Canada	TSX60	5738	-2.77E-06	1.91E-04	-12.4633	632.5226
Chile	IGPA	3051	-1.02E-05	1.01E-03	0.1495	1383.9292
China	SSEC	5738	-3.35E-06	3.49E-04	0.4217	34.0838
Colombia	IGBC	3677	-1.02E-04	6.32E-03	-13.0144	765.2614
Denmark	OMXS30	5738	-4.55E-06	2.93E-04	0.7788	87.6515
Egypt	EGX30	3524	1.15E-05	3.43E-04	-10.2243	433.9205
France	CAC40	5738	-1.77E-06	1.94E-04	0.1728	35.8979
Germany	DAX30	5738	-1.91E-06	2.63E-04	0.1157	178.5074
Greece	ATHEX	5738	-1.24E-05	5.73E-04	-11.5641	534.2029
India	NIFTY500	5726	-4.53E-06	3.10E-04	-2.2278	189.5747
Indonesia	IDX	5559	-3.07E-06	4.62E-04	1.4062	323.6356
Ireland	ISEQ	4668	-5.01E-07	5.61E-04	1.8153	755.3168
Italy	MIB	3765	-2.42E-06	2.49E-04	1.0195	137.8080
Japan	NIKKEI	5736	9.70E-08	2.60E-04	0.5103	173.0262
Mexico	MEXBOL	5738	1.53E-07	3.79E-04	-7.0207	545.0629
Netherlands	AEX	5738	-2.35E-06	2.19E-04	0.8171	72.9405
South Korea	KOSPI	5737	-3.32E-06	2.74E-04	-0.1014	81.7754
Spain	IBEX35	5738	-2.60E-06	2.51E-04	-0.6446	118.8213
Sweden	OMXC20	4315	-8.83E-06	1.91E-03	-0.1317	1820.7358
Switzerland	SMI	5737	-1.32E-06	2.37E-04	2.0198	625.4418
Thailand	SET	5737	-4.10E-06	3.63E-04	4.6282	816.2656
Turkey	XU100	3051	-4.96E-06	2.72E-04	-0.2912	25.2252
UK	FTSE	5738	-1.02E-06	1.67E-04	5.2219	398.9530
US	SP500	5738	-1.47E-06	2.01E-04	1.1831	96.4707

3.5 Empirical results

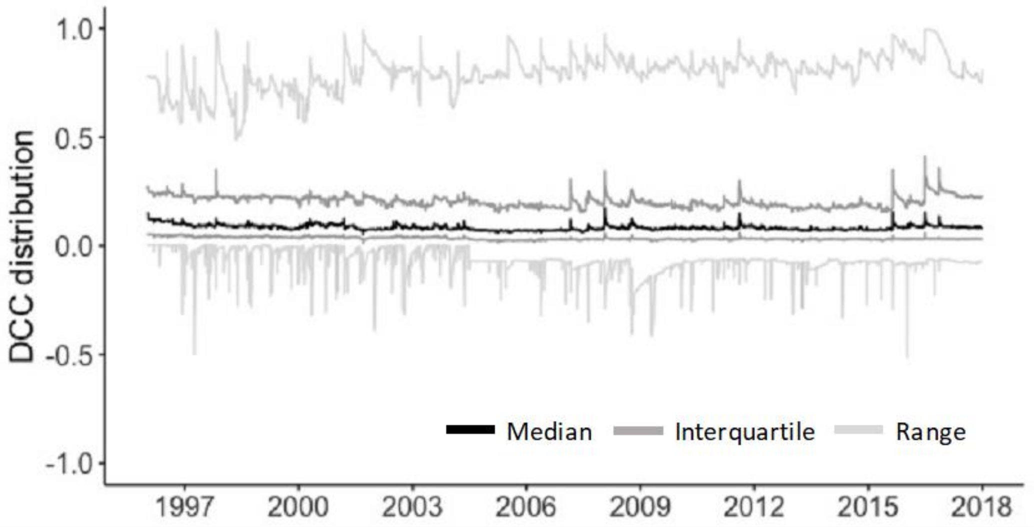
This section presents and discusses our empirical results. The first part focuses on the DCCs of volatility changes and shows that volatility changes become much more correlated as time passes by peaking at the period around the Global Financial Crisis and the start of the ensuing sovereign debt crisis. The second part builds upon the results of the first part and presents the day-to-day evolution of the measures of connectedness that we have derived from network analysis and illustrates the impact of some extraordinary economic events. The third part, building on the results of the previous two parts, examine the directional risk spillovers by applying the model of variance decomposition of forecast errors.

3.5.1 Dynamic conditional correlation of volatility changes

After applying DCC model (R. Engle, 2002) to the volatility changes, we obtained the daily conditional correlations between every pair of 25 stock volatility changes for the last 22 years. Equivalently, the results can be thought of as belonging to 5740 correlation matrices. The conditional correlations are then the net that spreads among some of the 25 vertices. Since the links of this net change over time then so do the number of vertices and weights of links constituting what is considered a dynamic network. It is worth noting that as some of the sample countries are gradually joining the market, the complete dynamic graph eventually grows to 25 vertices and 300 edges. Hence, we present the basic statistics of the weighted adjacency matrices in the time-evolving fashion and the 300 links in graphs.

Our findings suggest that market volatility positively depends on one another in most of the cases, and the statistics of the correlation matrix varies from day-to-day . However, the level of a rolling average window of DCCs tends to be stable around a small positive value throughout the time. Moreover, as shown in Figure 3.3, the range of DCCs is also both asymmetrical and with some local peaks of the median and upper quartile. For a large amount of market pairs, their volatility dependence suddenly increases with the occurrence of the aforementioned extraordinary events. On the other hand, there are large spikes in the DCC minimums all the time, which may imply market decoupling in many circumstances, suggesting that there might be some good chances to diversify further some of the risk away.

Figure 3.3: Median of the daily DCC.



Note: Black line in the middle is the median of correlation matrix; dark-grey lines are the interquartile; light-grey lines are the range.

Overall, we observe that volatility changes become much more correlated as time passes by peaking at the 2006-09, which roughly corresponds to the events before the Global Financial Crisis and the start of ensuing sovereign debt crisis. Figure 3.4 contains the two-year non-overlapping window of the respective correlations. In particular, we observe that there are more edges that become visible in the graph, which signifies that the volatility change between more countries become synchronized. We also observe that several edges become darker, which signifies that the magnitude of the comovement rises. In the most recent window, 2016-2017, the level of interaction in the network peaks again. Given that the correlations in volatility changes peak at the crisis period, we are effectively providing support to those who claim that volatility comovements become more acute during financial crises.

Moreover, the comovements of volatility changes are quite heterogeneous for the developing markets. Volatility changes in the stock market exchanges of developing economies are correlated neither with one another nor with those of developed economies. The exceptions are Mexico, Turkey and Indonesia. Volatility changes of Mexico are correlated for the whole sample mildly with those of the US. This fact did not change even after 2007/8 crisis. The same goes for Turkey the volatility changes of which are correlated to those of the Netherlands. As for Indonesia, the volatility changes mildly correlate with those of Australia and only during 2006-09.

In contrast, volatility changes amongst the Eurozone countries seem to be very correlated primarily after the introduction of the euro. Interestingly, volatility changes amongst the GIPSI countries are not uniform. Greece and Ireland seem to be more mildly correlated than Spain and Italy with the rest of the other Eurozone economies, i.e. France, Germany and Netherlands. Finally, the volatility changes of the remaining countries of the European Union with the Eurozone economies seem to become more and more correlated over time, peaking at the period of the 2007/8 crisis, dropping slightly in 2012-13 and peaking again in 2016-17.

Figure 3.4: Pairwise unidirectional connectedness 1996-2017.

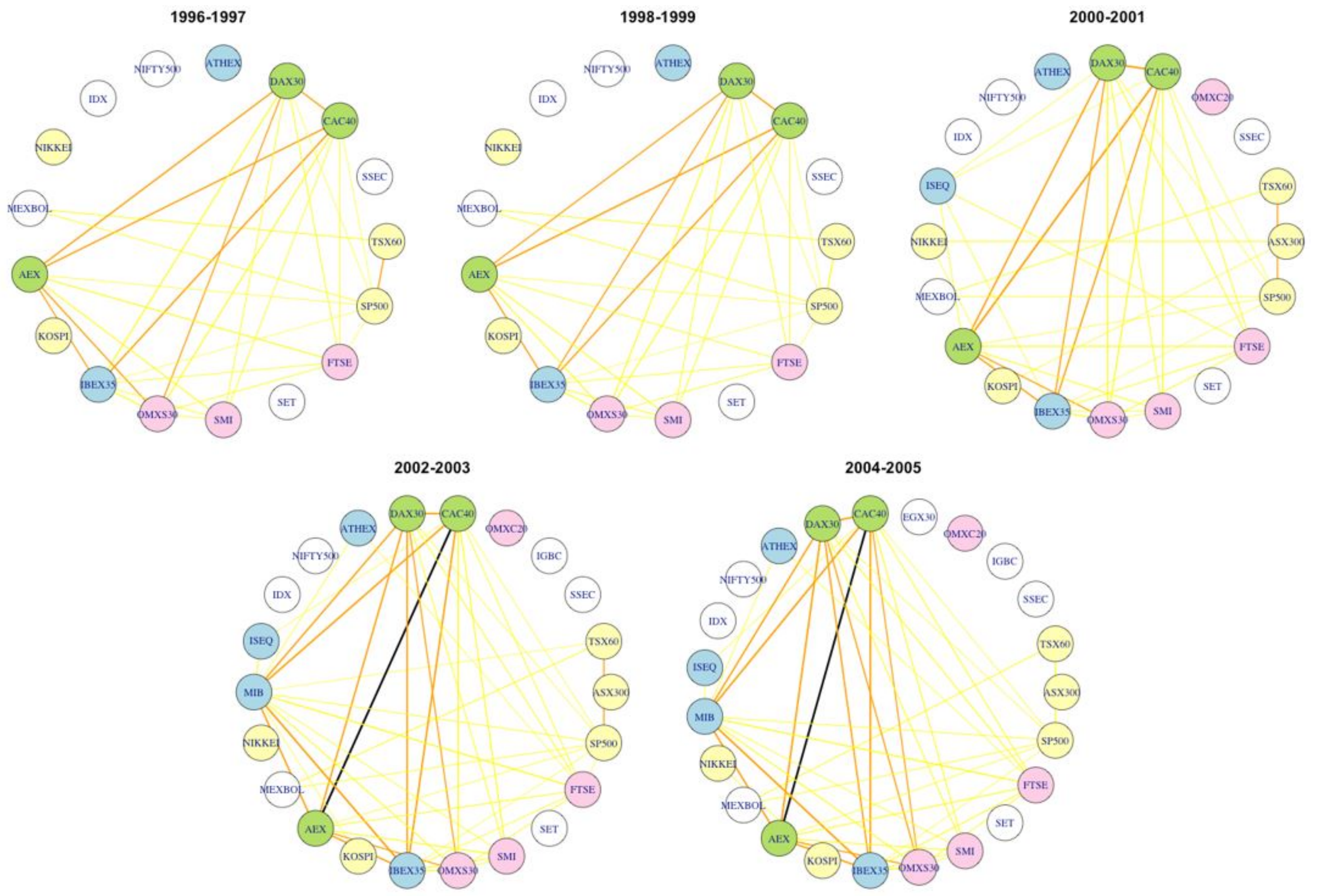


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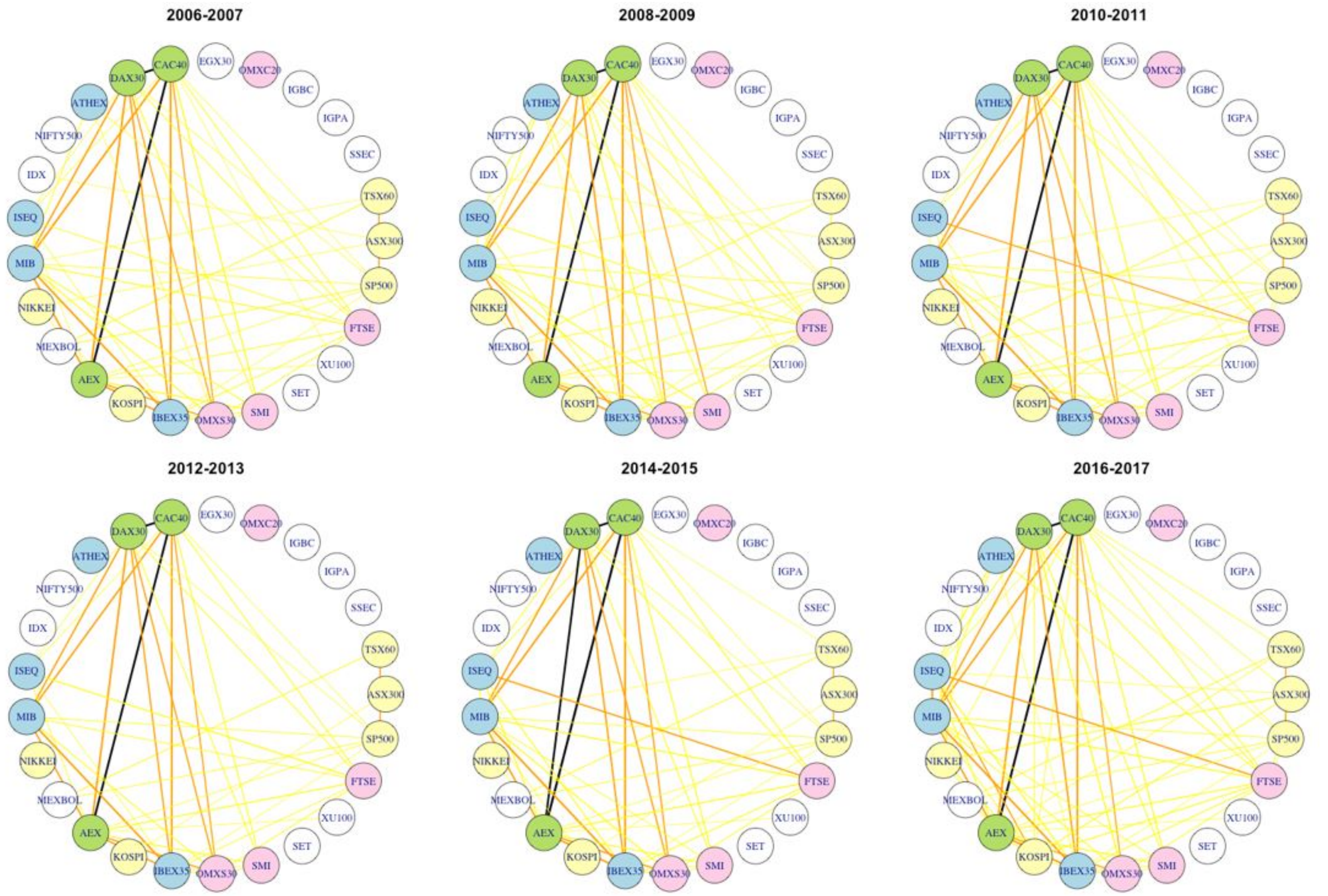
Figure 3.4 Continued from the previous page.



Links are differentiated by levels. Mild level in yellow, DCC in 0.25-0.5; medium level in orange, DCC in 0.5-0.75 and extreme level in black, DCC in 0.75-1. The different colour of the nodes groups the stock markets into markets developing (white), part of the GIPSI (blue), Eurozone (green), other European Union (purple) and other developed (beige).

3.5.2 Day-to-day evolution of connectedness and the impact of economic events

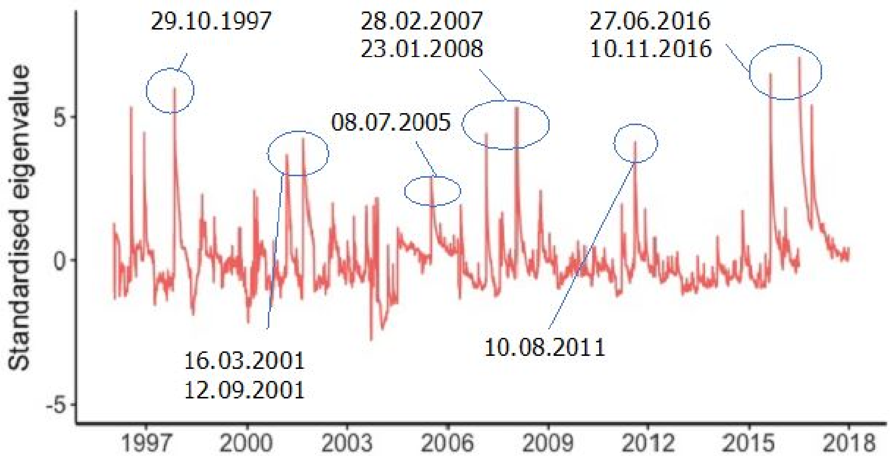
In this section, we discuss the topological features of the dynamic graph constructed by DCCs and how it evolves over time. Figure 3.5 contains the evolution of connectedness based on the eigenvalue and diameter of the complete graph and normalised length of minimum spanning tree. We also signify some extremums that correspond to specific major economic and political events. In general, the day-to-day network measures are relatively stable at a certain level (see the rolling median of eigenvalue in Figure 4.1), except for the large spikes on the dates of which can be readily associated with an extraordinary event that took place on or around these dates. The dates of the extrema highly overlap in all three measure. Table 3.2 tabulates the information of some eye-catching extrema.

All events have contributed to the rise of the level of connectedness across the examined stock markets; and also of the market heterogeneity. The ten events listed in Table 3.2 are all around the date of centrality score local maxima, which indicates a highly-connected volatility transmission net. At the same time, the integration measure reaches one of its lowest values, which suggests that in the core structure represented by the minimum spanning tree, the average distance between any two components is strikingly small. Both of the measures signify a highly connected graph. In contrast, the diameter measure reaches its local maxima at those dates, which suggests an unusually long largest-route in the graph.

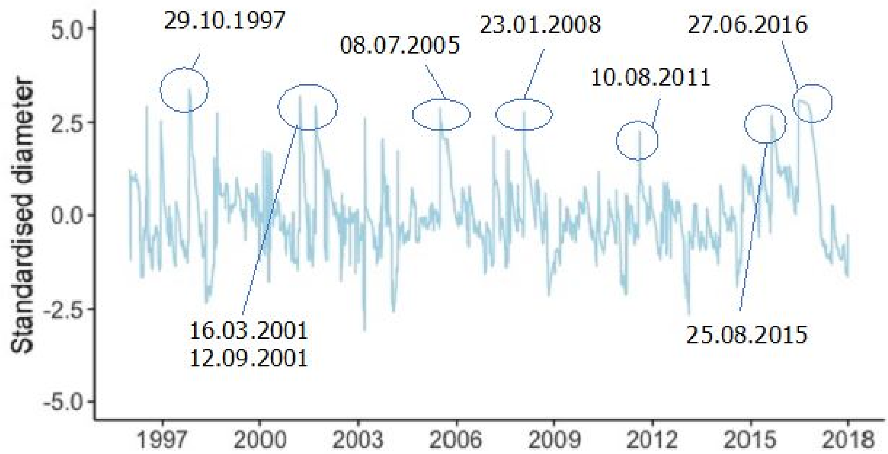
Furthermore, the level of extrema on those dates differs. The six predominant stock events are mostly large market downturns in several major economies—the large drop and bounce of the DJIA on the 27$^{\text{th}}$ and 28$^{\text{th}}$ October 1997; the largest one-week loss of DJIA on the 16$^{\text{th}}$ of March, 2001; the largest fall of Chinese stock in ten years and the large slide of DJIA on the 27$^{\text{th}}$ February 2007; the world stock market downturn following the subprime crisis on the 23$^{\text{rd}}$ of January 2008; the August 2011 stock markets fall across the US, Middle East, Europe and Asia and Standard and Poor's downgrade of the U.S. sovereign credit rating on the 8$^{\text{th}}$ of August 2011 and the "Black Monday" of the U.S. and Chinese stock market, on the 24$^{\text{th}}$ August 2015. Interestingly, the most influential events include not only stock market events, but also two prominent political events, the UK European Union referendum and the 2016 US presidential election, and two terrorist attacks, the

9/11 attacks of 2001 and the London bombing attacks, on the 7^{th} July 2005. Interestingly, the Brexit referendum seems to be the most influential event in terms of the daily market connectedness.

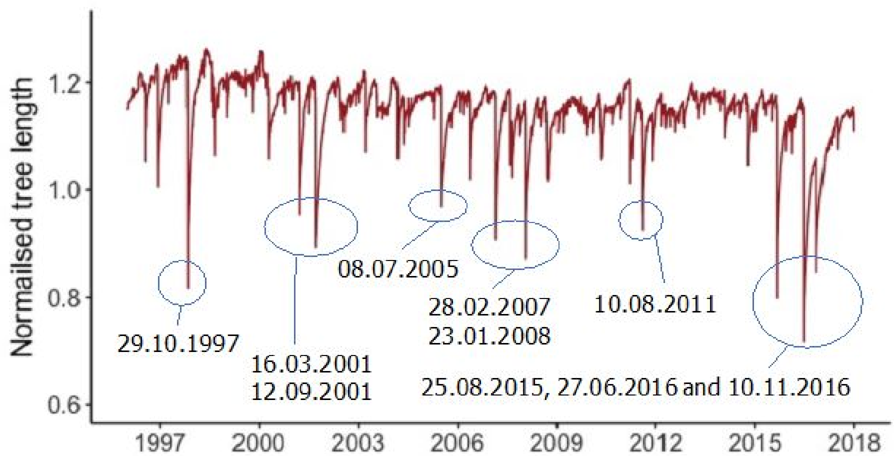
Figure 3.5: Measures of connectedness.



(a) Eigencentrality score of the complete graph.



(b) Diameter of the complete graph.



(c) Integration degree of the minimum spanning tree.

Note: The extreme values which are circled out match the occurrence of influential events, and listed in the following table.

Figure 3.6: Weekly (grey) and two-weeks (black) rolling median of the eigenvalue.

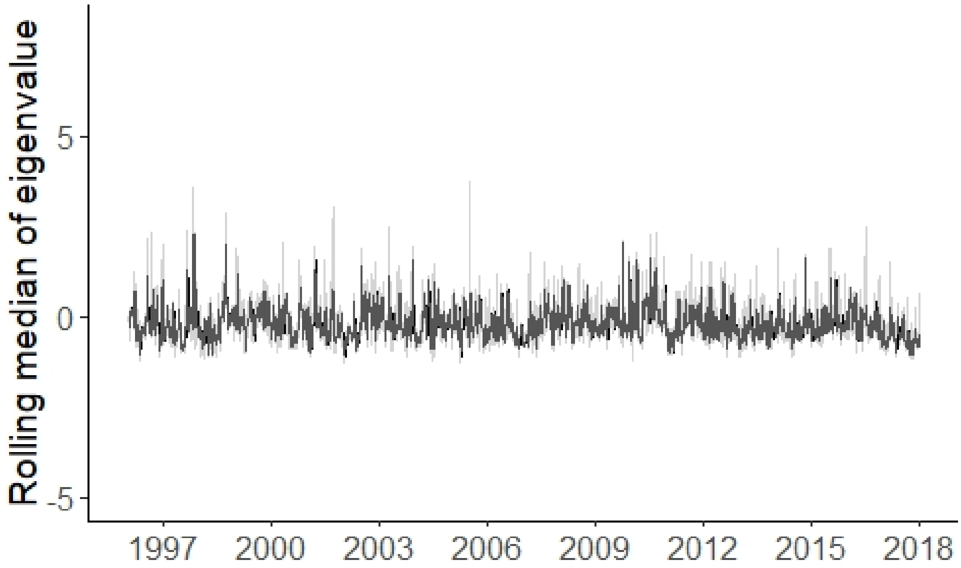


Table 3.2: Extreme values in network measures and their matching extraordinary events

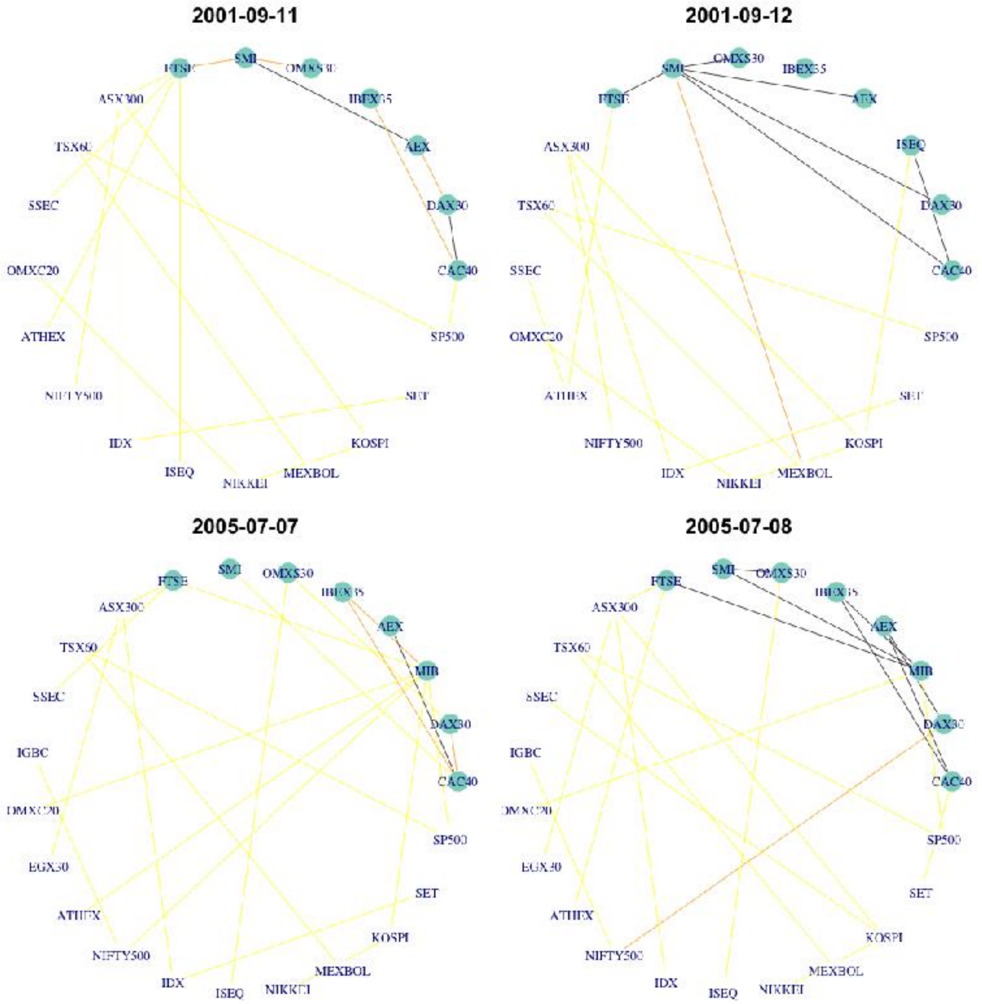
Extraordinary event			Eigenvalue	Diameter	Integration degree
Large drop of the DJIA (-7.1%) and followed by the first one-day one billion trade (+4.7%)	Official date	27 Oct 1997	0.3985	-0.0535	1.2033
	Empirical date	29 Oct 1997	5.9537	3.3721	0.8173
The largest one-week loss of DJIA	Official date	12 Mar 2001	-0.4643	-0.4261	1.2009
	Empirical date	16 Mar 2001	3.6492	3.1772	0.9984
9/11 terrorist attacks.	Official date	11 Sep 2001	0.1528	-0.4724	1.1521
	Empirical date	12 Sep 2001	4.1307	2.8494	0.9017
London bombings and followed by London Stock Exchange's special measures to restrict panic selling	Official date	07 Jul 2005	0.0166	-0.1793	1.1914
	Empirical date	08 Jul 2005	2.8806	2.8778	0.9703
Largest fall of Chinese stock in 10 years; biggest one-day slide of DJIA after 9/11 attacks	Official date	27 Feb 2007	-0.7128	-1.2677	1.1772
	Empirical date	28 Feb 2007	4.3986	2.1218	0.9101
World stock market downturn	Official date	22 Jan 2008	2.9826	1.3478	0.9781
	Empirical date	23 Jan 2008	5.2723	2.7835	0.8722
August 2011 stock markets fall, across the US, Middle East, Europe and Asia	Official date	04 Aug 2011	0.2063	0.8610	1.1243
	Empirical date	10 Aug 2011	4.1125	1.4106	0.9254
"Black Monday" of Chinese stock market, and then followed by the largest drop of the DJIA	Official date	24 Aug 2015	0.4683	0.4609	1.1251
	Empirical date	25 Aug 2015	6.4637	2.6899	0.7987
UK European Union membership referendum	Official date	23 Jun 2016	-0.2213	0.3548	1.1535
	Empirical date	27 Jun 2016	8.2872	3.1056	0.7180
US presidential transition	Official date	10 Nov 2016	1.1269	2.2665	1.0588
	Empirical date	10 Nov 2016	5.3469	2.3034	0.8481

Furthermore, the evolution of community and minimum spanning tree during the particular event period are quite informative. We exhibit the minimum spanning tree for all events from three categories in Figure 3.7-3.9. The vertex cluster in the tree matches the communities identified by the Potts method. Major stock markets in the European Union, namely, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland and the UK are generally more close to one another than the rest of the markets in the graph, which implies smaller distance in the minimum spanning tree for the same membership from community detection. Linkages in this country group leap to the extreme level after the occurrence of the aforementioned extraordinary events, so we denote the community that contains these eight EU countries as the high transmission community.

With respect to the measured changes in the network structure that are caused by the abnormal events, we observe that they are not homogeneous. For the terrorist attacks and the financial turmoil aftermath of the subprime bubble burst, only some other EU markets, such as the rest of the GIPSI and Denmark, join the high transmission community. Surprisingly, the other large advanced markets are not closely related to this community when the market connectedness is extremely intensive. The only exception is the US, which joined the clustering once at the time of financial turbulence, on the 27th February 2007 (see Figure 3.7 and Figure 3.8).

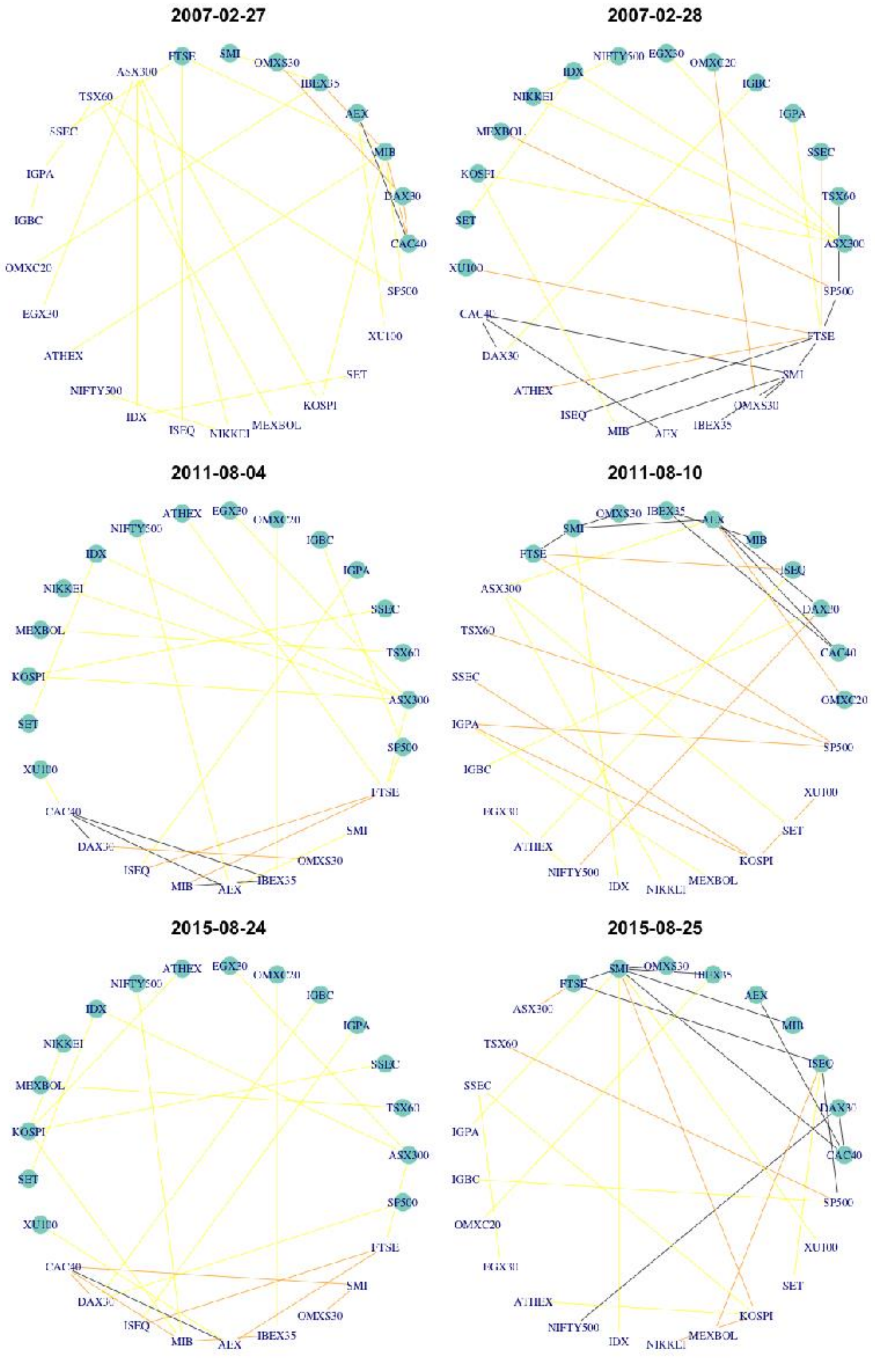
Interestingly, the recent political events seem more influential to the network structure, indicated a systemic impact upon the developed markets. The sample markets generally belong to two cohesive subnetworks with regards to the degree of development, known as the divide between developed and developing markets is palpable. More interestingly, before the Brexit referendum, all markets are grouped into two communities, one of which contains seven of the high transmission community members, and another for the rest. On the 27$^{\text{th}}$ of June 2016, all advanced markets except for Sweden and Canada were joining the former group, with an extreme level of volatility comovements. Similarly, from the 8$^{\text{th}}$ to the 10$^{\text{th}}$ of November 2016, Australia and Japan merged into the community with large volatility comovements, and left Canada, Denmark and the US with the emerging market in a mildly connected subnetwork.

Figure 3.7: Impact of terrorist attacks on minimum spanning tree.



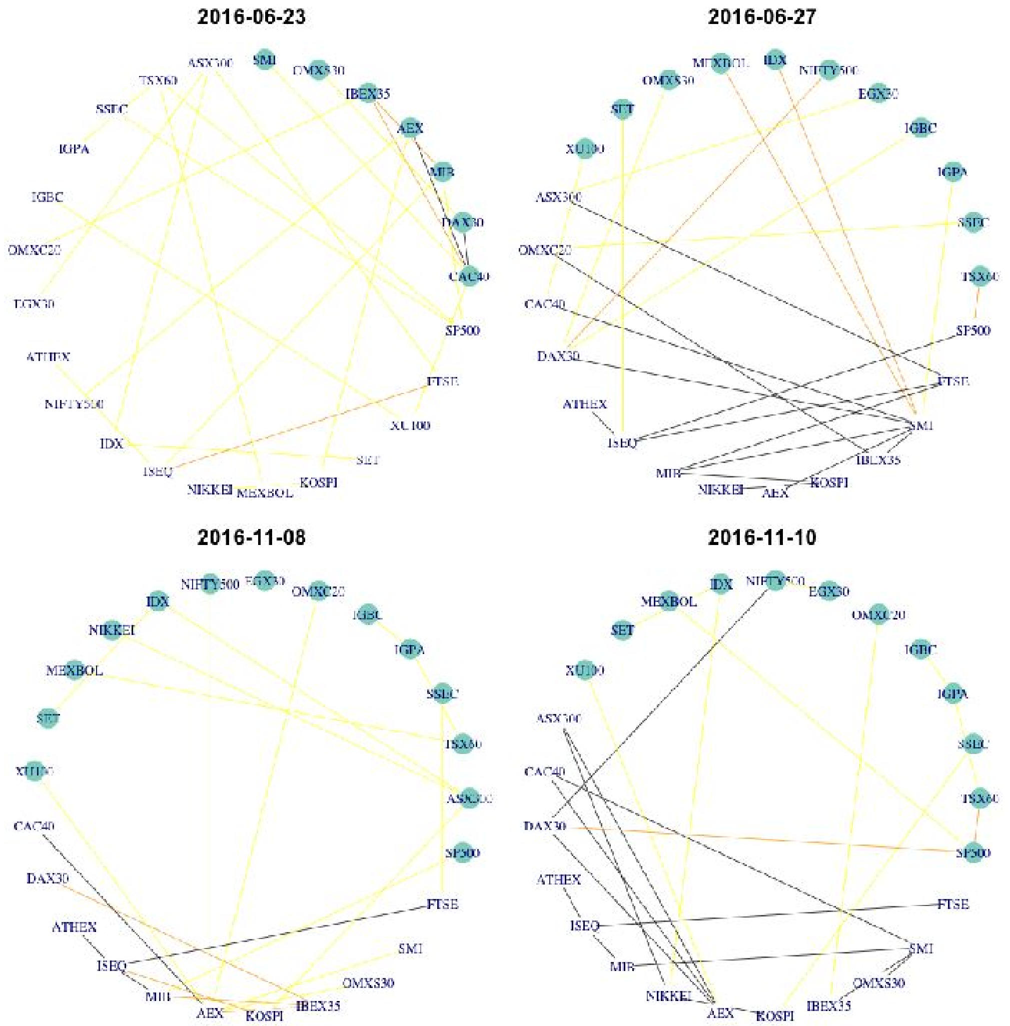
Note: Links are differentiated by distance. Long distance in yellow, $d_{ij} \in (1, 2)$; medium distance in orange, $d_{ij} \in (\sqrt{0.5}, 1)$ and short distance in black, $d_{ij} \in (0, \sqrt{0.5})$. Vertices are coloured according to the community membership.

Figure 3.8: Impact of stock market crashes on minimum spanning tree.



Note: Links are differentiated by distance. Long distance in yellow, $d_{ij} \in (1, 2)$; medium distance in orange, $d_{ij} \in (\sqrt{0.5}, 1)$ and short distance in black, $d_{ij} \in (0, \sqrt{0.5})$. Vertices are coloured according to the community membership.

Figure 3.9: Impact of political events on minimum spanning tree.



Note: Links are differentiated by distance. Long distance in yellow, $d_{ij} \in (1, 2)$; medium distance in orange, $d_{ij} \in (\sqrt{0.5}, 1)$ and short distance in black, $d_{ij} \in (0, \sqrt{0.5})$. Vertices are coloured according to the community membership.

3.5.3 Volatility spillovers

To further examine the directional risk spillovers, we also focus in this part onto the model of variance decomposition of forecast errors. The dataset is divided into two phase, 1996-2006 and 2007-2017. During the first phase, the network contains 16 markets, while in the second phase, these market maintained with 9 more markets joining the network. The results are based on VAR(1) models and variance decompositions of 10 step-ahead forecast errors. The construction of the spillover index follows the idea of Diebold and Yılmaz (2014). Formule are derived in Appendix D.

The directional information of the two phases is presented in Table 3.3 and Table 3.4. The total volatility spillover index is at the right-bottom of the table, which is the ratio of the total off-diagonal elements to the sum of all entries. The decomposed information of the volatility input and output is given in the other entries. Each row is the corresponding proportion of the estimated contribution to the forecast error variance, so the summation of every row is 100%. The diagonal entries are effectively their own connectedness, which, as expected, is the largest influence for most of the markets. In addition, the off-diagonal row sum represents the contribution from the others, labeled as 'From'. The off-diagonal column sum is the contribution to the others, labeled as 'To'. The net volatility spillover is the difference of 'To' and 'From'.

We observe that in the phase of 1996-2006, the significant off-diagonal entries are mainly observed from the EU markets, and the highest five values of connectedness are observed from AEX-CAC40 (53.95%), DAX30-CAC40 (45.51%), SMI-CAC40 (37.18%), IBEX35-CAC40 (29.77%), with one exception being SP500-TSX60 (41.45%). Markets which received the largest spillovers from the others are AEX, SMI, SP500, DAX30 and IBEX35. The stock market that contributed the largest volatility to the others are CAC40 and TSX60. In the first phase, the majority were risk receivers, while CAC40 and TSX60 were the risk contributors.

During 2007-2017, the total volatility spillovers increased from 23.73%. to 29.17%. Large off-diagonal entries appear in the pair of DAX30-CAC40 (49.8%), AEX-CAC40 (49.7%), IBEX35-CAC40 (38.78%), MIB-CAC40 (34.49%) and OMXS-CAC40 (22.46%) .The EU market performed the largest volatility output in the network by CAC40 and also the largest volatility input which is taken by several large markets such as AEX (69.46%), FTSE (65.68%), DAX30 (63.13%) and IBEX35 (60.34%). The markets that are least affected by the spillovers are SSEC (2.34%), IGPA (3.75%) and OMXC20 (5.51%).

Table 3.3: Volatility spillover of 16 benchmark stock market during 1996-2006.

	TSX60	SSEC	CAC40	DAX30	ATHEX	NIFTY	NIKKEI	MEXBOL	AEX	KOSPI	IBEX35	OMXS30	SMI	SET	FTSE	SP500	**From**
TSX60	97.26	0.00	0.01	0.09	0.28	0.01	0.18	0.00	0.29	0.01	0.01	0.96	0.17	0.01	0.20	0.51	2.74
SSEC	0.14	99.46	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.14	0.06	0.08	0.00	0.06	0.00	0.54
CAC40	1.18	0.02	93.90	0.99	0.70	0.00	0.22	0.04	0.00	0.00	1.51	0.02	0.53	0.06	0.15	0.67	6.10
DAX30	1.76	0.09	45.51	50.86	0.36	0.00	0.19	0.02	0.00	0.00	0.32	0.13	0.01	0.09	0.37	0.29	49.14
ATHEX	0.04	0.10	2.01	2.60	92.19	0.92	0.38	0.13	0.05	0.23	0.52	0.01	0.15	0.04	0.28	0.34	7.81
NIFTY	0.14	0.01	0.06	0.09	0.16	98.45	0.27	0.16	0.00	0.32	0.05	0.01	0.01	0.00	0.17	0.10	1.55
NIKKEI	1.09	0.08	0.69	0.67	0.21	0.14	95.02	0.31	0.09	0.18	0.16	0.03	0.01	0.00	0.01	1.32	4.98
MEXBOL	13.76	0.21	2.32	0.80	0.03	0.05	0.69	74.04	0.48	0.11	4.67	1.24	1.27	0.01	0.07	0.25	25.96
AEX	1.98	0.10	53.95	2.23	0.75	0.04	0.26	0.46	37.09	0.08	1.70	0.39	0.26	0.11	0.29	0.30	62.91
KOSPI	0.21	0.01	0.24	0.46	0.06	0.60	2.55	0.16	0.17	95.15	0.11	0.04	0.01	0.04	0.07	0.12	4.85
IBEX35	3.58	0.01	29.77	1.21	0.29	0.10	0.11	5.73	1.29	0.17	56.51	0.07	0.20	0.04	0.09	0.83	43.49
OMXS30	2.67	0.04	19.63	4.77	0.12	0.08	1.01	3.01	0.58	0.05	2.11	65.46	0.29	0.12	0.00	0.05	34.54
SMI	2.93	0.01	37.18	1.99	0.39	0.00	0.11	4.07	7.69	0.07	6.47	0.34	38.16	0.04	0.38	0.17	61.84
SET	0.04	0.12	0.41	0.03	0.15	0.66	0.05	0.05	0.07	0.11	0.02	0.04	0.00	98.22	0.00	0.04	1.78
FTSE	2.89	0.04	10.05	1.88	1.38	0.90	0.50	0.29	0.18	0.04	0.77	0.45	0.15	0.13	80.28	0.06	19.72
SP500	41.45	0.07	1.72	1.71	0.30	0.02	0.41	3.60	0.62	0.04	0.11	1.10	0.45	0.03	0.12	48.25	51.75
To	73.87	0.92	203.56	19.54	5.17	3.53	6.93	18.03	11.52	1.42	18.67	4.89	3.59	0.72	2.27	5.07	23.73
NET	71.13	0.38	197.46	-29.61	-2.64	1.98	1.95	-7.92	-51.39	-3.43	-24.81	-29.65	-58.25	-1.06	-17.45	-46.68	

Table 3.4: Volatility spillover of 25 stock market during 2007-2017.

	ASX300	TSX60	SSEC	IGPA	IGBC	OMXC20	EGX30	CAC40	DAX30	ATHEX	NIFTY	IDX	ISEQ
ASX300	78.49	0.40	0.01	0.06	0.11	0.11	0.69	3.91	0.22	0.01	0.63	0.04	1.25
TSX60	1.33	86.84	0.04	0.00	1.06	0.01	0.91	0.11	0.23	0.10	0.04	0.25	0.99
SSEC	0.28	0.23	97.66	0.00	0.04	0.02	0.03	0.03	0.43	0.07	0.13	0.00	0.02
IGPA	0.07	0.41	0.02	96.25	0.03	0.00	0.06	0.08	0.04	0.01	0.25	0.02	0.00
IGBC	4.87	3.46	0.58	0.11	77.32	0.03	1.01	0.11	1.60	0.06	3.63	1.27	0.04
OMXC20	0.48	1.20	0.02	0.01	1.04	94.49	0.22	0.43	0.11	0.13	0.04	0.26	0.13
EGX30	0.29	2.76	0.03	0.04	0.72	0.23	87.40	0.48	0.03	0.01	0.09	4.53	0.30
CAC40	2.17	2.28	0.02	0.21	3.94	3.54	2.63	82.24	0.06	0.03	0.93	0.79	0.08
DAX30	2.21	2.03	0.04	0.31	0.97	1.89	1.51	49.80	36.87	0.37	0.98	0.13	0.10
ATHEX	1.95	0.30	0.05	0.05	0.20	1.03	0.55	2.35	1.27	88.74	0.38	0.04	1.26
NIFTY	0.96	1.19	0.14	0.45	3.37	0.05	0.10	0.89	0.47	1.28	88.26	0.58	0.15
IDX	5.78	2.31	0.37	0.06	8.14	0.25	1.67	0.99	0.16	0.03	1.87	73.40	0.25
ISEQ	3.29	1.93	1.21	0.03	0.12	1.28	0.45	4.85	0.10	3.06	1.12	0.04	76.62
MIB	2.05	2.40	0.01	0.30	1.15	2.40	0.47	34.49	0.48	1.98	0.59	0.08	5.61
NIKKEI	4.45	0.82	0.32	0.11	5.81	0.05	2.66	0.41	0.64	0.35	0.24	1.24	0.60
MEXBOL	0.47	12.83	0.22	0.21	0.63	0.06	0.48	2.51	1.44	0.06	1.97	0.16	0.50
AEX	1.34	4.24	0.07	0.08	3.61	2.37	3.70	49.70	1.31	0.14	0.87	0.54	0.06
KOSPI	5.71	0.36	0.31	0.13	0.29	0.13	0.33	3.45	1.84	0.60	5.84	0.93	0.01
IBEX35	0.70	1.37	0.10	0.07	1.25	6.27	0.27	38.78	0.48	0.44	0.25	0.05	1.20
OMXS30	3.52	3.25	0.30	0.04	4.71	2.37	1.51	22.46	3.04	0.44	1.25	0.17	3.68
SMI	1.08	0.85	0.01	0.00	1.35	0.18	0.14	15.57	0.15	0.03	0.26	0.19	0.06
SET	1.19	6.19	0.19	0.01	0.27	0.12	0.58	0.91	1.53	0.52	0.75	0.63	0.22
XU100	3.56	0.87	0.02	0.43	2.09	1.13	5.12	6.88	0.80	0.09	0.35	0.34	1.04
FTSE	8.89	2.43	0.05	0.21	2.53	2.75	0.94	12.51	0.27	5.69	0.17	0.65	18.86
SP500	1.18	14.43	0.24	0.19	0.51	0.02	2.85	4.31	1.85	0.14	1.35	0.49	0.13
To	57.80	68.53	4.39	3.11	43.94	26.32	28.90	256.00	18.54	15.65	23.97	13.43	36.55
Net	36.29	55.38	2.05	-0.64	21.26	20.81	16.30	238.23	-44.59	4.38	12.23	-13.17	13.18

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Table 3.4 Continued from the previous page.

	MIB	NIKKEI	MEXBOL	AEX	KOSPI	IBEX35	OMXS30	SMI	SET	XU100	FTSE	SP500	From
ASX300	0.14	3.54	2.61	0.05	0.20	0.09	0.37	0.40	0.11	0.06	0.69	5.82	21.51
TSX60	1.13	1.42	0.14	3.54	0.11	0.62	0.19	0.26	0.06	0.05	0.00	0.54	13.16
SSEC	0.19	0.03	0.04	0.02	0.07	0.06	0.02	0.26	0.00	0.07	0.18	0.12	2.34
IGPA	0.03	0.00	0.08	0.03	2.15	0.03	0.04	0.04	0.02	0.05	0.23	0.04	3.75
IGBC	0.29	0.07	1.56	1.84	0.14	0.02	0.12	0.06	0.30	0.04	0.90	0.57	22.68
OMXC20	0.06	0.35	0.14	0.00	0.03	0.40	0.17	0.00	0.18	0.07	0.02	0.02	5.51
EGX30	0.06	0.17	0.23	0.05	0.07	0.14	0.05	0.02	1.10	0.27	0.76	0.18	12.60
CAC40	0.12	0.09	0.36	0.04	0.00	0.00	0.19	0.07	0.01	0.02	0.01	0.18	17.76
DAX30	1.14	0.09	0.26	0.11	0.00	0.07	0.12	0.11	0.01	0.01	0.02	0.85	63.13
ATHEX	0.29	0.07	0.10	0.08	0.54	0.02	0.09	0.02	0.01	0.24	0.20	0.18	11.26
NIFTY	0.09	0.06	0.23	0.04	0.20	0.52	0.53	0.05	0.28	0.05	0.02	0.06	11.74
IDX	0.04	0.09	0.75	0.07	0.01	0.13	0.28	0.01	1.32	0.00	0.03	1.97	26.60
ISEQ	0.13	0.15	0.55	1.28	0.03	0.55	0.22	0.01	0.43	0.14	1.23	1.17	23.38
MIB	46.64	0.20	0.10	0.06	0.24	0.36	0.02	0.01	0.00	0.09	0.02	0.26	53.36
NIKKEI	1.15	74.65	1.38	1.13	0.43	0.27	0.63	0.15	0.09	0.01	1.75	0.64	25.35
MEXBOL	0.11	0.09	76.89	0.29	0.62	0.08	0.23	0.03	0.03	0.02	0.03	0.04	23.11
AEX	0.07	0.07	0.33	30.54	0.30	0.01	0.27	0.13	0.01	0.01	0.19	0.02	69.46
KOSPI	0.13	1.10	4.02	0.28	68.58	0.32	1.99	0.03	0.58	0.03	0.10	2.89	31.42
IBEX35	5.98	0.15	0.27	0.88	0.17	39.66	0.36	0.01	0.13	0.23	0.67	0.26	60.34
OMXS30	1.04	0.32	0.12	1.02	1.39	0.41	46.37	0.02	0.01	0.01	0.07	2.48	53.63
SMI	0.12	0.06	0.24	0.09	0.07	0.71	0.33	78.32	0.01	0.02	0.11	0.06	21.68
SET	0.64	0.16	0.34	0.49	0.27	0.14	0.53	0.09	83.94	0.02	0.05	0.22	16.06
XU100	0.12	0.47	0.27	1.13	0.08	0.10	0.28	0.07	0.02	74.48	0.11	0.16	25.52
FTSE	2.57	0.11	0.60	1.90	0.27	0.15	2.58	0.10	0.03	0.18	34.32	1.23	65.68
SP500	0.12	0.47	15.90	0.36	1.01	0.33	1.75	0.10	0.20	0.02	0.26	51.78	48.22
To	15.77	9.33	30.62	14.78	8.43	5.54	11.37	2.05	4.94	1.70	7.67	19.96	29.17
Net	-37.59	-16.02	7.51	-54.69	-22.99	-54.81	-42.26	-19.64	-11.11	-23.82	-58.02	-28.26	

3.6 Discussions

Generally, our findings are different to the literature that claims a substantial volatility integration. From the perspective of network measures, the overall connectedness have always been around some natural level, which did not increase over time.

What lead to a temporary increased connectedness is the degree of economic shock, particularly from developed countries. Ehrmann and Fratzscher (2009) pointed out the strong impact of US economic shocks, which remained true in this work, as the 9/11 terrorist attack and the recent US presidential transition provoked large stock volatility comovement across globe. Other major events in the EU also seem to have increased the overall level of connectedness. The eurozone crisis, the London bomb attacks and even the Brexit referendum are amongst them. However, the effect of those major economic shocks may not be transient; but it is clearly short-term. It does not take long for the overall connectedness to return back to its neutral level again.

In addition to the above, we find that the extremums of network measures were always associated with negative news which is in line with what Koutmos and Booth (1995). Such results are also consistent with Berben and Jansen (2005) who claim that positive shocks probably reduce volatility, which in turn results to a smaller level of volatility comovement across markets.

By monitoring the graph features of the equity network, we found that all types of negative events would possibly increase the connectedness, while the diameter was enhanced at the same time. This result is also found in Eng-Uthaiwat (2018) although we disagree with their interpretation that the indication of diameter on crisis period is rather limited. The large eccentricity is a probable feature of market decoupling, when the outliers in the intensified volatility transmission net tend to be more heterogeneous. This finding aligns with Ehrmann and Fratzscher (2009) who find that the developing markets barely exhibit volatility comovements with the advanced markets. Under the financial turmoil or monetary policy shocks from US and EU, the stock markets in emerging countries such as China, India, Indonesia, Chile, Egypt, and the like were not inter-correlated.

Finally, it is worth noting that a similar decoupling effect was also found in the European market. The stock markets in the centre of the network are mainly France, Germany, Netherlands, Spain and Sweden, which are some of the largest markets and bonded by the euro. A similar phenomenon was also pointed out by MacDonald et al. (2018) for European Debt crisis. The peripheral countries are decoupled from the largest markets of the Eurozone.

3.7 Summary

In this work, we combine the dynamic conditional correlation and the correlation-based network analysis to investigate market integration of volatility transmission. Using Parkinson volatility estimators and data from a large set of countries, we have found evidence that suggests that volatility comovements of the stock markets across the globe have increased over time. The period of the 2006-09 seems to have raised these comovements even higher which is in accordance to the respective literature that finds that during periods of major economic turmoil, the volatility of financial markets moves in the same direction. However, this synchronisation is neither uniform nor universal. Indeed, the developing economies seem to exhibit volatility changes that are not only uncorrelated with the developing countries, but they are uncorrelated to one another as well. This could suggest that there is far less financial market integration than what was previously thought between the developed and developing world. Furthermore, the day-to-day values of measures of connectedness have revealed that the effect of many major economic events has increased volatility comovements, suggesting that these events could be associated with changes in the systemic structure of the global financial system. Especially the unexpected political events have extensive impact.

In general, our findings suggest that the benefits of international diversification are actually much more moderate than typically thought, at least as a shield against major economic events. However, there are still opportunities for the international investor especially if interested in expanding into developing markets which appear to remain unaffected by the growing comovement of the developed ones.

Chapter 4

The impact of stock volatility on foreign exchange returns

4.1 Introduction

Due to the development of the global financial system and the concomitant increase of interdependence across financial markets, quite often dramatic events such as stock market crashes resulted in some form of economic meltdown for the (broader) region. Likewise, equity risk spillovers to other financial markets seem to be the norm. This is especially the case for the foreign exchange market particularly after the exchange rate arrangements became more flexible following the breakup of the Bretton Woods Agreement. Therefore, since 'more floats and less pegs' constitute many more risk factors to be involved in the determination of the foreign exchange rates, it is only reasonable to expect that stock market volatility also plays a crucial role. This (potential) relationship is the focus of this chapter.

In the post Bretton Woods era, credit decoupled from broad money and grew rapidly. For example, in times of thriving financial market, liquidity moved typically from physical and productive investments to the financial sector. The ensuing availability of bank loans backed by some collateral assets becomes a major factor in the rise of those asset prices. In turn, the credit of borrowers expands, as the value of the collateral assets rises. Consequently, the credit creation for consumption and financial transactions stimulates inflation that further increases the demanded nominal rates of return which eventually contributes to the financial system's fragility. This self-reinforcing mechanism is often referred to as the "financial accelerator"[1].

However, when there is a (negative) liquidity shock to this seemingly benevolent loop, the market participants may engage in panic selling (a demand effect), financial intermediaries may withdraw from providing liquidity (a supply effect), or both, leading to what is referred to as "illiquidity spirals" (Brunnermeier and Pedersen, 2009). Once such a liquidity shock 'hits' a large market, the expectations of market participants is that the future volatility will increase. As a result, the margin-setting financiers require larger margins which further restrict speculators and even noise traders from providing market liquidity, because the liquidity providers become liquidity demanders by reducing their positions in

[1] This concept is introduced in the series of studies by Bernanke, Gertler and Gilchrist in 1980s and 1990s.

risky assets.

In the episode of the recent financial turmoil, the equity market seemed to be the major volatility exporter and stress transmitter. Diebold and Yilmaz (2012) confirmed significant volatility transmission which began in 2007, and highlighted the spillovers from stock market to other markets. Similarly, Apostolakis and Papadopoulos (2015) pointed out that the securities market, especially the US market, was dominant in stress transmission, not only for the respective domestic market, but also across the globe. But other than that, very little do we know as to what extend do foreign exchange rate returns depend on stock market volatility.

In this context, this work examines the effect of stock market volatility on foreign exchange rate returns. Specifically, we look at how stock market volatility from the nine largest stock exchanges are linked to the foreign exchange rate returns of both developed and developing countries. The pairwise dependency is captured by the Dynamic Conditional Correlations (DCC) model (R. Engle, 2002). Then, building upon a principal component analysis that aims to capture the joint variation of the volatility changes in the global equity market, we proxy the effect of the risk transmission channel between stock and foreign exchange market.

The remainder of the chapter is structured as followed. Section 4.2 reviews the literature primarily on the relationship between excess returns and market volatility. Section 4.3 contains the methodology while Section 4.4 describes the data. Section 4.5 presents and discusses respectively the empirical findings. Section 4.6 summarises and concludes this work.

4.2 Literature review

There are two strands of the finance literature that this study is directly relevant to. The first strand is about the much more general relationship between risk and return in financial markets; or, more accurately, given that the notion of risk has been invariably in many different contexts and therefore suffers from multiple definitions, the relationship between return and volatility. This is an important starting point because unlike what we do here, the relationship has been studied almost exclusively for the same market types. This is the consequence of the direct and therefore almost self-evident impact of one market type to the other. As noted later, this strand is not as simple as it was initially assumed. The second strand of literature is about the cross-market relationship between stock market and foreign exchange markets[2]. This has been focused either on the relationship between levels, or on the relationship between volatilities and in turn provides effectively the backbone for motivating our research. The remainder of this section overviews first the former strand and then the later one.

4.2.1 The relationship between return and volatility

The literature on the relationship between return and volatility has proved to be quite exciting because the empirical results provided are rather mixed. The traditional view, for which Merton (1987) is often cited, suggests that there is a positive relationship between return and risk and the general argument behind this view is that firms that with larger common-factor exposure are typically found to tend to have higher returns. An alternative explanation was given by Barberis and Huang (2001). They focused on this relationship from the perspective of investors psychology. The argument that they developed was that because loss averse causes asymmetrical reaction to gains and losses, and the narrow framing, stock or portfolio that had high returns would be excessively volatile.

The more recent view, such as that of Ang, Hodrick, Xing, and Zhang (2006), implies that the relationship between return and risk is negative although the study has been criticized that it focused on a small subset of possible assets which experienced high volatilities. However, Adrian and Rosenberg (2008) presented similar empirical findings, and pointed out that short-run volatility implied the tightness of financial constrains and the long-run volatility was a different measure that could be affected by business cycle.

A third view is that the relationship between expected returns and volatility does not exist and the estimates are not significant. In particular, Huang, Liu, Rhee, and Zhang (2009) argued that although volatility on based on daily frequency data tended to have significant negative correlation with the expected returns, once return reversals were controlled, the negative relationship disappeared, while the estimation based on monthly data

[2]This literature has been reviewed in Chapter 1 so instead of duplicating the material here, we focus primarily on the specific aspects of that research that is more directly relevant to the purposes of this chapter.

remained significantly positive. This is also in line with Fu (2009) who stated that the relationship between the volatility and returns cannot be explained in a static way, because the time-varying nature of risk would make inference be sample dependent.

To address such conflicting views, a good amount of literature has attempted to examine various factors that might affect the relationship to the extent that it generates contradictory results. In this spirit, Bali and Cakici (2008) investigated factors such as the frequency of data, the weighting scheme of the estimates, and the presence of breakpoints, and found that all those were potential determinants of the return-volatility relationship. Similarly, Anderson, Ghysels, and Juergens (2009) proposed a two factor model, which decompose the volatility to risk and uncertainty, both of which imply an unknown outcome, but uncertainty differs from risk in that unlike the latter there cannot be any prior knowledge of the underlying distribution. Based on this, they derived that uncertainty was the significant positive factor of market excess returns, while risk was not. Finally, it is worth noting Hameed, Kang, and Viswanathan (2010) who suggested that volatility spillovers also appear to be asymmetrical in terms of shocks. Consequently, a decrease in asset prices may affect liquidity much more than an increase.

4.2.2 The relationship between FX and SX markets

The literature on the relationship between the foreign exchange market and the stock market although it has been continuously growing, it has yet to reach a conclusive consensus. It has so far provided rather mixed results.[3] For example, early empirical evidences in Phylaktis and Ravazzolo (2005) suggested that the foreign exchange and stock markets were positively related, at least across the Pacific Basin countries which they focused on. In contrast, Grammatikos and Vermeulen (2012) found that the 2007/8 crisis was pivotal in changing the relationship. Specifically, their results suggest that before the crisis the two markets were negatively correlated; after the crisis, they became positively correlated.

A tangent albeit directly relevant strand of literature looks at the spillover effect that might exist between the foreign exchange and stock markets. Typically, these spillovers

[3] As mentioned before, much of the literature on the mutual effect between the two markets is covered in Section 2.2.3 so it would be superfluous to duplicate this information here. Instead we focus on overviewing some of its aspects that are directly relevant to the work we undertake in this chapter.

are found to be asymmetric. For example, Apergis and Rezitis (2001) found meteor shower effects from the foreign exchange market to the stock exchange market; but not the other way around. But typically the direction of the relationship is found to be the exact opposite. For example, more recently Diebold and Yilmaz (2012), who studied volatility spillovers among four major asset classes, found that the impact of spillovers from the other markets to the foreign exchange market was relatively large especially during the global financial crisis, when the foreign exchange market received sizable net volatility spillovers from stock, bond and commodity markets.

The same theme, that stock market is typically the source of spillovers to other markets including the foreign exchange market, is found by several other studies as well. For example, Apostolakis and Papadopoulos (2015) found that the stock market was the principal stress transmitter when compared to the foreign exchange market. Similarly for Caporale et al. (2014) who focused specifically on developed markets, and emphasized the causality effect between the US and the UK; and also for Lin (2012) who focused on emerging markets and also found that the major spillover channel is from stock prices to exchange rates.

Finally, another strand of literature that is also tangent but relevant even somewhat more remotely, focuses on developing economies and the impact that financial liberalization had on them. In particular, market liberalization has typically been promoted as quite beneficial for an economy. For example, Bekaert and Wu (2000), and Bekaert, Harvey, and Lumsdaine (2002) argues that economic openness of the country is a reliable predictor of economic growth. Given that the stock markets are often thought of as mirroring the state of the economy, this would imply a positive relationship between stock markets and foreign exchange markets. However, the counter side of financial liberalization is that a liberalized market would be more susceptible to global shocks. This is why for example, (Reinhart and Rogoff, 2009) found that the stability of the banking sector is negatively affected by the degree of financial liberalization. Consequently, because capital controls and a pegged exchange rate are typical features of developing economies, in terms of risk receiving, the level of development is clearly a key factor that determines the relationship between foreign exchange and stock markets.

4.3 Methodology

The primary focus of this chapter is to examine the potential time-varying relationship between foreign exchange rates and the stock market volatility. Therefore, there are two components into our analysis, namely the measurement of stock market volatility and the modeling of the time-varying relationship between this and of the foreign exchange rates.

In terms of stock market volatility, we focus on range-based volatility estimators as discussed in detail in the Methodology section of Chapter 2, although the results are rather similar so the ones reported are based on the Parkinson estimator. Moreover, it should be noted that we follow the same practice that we follow there namely, we use the first difference of the volatility proxy. The reasons why we do so are also explained in detail in the Methodology section of Chapter 2.

In terms of modeling the time-varying relationship between foreign exchange rate returns and stock market volatility changes, we adopt the DCC model of R. Engle (2002) which has been presented and discussed in detail in the Methodology section of Chapter 1.

The above analysis focuses on the comovements between each pair of series. However, we can go further and adopt the view of the literature that claims that stock markets are the ones that affect the foreign exchange markets. To do so, we need to also take explicitly into account the asymmetric effect of stock markets onto the foreign exchange market. For this reason, we also estimate autoregressive models of foreign exchange rate returns for which the stock market volatility changes are considered as exogenous:

$$r_t = \alpha + \beta r_{t-1} + \sum_{i=1}^{m} \eta_i d_{t,i}, \tag{4.1}$$

where r_t is the return of foreign exchange and $d_{t,i}$ is the contemporary volatility from stock market. It is worth noting that only the first lag was used because the markets considered are quite established and it is unlikely that for daily frequency the weak form of market efficiency will not hold. Moreover, it is generally known that mean effects are rather small, and indeed, in anticipation of the results, this is what we also find.

Apart from looking at each of the impact upon the foreign exchange rate returns of the volatility change of each stock market individually, it is possible to make a more general assumption namely that there is a kind of global stock market volatility proxy. By making such an assumption then a more plausible approach would be to aggregate the stock market volatility changes of the different series so as to proxy the volatility changes of this global stock market. We do so by carrying out factor analysis to determine a sufficient number of principal component of these volatility changes that are then used as exogenous variables instead. In particular, denote the standardized volatility changes of all considered stock indices as $v_t = (v_{1,t}, v_{2,t}, \ldots, v_{m,t})^T$, and the correlation matrix of $v_{i,t}$ is a diagonalized as $P = u\lambda u^T$. Hence, the eigenvalues stands for the variance of the principal component, $\alpha_{i,t}$ (Jolliffe, 1986). The changes of volatility can be expresses by the first principal component as

$$v_t = u_1 \alpha_{1,t} + \eta_t, \tag{4.2}$$

$$\eta_t = \sum_{i=2}^{m} u_i \alpha_{i,t}. \tag{4.3}$$

Interestingly, the mathematical expression of the respective model is as before, only now $d_{t,j}$ refers to the respective component of the volatility changes of the notional global stock market.

Finally, it is worth noting that because of the asynchronicity in the sample markets, the correlations between the two series could be underestimated. The common approach to addressing this issue is some form of aggregation, often by using weekly data. However, by doing so the daily dynamics would be neglected. Alternatively, the approach of Burns and Engle (1998) and Riskmetrics$^{\text{TM}}$, limit the impact of the lack of synchronization by using a rolling window to average the series. In line with such methods, we estimate the time-varying correlation after we apply a rolling average filter on the series, with rolling windows ranging from two to four. The mean-effects are naturally captured by the autoregressive component of the mean equation.

4.4 Data

The data of this chapter comprise the daily returns of 10 foreign exchanges, and range-based volatility of 9 stock indices. The data spans from the 1st of January 1996 to the 31th of December 2017. The FX returns was used in the first chapter, and here simplifies the dataset to 5 major currencies, Canadian dollar, euro, Japanese yen, Swiss franc and English sterling, and 5 currencies of the BRICS country group. Some descriptive statistics of 10 FX return series is in Table 2.2. The equity market indices are from the top 9 largest stock exchanges, TSX60, SSEC, CAC40, DAX30, NIFT500, NIKKEI, SMI, FTSE and SP500. Volatility follows the Parkinson estimation that was used in the second chapter. Table 3.1 presents the statistics of the volatilities. The respective graphs of the sample series are in Section 3.4.

4.5 Empirical results

Following the Methodology, this part contains four section. The first is about the Dynamic Conditional Correlations (DCCs) between the foreign exchange (FX) rate returns and the volatility changes of stock market or stock exchange (SX) returns. The second section is about the impact of each individual SX volatility changes onto the FX rate returns. The third section is about the impact of the principal components of SX volatility changes onto the FX returns. Finally, the last section discusses our results.

4.5.1 The DCCs between the FX returns and the volatility changes of the SX returns

In general, correlations between foreign exchange returns and stock market volatility changes range from -50% to 50% and compared to correlations of market returns, as shown in Chapter 1, they are relatively weak. In fact, the correlations in many market pairs show very little variability, to the point of being almost constant (non-dynamic i.e. static) and close to zero. We present the results of the DCC trajectories that have some substantial variability and are significantly different from zero. Figure 4.1 presents 32 market pairs (out of the 90) focused on the developed markets while Figure 4.2 presents the respective market pairs for the BRICS markets. Also, as an indication, in each graph we highlight four major financial events, namely the start of the 1997 Asia crisis, the 2001 dot-com bubble burst, the 2007 subprime bubble burst, and the start of the Eurozone crisis as well as a most recent economic event namely the Brexit referendum.

In general, the major developed markets are more correlated and from visual inspection it appears that changes in the dynamics of correlation can be associated to the extraordinary events that we highlight on the graphs. On average, the correlations in the developed markets are negative or around zero. The Canadian dollar seem to be a sole exception, by being positively correlated to the volatility changes of the major stock market indices.

After the subprime bubble burst, Euro had increasing correlations with the stock market volatilities of CAC40, DAX30, SP500 and TSX60. It declined gradually after the series of bailout, but suddenly increased during the period of the Brexit referendum. Similar dynamics occurred to the correlations of CAD-SMI, CHF-CAC40, CHF-DAX30, CHF-SP500, CHF-TSX60 and GBP-DAX30. In contrast, the correlations between the returns of the Japanese yen and the major stock market volatility changes are generally negative, and declined during the episode of financial crisis 2007/08, Eurozone crisis and the Brexit.

The exactly opposite situation seem to be the case for the BRICS developing markets. Here, the correlations are positive throughout the sample period. However, each of the BRICS has different dynamics. The Brazilian real had extremely large correlation with the largest equity markets, particularly DAX30 and FTSE during the 1999 Brazilian currency crisis. The Chinese yuan was more sensitive to the volatility in NIFTY500 than to the other advance markets. Its correlation with the stock market volatility changes only increased in the mid-2015, when the global stock market had a flash drop. The Indian rupee was more correlated with DAX30 and TSX60, and correlations increased largely in the period of the global financial turmoil. The Russian ruble had the most sensitive relation with the uncertainty of major equity market. The conditional correlations had many extreme spikes around the disruptive events. Lastly, the South African rand was positively correlated with the volatility changes of SMI, DAX30 and FTSE; the correlation peaked at around 2012.

Figure 4.1: Dynamic conditional correlations of the returns of major foreign exchanges and the volatility of benchmark stock indices.

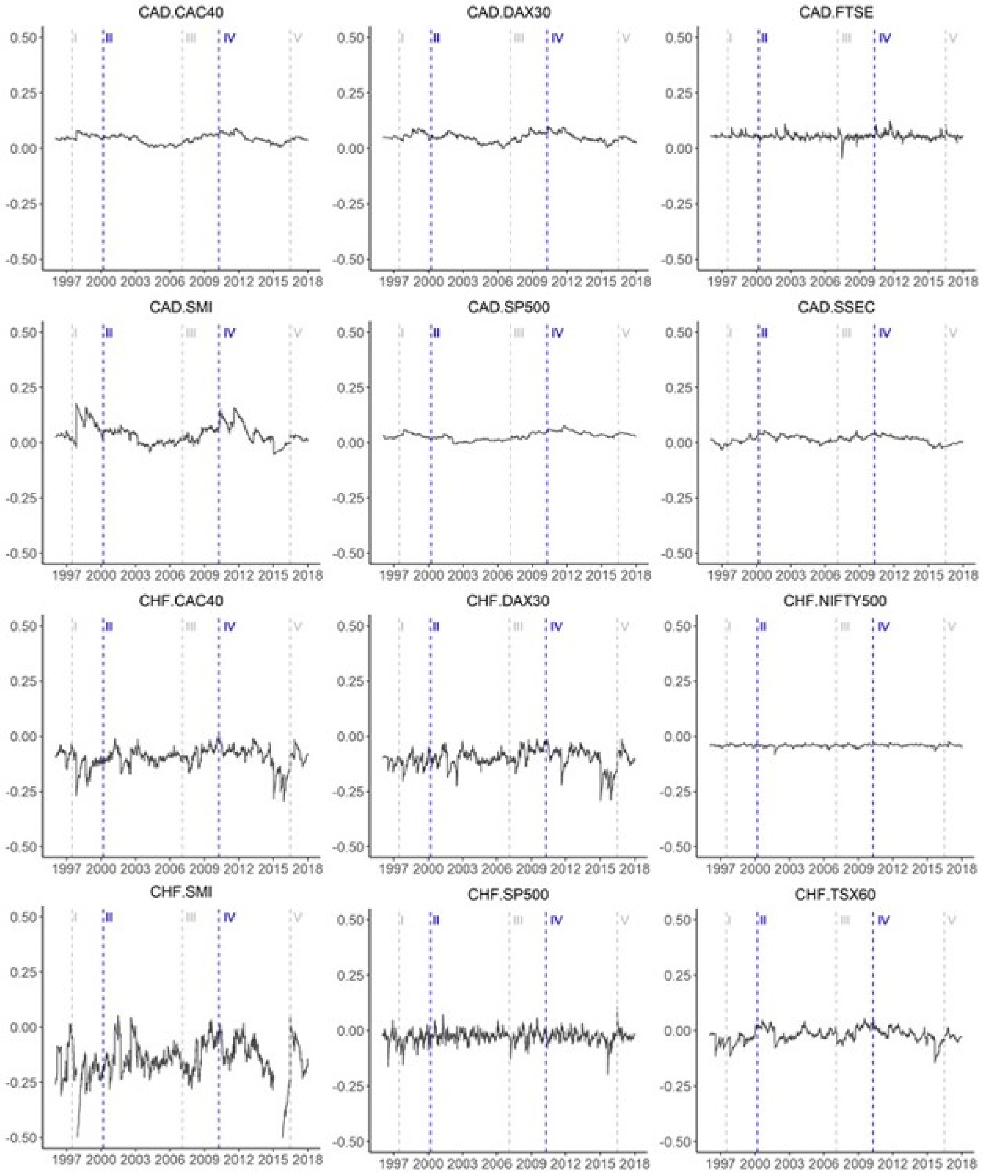

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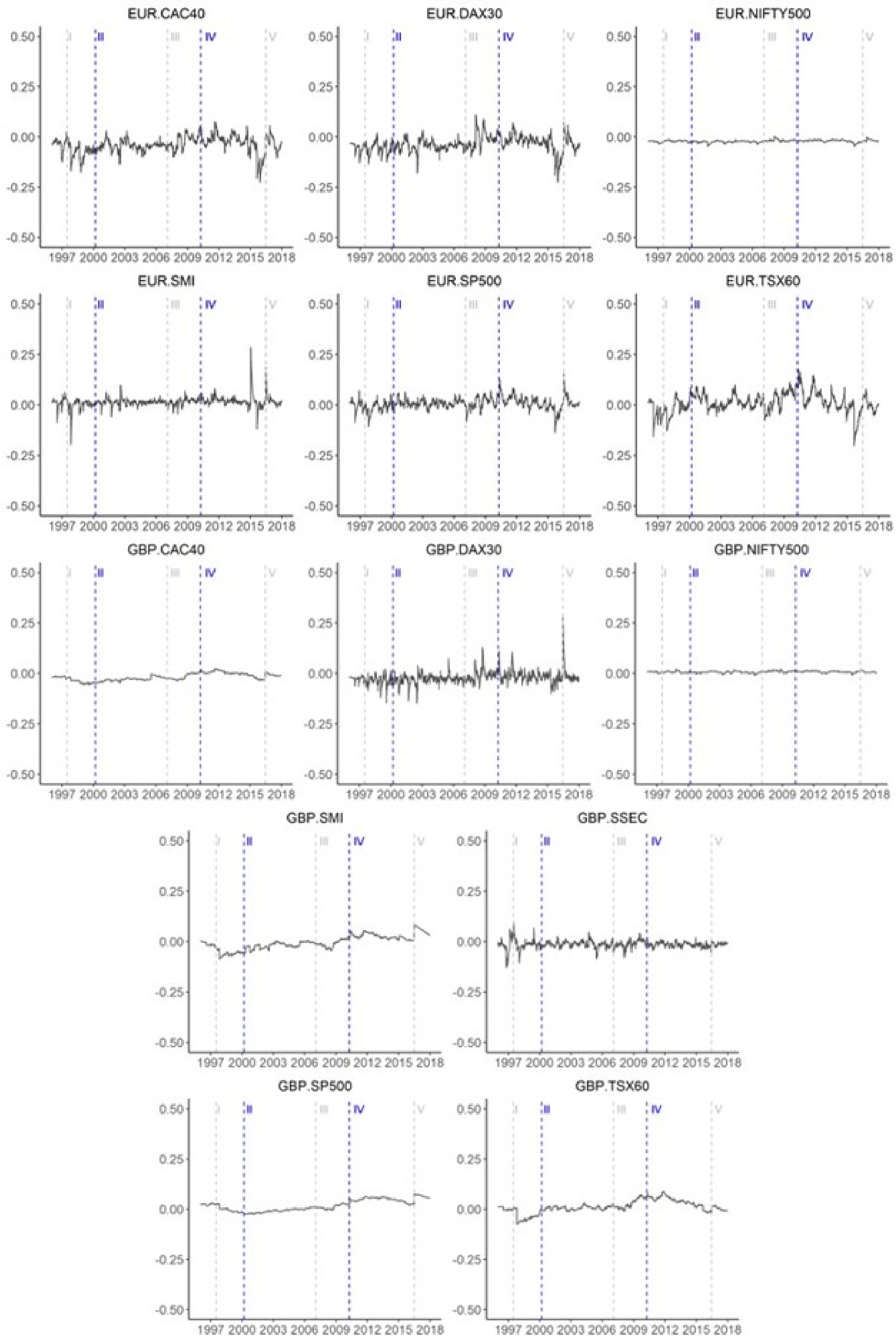
Figure 4.1 Continued from the previous page.



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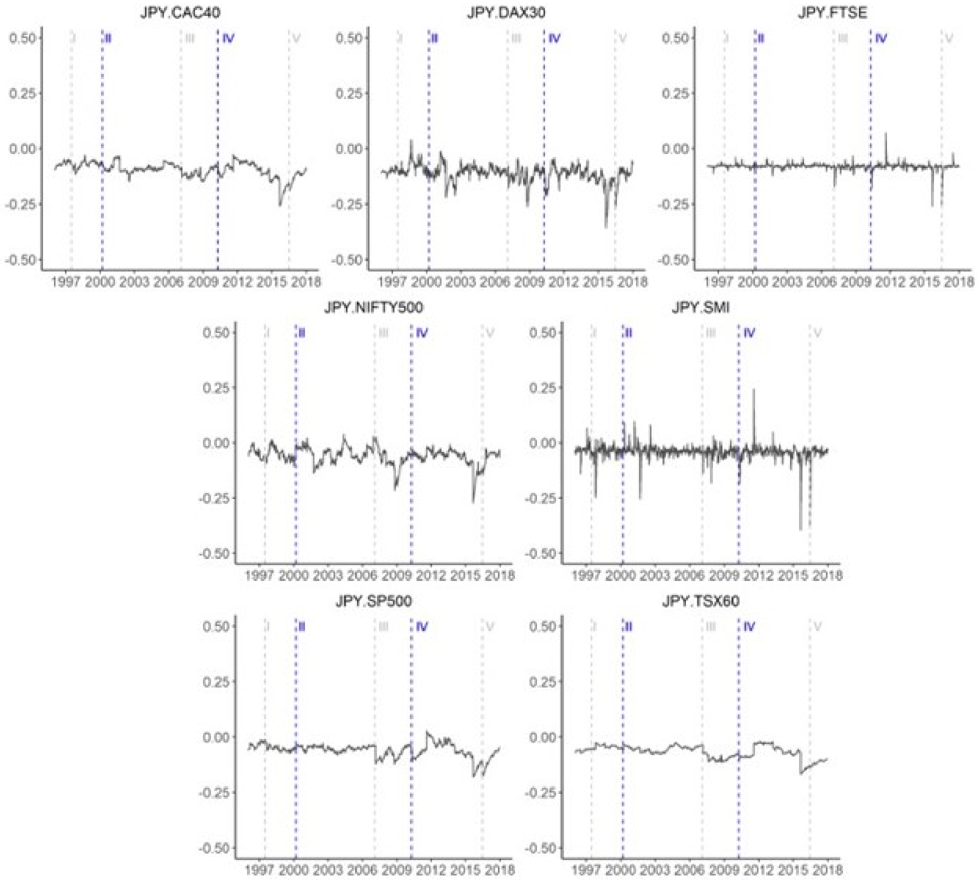
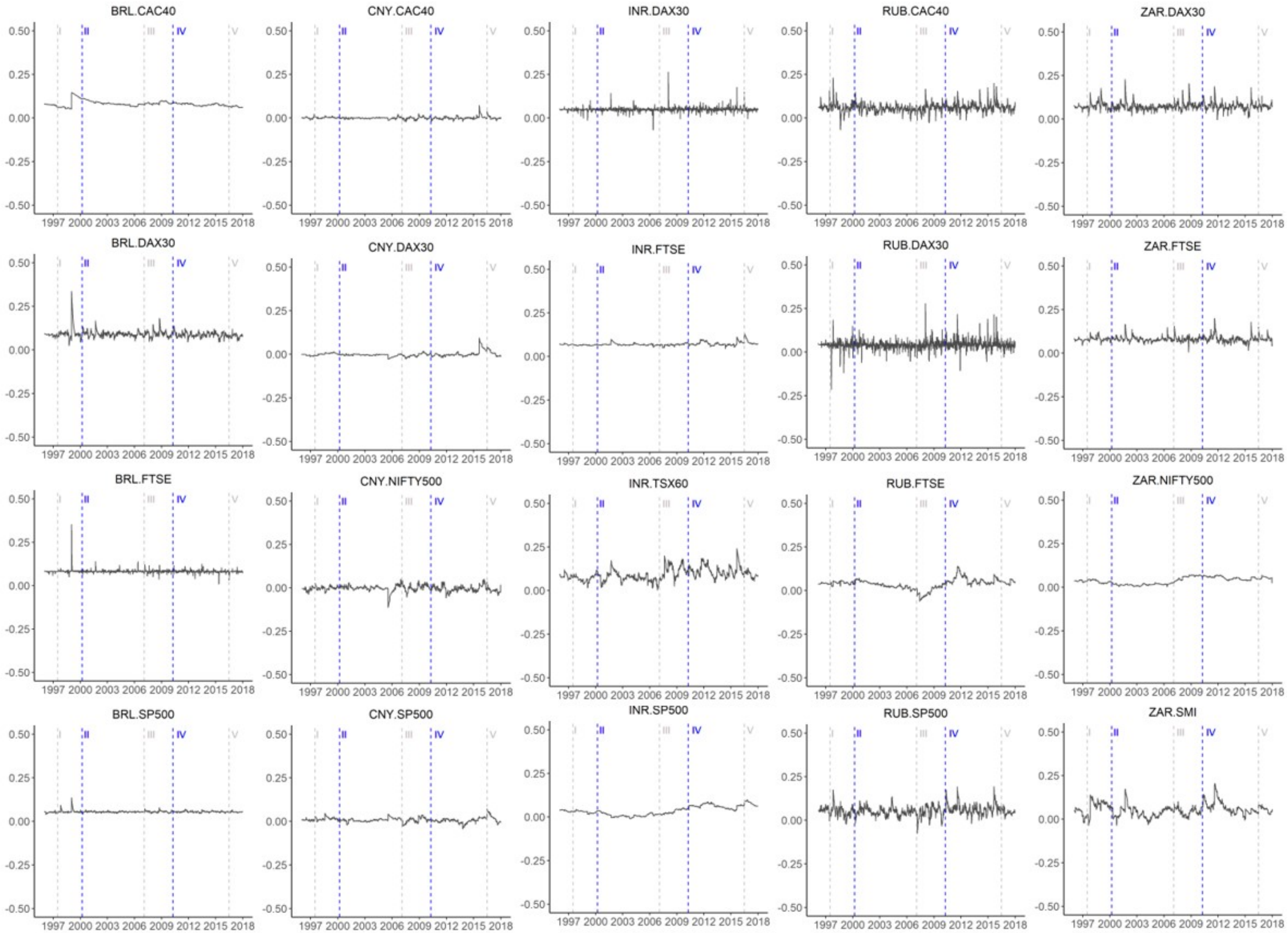


Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum.

Figure 4.2: Dynamic conditional correlations of the returns of BRICS foreign exchanges and the volatility of benchmark stock indices.



Note: Events I to V which are marked by the dash lines, refer to accordingly to the 1997 Asia crisis, dot-com bubble burst, subprime bubble burst, Eurozone crisis and Brexit referendum.

4.5.2 The impact of individual SX volatility changes upon the FX returns

The autoregressive models produced some notable results, which are presented in Table 4.1-4.4. Table 4.1 is the autoregressive estimation on the original series, and the estimation on rolling averages are shown in Table 4.2-4.4, corresponding to the window width of 2-4.

Similar to what was found in the conditional correlations, the cross-country return-volatility relations were generally positive, while the domestic FX-SX relation was negative. There were a few exceptions. The volatility changes of CAC40 and NIFTY500 had a negative effect on the returns of the Japanese yen; the increase in the volatility changes of FTSE and SP500 caused a drop in the Brazilian real; SMI also had small but significant impact on the returns of Chinese yuan.

In addition, the US stock market is clearly the dominant volatility exporter. The major five FX rate returns, apart from the Japanese yen, and the BRICS, apart from the Chinese yuan and the Russian rouble, were all significantly affected by the volatility changes of SP500. In particular, the coefficient estimation of SP500 was 4.07 for the Canadian dollar, 4.16 for the euro and 6.12 for the Indian rupee. Following the SP500, CAC40, FTSE and SMI also had a relatively large impact upon some of the major FX rate returns. The CAC40 had a coefficient estimate of 7.42 for the Brazilian real; the SMI affected the Russian ruble by 3.31; and the FTSE had a coefficient estimate of 2.98 for the South African rand.

Table 4.1: AR(1) models using original data.

Foreign exchange		Intercept	AR1	TSX60	SSEC	CAC40	DAX30	NIFTY500	NIKKEI	SMI	FTSE	SP500
CAD	Coefficient	-6.93E-06	-0.0119	0.2160	-0.0362	0.7979	0.1301	0.2202	**0.7952**	0.2686	**2.7775**	**2.2202**
	Standard error	7.12E-05	0.0134	0.4222	0.2048	0.5655	0.3798	0.2317	0.2842	0.3506	0.8416	0.7272
EUR	Coefficient	1.55E-05	0.0101	**1.5960**	-0.5280	-1.1635	0.3166	-0.4570	0.0711	0.0594	0.3072	**2.7819**
	Standard error	8.10E-05	0.0132	0.4695	0.2268	0.6260	0.4202	0.2575	0.3153	0.3874	0.4754	0.4117
JPY	Coefficient	-3.47E-06	0.0021	-1.1863	0.0426	-1.6161	-1.0196	**-0.9858**	**-1.5943**	0.1906	0.2359	-0.0126
	Standard error	8.90E-05	0.0132	0.5222	0.2527	0.6977	0.4681	0.2862	0.3511	0.4319	0.0845	0.0729
CHF	Coefficient	-4.13E-05	0.0206	**1.2676**	-0.4810	-0.4791	-0.6384	-0.8061	-0.3130	**-2.2702**	0.7843	0.7610
	Standard error	9.13E-05	0.0132	0.5242	0.2528	0.6975	0.4679	0.2874	0.3517	0.4318	0.5262	0.4536
GBP	Coefficient	2.76E-05	**0.0505**	**1.5627**	-0.1508	-0.0838	-0.3096	-0.0667	0.2628	-0.5995	**1.0531**	0.6101
	Standard error	7.96E-05	0.0132	0.4386	0.2104	0.5801	0.3895	0.2405	0.2938	0.3581	0.3117	0.2693
BRL	Coefficient	2.37E-04	**0.0475**	-0.2217	-0.3433	**5.5803**	0.8864	**1.6792**	0.4161	-0.2662	**-2.1234**	-0.8060
	Standard error	1.36E-04	0.0133	0.7567	0.3631	1.0026	0.6716	0.4147	0.5066	0.6181	0.5863	0.5058
CNY	Coefficient	-4.20E-05	**0.0348**	0.2209	-0.0023	0.0499	0.0184	0.0177	-0.0338	-0.1772	0.5353	0.9778
	Standard error	1.87E-05	0.0132	0.0758	0.0364	0.1005	0.0674	0.0415	0.0508	0.0621	1.3003	1.1242
INR	Coefficient	1.08E-04	**0.0630**	**0.8003**	0.0553	0.2875	0.0882	**0.4790**	0.3566	0.0630	**1.8985**	**4.0496**
	Standard error	5.28E-05	0.0132	0.2810	0.1345	0.3708	0.2486	0.1540	0.1880	0.2287	0.8705	0.7527
RUB	Coefficient	4.48E-04	0.1104	**3.7076**	-0.8130	-0.9448	1.6337	0.0208	0.5304	0.9865	-0.4637	0.2770
	Standard error	2.30E-04	0.0132	1.1824	0.5624	1.5463	1.0360	0.6482	0.7884	0.9518	0.5863	0.5057
ZAR	Coefficient	2.30E-04	0.0243	0.7458	-0.2537	1.0219	1.0646	0.7525	**1.5722**	0.4163	**3.3317**	**1.1277**
	Standard error	1.36E-04	0.0133	0.7804	0.3754	1.0355	0.6948	0.4274	0.5228	0.6406	0.4877	0.4209

Note: Coefficient estimations which are in bold are significant.

Table 4.2: AR(1) models using two-days rolling average.

Foreign exchange		Intercept	AR1	TSX60	SSEC	CAC40	DAX30	NIFTY500	NIKKEI	SMI	FTSE	SP500
CAD	Coefficient	-6.39E-06	**0.4835**	0.1160	-0.2559	0.5771	0.0703	0.2791	0.3485	0.8829	0.9635	**4.0745**
	Standard error	8.52E-05	0.0116	0.4296	0.2166	0.6082	0.4125	0.2343	0.3082	0.3836	0.9343	0.7791
EUR	Coefficient	1.74E-05	**0.5016**	**1.5491**	-0.5708	-0.9585	0.4452	-0.3556	-0.1608	0.2159	-0.2740	**4.1561**
	Standard error	9.84E-05	0.0114	0.4787	0.2409	0.6760	0.4583	0.2609	0.3430	0.4260	0.5081	0.4244
JPY	Coefficient	-2.52E-06	**0.4948**	-0.9751	0.3363	**-1.8308**	-0.6825	**-0.8974**	**-1.5310**	0.0257	**0.3063**	0.0382
	Standard error	1.08E-04	0.0115	0.5325	0.2681	0.7528	0.5102	0.2902	0.3817	0.4746	0.0918	0.0766
CHF	Coefficient	-3.98E-05	**0.5024**	**1.3780**	-0.4645	0.8703	-1.1352	-0.6622	-0.1128	**-3.2069**	0.4518	**1.1014**
	Standard error	1.11E-04	0.0114	0.5380	0.2706	0.7596	0.5149	0.2932	0.3854	0.4787	0.5647	0.4710
GBP	Coefficient	3.09E-05	**0.5079**	**1.7025**	-0.2461	-0.1394	0.5267	0.0320	-0.2015	-0.6380	**1.1603**	**1.0851**
	Standard error	9.55E-05	0.0114	0.4577	0.2301	0.6458	0.4379	0.2495	0.3280	0.4069	0.3430	0.2862
BRL	Coefficient	2.38E-04	**0.5016**	-1.1102	-0.4172	**7.4162**	0.7073	**1.6333**	0.0935	-0.0425	**-2.2811**	**-1.2348**
	Standard error	1.62E-04	0.0115	0.7926	0.3983	1.1187	0.7582	0.4316	0.5673	0.7047	0.6287	0.5247
CNY	Coefficient	-4.20E-05	**0.5117**	**0.2290**	-0.0206	0.0785	0.0201	0.0008	-0.0706	**-0.2399**	1.1801	-1.5885
	Standard error	2.09E-05	0.0114	0.0780	0.0392	0.1099	0.0745	0.0425	0.0559	0.0692	1.4160	1.1809
INR	Coefficient	1.10E-04	**0.5241**	**0.9847**	-0.0832	0.7054	-0.0150	**0.4418**	0.2178	0.1786	1.2830	**6.1159**
	Standard error	6.39E-05	0.0113	0.2918	0.1464	0.4108	0.2784	0.1590	0.2092	0.2586	0.9503	0.7931
RUB	Coefficient	4.46E-04	**0.5745**	**3.5720**	-1.0388	-1.9754	**2.5974**	-0.0314	-0.1309	**3.3100**	-0.6614	0.1623
	Standard error	2.95E-04	0.0108	1.2126	0.6055	1.6971	1.1499	0.6608	0.8699	1.0670	0.6344	0.5293
ZAR	Coefficient	2.35E-04	**0.4945**	-0.8366	-0.1616	0.9891	1.8205	**1.4821**	0.2355	1.3594	**2.9824**	**1.4060**
	Standard error	1.62E-04	0.0115	0.8052	0.4052	1.1375	0.7711	0.4386	0.5765	0.7172	0.5394	0.4499

Note: Coefficient estimations which are in bold are significant.

Table 4.3: AR(1) models using three-days rolling average.

Foreign exchange		Intercept	AR1	TSX60	SSEC	CAC40	DAX30	NIFTY500	NIKKEI	SMI	FTSE	SP500
CAD	Coefficient	-6.39E-06	**0.4835**	0.1160	-0.2559	0.5771	0.0703	0.2791	0.3485	0.8829	**3.8525**	**3.1176**
	Standard error	8.52E-05	0.0116	0.4296	0.2166	0.6082	0.4125	0.2343	0.3082	0.3836	0.8838	0.7797
EUR	Coefficient	1.74E-05	**0.5016**	**1.5491**	-0.5708	-0.9585	0.4452	-0.3556	-0.1608	0.2159	0.5668	**2.2689**
	Standard error	9.84E-05	0.0114	0.4787	0.2409	0.6760	0.4583	0.2609	0.3430	0.4260	0.4875	0.4309
JPY	Coefficient	-2.52E-06	**0.4948**	-0.9751	0.3363	**-1.8308**	-0.6825	**-0.8974**	**-1.5310**	0.0257	0.1672	-0.0001
	Standard error	1.08E-04	0.0115	0.5325	0.2681	0.7528	0.5102	0.2902	0.3817	0.4746	0.0866	0.0764
CHF	Coefficient	-3.98E-05	**0.5024**	**1.3780**	-0.4645	0.8703	-1.1352	-0.6622	-0.1128	**-3.2069**	0.9093	0.2752
	Standard error	1.11E-04	0.0114	0.5380	0.2706	0.7596	0.5149	0.2932	0.3854	0.4787	0.5536	0.4883
GBP	Coefficient	3.09E-05	**0.5079**	**1.7025**	-0.2461	-0.1394	0.5267	0.0320	-0.2015	-0.6380	0.7965	0.4986
	Standard error	9.55E-05	0.0114	0.4577	0.2301	0.6458	0.4379	0.2495	0.3280	0.4069	0.3319	0.2929
BRL	Coefficient	2.38E-04	**0.5016**	-1.1102	-0.4172	**7.4162**	0.7073	**1.6333**	0.0935	-0.0425	**-1.6133**	**-1.4510**
	Standard error	1.62E-04	0.0115	0.7926	0.3983	1.1187	0.7582	0.4316	0.5673	0.7047	0.6139	0.5416
CNY	Coefficient	-4.20E-05	**0.5117**	0.2290	-0.0206	0.0785	0.0201	0.0008	-0.0706	**-0.2399**	1.8194	-1.2581
	Standard error	2.09E-05	0.0114	0.0780	0.0392	0.1099	0.0745	0.0425	0.0559	0.0692	1.4399	1.2705
INR	Coefficient	1.10E-04	**0.5241**	**0.9847**	-0.0832	0.7054	-0.0150	**0.4418**	0.2178	0.1786	**3.2131**	**4.1665**
	Standard error	6.39E-05	0.0113	0.2918	0.1464	0.4108	0.2784	0.1590	0.2092	0.2586	0.9267	0.8181
RUB	Coefficient	4.46E-04	**0.5745**	**3.5720**	-1.0388	-1.9754	2.5974	-0.0314	-0.1309	**3.3100**	-0.2204	-0.3269
	Standard error	2.95E-04	0.0108	1.2126	0.6055	1.6971	1.1499	0.6608	0.8699	1.0670	0.6164	0.5437
ZAR	Coefficient	2.35E-04	**0.4945**	-0.8366	-0.1616	0.9891	1.8205	**1.4821**	0.2355	1.3594	**4.1701**	0.7991
	Standard error	1.62E-04	0.0115	0.8052	0.4052	1.1375	0.7711	0.4386	0.5765	0.7172	0.5252	0.4633

Note: Coefficient estimations which are in bold are significant.

Table 4.4: AR(1) models using four-days rolling average.

Foreign exchange		Intercept	AR1	TSX60	SSEC	CAC40	DAX30	NIFTY500	NIKKEI	SMI	FTSE	SP500
CAD	Coefficient	-4.79E-06	**0.7419**	0.5452	0.3525	1.1570	0.0337	0.2441	**0.9454**	-0.1305	**5.0548**	1.3214
	Standard error	9.16E-05	0.0089	0.4281	0.2195	0.5934	0.3951	0.2408	0.3030	0.3727	0.8869	0.7968
EUR	Coefficient	1.82E-05	**0.7550**	**1.6214**	-0.2178	-1.4955	0.2992	-0.5653	0.1845	0.2557	0.3234	**2.5403**
	Standard error	1.07E-04	0.0087	0.4737	0.2424	0.6552	0.4362	0.2663	0.3347	0.4112	0.5024	0.4517
JPY	Coefficient	-4.97E-06	**0.7448**	**-1.8779**	0.0013	**-2.2089**	**-1.2528**	**-0.8932**	**-1.1455**	0.7761	0.4037	-0.0085
	Standard error	1.15E-04	0.0088	0.5321	0.2727	0.7373	0.4908	0.2992	0.3761	0.4630	0.0888	0.0798
CHF	Coefficient	-3.84E-05	**0.7542**	1.2512	-0.2767	-1.1447	-0.5554	**-1.0083**	-0.1107	**-1.8708**	**1.4916**	0.2401
	Standard error	1.20E-04	0.0087	0.5341	0.2734	0.7390	0.4919	0.3003	0.3774	0.4638	0.5546	0.4981
GBP	Coefficient	3.34E-05	**0.7571**	**2.2159**	-0.0241	-0.4856	0.3215	-0.0820	0.2899	-0.5822	**1.4767**	**0.7436**
	Standard error	1.03E-04	0.0086	0.4512	0.2308	0.6239	0.4154	0.2537	0.3188	0.3915	0.3303	0.2968
BRL	Coefficient	2.39E-04	**0.7694**	0.0518	-0.1680	**7.4554**	-0.1678	1.5321	-1.0154	-0.9792	**-2.0066**	-0.3873
	Standard error	1.82E-04	0.0084	0.7598	0.3878	1.0482	0.6977	0.4268	0.5368	0.6572	0.6242	0.5608
CNY	Coefficient	-4.14E-05	**0.7745**	**0.2493**	-0.0279	-0.0120	0.0225	0.0336	-0.0112	-0.1600	2.1423	1.9820
	Standard error	2.28E-05	0.0084	0.0761	0.0388	0.1049	0.0699	0.0428	0.0538	0.0658	1.6819	1.5098
INR	Coefficient	1.09E-04	**0.7803**	0.6447	0.0337	0.8524	-0.1804	0.3706	0.3338	0.0447	2.2365	**3.1991**
	Standard error	7.23E-05	0.0083	0.2834	0.1445	0.3904	0.2599	0.1592	0.2004	0.2447	0.9261	0.8323
RUB	Coefficient	4.46E-04	**0.7237**	2.0169	-1.1989	-1.4218	1.7628	0.2643	-0.2331	1.6885	0.1799	0.1567
	Standard error	2.83E-04	0.0091	1.4274	0.7351	1.9863	1.3219	0.8038	1.0081	1.2505	0.6255	0.5618
ZAR	Coefficient	2.31E-04	**0.7506**	0.8912	0.1010	1.4869	0.9992	0.4264	0.8536	1.3263	**4.1391**	0.6505
	Standard error	1.74E-04	0.0087	0.7912	0.4047	1.0940	0.7283	0.4445	0.5585	0.6868	0.5281	0.4743

Note: Coefficient estimations which are in bold are significant.

4.5.3 The impact of the principal components of SX volatility changes upon the FX returns

The factor loadings of each index are presented in Table 4.5 according to principal component analysis (PCA). More than 50% of the variances can be explained by three principal components (PC). The explained variance with regard to the PC are shown in Figure 4.3. Described by the first two important components, the major indices roughly move in five directions, which is shown in Figure 4.4. SP500 and TSX60 have the similar weights of PC1 and PC2. European continental market is the second group, which contains CAC40, DAX30 and SMI. FTSE shares similar weight of PC1 with the continental market, not PC2. NIKKEI and NIFTY500 are more or less in the same direction, while NIKKEI is more correlated with the principal factors. SSEC is related to PC2 and seems to be barely affected by PC1. Additionally, the plane of PC1 and PC2 successfully separates the events that associate some abnormal volatility changes, such as the 11th of September 2001, the 24th of June 2016 as well as the days of the last quarter of 2008.

Finally, Table 4.6 shows the estimation results from our last model. The first and second principal components (PC) significantly affect the five major currencies, but their impact on BRICS countries are not uniformly significant. The South African rand is sensitive to both PC1 and PC2 but only PC1 has any statistically significant impact onto the Brazilian real. The same holds true for the Indian rupee.

Figure 4.3: Explained variance by principal component.

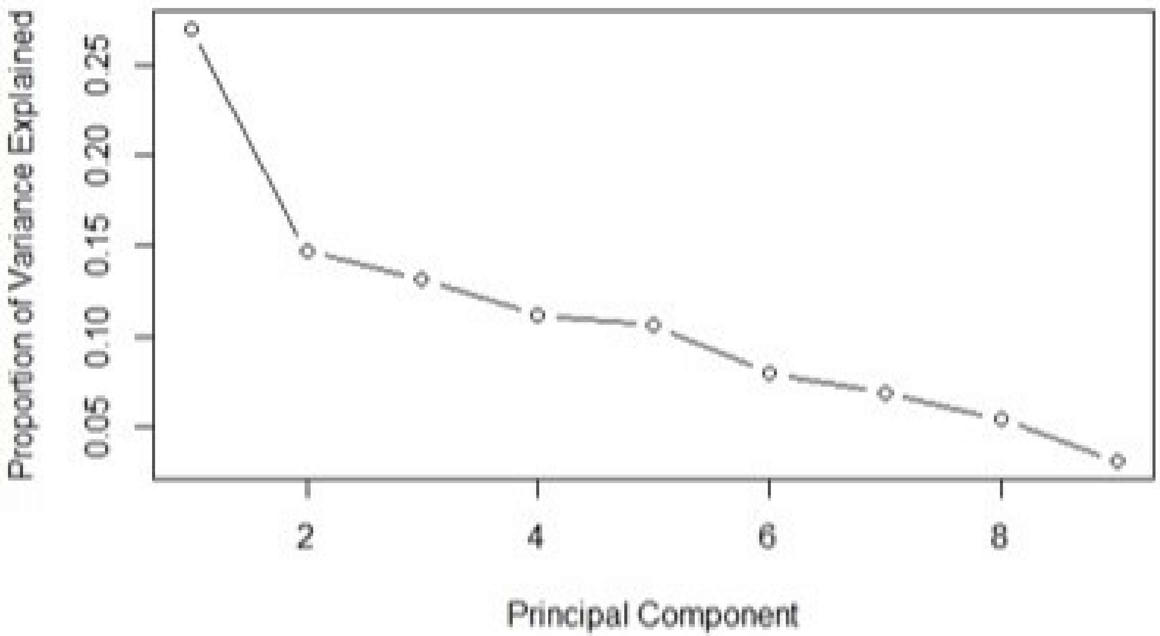
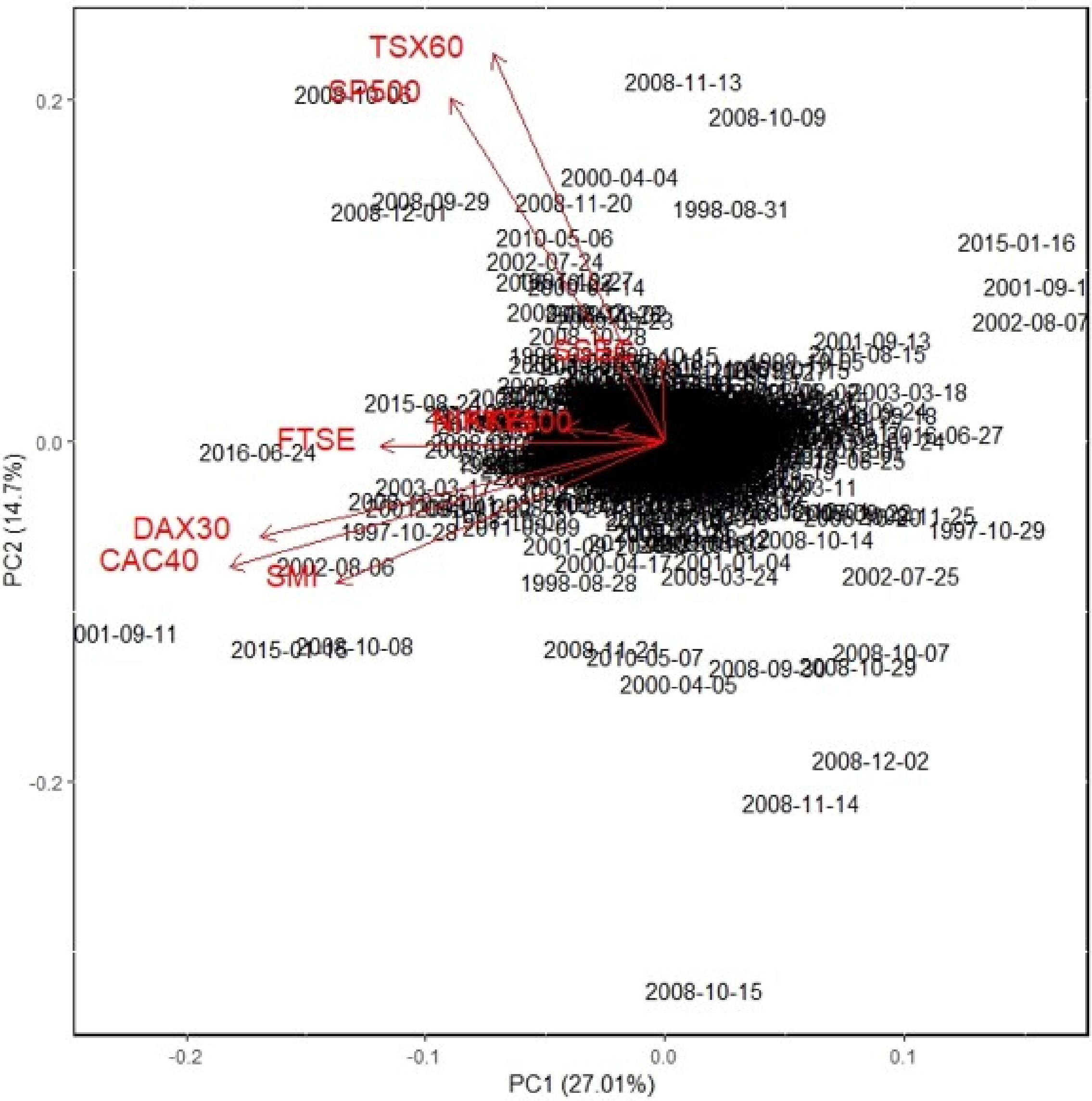


Table 4.5: Structure of principal component: the weights of the stock indices.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
TSX60	-0.2164	0.6848	-0.0862	0.1387	-0.0159	-0.1682	-0.2423	0.6082	-0.0175
SSEC	-0.0047	0.1460	-0.0546	-0.9648	-0.1065	0.1624	-0.0395	0.0730	0.0125
CAC40	-0.5486	-0.2237	0.0879	-0.0339	-0.0131	0.0446	0.1626	0.1315	-0.7708
DAX30	-0.5091	-0.1689	0.1796	-0.0110	-0.0399	0.0619	0.5040	0.2709	0.5891
NIFTY	-0.0642	0.0195	-0.4597	0.1051	-0.8631	-0.0337	0.1110	-0.1217	-0.0017
NIKKEI	-0.1259	0.0228	-0.6855	-0.1052	0.4369	-0.4594	0.2810	-0.1470	0.0097
SMI	-0.4136	-0.2522	0.1489	-0.1057	-0.0994	-0.5040	-0.6235	-0.2027	0.1957
FTSE	-0.3588	-0.0101	-0.4033	0.1222	0.2023	0.6880	-0.3709	-0.1495	0.1396
SP500	-0.2704	0.6054	0.2892	0.0188	0.0011	0.0048	0.2043	-0.6590	-0.0202

Figure 4.4: Principal component analysis, first two factors.



Note: Datapoints are presented by the dates. Each red vector is the direction of each market composite combining the first two principal components.

Table 4.6: AR(1) models using principal components as exogenous variables.

Foreign exchange		Intercept	AR1	PC1	PC2	PC3
CAD	Coefficient	-1.47E-05	-8.86E-03	**-3.38E-04**	**3.14E-04**	-5.96E-06
	Standard error	7.15E-05	1.33E-02	4.78E-05	6.33E-05	6.67E-05
EUR	Coefficient	1.44E-05	8.19E-03	-7.10E-05	**3.04E-04**	2.47E-05
	Standard error	8.09E-05	1.32E-02	5.24E-05	6.99E-05	7.37E-05
JPY	Coefficient	1.18E-05	2.44E-03	**5.82E-04**	-1.59E-04	**4.71E-04**
	Standard error	8.91E-05	1.32E-02	5.79E-05	7.75E-05	8.17E-05
CHF	Coefficient	-3.45E-05	2.00E-02	**3.47E-04**	**3.54E-04**	8.78E-05
	Standard error	9.14E-05	1.32E-02	5.80E-05	7.77E-05	8.19E-05
GBP	Coefficient	1.93E-05	4.78E-02	**-2.25E-04**	**3.83E-04**	-2.59E-04
	Standard error	7.96E-05	1.32E-02	4.90E-05	6.53E-05	6.87E-05
BRL	Coefficient	2.14E-04	4.72E-02	**-1.01E-03**	-3.22E-05	-2.31E-04
	Standard error	1.36E-04	1.32E-02	8.24E-05	1.11E-04	1.17E-04
CNY	Coefficient	-4.28E-05	3.37E-02	-1.22E-05	3.44E-05	-2.13E-05
	Standard error	1.87E-05	1.32E-02	1.55E-05	1.72E-05	1.76E-05
INR	Coefficient	1.00E-04	6.29E-02	**-1.99E-04**	1.65E-04	-1.70E-04
	Standard error	5.28E-05	1.32E-02	3.29E-05	4.29E-05	4.49E-05
RUB	Coefficient	4.36E-04	1.10E-01	-4.70E-04	4.69E-04	-3.06E-05
	Standard error	2.30E-04	1.32E-02	1.26E-04	1.71E-04	1.80E-04
ZAR	Coefficient	2.14E-04	2.64E-02	**-7.22E-04**	**4.73E-04**	-2.04E-04
	Standard error	1.36E-04	1.33E-02	8.50E-05	1.14E-04	1.21E-04

Note: Coefficient estimations which are in bold are significant.

4.5.4 Discussion of the empirical results

Overall, we find that the DCC model suggests that the linkage between foreign exchange rate returns and stock market volatility changes differs between developed and developing markets. Moreover, volatility changes from stock markets is clearly a significant factor in the determination of the foreign exchange returns.

Different to the return-return relation between stock and foreign exchange markets, the impact of stock market volatility on currencies of developed markets tended to be heterogeneous. In accordance to what Fu (2009) suggested, we find that the return-volatility relation is time-varying, and moreover it seems sensitive to major economic shocks during which the return-volatility relationship became extreme. However, such change was relatively short-lived and did not affect the overall level of the correlation. On the other hand, the currencies of BRIC mostly have positive correlations with the equity market volatility changes and particularly during the tranquil period. Nevertheless, the level of comovements is much lower than what it is for the developed markets.

When it comes down to the impact of the volatility changes of each individual stock market upon the foreign exchange rate returns, our results suggest that the coefficient estimates are on average positive. In other words, in most cases we find that increased volatility changes lead to increased changes of the foreign exchanges rates. This result is contrast to previous literature that suggests estimation based on daily data tends to produce negative relation (see Bali and Cakici, 2008, Huang et al., 2009 for example). Particularly, volatility change of the US stock market was the most influential factor for most of the currencies (significant in the estimation of seven foreign exchange rates). Nevertheless, the results are aligned with Phylaktis and Ravazzolo (2005) and Apostolakis and Papadopoulos (2015), in that overall the US equity risk is an important "causing" variable.

Finally, when using the principle component analysis to proxy the global stock market volatility changes, we find that the first two factors are statistically significant in determining the foreign exchange rate returns. Interestingly, the first principal component has a negative effect while the second one is positive. The Chinese yuan and the Russian ruble are the only exceptions to this rule and they seem not to be generally affected by these principal components.

4.6 Summary

This work investigates the cross-globe impacts of stock volatility on forex market. The methods include the DCC model of (R. Engle, 2002) and AR model. The major finding is twofold. The stock volatility has positive effect on foreign exchange return, while such effect tends to be negative in domestic market. This finding contributes to the risk premium puzzle. In addition, variation in stock volatility can be concentrated to a few principal components, which is also significant in the pricing of foreign exchange. On the other hand, emerging market, represented by BRICS is less affected by volatility of the largest stock markets. In particular, Chinese yuan and Russian ruble barely received shocks from the major equity markets.

Chapter 5

Conclusions and future work

This thesis examines the comovements of financial markets based on a variety set of specifications and techniques.

Chapter 2 investigates the comovements of equity and foreign exchange returns. Major implication of this study is twofold. Exchange rate and the domestic stock composite is generally positively correlated (see in Section 2.5.3). The relation between stock and foreign exchange market depends on various conditions, for instance the level of financial market development, the openness of foreign exchange market, the status of world economy, and so on. Particularly, around the times of economic instability, such as the 1997 Asia crisis and the dot-com bubble burst, these relationships fluctuated quite substantially. Similarly, just before 2007/8 financial crisis, the pairwise dependence are intensified.

Based on the level of correlations, market integration can be recognized in certain country group. Strongest market correlation appeared in the European Union, which is followed by the other major developed countries. Major markets effectively influence some large emerging market such as BRICS, because of the increasingly tighter trade links, and the openness of their financial market. Whereas financial market dependence among developing countries is relatively mild, regardless of the geographical trade advantage. In conclusion, the findings implies a dichotomy between developed and developing markets with respect to the foreign exchange and stock market dependence.

An interesting byproduct of the results of Chapter 2 is that by summarising the time-varying correlations, we have also ended up with dating the starting, peak, and ending time points of the 2007 financial crisis and the ensuring sovereign crisis. Based on this, we observe that during 2002-2006, the period of ‘tranquility before the storm’, the pairwise market dependence was generally mild. From around the fourth quarter of 2006, the correlation deviated from its natural level and peaked during the second quarter of 2010 and fourth quarter of 2012. The time after that can be seen as the ‘recovery period’. However, developing markets, such as the BRICS, which were much less affected by the Global financial crisis in terms of magnitudes, returned to the level of the ‘tranquil period’ much earlier (around 2015), unlike developed markets, and particularly those in the centre of the sovereign crisis, (not before 2017).

Chapter 3 examines volatility connectedness of stock markets using network analysis. Treating the international equity market as a network proved an efficient way to reveal the collective dynamic properties. This work contributes to the literature in many ways, one of which is that the methodology is rather novel to the volatility transmission analysis. To incorporate network analysis, both well-established measures (diameter and the integration degree) and promising ones (centrality and community detection) have been examined and showed that the exploration of network analysis could be a very promising avenue for new insights. Because the theory of financial network analysis is still in its infant phase, this work implies a rather interesting direction of successive work.

The major finding in Chapter 3 is that there seems to be a natural level of pairwise dependence of volatility. Extraordinary events, especially negative news such as financial crises, major policy shifts or terrorist attacks, do indeed affect this volatility dependence; but while the impact is not transient, it is certainly not highly persistent. Volatility dependence could be mainly determined by some underlying fundamental factors quite different to return dependence.

The implication on financial market is that the hypothesis of growing integration across stock markets does not actually hold, at least with respect to the degree of comovements of volatility. The sudden increase of marketed connectedness appeared mainly in major markets, while the developing countries were mildly associated with major countries and barely correlated to one another. The volatility transmission is rather limited.

Finally, Chapter 4 investigates an distinctive form of market dependence by building on the results of existing literature that stock markets are much more sensitive to changes in the state of an economy, at least in comparison to the foreign exchange markets. Stock market volatility, especially when aggregated to proxy the volatility of some notional global stock market, is indeed a significant factor of determining foreign exchange returns. Although the sample was quite comprehensive, the only exceptions proved to be just the Chinese yuan and the Russian ruble – exceptions that may well exist due to their much more controlled foreign exchange rate policy. In any case, this implies a quite fruitful avenue for future research.

Abbreviations

AIC Akaike information criterion

BIC Bayesian information criterion

CCC Constant Conditional Correlation

CUSUM cumulative sum

DCC Dynamic Conditional Correlation

GARCH Generalized AutoRegressive Conditional Heteroskedasticity

OECD Organisation for Economic Co-operation and Development

PELT pruned exact linear time

VAR vector autoregressive

Appendices

A Review of break test

The existing break tests adapted to financial time series can be roughly divided into two branches, asymptotic method and Bayesian approach. Asymptotic method is long-standing. To avoid the tediously long review of this string, we briefly summarise CUSUM-type break tests and likelihood ratio tests under serial dependence settings. Additionally, a new angle, Bayesian framework attracts high attentions in recent years, because it allows model selection which averages out model uncertainty. Bayesian paradigm is also handy for forecasting by design, so we also cover the recent research on forecasting. The prerequisite for this method is the specification of prior distributions, which has been the source of some debate. We cover Bayes-type detection and Bayesian estimation in the last sub-section.

A.1 Asymptotic methods

Generally speaking, there are two ways to deal with breaks in time series data. One is to combine structural breaks with a time series model, such as ARMA and GARCH-type. Test statistics varies on the choice of time series model. The other type of approach, non-parametric tests could avoid the parametric setting by establishing functional central limit theorems for dependent case. Hypothesis test is remained in designing break tests. This approach quantifies the dependence on the test statistics and allows test in long-run variances and second-order properties such as autocorrelations. This is advantageous when model misspecification becomes an issue Aue and Horváth (2013).

CUSUM-type test is widely used as non-parametric approach, because it avoids making explicit descriptions of the dependence structure in the data. Here describe CUSUM under dependent setting that test breaks in unconditional mean, correlation and volatility. Assume that n observations $\{r_t\}$ are taken from the signal-plus-noise model,

$$r_t = \mu_t + \varepsilon_t,$$

which has $E[\varepsilon_t] = 0$ and $E[\varepsilon_t^2] = \sigma^2$. To test whether the unconditional mean has changed at least once during the observation period. The CUSUM process of the observations is

$$Z_n(x) = \frac{1}{\sqrt{n}} \left(\sum_{t=1}^{\lfloor nx \rfloor} r_t - \frac{\lfloor nx \rfloor}{n} \sum_{t=1}^{n} r_t \right), \quad x \in [0, 1]$$

which is independent of the unknown mean μ. This process compares the sample mean of k, (all possible $k < n$) observations with the global sample mean of all observations. The test statistics is

$$M_n = \frac{1}{\widehat{\omega_n}} \max_{1 \leq k \leq n} Z_n \left(\frac{k}{n} \right).$$

H_0 holds (mean is constant) if this value is small, else H_0 is rejected.

Assume we are reasonably confident in the AR (1) setting, then the CUSUM process for correlation is

$$\frac{1}{\sqrt{n}} \sup \left| \sum_{t=1}^{\lfloor nx \rfloor} r_t - \frac{\lfloor nx \rfloor}{n} \sum_{t=1}^{n} r_t \right| \to \kappa(1-\kappa)\sigma^2 \left| \frac{1}{1-\phi^2} - \frac{1}{1-\phi_*^2} \right|,$$

where ϕ is the autoregressive parameters such that under H_0, $E[r_t^2] = \sigma^2/(1-\phi^2)$ and under H_a, ϕ changes to ϕ_* at $k^* = \lfloor \kappa n \rfloor$ for some $\kappa \in (0, 1)$.

Assume the observations fit GARCH (1,1), CUSUM for volatility can be test by M_n if the structural break occurs close to the sample center, otherwise weighted version of CUSUM is applied,$W_n = \sup Z_n(x)/(\widehat{\omega_n} q(x))$, where q is a weight function, for instance $q(x) = \sqrt{x(1-x)}$. Once the null (conditional variances, $\sigma_t^2 : t \in Z$ are stationary process) is rejected, the time of occurrence of break points $\kappa^* = \lfloor n\kappa \rfloor$ can be estimated through

$$\widehat{\kappa_n} = \frac{1}{n} \arg\max_k Z_n(k/n).$$

In a long financial series, there are potentially more structural changes in the financial series. The common way is to build single break test on an iterative scheme. The earliest way is binary search method (BS), originated and developed by Edwards and Cavalli-Sforza (1965), Scott and Knott (1974). BS works in general settings on CUSUM procedures. The largest value in the neighbourhood of a break point is where to split the sample into two. Repeat the same steps on the subsamples until there is no such data point exists. ICSS algorithm Inclan and Tiao (1994) also enables multiple discrete changes to be identified in an iterative scheme. Starting from the initial period, variance is stationary until a sudden change appears. Take away the first series segment and repeat last step until all changes are identified. It can be applied in either ascending or descending time order.

Test differs with respect to properties in which breaks may exist. Here list a few tests that represent the different aims, but there are much more tests that we are not able to cover them all. Horváth and Kokoszka (1997) study changes in mean and prove that the estimators converge indistribution to functional of fractional Brownian motion under suitable normalization. Kokoszka, Leipus, et al. (2000) detect breaks in the parameters of ARCH processes. Giraitis et al. (2003) examine the persistence of breaks in volatility, which contributes to disentangling structural breaks from unit roots. Cavaliere and Robert Taylor (2008), Harvey, Leybourne, and Taylor (2010) consider breaks in mean and/or variance in long-time observations and unit root problem as well.

The parametric settings describe explicitly the dependence structure in time series. Change can occur in regression coefficients and covariance matrix of the errors. In linear regression model, assume that observations are $(Y_1, X_1')', \ldots, (Y_n, X_n')'$ in the model,

$$Y_t = \beta_t' X_t + \varepsilon_t, \quad t \in Z.$$

The null is that the estimated β_t (usually through least-squares method) is constant. The hypothesis can be test through classic liner hypothesis test, such as likelihood ratio statistics, Wald test, and Lagrange multiplier (LM). For applications of Wald-type test, see Vogelsang (1997) and Bai and Perron (1998), and for LM test, see Lee and Strazicich (2003). Here discuss structural break procedures based on likelihood ratio statistics. Hinkley and Hinkley (1970) firstly use likelihood approach to detect breaks in mean of a sequence of normally distributed observations. Tang and Gupta (1987) extend the approach for changes in variance. Whereas, likelihood-based method is mostly used to detecting changes in a subset of parameter.

Assume that d-dimensional process $(Y_t : t \in Z)$ and its underlying distribution is captured by parameter vector θ_t. The aim of the likelihood ratio method is to detect an unknown changepoint in θ_t. Technically, it is to test the null hypothesis that θ_t is constant against change in mean and/or covariance. If the existence of breaks is confirmed, breakdates are estimated through maximum likelihood estimation (MLE). If a break is located at time point k, the likelihood $L_k(\theta, \theta^*)$ can be compared to the one from the null model via likelihood ratio,

$$\Lambda_k = \frac{\max L_n(\theta)}{\max L_k(\theta, \theta^*)} = \frac{L_n(\widehat{\theta_n})}{L_k(\widehat{\theta_k}, \widehat{\theta_n^*})}.$$

The null is rejected when the maximally selected likelihood ratio $Z_n = \max_{1 \le k \le n}(-2 \log \Lambda_k)$ is large Gombay and Horvath (1990).

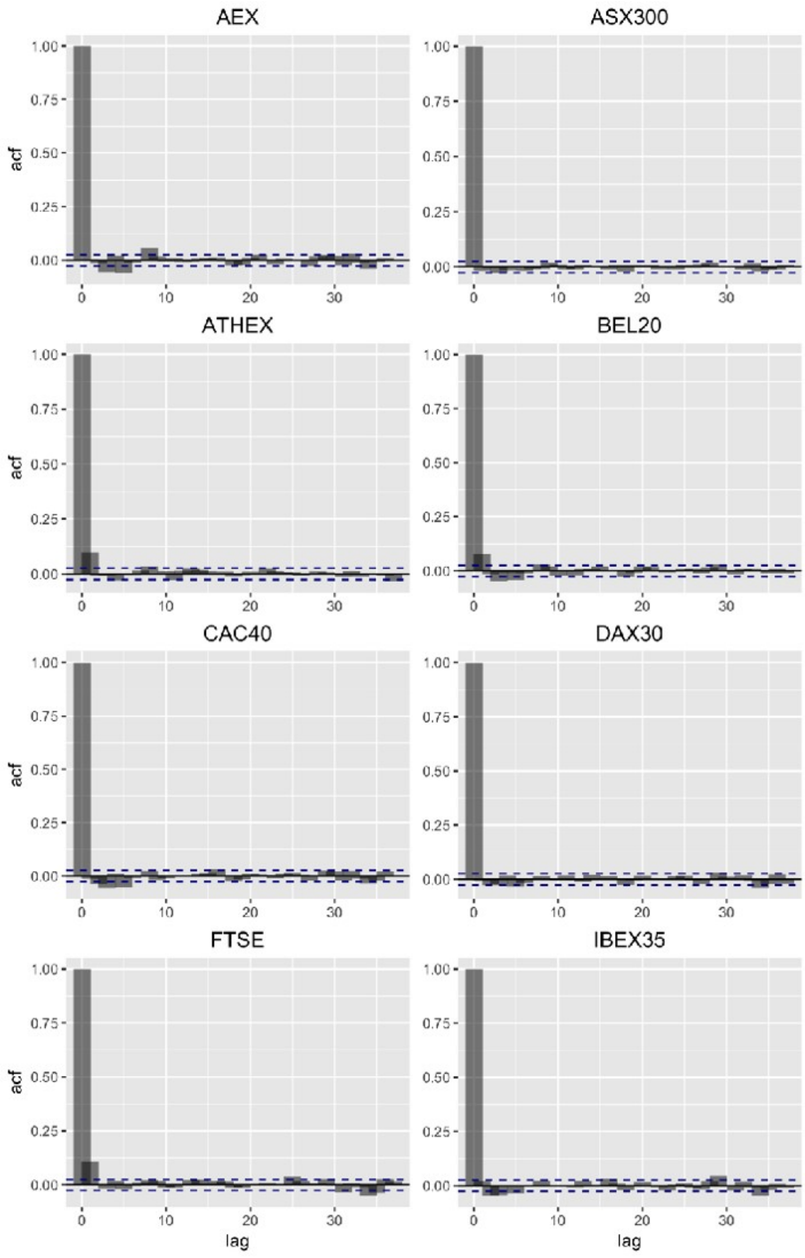
Multiple-break test based on time series model can be named a few. Tests built on Binary Segmentation is only an approximate solution, because the location of a current breakpoint depends on the locations of previously identified breaks. The idea of most methods estimating breakpoints is to minimize a criterion function. One of the most popular approach is Bai and Perron (1998). Beginning with a model of no breaks, the test is applied to each possible segment of data associated with a model containing an additional break. Rejection of the null hypothesis of l breaks in favour of a model with $l+1$ breaks is warranted if the overall minimal value of the sum of squared residuals is sufficiently smaller with $l+1$ breaks the the value obtained from the model with l breaks. The break selected is the one associated with the overall minimum. In time series models, quasi-likelihood method can be used when it is difficult to compute the joint distribution of the observed series. Braun, Braun, and Müller (2000) developed the algorithm of quasi maximum likelihood method (QML) for breakpoints in mean when the variance is dependent on mean. The extension developed by Qu and Perron (2007) estimates structural changes in multivariate regression model.

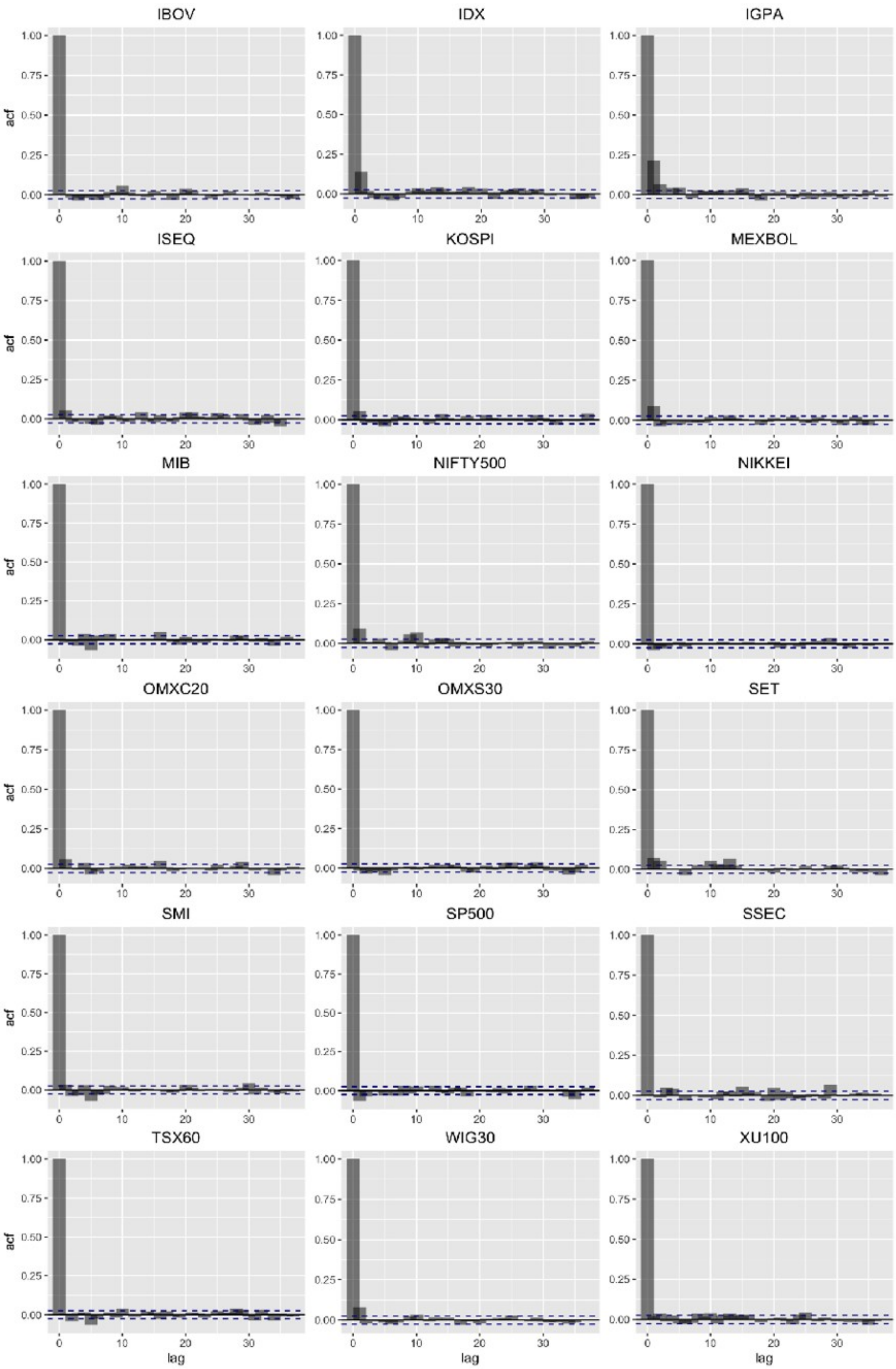
A.2 Bayesian methods for time series

Bayesian method estimates the breakpoint using the posterior distribution, of which the prior distribution can be specified over mean, variance or a set of parameters. With the knowledge of the prior probability for there being a changepoint, the Markov chain Monte Carlo (MCMC) performed to draw a chain that converges to the posterior distribution. There are several ways to generate such a chain/random walk, Metropolis-Hastings algorithm, Gibbs sampler or reversible jumps, introduced by Green (1995). The number of structural breaks is determined by the most appropriate model from marginal likelihoods, posterior odds ratio and Schwarz's Bayesian model selection criterion. Articles that contributes to in this area are Yao (1988), Barry and Hartigan (1993), Wang and Zivot (2000) and Fearnhead (2006).

Initially, multiple Bayesian framework needs to specify a prior for the number of regimes and location of breaks. An important strand starts from Chib (1998) that a hierarchical prior structure is proposed, which generated an enormous literature. The idea of using hierarchical priors is to draw parameters from underlying distribution which is captured through set of hyperparametres that characterize the top layer of the hierarchy. An application by Pesaran (2006) assume the parameters of each segment are drawn from some common meta-distribution. Instead of discarding observations prior to the most recent break-point, Pesaran (2006) allow all the sample information including the size and frequency of past breaks to compute forecasts. Fearnhead (2006) suggests an approach that specify the priors indirectly through a distribution for the length of each segment. Koop and Potter (2007) follow this string and develop a Bayesian procedure that is a non-informative prior on the number of breakpoints. Recent work by Lai and Xing (2011) extends the multiple parameter change to a multiparametre exponential family and develop an empirical Bayes procedure for estimating parameters associated with each segment including the GARCH models.

B Correlogram of return data

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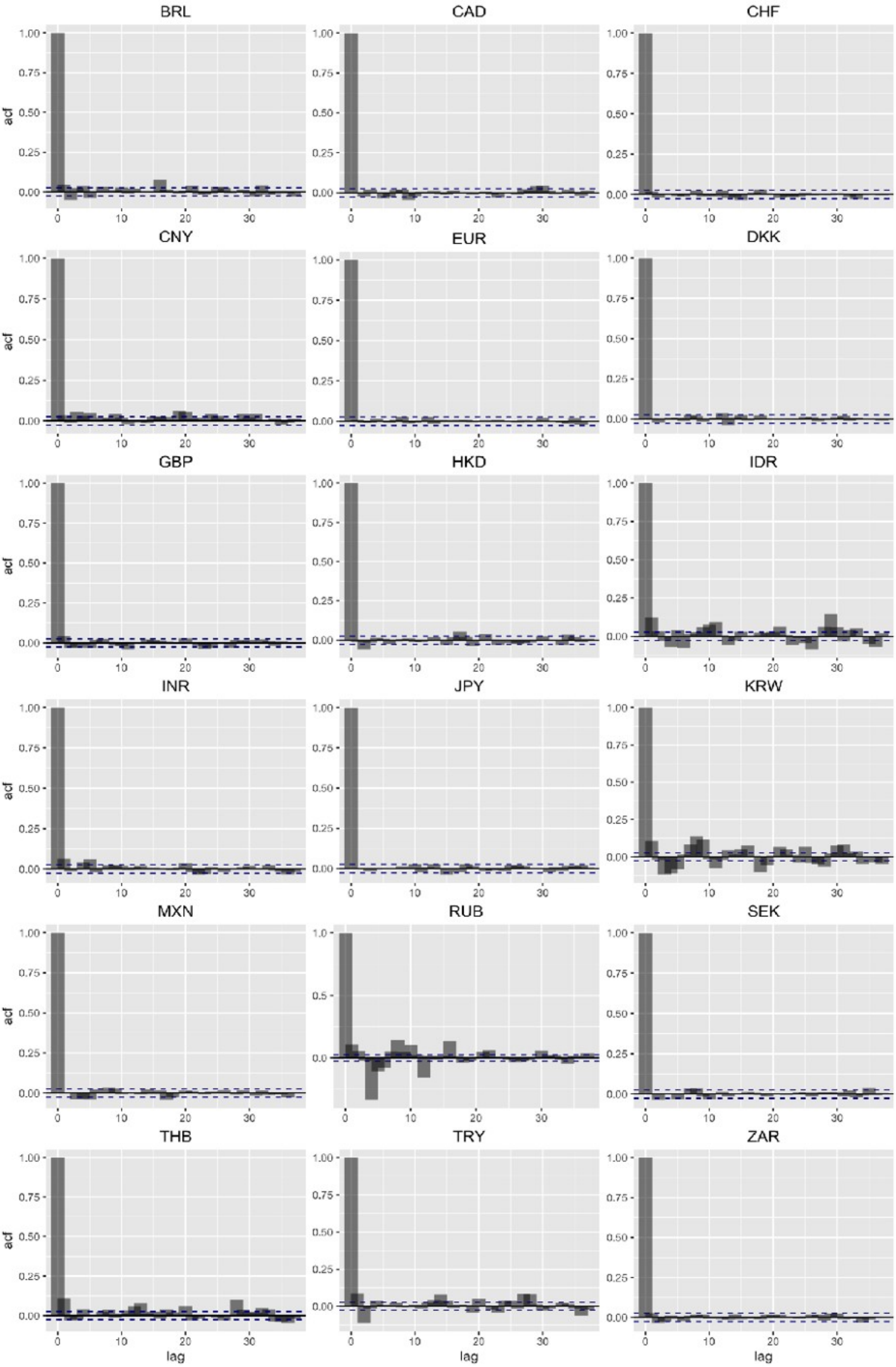
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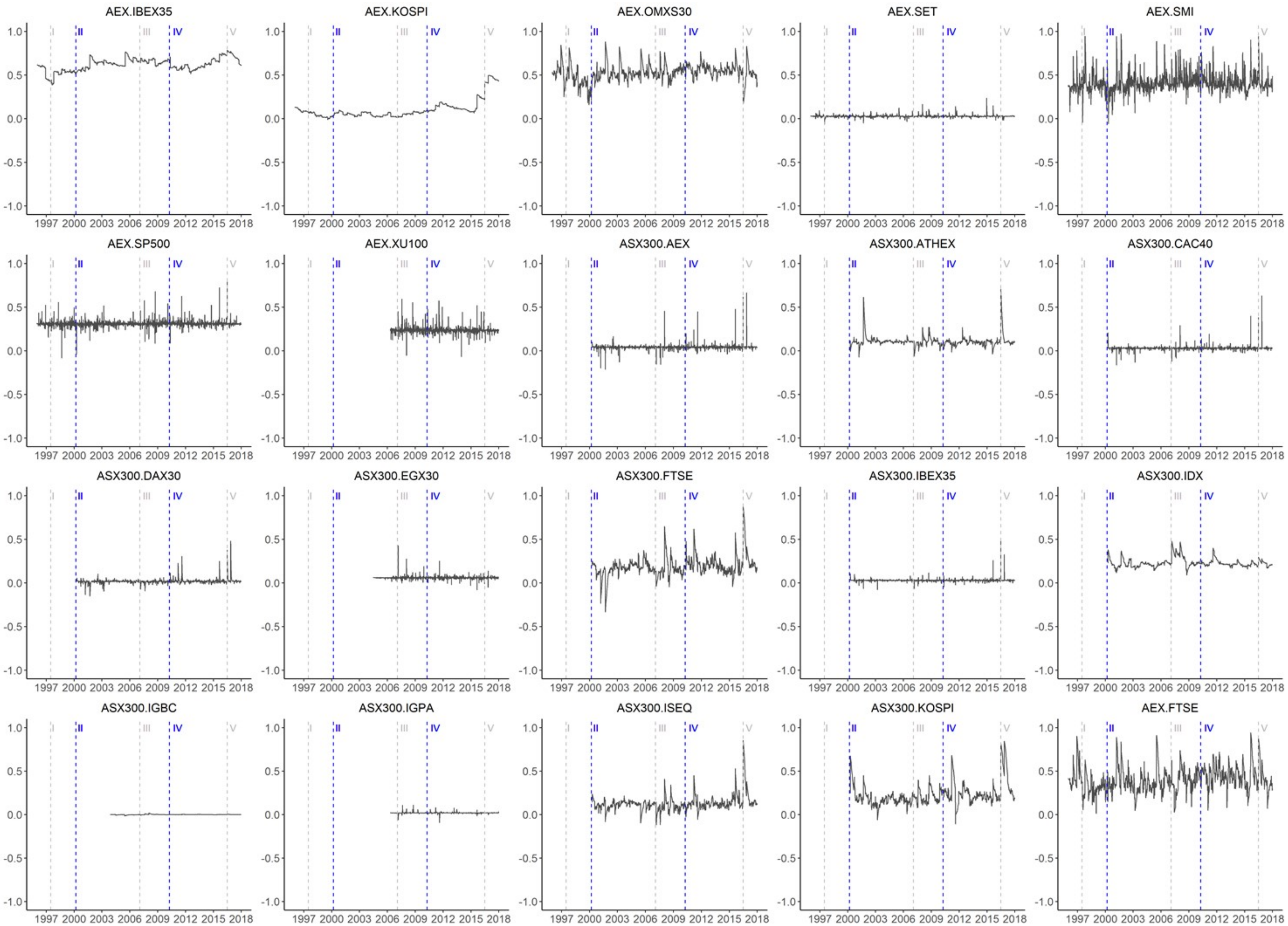
C Conditional correlations between 25 stock markets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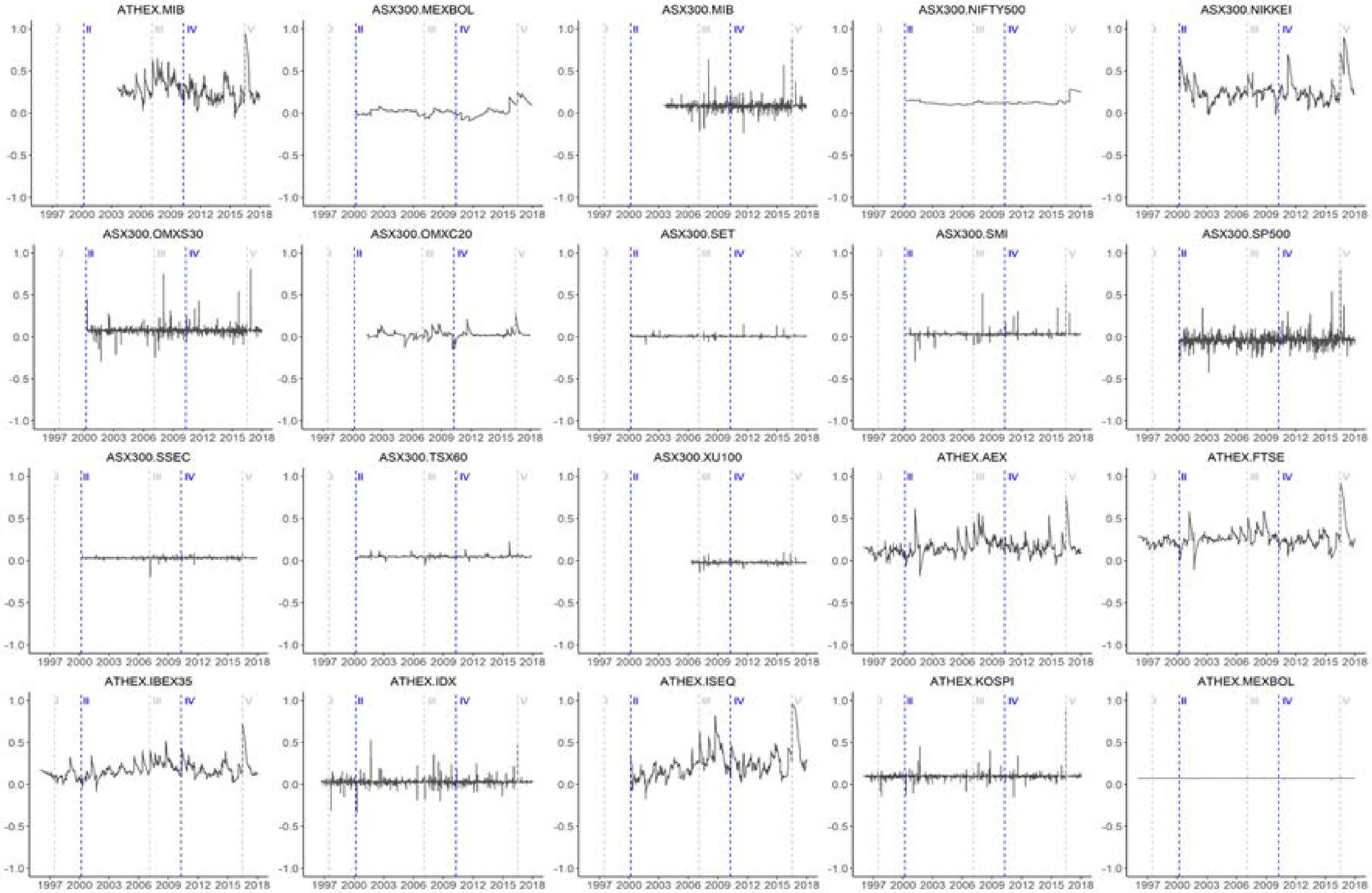
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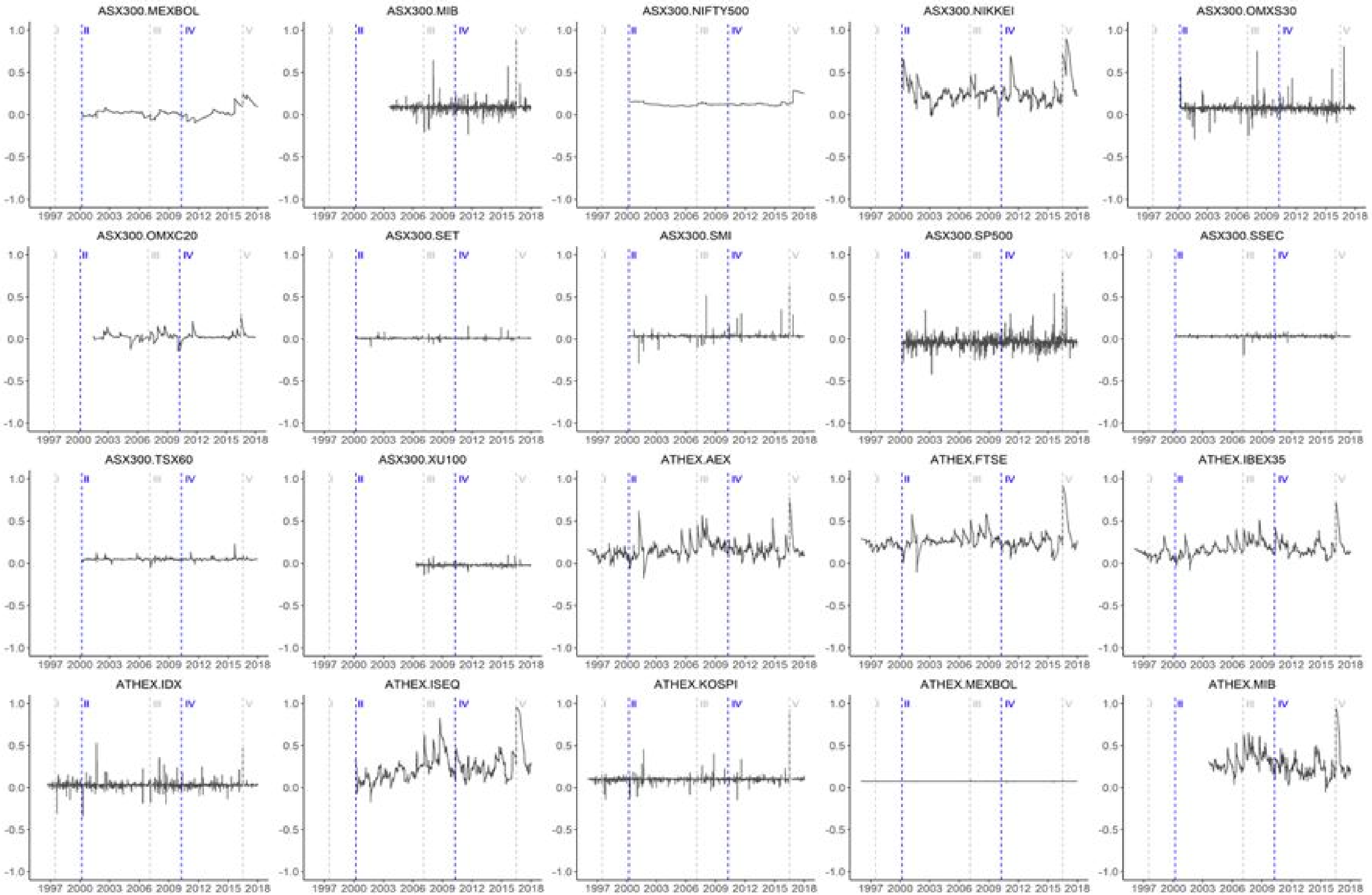
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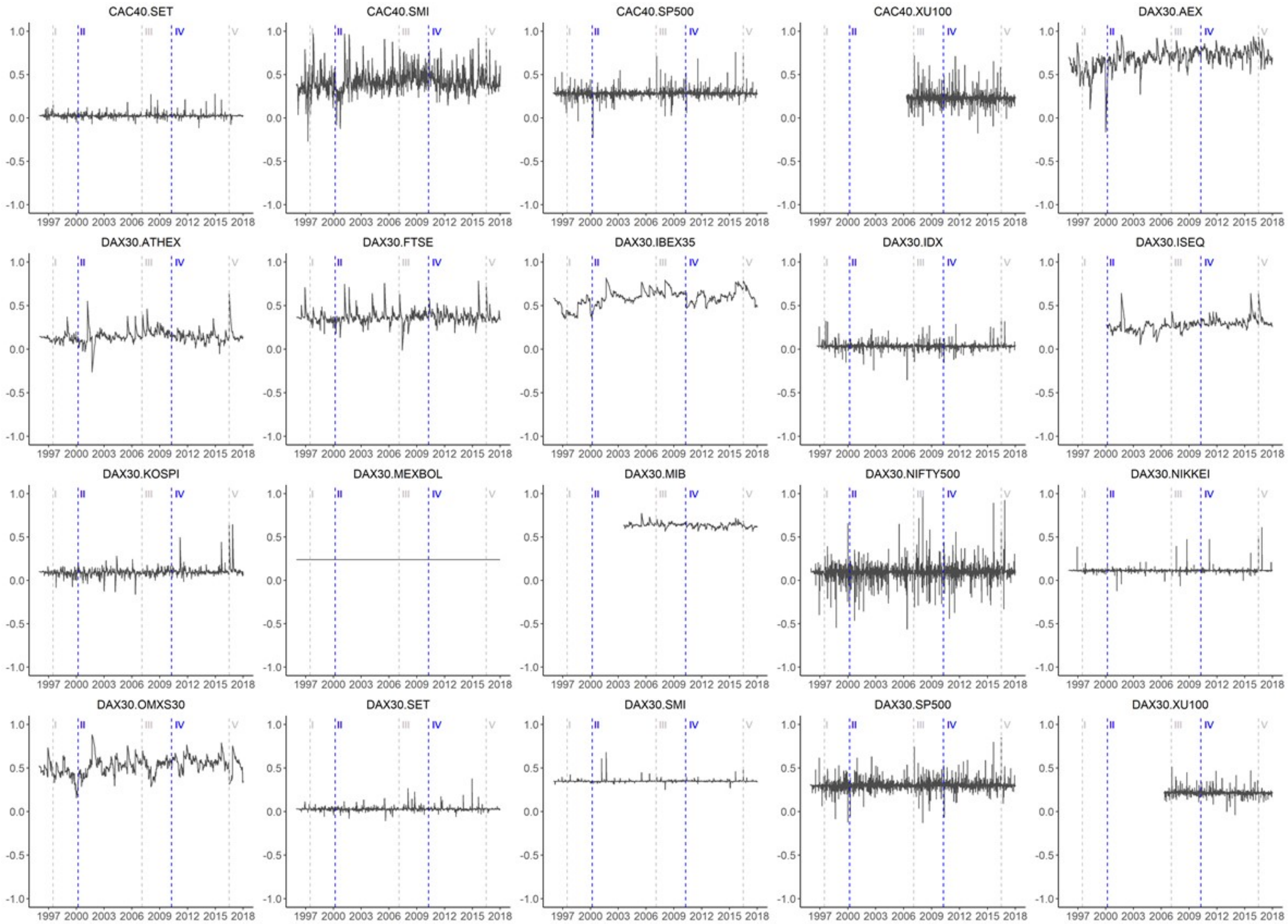
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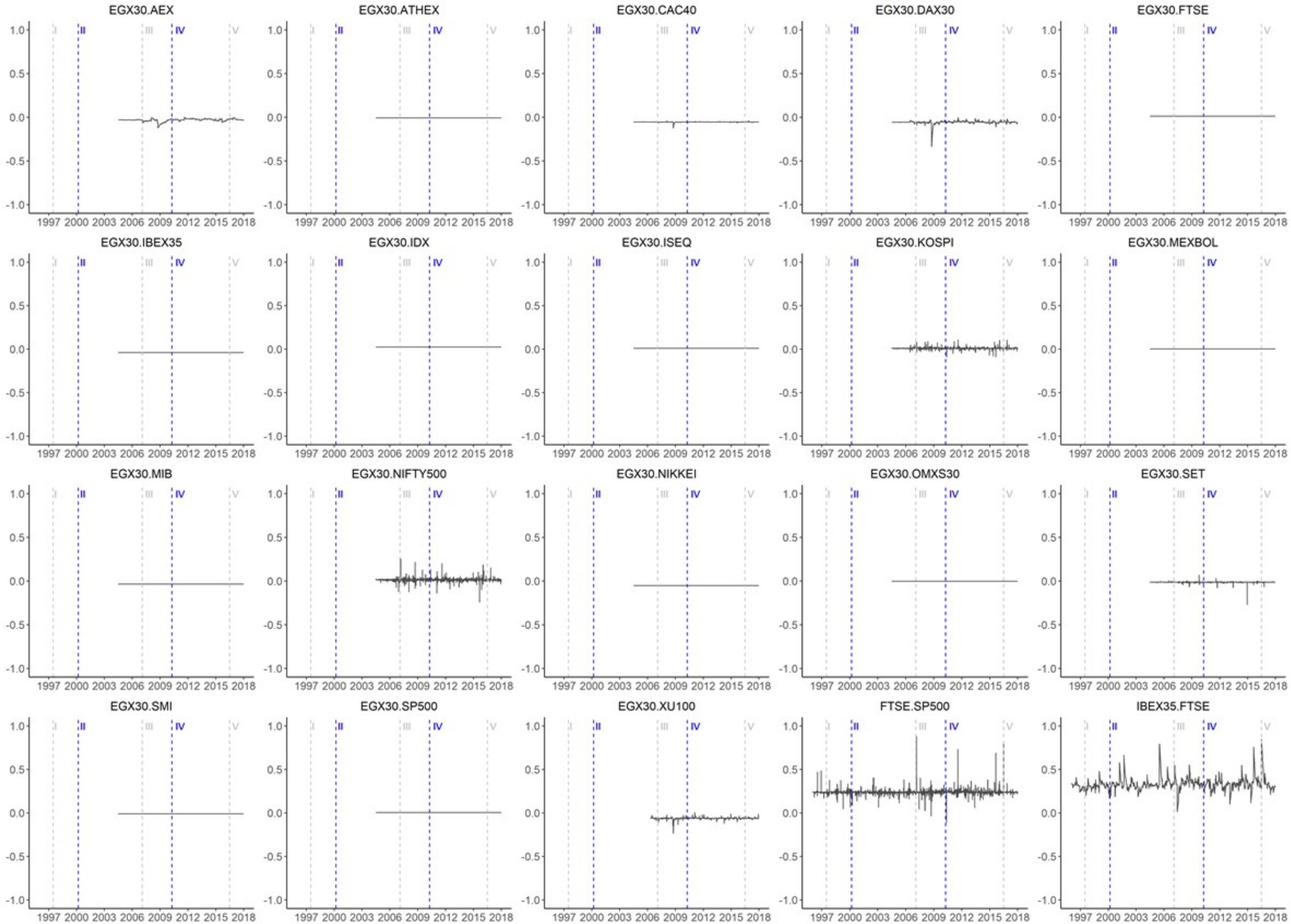
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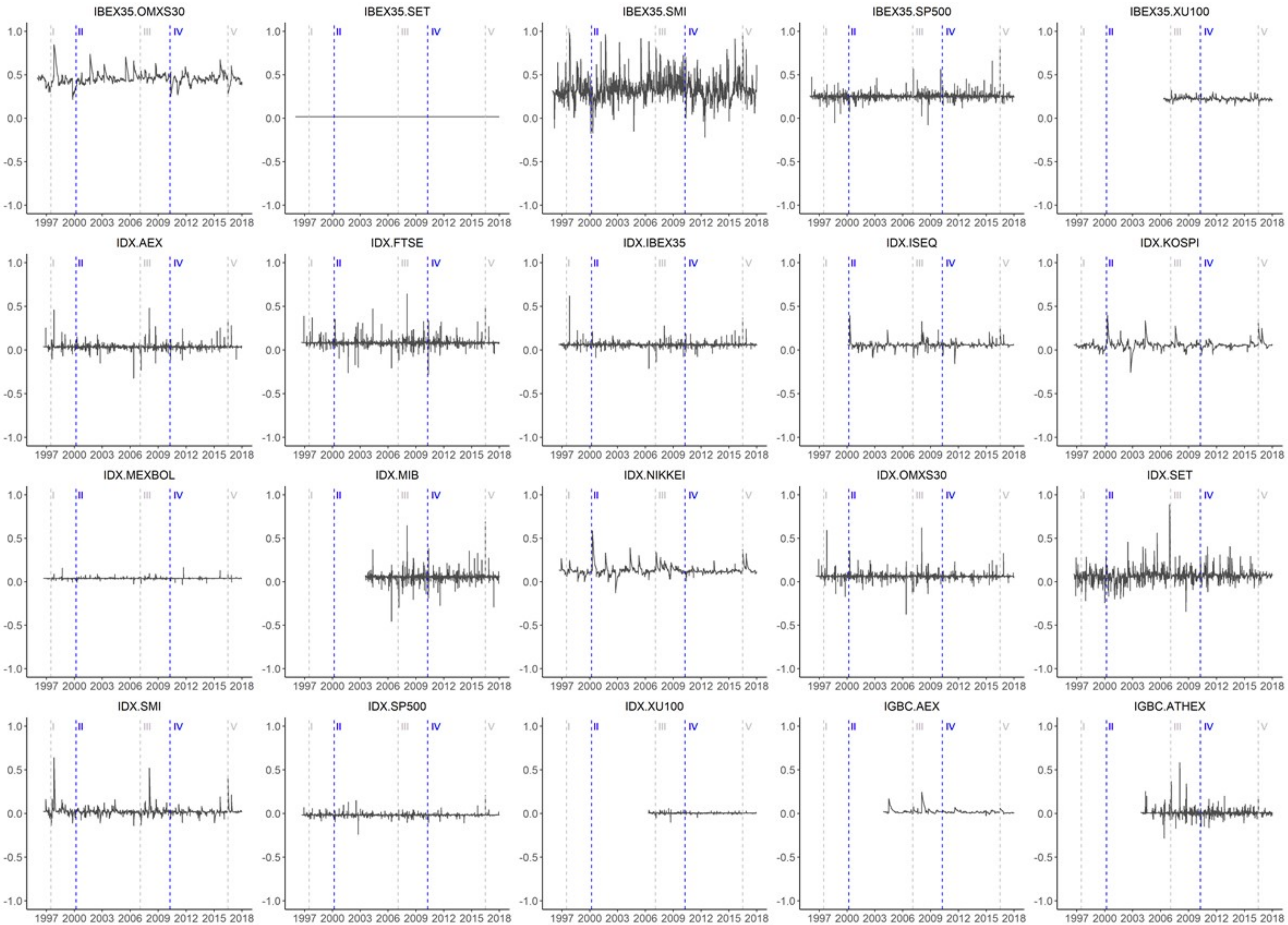
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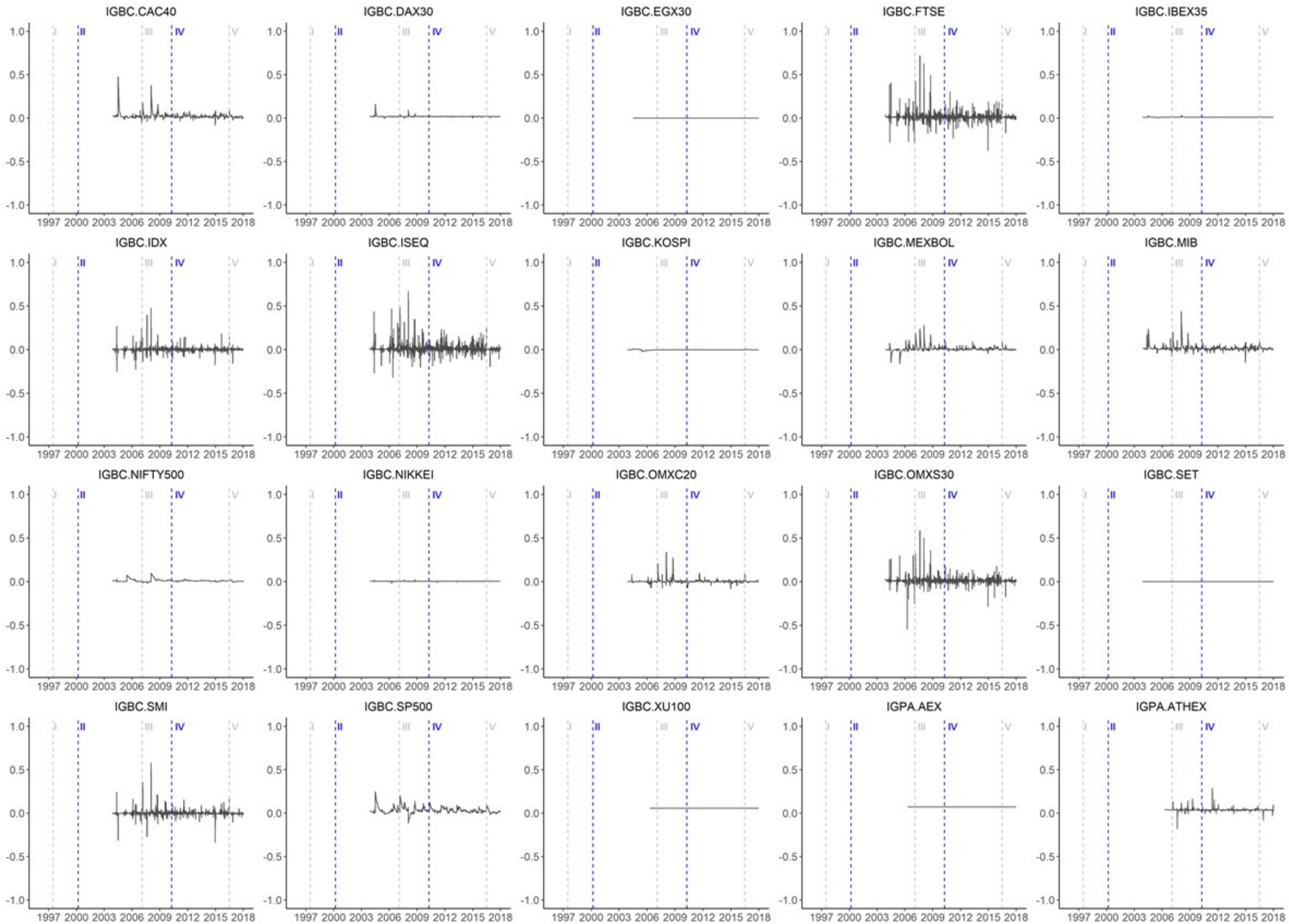
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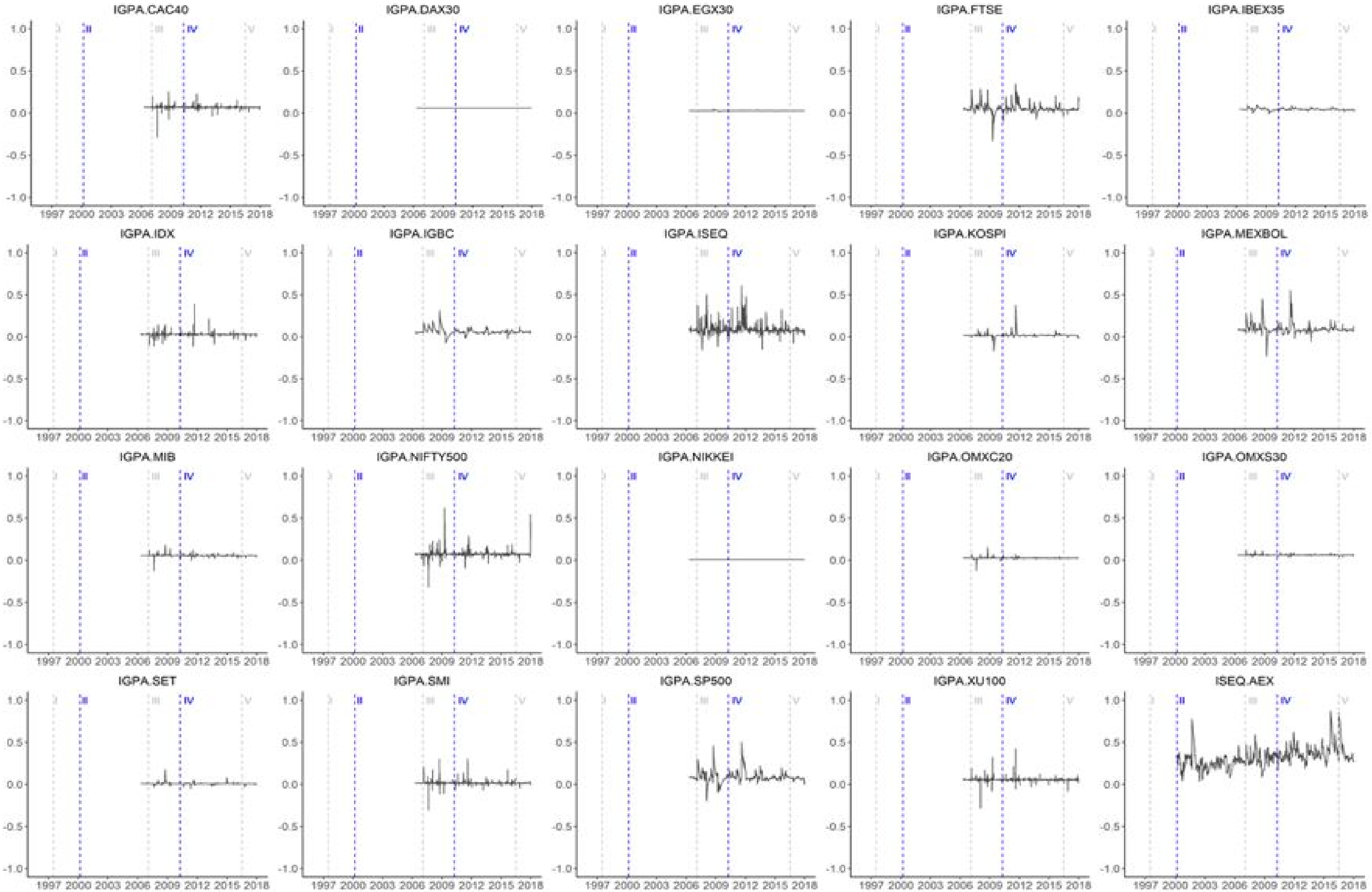
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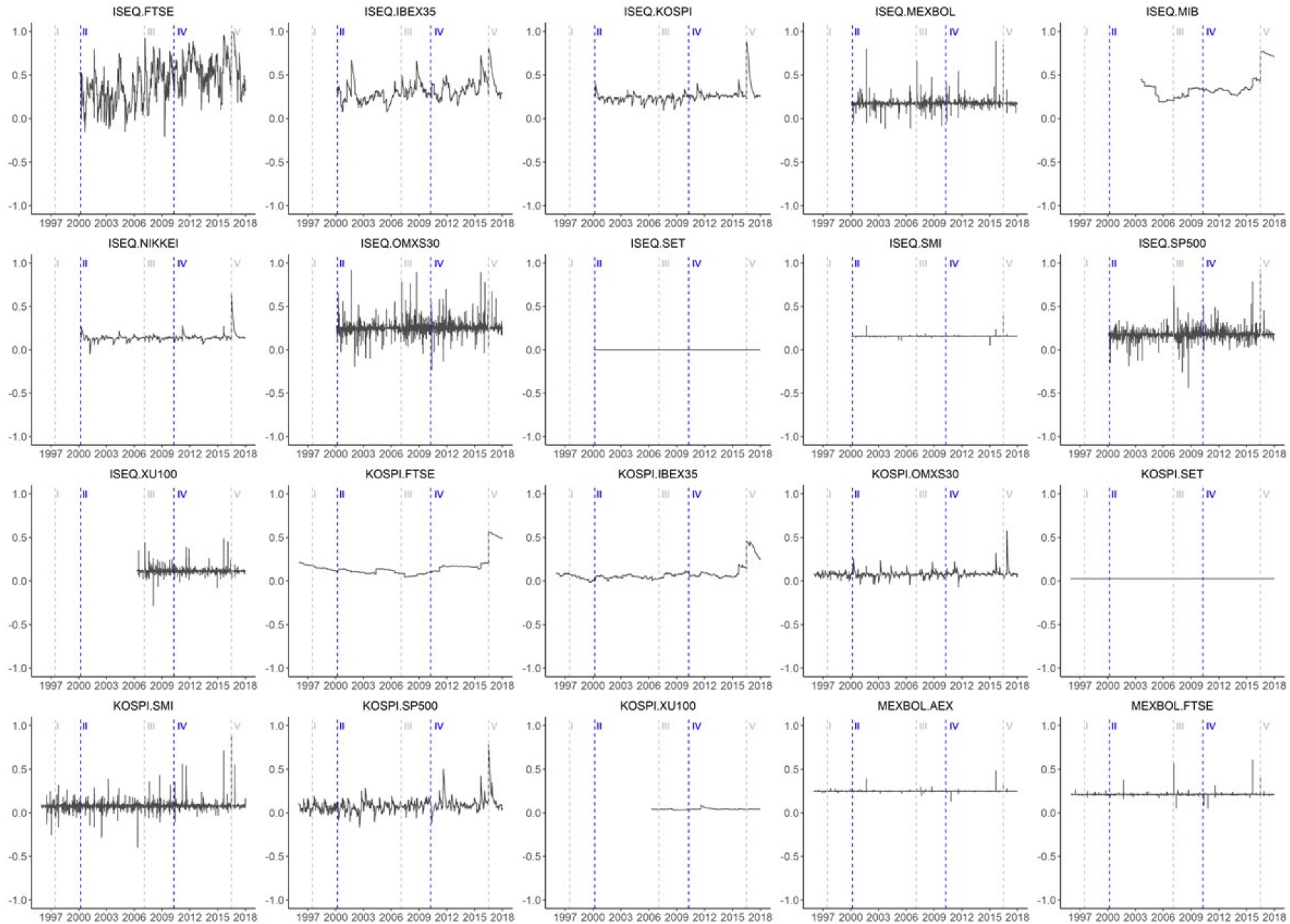
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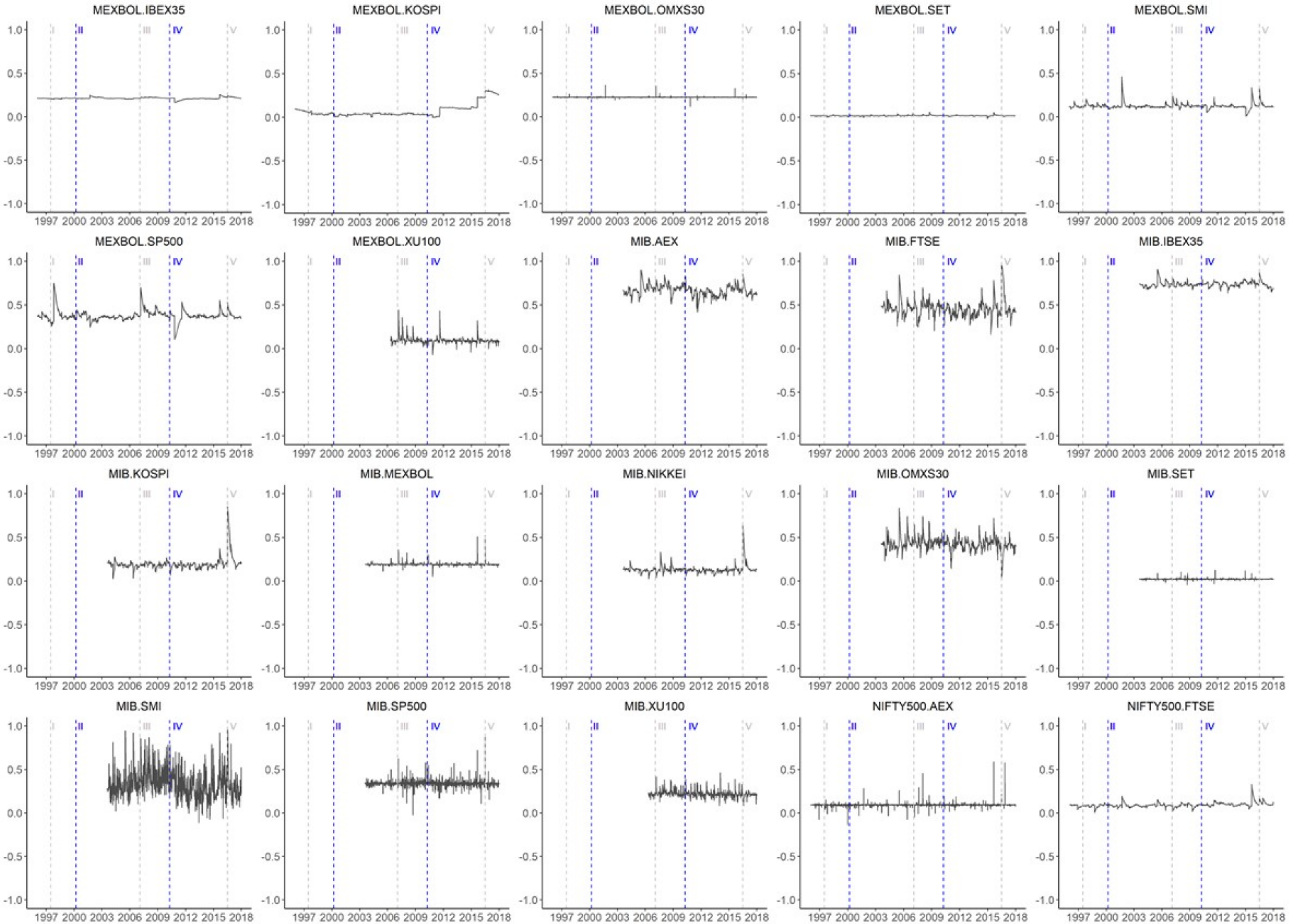
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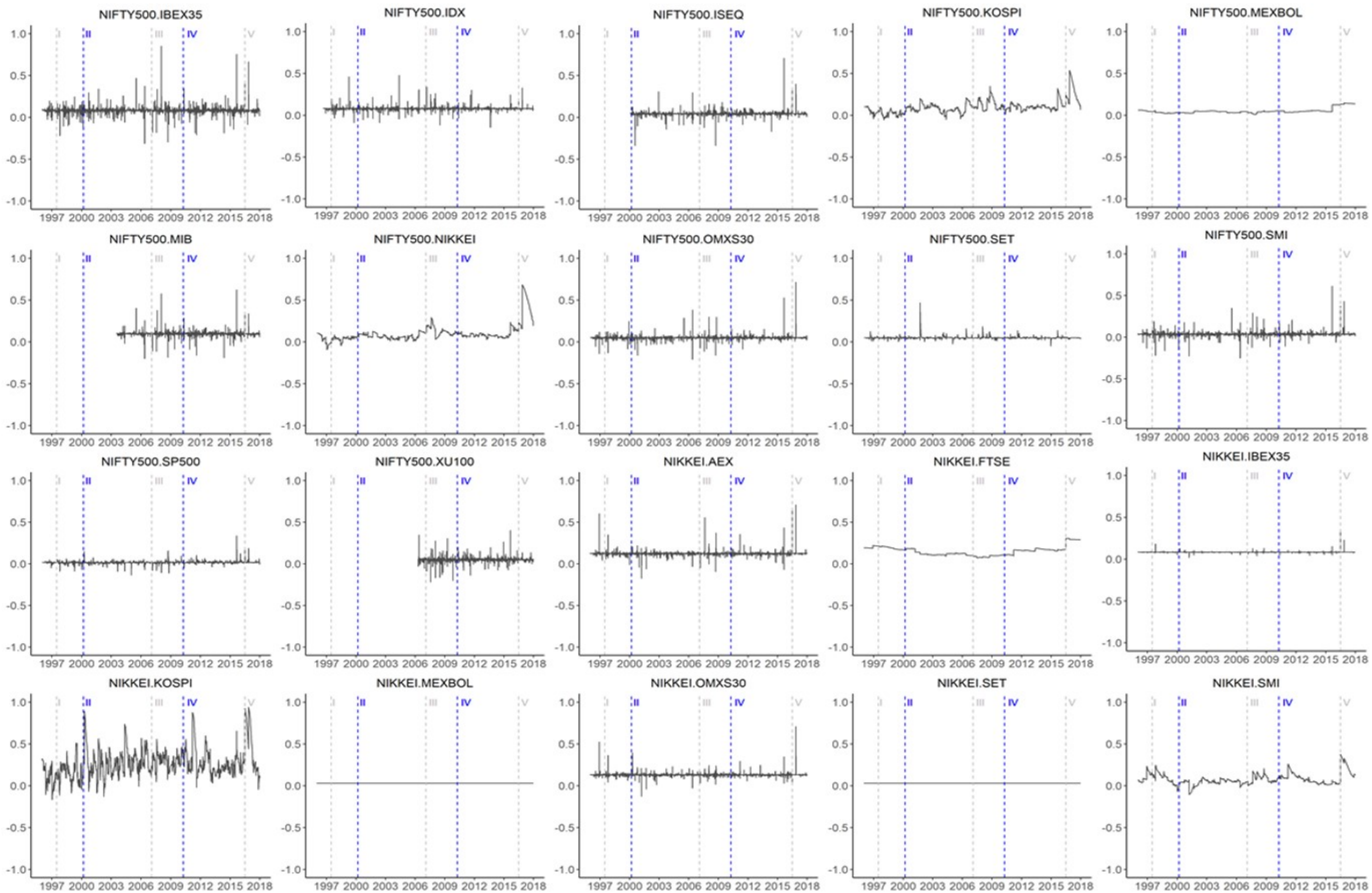
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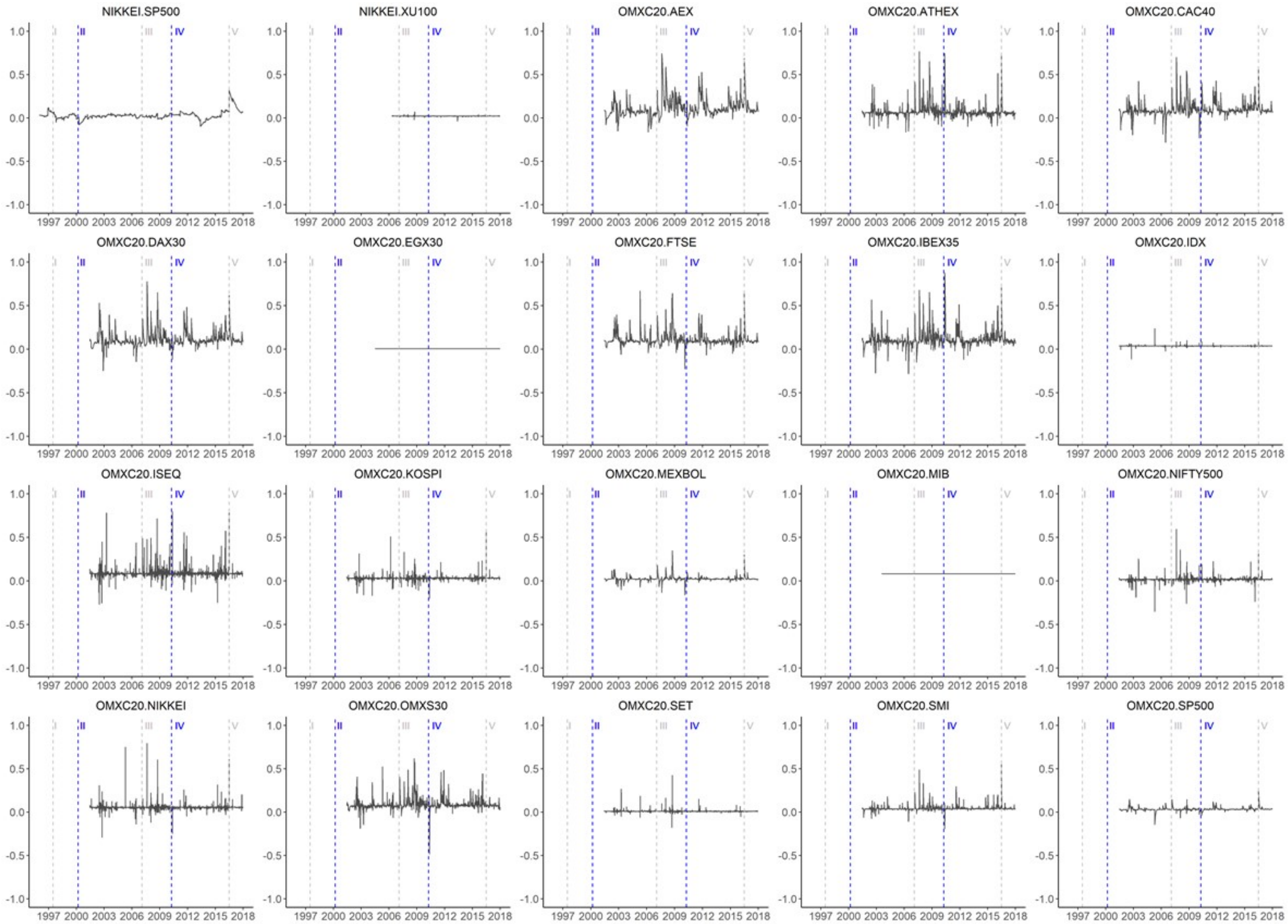
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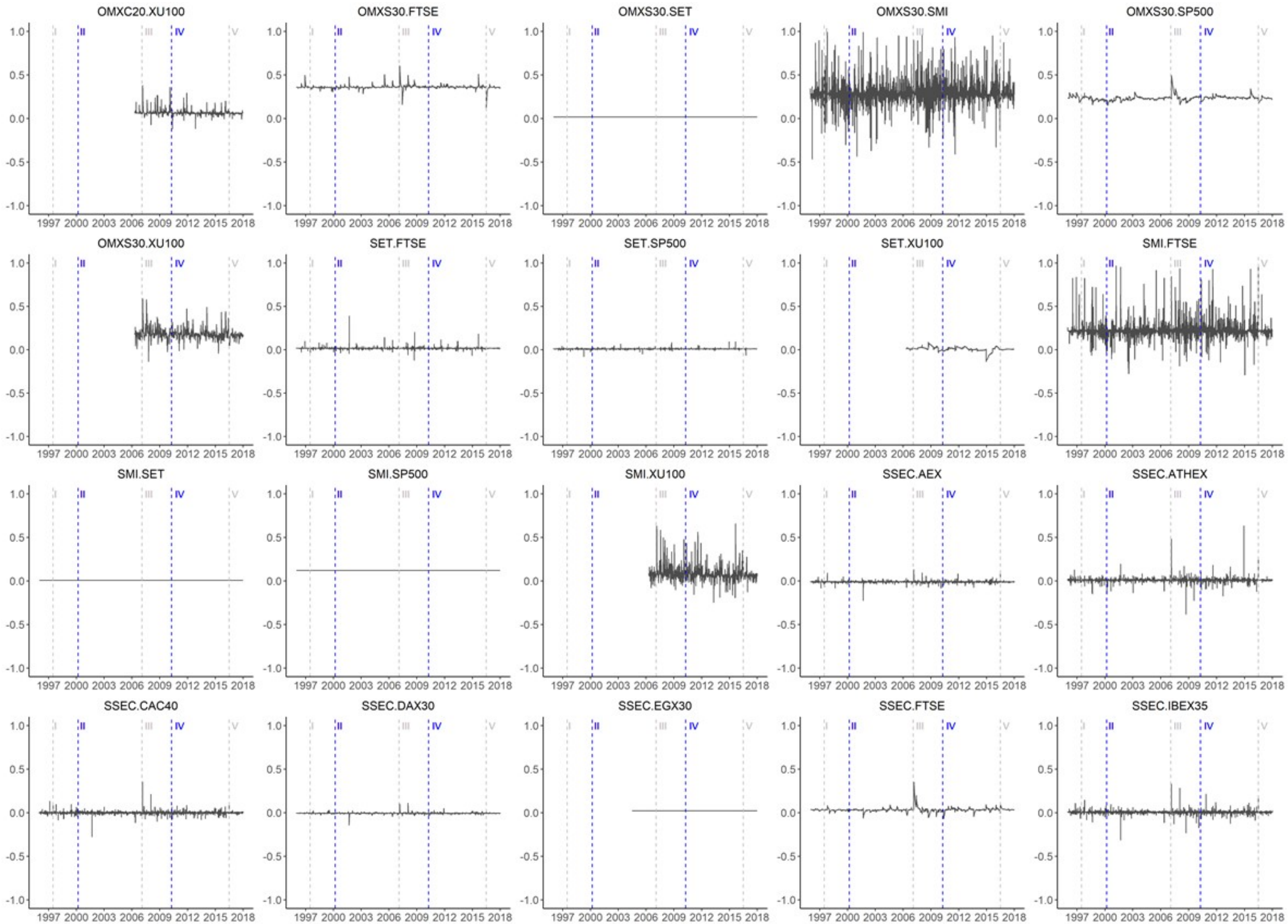
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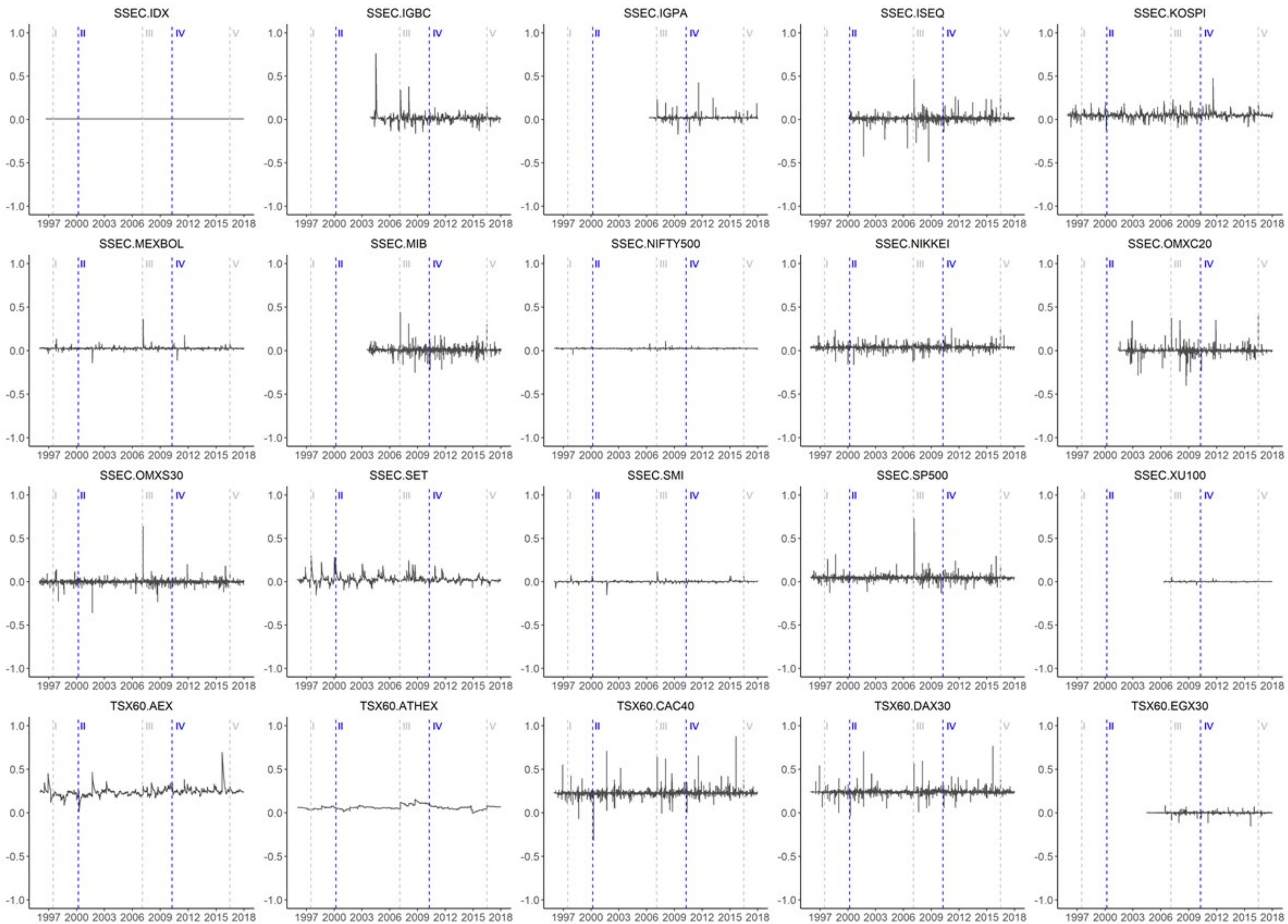
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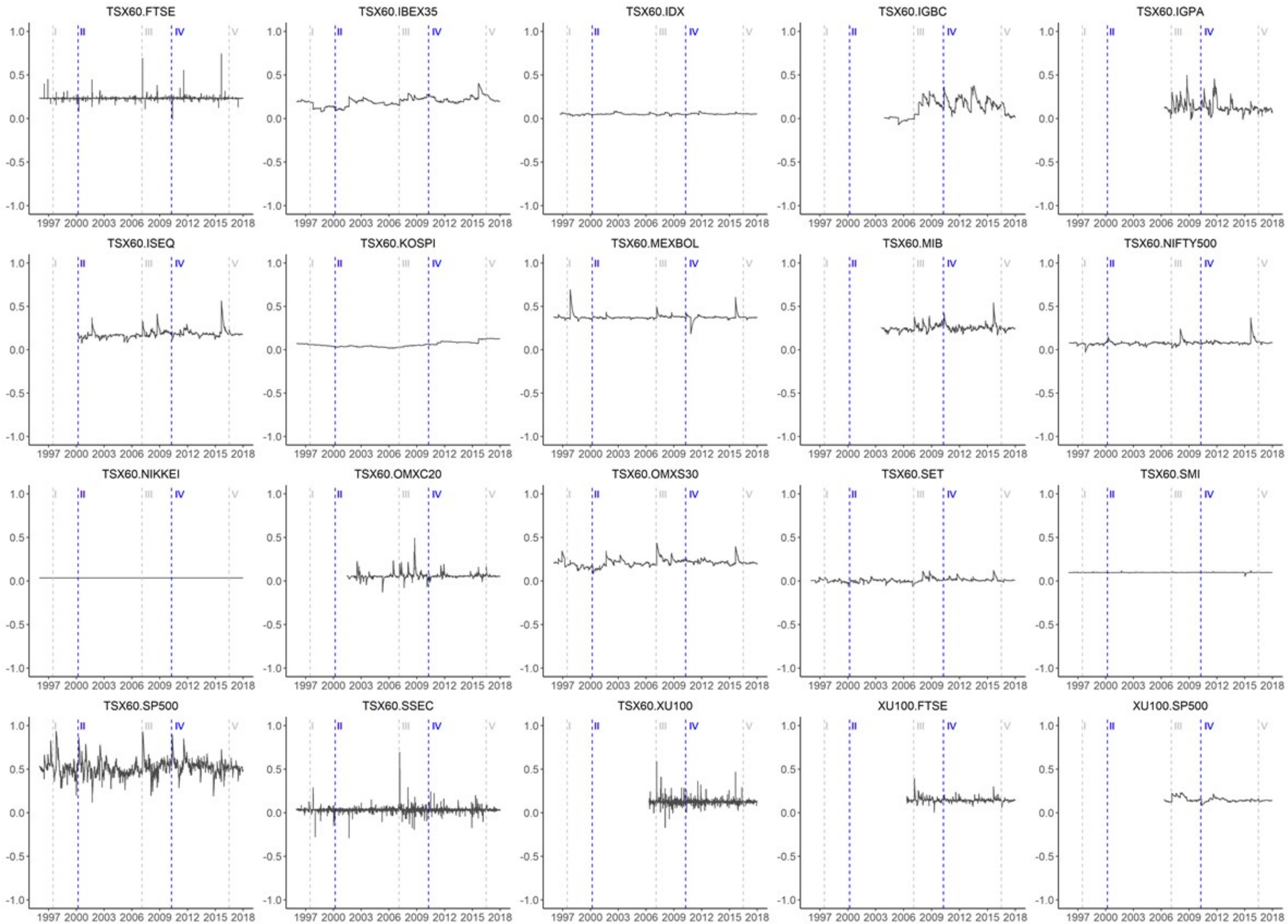
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D VAR forecast error variance decomposition

The first-order VAR can be denoted as

$$x_t = \Theta(L)\varepsilon_t,$$

where $\Theta(L)$ is the lag operator, $(1 - \Phi L)^{-1}$. It can be further derived as

$$x_t = A(L)\mu_t,$$

where $A(L) = \Theta(L)Q_t^{-1}$, $\mu_t = Q_t\varepsilon_t$ and $E(\mu_t\mu_t') = I$. The 1-step error is

$$e_{t+1,t} = A_0\mu_{t+1}.$$

Hence the volatility spillover index is

$$s = \frac{\sum_{h=0}^{H-1}\sum_{i,j=1}^{N} a_{h,ij}^2}{\sum_{h=0}^{H-1} trace(A_h A_h')} \times 100,$$

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