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Global Financial Crises and Time-varying Volatility Comovement in World Equity Markets

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Abstract

This paper studies volatility comovement in world equity markets between 1994 and 2008. Global volatility factors are extracted from a panel of monthly volatility proxies relating to 25 developed and 20 emerging stock markets. A dynamic factor model (FM) is estimated using two-year rolling window regressions. The FM's time-varying variance shares of global factors map variations in volatility comovement over time and across countries. The results indicate that global volatility linkages are particularly strong during financial crises in Asia (1997-8), Russia (1998), and the United States (2007-8). Emerging markets are less syncrhonised with world volatility than are developed markets. In particular, we observe decoupling between emerging and world volatilities between 2001 and 2007. Recoupling occurs during 2008, thus identifying emerging market investments as a temporary hedge against volatility spillovers from the US subprime crisis.

JEL Classification Numbers: F36, G01, G11, G15.

Keywords: Asset Market Linkages, Dynamic Factor Model, Financial Crisis, International Diversification, Volatility Comovement.

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1 Introduction

This paper uses a large-panel dynamic factor model (FM) to study volatility comovement between domestic and world equity markets. Global volatility factors are extracted from a panel of volatility proxies for 25 developed and 20 emerging markets. Based on the global factors, and using monthly data from 1994 to 2008, the FM quantifies time-variation in systematic and idiosyncratic components of variance in each market's volatility. Taking world volatility as a proxy for non-diversifiable risk, volatility comovement measures the sensitivity of domestic equity prices to globally systemic events.

The study is motivated by dynamic linkages between national stock markets. Invariably, volatility linkages strengthen during global financial crises, causing large degrees of interdependence and spillovers across internationally integrated markets.[1] Moreover, Ramachand and Susmel (1998), Ball and Touros (2000), Morana and Belltratti (2008), and others, provide evidence of a non-spurious positive relationship between volatility levels and correlations in cross-country returns.[2] The implication is that crises are associated with reduced benefits to international diversification and high risks to global financial stability. With these concerns in mind, the objective of the paper is to test for an association between variations in volatility comovement and the timing of financial crises. We measure and catalogue the cross-sectional responses of domestic volatilities to crises in Asia (1997-8), Russia (1998), Brazil (1999), and the United States (US, 2000, 2007-8).

Papers closely related to our own, include Dungey and Martin (2007), Dungey *et al.* (2010), and Morana and Beltratti (2008). Based on results from dynamic factor analyses, these authors document significant linkages between international asset markets. Furthermore, they provide evidence of close synchronisation in volatility transmission during crisis periods.

Relative to the above-mentioned studies, the key contributions of the current paper are as follows. Firstly, the cross-section under consideration has been extended to a

[1] In two seminal papers, Hamao, Masulis and Ng (1990) and King and Wadwhani (1990) provide evidence of large volatility transfers between developed equity markets in Japan, the United States, and the United Kingdom following the 1987 stock market crash. More recently, Diebold and Yilmaz (2009) develop volatility spillover indices to document dynamic volatility linkages in a panel of seven developed and 12 emerging equity markets.

[2] Refer to Forbes and Rigobon (2002) for an important disclaimer regarding robustness (or the lack thereof) of estimated correlation measures.

total of 45 equity markets, constituting over 95 percent of world market capitalisation.[3] Benefits associated with the larger panel include: Increased precision in latent factor extraction (Stock and Watson 2002); Greater generality of results pertaining to both developed and emerging markets; And, a closer approximation of the true drivers for *global* volatility transmission.

Secondly, our treatment of dynamics deviates from the traditional approach of pre-specifying non-crisis and crisis sample periods, and subsequently comparing results for the sub-samples. Instead, our results are derived from a sequence of two-year rolling-window FM regressions. Estimated in this way, the model may be interpreted as a variant of the time-varying-parameter FM (refer to Del Negro and Otrok 2008, Koop and Korobilis 2010, and Korobilis 2011). The estimation approach allows for a smooth mapping of cross-sectional volatility comovement through time. Permitting the parameters to evolve gradually in response to changes in the data enhances model fit, and avoids problems with *a priori* identification of structural breaks and crisis periods.

Thirdly, we analyse the underlying composition of the latent global volatility factors. Similar to Ludvigson and Ng (2007, 2009), we sequentially regress individual members from a comprehensive set of internationally relevant financial and fundamental variables on each of the identified factors. Thus, we provide an association between unobservable volatility factors and observable time series. This clarifies the relative importance of financial and fundamental indicators in global volatility transmission, and represents a first step towards a structural interpretation for this process.

The main results are summarised as follows. We identify three global factors for world volatility. Comovement of domestic volatilities with the factors differs considerably across countries and over time. We find that volatilities in Germany, the UK, and the US display consistently high degrees of comovement with the first of the identified global factors. Moreover, there appears to be a positive trend in the strength of volatility linkages between these major markets. In comparison, French and Japanese volatilities are largely idiosyncratic in nature. With the exception of Brazil, Mexico, Thailand and Turkey, emerging market volatility is characterised by low comovement relative to most developed markets.

Comovement between global factors and domestic volatilities in developed and emerging countries is especially high during crisis periods in Asian bond, Russian sovereign debt, and US subprime markets. We observe decoupling of emerging markets from global factors between 2001 and 2007. However, there is clear evidence of recoupling

[3] In comparison, Dungey and Martin (2007) and Dungey *et al.* (2010) base their studies on panels consisting of six countries. The analysis in Morana and Beltratti (2008) pertains to only four developed markets.

with world volatility in 2008. Thus, the benefits to diversification associated with investing in emerging markets during the subprime crisis are short-lived.

With regards factor composition, we find that financial variables are more closely associated with global factors than are fundamentals. Factor One is generally important to domestic volatility dynamics in developed countries; Factor Two is correlated with Latin American emerging markets, particularly Mexico; and Factor Three is a driver of volatility conditions in Asian emerging economies. Furthermore, Factor One and Factor Two are identified as proxies for volatility conditions in global bond and commodity markets.

The remainder of the paper is organised as follows. Section 2 provides a short review of the relevant literature. In Section 3, we introduce the FM and discuss its estimation. Details of data and the extraction of global factors appear in Section 4. This is followed by discussion of the results in Section 5. Section 6 concludes.

2 Literature Review

Several existing papers use dynamic factor analysis to investigate international asset market linkages. Dungey and Martin (2007) provide a theoretical motivation for a FM that captures interrelationships between returns across equity and currency markets.[4] GARCH specifications for conditional factor volatilities reflect the time-varying characteristics of financial data. The model is applied to a panel of six countries effected by the Asian crisis (Australia, Indonesia, Korea, Malaysia, Thailand, and the US). The results suggest a high degree of comovement in volatilities during the crisis period. Spillovers and contagion in asset market returns contribute meaningfully to increases in domestic volatilities from pre-crisis to crisis levels. This includes a significant volatility injection from the US to Australia – countries not directly associated with the onset of the crisis.

Dungey *et al.* (2010) adopt a similar approach to measure linkages between equity and bond markets during five distinct crisis periods between 1998 and 2007. Consistently, the authors report an important role for spillovers and contagion for all the countries included in their panel (Argentina, Brazil, Canada, Mexico, Russia, and the US).[5] Significant international market linkages are measured for every crisis period. Volatility linkages are especially prominent during the Russian debt and US subprime crises.

[4]From a purely theoretical view point, Kodres and Pritsker (2002) provide a clear justification for the applicability of the FM to studies of asset market linkages.

[5]Dungey *et al.* (2010) perform a robustness test wherein the panel is extended to include Australia, Germany, Japan, and the United Kingdom. The results of this test are similar to those for the smaller panel.

Using the conditional capital asset pricing model (Merton 1973) as a theoretical foundation, Morana and Beltratti (2008) propose a close connection between stock market linkages and financial integration. FMs are used to assess degrees of comovement between equity prices, returns, volatilities, and correlations in Germany, Japan, the United Kingdom (UK), and the US. Results from three sub-samples – specifically, 1973-1982, 1983-1992, and 1993-2004 – indicate a trend towards greater volatility interdependence between European and US markets. However, in relative terms, Japanese asset price dynamics are driven predominantly by idiosyncratic factors. With regards to comovement in volatility, Morana and Beltratti (2008) identify two common factors, with the first of these factors explaining important shares of variances in volatility levels (76 percent for Germany, 60 percent for Japan and the US, and 37 percent for the UK).

3 Methodology

The key advantage of the FM-methodology lies in its ability to maximise information content without sacrificing parsimony. Principal component analysis allows for the extraction of common factors that explain the majority of variations in cross-sectional data. With closely integrated markets, the number of factors needed to explain variability in world volatility is naturally small.

A disadvantage of the FM is that the common factors are unobservable, and thus difficult to interpret. To address this limitation, Forni *et al.* (2009) and Ludvigson and Ng (2007, 2009) investigate factor composition by regressing a large set of observable variables on the individual factors. We follow a similar approach to identify the drivers of volatility comovement in world equity markets.

3.1 The Factor Model

This paper applies the FM to a vector $Y_t = (y_{1t}, y_{2t}, ..., y_{Mt})'$ of proxies for period-t volatility in M distinct stock indices. The cross-section is chosen to be representative of the world equity market (in terms of cumulative market capitalisation). We assume that Y_t follows a covariance stationary process standardised to have zero mean and unit variance. The model decomposes each member of Y_t into two components. The first component, is a common vector $F_t = (f_{1t}, f_{2t}, ..., f_{Kt})'$ of K global volatility factors that satisfy $f_{it} \cdot f_{jt} = 0$ for all $i \neq j$, and where $K < M$. We refer to F_t as a set of "global" factors because it is constructed using all the information contained in Y_t. The explanatory power of F_t for variations in the dependent variable y_{mt} measures period-t comovement between volatility levels in market m and world equities. The second component, is a vector $E_t = (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{Mt})$ of idiosyncratic volatility factors and measurement errors, with $\varepsilon_{mt} \cdot f_{it} = 0$ for all i, m, and $\varepsilon_m \cdot \varepsilon_n = 0$ for $m \neq n$. The idiosyncratic factors may be weakly autocorrelated (but autocorrelation vanishes as $M \to \infty$). Supposing that the FM is correctly specified, the relative size of E_t is inversely related to the degree of integration in world equity market volatilities during period t. Consistently large values for ε_{mt} over time indicate that volatility in market m is driven predominantly by domestic news.

The model takes the following form:

$$Y_t = \Gamma + \Lambda F_t + E_t \tag{1}$$

where $\Gamma = (\gamma_1, \gamma_2, ..., \gamma_M)'$ is a $M \times 1$ vector of intercept terms and $\Lambda = (\lambda_1, \lambda_2, ..., \lambda_M)'$ is a $M \times K$ matrix of constant factor loadings (λ_m represents a $K \times 1$ column vector of parameters). Since F_t is unobservable, its value is approximated using an autoregressive representation. In the case of our FM, the optimal lag order of one is determined for by minimising the Bayesian information criterion (BIC).[6] Thus, we have

$$\hat{F}_t = A + BF_{t-1} + U_t$$

where A is a $K \times 1$ intercept vector, B is a $K \times K$ coefficient matrix, and U_t a $K \times 1$ vector of residuals. Hence, (1) becomes:

$$Y_t = \hat{\Gamma} + \hat{\Lambda}\hat{F}_t + \Xi_t \tag{2}$$

3.2 Estimation and Factor Compostion

R-squared statistics obtained from (2) measure the variance shares of Y_t that are explained by $\hat{\Lambda}'\hat{F}_t$. These statistics provide proxies for time-aggregated volatility comovement in the cross-section. However, it is well-known that stock market volatility is time-varying. Furthermore, empirical evidence points to non-constant volatility linkages between national stock markets, especially in sample periods that contain financial crises (Diebold and Yilmaz 2009). A suitable means of capturing volatility dynamics is provided by the time-varying-paramemter FM (TVP-FM; Del Negro and Otrok 2008, Koop and Korobilis 2010, and Korobilis 2011). As the name suggests, factor loadings change over time in the TVP-FM. But, in the absence of sensible restrictions on the model, this inevitably leads to over-parameterisation.

[6] Results of the lag specification test are available from the authors upon request.

As an alternative to the TVP-FM, we estimate (2) by means of 24-period (two-year) rolling-window regressions.[7] The use of rolling-window regressions has two advantages. Firstly, similar to the TVP-FM, rolling-window factor loadings are continuously re-estimated to reflect changes in the data through time. Providing for possible structural change in the volatility process increases the flexibility of the model and improves estimation accuracy. Furthermore, rolling-window estimation conveniently sidesteps the difficulties associated with the identification of financial crisis periods. The second advantage is that by consecutively shifting the estimation window forward through time, we obtain a sequence of R-squared statistics for each dependent variable. These sequences provide cross-sectional mappings of volatility comovement as a continuous function of time.

With regards the composition of factors, we consider world equity volatility as being correlated with a vector $X_t = (x_{1t}, x_{2t}, ..., x_{Lt})'$ of L possible variables. X_t contains a combination of volatility proxies for financial and fundamental indicators. Financial variables are likely to matter due to the interconnectedness of global equity portfolios. Interconnectivity of investors creates the possibility for volatility contagion and spillovers between countries, even when these countries have seemingly independent domestic fundamentals. However, to the extent that equity prices ultimately reflect economic reality, fundamental volatility is also expected to play a role in financial volatility transmission. For example, using quarterly data, Diebold and Yilmaz (2010) provide evidence of one-way causality from GDP volatility to equity volatility across a broad cross-section of countries.

In estimating factor composition, members of X_t are sequentially regressed on each of the individual factors:

$$x_{\ell it} = \hat{\alpha}_{\ell i} + \hat{\phi}_{\ell i}\hat{f}_{it} + \omega_{\ell it} \tag{3}$$

where, for $\ell = 1, 2, ..., L$ and $i = 1, 2, ..., R$, $\hat{\alpha}_{i\ell}$ and $\hat{\phi}_{i\ell}$ are estimated coefficients, and $\omega_{i\ell t}$ is a residual term. The R-squared statistics from (3) measure the strength of the relationship between observable variables and latent factors.

4 Data and Factor Extraction

The accuracy of the FM depends critically on the size of the chosen data panel. Stock and Watson (2002) demonstrate that when the ratio of the number of variables to factors

[7] The lenght of the estimation window has been limited to 24 periods in order to adequately capture dynamics in the data. The reported results are robust to alternative window specifications of 36 and 48 periods. Results relating to the latter alternatives are available from the authors upon request.

is large, extraction of latent factors is achieved with a high degree of precision. Moreover, the use of a large data set is important to obtain a true representation of *global* volatility factors. Hence, we base our analysis on a large panel consisting of data for 25 developed and 20 emerging equity markets obtained from Datastream.[8] Up to five volatility proxies from each market are included in the panel. These proxies relate to the various countries' composite stock indices and, where available, individual market sectors (industrials, oil and gas, financials, and basic materials). In total, the data set contains 192 time series from January 1994 to December 2008. On average, the cross-section constitutes over 95 percent of annual world market capitalisation during the sample period.[9]

The panel data allows for comparison of volatility comovement across individual countries. However, it is also of interest to compare volatility transmission for globally significant groupings of equity markets. To facilitate such an analysis, we construct twelve indices consisting of different combinations of markets included in the panel. Most significant among the constructed indices, are those relating, respectively, to the developed markets, the emerging markets, and the world as a whole (where the latter index is proxied by all markets in the panel). Comovement of these indices with global factors is discussed at length in Section 5.2. The remaining indices represent subsets of developed markets (in Australasia, Europe, and the G7) and emerging markets (in Asia, the BRICS, the E7, Europe, and Latin America).[10] The discussion of volatility comovement in the latter indices appears in Appendix B. The various indices are constructed as weighted averages of returns for individual countries. The relevant weight for each country is calculated as that country's share of market capitalisation relative to all markets included in the index. The weights are updated annually to reflect changes in relative market sizes over time. Changing shares of world market capitalisation for the indices are depicted in Figure 1.

Volatility proxies are constructed as squared returns of observed closing stock prices. We use the monthly data frequency to avoid problems related to non-synchronous trading hours across countries located in different time-zones. An added benefit of monthly data,

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[8]Market typology emphasises the stage of development of the different equity markets, and not necessarily the development of the countries that host those markets. Our catogorisation is consistent with the FTSE country classification review for 2010 (obtained from the FTSE website: http://www.ftse.com/Indices/Country_Classification/Downloads/FTSE_Country_Matrix_June2011_Post_2010_Changes.pdf). Refer to Table A.1 in Appendix A for the list of countries included in the panel.

[9]The calculation of market capitalisation in the panel relative to the world is based on data obtained from the World Bank's website (http://data.worldbank.org/indicator/CM.MKT.LCAP.CD). No market capitalisation data is available for Taiwan.

[10]BRICS refers to Brazil, Russia, India, China, and South Africa. The E7 is a collection of seven major emerging markets. Refer to Table A.2 in Appendix A for details of the strategic indices' compositions.

is that it allows for inclusion of fundamentals in the factor composition analysis. A total of 67 macroeconomic variables are used to evaluate equity volatility dependence on real activity. These variables include volatility proxies for log differences in bond yields, consumer price indices, commodity prices, exchange rates, industrial production, and interest rates.[11] We also consider factor composition with respect to financial variables. The set of financial indicators consists of the 45 individual stock markets included in the data panel, as well as the constructed strategic indices.

Volatility plots for the strategic market indices are displayed in Figure 2. Comparison of the graphs indicates that emerging markets are more volatile than developed markets. This is consistent with the notion of a positive risk-premium in emerging finance (Bekaert and Harvey 1997, De Santis and Imrohoroglu 1997, and Richards 1996). Clearly, all markets exhibit considerable time-variation in volatility. In this respect, there appear to be similarities in the timing of large volatility shocks across different indices. For three quarters of all indices, October 2008 represents the most volatile period in the sample, demonstrating the global impact of the subprime crisis on equity pricing. In the case of the Asian Tigers (excluding Taiwan), the highest level of volatility is recorded when the Asian crisis spreads to Hong Kong during October 1997. The second largest spike in volatility of the emerging index occurs at roughly the same time. The most volatile period in Latin America coincides with the beginning of the Russian crisis in August 1998. The considerable effect of this crisis on the developed and BRICS indices is evident from the relevant volatility plots. Markets in emerging Europe are especially volatile during December 1999. This period is also associated with above-average volatilities in developed Europe and the E7. Finally, we identify September 2001 to July 2002 as a turbulent period in developed European, G7, and world indices.

The above observations motivate the study of international volatility linkages during financial crises. To formally assess these linkages, we proceed by extracting global volatility factors. This requires that we determine the appropriate number of factors to include in the FM. Application of the Bai and Ng (2002, henceforth BN) approach to our data set indicates that there are five common factors (detected by means of the lowest IC_{p2}). In contrast, the principal component (PC) approach suggests only two factors, given that the third factor explains less than 5% of variations in the panel. However, we base our factor selection on the test developed by Alessi, Barigozzi and Capasso (2010, henceforth ABC), which improves on BN in terms of robustness. According to the ABC test, three global volatility factors represents an optimal choice.[12]

[11] Table A.3 in the Appendix A provides of list of the macroeconomic variables included in the analysis.

[12] Results of tests for number of common factors are available from the authors upon request.

5 Empirical Results

5.1 Variations in Volatility Comovement

R-squared statistics obtained from the FM measure variance shares of domestic volatility levels explained by fluctuations in global volatility factors. At one extreme, if the estimated R-squared value is zero, the FM suggests that domestic volatility dynamics are independent of foreign volatilities. On the other hand, an R-square of unity indicates that domestic volatility is imported in totality. This provides a natural index for volatility comovement in world equity markets. Of central interest to our analysis, are variations in comovement over time and across countries. Thus, two-year rolling-window estimates of the FM are particularly useful, as they provide consecutive snapshots of volatility linkages in the cross-section.

Figure 3 depicts volatility comovement plots (sequences of time-varying R-squared statistics) for each of the 45 markets included in the panel. Comparison of these plots suggest three time-trends that are common to the majority of countries. Volatility comovement is increasing from the beginning of the estimation period until 2000. This period includes a spell of especially strong dependence on global factors from 1998 to 2000. For some markets (notably, Germany, Netherlands, the UK, and the US), the trend towards stronger international volatility linkages continues up until the end of 2004. But, in general, the importance of global volatility factors diminishes between 2001 and the beginning of 2007, suggesting a lower degree of systematic volatility in world equities. The latter period is followed by unanimous increases in comovement measures during 2008, with R-squared values approaching unity for many countries.[13]

To ease comparison across different countries, we analyse averages of time-varying R-squared statistics. The average comovement measures are reported in Table 1. The results indicate that volatility is most closely synchronised with global factors in developed markets. In particular, European volatility is strongly comoving with world volatility. Average comovement exceeds 60 percent for Germany, Netherlands, and the UK, and 51 percent for Belgium, Italy, Spain, and Switzerland. These values are greater than estimated comovement of 51 percent for the US. This is perhaps surprising, since US equities account for an overwhelming share of world market capitalisation (a sample average of 42 percent). However, a degree of idiosyncrasy in US volatility is to be expected given the frequency of large shocks with origins in the US economy (for example, Long-Term Capital Management, the dot-com bubble, and sub-prime crisis). Hong Kong and

[13] Two exceptions to this finding, are Isreal and Phillipines, where comovement is relatively low in 2007-8. Due to missing data observations (refer to Appendix A, Table A.1), we are unable to estimate volatility comovement for Czech Republic, Pakistan, and Singapore for the full duration of 2008.

Singapore complete the list of ten developed markets with greatest dependence on world volatility levels, with average comovement statistics of 49 and 51 percent, respectively.

Not all developed markets are well-integrated with global factors. In particular, the results for France and Japan have interesting implications. These markets constitute considerable portions of world market capitalisation (sample averages of 4 percent for France and 12 percent for Japan). However, with time-aggregated comovement of only 39 and 27 percent, global factors are relatively poor predictors of volatilities in these countries. Compared with other major markets, Figures 3 indicates relatively low levels of volatility comovement in France during 1996 to mid-2001. In this respect, France appears to be one of few countries in Europe (and in the world) that successfully escapes volatility contagion from the Asian, Brazillian, and Russian crises. In contrast, we observe that between 2002 and the end of the sample period, France's comovement dynamics are similar to those for Denmark, Spain and the US. These observations suggest that France has become more integrated with world financial markets over time. In the case of Japan, volatility linkages appear fairly robust from 1997 to 2000, and also during 2007-8. Sensitivity to global factors during the first period is related to common exposures between the financial sectors in Japan and countries immediately affected by the Asian crisis.[14] In the second period, the increase in volatility comovement coincides with the onset of the subprime crisis. But, in the absence of financial crises, we find that Japanese volatility is predominantly driven by idiosyncrasies, thus corroborating Morana and Beltratti's (2008) conclusion of weak synchronisation between Japanese and developed market volatilities. The relative importance of domestic shocks to the Japanese market may be attributed to structural problems inherited from the disinflationary experience of the 1990s (the so-called "lost decade" in Japan). Other developed markets with low average degrees of comovement include Finland (20 percent), Ireland (22 percent), Israel (22 percent), and New Zealand (20 percent). All of these markets constitute less than one percent of developed market capitalisation (refer to Table A.1 in Appendix A).

Among emerging markets, global factors are important determinants of volatility in Latin America. This may be attributed to the proximity of these countries with major developed markets in Canada and the US. Most notably, average comovement equals 54 percent for Brazil and 47 percent in the case of Mexico. The comovement plots for these markets – which are not dissimilar to those for Canada and the US – peak at values of approximately 90 percent during 1998 to 2000, and 2008. Parallel increases in foreign volatility dependence are also observed for Argentina and Chile, thus identifying Latin

[14] The most notable Japanese failure during the Asian crisis occurs on 24 November 1997, when Yamaichi Securities announces its bankrupcy (Kaminsky and Schmukler 1999).

America as a receiver of volatility injections subsequent to crises in Asia, Russia, and the US. Spikes in volatility comovement occur at roughly the same times for most emerging markets in Asia and Europe. On average, half of the variance in volatility for Thailand is explained by variations in global factors. The factors are related to 44 percent of average volatility in Hungary and 49 percent in Turkey.

Excluding crisis periods, the determinants of volatility in China, Phillipines, and South Africa, are predominantly idiosyncratic in nature. With average comovement of only 13 percent, China is the country least effected by global factors. Low synchronisation with world volatility, in spite of the growing size of the Chinese market, is due to the imposition of strict domestic capital controls. Continued accumulation of foreign exchange reserves and double digit growth rates may also contribute to China's insulation from smaller shocks to the global financial system. Low comovement in Philipines (15 percent) is reflective of its small size relative to other emerging markets (a sample average of 2.2 percent of emerging market capitalisation). For South Africa, average comovement of 17 percent indicates the importance of domestic shocks to volatility transmission. An example of such a shock is the South African currency crisis of 2001. Duncan and Kabundi (2011) provide evidence of volatility spillovers from the currency market to South African equities between 2001 and mid-2006.

5.2 Comovement in Developed, Emerging and World Volatilities during Financial Crises

In what follows, we consider volatility comovement measures relating to the developed, emerging, and world strategic market indices. Full-sample estimation of the FM indicates that global factors account for the majority of variations in index volatilities. Comovement is estimated at 87 percent for the world, 86 percent for developed markets, and 69 percent for emerging markets, implying a consistently high degree of interdependence between domestic and foreign volatility levels. However, the generality of this conclusion is conditional on the stability of international volatility linkages.

Two-year rolling-window regressions of the FM suggest instability in volatility transmission over time. Figure 4 depicts time-varying volatility comovement for the three indices. Also identified, are periods of major financial crisis that are contained within the sample. For each index, there is a clear association between the timing of financial crises and local maxima in comovement.

Aggregating across the rolling regressions, the global factors explain 72, 70, and 57 percent of volatilities in the world, developed, and emerging indices. The developed and world comovement plots are highly correlated. This is expected, as developed markets constitute an average of 90.5 percent of the panel's market capitalisation. Comovement in developed markets exceeds comovement in emerging markets in two-out-of-every-three periods. This confirms our earlier conclusion of greater synchronisation between domestic and foreign volatilities in the case of developed markets. The main exception to this observation occurs from 1996 to 1999, during which time changes in emerging comovement lead those for developed markets. High sensitivity of emerging volatility to global factors in the late 1990s is due to the recurrence of financial crises with origins in emerging countries.

Global factors explain only 13 percent of emerging volatility in December 1995, the first estimation point. However, comovement increases rapidly in subsequent periods, peaking at 73 percent during March to June of 1997. The latter period coincides with growing speculative pressure on the Thai baht, culminating in its eventual devaluation on 2 July 1997. This marks the beginning of the Asian crisis.[15] The corresponding turning point in developed comovement occurs in October 1997, when Hong Kong loses 30 percent of its market value. Volatility linkages weaken during the first half of 1998, as relative stability returns to world markets.

But, recovery from the Asian crisis is short-lived. A further four major global shocks arrive within the space of two years. The Russian crisis begins on 17 August 1998 with the announcement of a deferral in government debt repayments. Uncertainty mounts in world bond markets in September 1998, when Long-Term Capital Manangement receives a bailout package in the US. This is followed by currency crisis in Brazil, and ultimate devaluation of the real on 15 January 1999. Finally, the bursting of the US dot-com bubble occurs between February and June 2000. We observe a dramatic response in volatility linkages during the time interval corresponding with these events. Emerging comovement reaches its maximum value of 98 percent in August 1998. Comovement of 92 percent is recorded for the developed index in the same period. Following this, comovement exceeds 88 percent for all three indices up until June 2000, indicating a sustained period of commonality in the drivers for developed and emerging volatility transmission.

In contrast, we see signs of divergence in the determinants of emerging and world volatility levels between 2001 and 2007. Whilst global factors continue to predominate in developed volatility transmission, there is rising importance of idiosyncratic factors in the case of emerging markets. Lower sensitivity to foreign volatility is the result of emerging markets' financial and fiscal reforms, greater policy discipline, and accumulation of foreign exchange reserves. Coinciding with the September 2001 terrorist attacks, developed comovement increases from 58 to 87 percent. Developed market volatility

[15] Refer to Kaminsky and Schmukler (1999) for a detailed chronology of the Asian crisis.

linkages continue to strengthen, with comovement reaching 95 percent in July 2004. During the same period, emerging comovement declines from 70 percent to 56 percent (including a momentary fall to below 15 percent in November 2003). The developed and emerging comovement plots continue to move in opposite directions during 2005 to 2006. Following a temporary decline to 21 percent between January and April 2006, developed comovement begins to rise again in the lead-up to the US subprime crisis.[16] As funding difficulties associated with two Bear Sterns' hedge funds become public in June 2007, developed comovement reaches 63 percent. At the same stage, with comovement of only 14 percent, emerging markets appear to be unaffected by the crisis.

The next major shock occurs during January 2008 when rating agency Fitch downgrades US monoline insurer Ambac, thus generating heightened uncertainty regarding the sustainability of structured credit contracts. The uncertainty spills over into the equity market, and consequently comovement in the developed index jumps from 51 to 93 percent. In this case, emerging markets are also significantly effected, with comovement more than doubling in value, from 20 to 53 percent. Following the failure of Lehman Brothers in mid-September, developed comovement increases further, reaching its sample maximum of 98 percent in October. At this point, the connection between developed and emerging comovement is firmly reestablished, with global factors explaining 92 percent of the variations in emerging market volatility.

In summary, we provide evidence of heightened volatility comovement during financial crises in both developed and emerging economies. We observe signs of decoupling in emerging market volatility from global factors during 2001 to 2007. Hence, emerging markets provide an effective hedge against systematic risk associated with the early stages of the subprime crisis. But the benefits to diversification are temporary, as global factors ultimately dominate volatility transmission during the latter stages of 2008.

5.3 Factor Composition

Table 2 reports results of sequentially regressing volatility proxies in the panel and the set of strategic market indices on the individual global volatility factors. In general, the greatest R-square statistics are estimated when regressing financial variables on the first factor. Factor One accounts for 86, 85, and 65 percent respectively, of variations in world, developed and emerging market volatility. In comparison, none of the corresponding statistics for Factor Two and Factor Three exceed 5 percent. For individual countries, Factor One is most closely related to volatilities in Japan, the UK, and the US (with respective R-squares of 59, 58, and 65 percent). Thus, we conclude that Factor One is

[16] Consult Brunnermeier (2009) for an in-depth account of the subprime crisis.

best identified as a developed financials volatility factor.

In contrast, the relative importance of the second and third factors is most evident for regional groupings of the emerging markets. Factor Two explains 19 percent of volatility changes in emerging Europe and 32 percent in Latin American countries. For individual countries, R-squares of 30 percent for Mexico and 15 percent for Russia indicate correlation of these markets with Factor Two. On the other hand, with a variance share of 22 percent, Factor Three is of greatest relative consequence to volatility levels in the Asia Tigers (excluding Taiwan). Consistently, we estimate R-squared statistics ranging between 24 and 35 percent for Hong Kong, Singapore, South Korea, and Thailand.

Relationships between global volatility factors and fundamental indicators are considered in Table 3.[17] The explanatory powers of Factor One are greatest for volatility proxies from a variety of bond and commodity market indices. Thus, in addition to capturing volatility conditions in developed markets, Factor One represents a proxy for commodity and bond price volatilities. Although the global volatility factors are constructed to be mutually orthogonal, Table 3 indicates a similar interpretation for the composition of Factor Two with respect to global fundamentals. The highest R-square statistics for the first and second factors (66 and 61 percent, respectively) are estimated when the Dow Jones (UBS/AIG) commodity index is the dependent variable. Moreover, Factor One and Factor Two both explain meaningful shares (between 31 and 38 percent) of volatility in bond indices recorded by Barclays and J.P. Morgan.

With respective R-squares of 50 and 41 percent, Factor Two is also relevant to volatility in the US/Russian nominal exchange rate and the South African 10-year government bond yield (with respective R-squares of 50 and 41 percent). Unique to Factor Two, is the fact that it has greater explanatory power for fundamental variables than it does for financial variables.

In regressions of fundamental indicators on Factor Three, all resulting R-squared statistics are less than or equal to 13 percent in magnitude. This makes it difficult to draw firm conclusions regarding factor composition. Fundamentals most closely related to Factor Three are US capacity utilisation and industrial production. Of secondary importance, are the Euro marginal lending rate and trade-weighted-index (both with R-squares of 11 percent), and the price of platinum (with an R-square of 8 percent).

[17] In the interest of brevity, the reported results relate only to variables with the highest estimated R-squared statistics for each factor. Complete results of the composition analysis (for both financial and fundamental variables) are available from the authors upon request.

6 Conclusion

This paper investigates comovement of monthly volatilities in world equity markets with global volatility factors during 1994 to 2008. Three global factors are extracted from a panel of 45 national stock markets which constitutes over 95 percent of world market capitalisation. Results from the FM provide compelling evidence of time-variation in international volatility transmission. In particular, volatility linkages are found to strengthen sharply during financial crises in Asia (1997-8), Russia (1998), and the US (2007-8).

Furthermore, there is a large degree of heterogeneity in volatility linkages for different countries in the panel. Whilst developed markets in Germany, Hong Kong, Singapore, the UK, and the US are closely integrated with global factors, volatilities in France and Japan are predominantly driven by idiosyncrasies. Similarly, there is considerable variance in comovement across emerging markets. Foreign volatilities are influential to equity prices in Brazil, Mexico, Thailand and Turkey, but less so in countries such as China, Phillipines and South Africa. As a group, the emerging markets are less synchronised with world volatility than are developed markets. In particular, we observe decoupling between emerging and world volatilities between 2001 and 2007. Recoupling occurs during 2008, thus identifying emerging market investments as a temporary hedge against volatility spillovers from the US subprime crisis.

It would be beneficial for future research to investigate the structural properties of international volatility transmission. As a first step in this direction, we analyse the composition of the global volatility factors. Factor One is identified as a developed market volatility factor. On the other hand, Factor Two is correlated with volatility levels in Latin America, whilst Factor Three is associated with markets in emerging Asia. In addition, Factor One and Factor Two are proxies for uncertainty in global bond and commodity markets. The latter finding suggests an extension of the current analysis to account for asset market linkages which may exist across different asset classes.

Appendix A

The market typology used in this paper is consistent with FTSE's market classification review of 2010. The markets included in the data panel are listed in Table A.1, along with details of missing data observations and indices. Relative market capitalisations for the various markets, used to calculate mean weights of the developed and emerging index, are also reported. Table A.2 provides details regarding the mean proportions of individual market returns constituting the remaining strategic market indices. Finally,

Table A.3 identifies the fundamental indicators that are used in the factor composition analysis .

Appendix B

Figure B.1 depicts time-varying volatility comovement for nine indices of equity market groupings that are of strategic importance to international investors. As expected, there are similarities between comovement plots for individual countries that constitute the various indices, and the comovement plots for the indices themselves. Time-aggregated R-squared statistics of 80 and 58 percent for European developed and emerging indices, are consistent with our earlier conclusion that European volatility is closely integrated with global factors. By implication, these markets are especially sensitive to foreign volatility shocks. In contrast, developed and emerging markets in Australasia are much less effected by foreign volatilities.[18] This reflects the important role for idiosyncrasies in China and Japan, whose markets constitute the largest shares of the Asian emerging and Australasian developed indices, respectively.

More generally, comparison of comovement for the E7 and G7 suggests that volatility linkages in major emerging markets are generally weaker than the corresponding linkages for important developed markets. Nevertheless, increases in E7 comovement lead those for the G7 from the beginning of the estimation period up until the Asian crisis. The regional impact of the Asian crisis is evidenced by large spikes in comovement for all Australasian indices during this period. Developed Europe and Latin America also appear to be significantly impacted by the Asian flu. Increasing volatility linkages during the Russian crisis are most perceptible for emerging Asia, BRICS, the E7, the G7, and Latin America. On the other hand, the dot-com crisis has a noticeable impact on volatility transmission in emerging Europe. We observe a uniform decline in comovement across all indices following the dot-com crisis. This decline is relatively persistent for the Asian emerging, Australasian developed, BRICS, E7, and Latin American indices, indicating a degree of decoupling from global volatility factors. From 2006 onwards, recoupling with the factors is led by increases in comovement for the developed indices of Austraulasia, Europe, and the G7. Relative to the other indices, increases in comovement associated with US subprime crisis are delayed for markets in emerging Asia, the BRICS, the E7, and, to some extent, Latin America. Thus, these indices are identified as possible hedges against systematic global volatility during the early stages of the subprime crisis.

[18] This statement does not apply to the Asian Tigers (excluding Taiwan), where integration with world volatility is relatively high.

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Table 1. Time-aggregted volatility comovement

Developed Markets:		Emerging Markets:	
Australia	0.42	Argentina	0.40
Austria	0.42	Brazil	0.54
Belgium	0.52	Chile	0.41
Canada	0.46	China	0.13
Denmark	0.49	Columbia	0.23
Finland	0.20	Czech Republic	0.31
France	0.39	Hungary	0.44
Germany	0.62	India	0.38
Greece	0.47	Indonesia	0.35
Hong Kong	0.49	Malaysia	0.38
Ireland	0.22	Mexico	0.47
Israel	0.22	Pakistan	0.24
Italy	0.56	Phillipines	0.15
Japan	0.27	Poland	0.34
Netherlands	0.63	Russia	0.35
New Zealand	0.20	South Africa	0.17
Norway	0.37	Sri Lanka	0.24
Portugal	0.44	Taiwan	0.25
Singapore	0.51	Thailand	0.50
South Korea	0.43	Turkey	0.49
Spain	0.52		
Sweden	0.30		
Switzerland	0.54		
United Kingdom	0.61		
United States	0.52		

Notes. Reported statistics are average R-squared's from two year rolling window regressions of the volatility proxy for each country's composite stock index on the global volatility factors.

Table 2. Factor composition results for selected financial variables

	Factor One	**Factor Two**	**Factor Three**
Strategic Indices:			
Asian Emerging	0.41	0.03	0.01
Asian Tigers (ex. Taiwan)	0.32	0.01	0.22
Australasian Developed	0.68	0.05	0.01
BRICS Emerging	0.55	0.00	0.00
Developed	0.85	0.01	0.01
E7	0.56	0.03	0.00
Emerging	0.65	0.04	0.00
European Developed	0.75	0.00	0.06
European Emerging	0.22	0.19	0.03
G7	0.81	0.02	0.01
Latin American Emerging	0.41	0.32	0.00
World	0.86	0.00	0.00
Individual Countries:			
Brazil	0.45	0.08	0.03
Germany	0.30	0.04	0.09
Hong Kong	0.26	0.01	0.24
Japan	0.59	0.05	0.00
Mexico	0.28	0.30	0.00
Singapore	0.31	0.10	0.27
South Korea	0.14	0.00	0.35
Russia	0.24	0.15	0.01
Thailand	0.30	0.01	0.33
UK	0.58	0.00	0.10
United States	0.65	0.07	0.00

Notes. Reported statistics are R-squared's from regressing the indicator variable on the individual factor.

Table 3. Factor identification using fundamental variables

Factor One:	#1	DJ UBS/AIG Commodity Futures Index	0.66
	#2	US Corporate Bond Yield (BAA)	0.44
	#3	Goldman Sachs Commodity Index	0.41
	#4	Barclays Euro Inflation-Linked Bond Index	0.38
	#5	Industrial Commodities Index	0.36
		J.P. Morgan Emerging Market Bond Spread	0.36
Factor Two:	#1	DJ UBS/AIG Commodity Futures Index	0.61
	#2	US Dollar/Russian Ruble Exchange Rate	0.50
	#3	SA 10-Year Government Bond Yield	0.41
	#4	J.P. Morgan Emerging Market Bond Spread	0.36
	#5	Barclays Euro Inflation-Linked Bond Index	0.31
Factor Three:	#1	US Capacity Utilisation	0.13
	#2	US Industrial Production	0.13
	#3	Euro Marginal Lending Rate	0.11
	#4	Euro Trade-Weighted-Index	0.11
	#5	Platinum Spot Price	0.08

Notes. Reported statistics are R-squared's from regressing the indicator variable on the individual factor. Results for the top 5 variables (in terms of explanatory power) for each factor are reported.

Table A.1. Market typology, mean market capitalisations, and missing observations

Developed Markets	Mean Relative Market Caps.	Missing Indices	Missing Data for Composite Index	Emerging Markets	Mean Relative Market Caps.	Missing Indices	Missing Data for Composite Index
Australia	1.8%	B, F, I, O		Argentina	3.6%		
Austria	0.2%			Brazil	11.7%	B, F, I, O	
Belgium	0.6%	O	11/2000 - 12/2001	Chile	3.6%		
Canada	3.1%			China	21.9%	O	1/1994 - 12/1996
Denmark	0.4%	O	1/1994 - 12/1995	Colombia	0.4%	I	1/1994 - 6/2001
Finland	0.6%	O		Czech Republic	0.8%	F	1/1994 - 3/1994; 8/2008 - 12/2008
France	4.4%						
Germany	3.9%	O		Hungary	0.6%	I, O	
Greece	0.3%	O		India	10.0%		
Hong Kong	2.2%			Indonesia	2.6%	O	
Ireland	0.2%			Malaysia	8.2%		
Israel	0.3%			Mexico	6.6%		
Italy	2.0%			Pakistan	0.3%		1/1994 - 12/2001 7/2008 - 12/2008
Japan	13.2%						
Netherlands	1.9%			Phillipines	2.2%		
New Zealand	0.0%	I	1/1994 - 12/2001	Poland	1.4%	B, F, I, O	
Norway	0.3%		1/1994 - 12/1995	Russia	6.3%	B, F, I, O	1/1994 - 8/1994
Portugal	0.2%			South Africa	12.9%		
Singapore	0.6%		3/2008 - 12/2008	Sri Lanka	0.1%	B, O	
South Korea	1.2%			Taiwan	N/A	O	
Spain	2.1%			Thailand	3.9%		
Sweden	1.1%	O		Turkey	2.9%		
Switzerland	2.6%	O					
United Kingdom	8.7%						
United States	47.8%						

Data source: Datastream. Mean relative market capitalisations are based on own calculations from market capitalisation data obtained from the World Bank's online database. Key for missing indices: B = Basic Materials; F = Financials; I = Industrials; O = Oil and Gas.

Table A.2. Composition of strategic market indices

Strategic Index	Countries and Approximate Mean Weightings
Asian Emerging:	China (44%), India (21.5%), Indonesia (6%), Malaysia (19%), Pakistan (0.6%), Sri Lanka (0.3%), Thailand (9%).
Asian Tigers (ex. Taiwan):	Hong Kong (55%), Singapore (16.5%), South Korea (28.5%).
Australasian Developed:	Australia (10%), Hong Kong (12%), Japan (68%), New Zealand (0.3%), Singapore (3%), South Korea (6.5%).
BRICS Emerging:	Brazil (20%), China (32%), India (16%), Russia (9%), South Africa (23%).
Developed:	All developed markets (as listed in Table A.1).
E7 Emerging:	Brazil (20%), China (32%), India (17%), Indonesia (5%), Mexico (12%), Russia (9%), Turkey (5%).
Emerging:	All emerging markets (as listed in Table A.1).
European Developed:	Austria (0.7%), Belgium (2%), Denmark (1%), Finland (2%), France (15%), Germany (13%), Greece (1%), Ireland (0.8%), Italy (7%), Netherlands (6.5%), Norway (1%), Portugal (0.7%), Spain (7%), Sweden (3.5%), Switzerland (8.5%), United Kingdom (29.5%).
European Emerging:	Czech Republic (15%), Hungary (10.5%), Poland (24.5%), Turkey (50%).
G7 Developed:	Canada (4%), France (5%), Germany (5%), Italy (2%), Japan (16%), United Kingdom (10%), United States (58%).
Latin American Emerging:	Argentina (13%), Brazil (46%), Chile (14%), Colombia (2%), Mexico (25%).
World:	All developed markets (90.5%), all emerging markets (9.5%).

Data source. Datastream; approximate mean weights are based on own calculations from World Bank market capitalisation data.

Table A.3. Fundamental variables used in factor composition analysis

Bond Indices:
- Barclays euro inflation-linked bond index
- Barclays US govt. inflation linked index
- Barclays world govt. inflation linked index
- Citigroup world govt. bond index
- J.P. Morgan emerging market bond spread
- J.P. Morgan global govt. bond index
- J.P. Morgan US govt. bond yield to maturity
- US AAA corporate bond yield
- US BAA corporate bond yield

Commodity Prices:
- Brent crude oil spot
- Dow Jones UBS/AIG commodity futures index
- Economist all commodities index
- Economist food index
- Economist metals index
- Economist industrial commodities index
- Gold spot
- Goldman Sachs Commodity Index
- Industrial Commodities Index
- Platinum spot

Consumer Price Indices (CPI) and Inflation:
- Brazillian Inflation
- Chinese Inflation
- European CPI
- G7 CPI
- Indian Inflation
- Russian CPI
- Russian Inflation
- South African Inflation
- US CPI

Interest Rates:
- Chinese discount rate
- European 10-year govt. bond rate
- European marginal lending rate
- European repo
- South African 10-year govt. bond rate
- South African repo rate
- US 10-year govt. bond rate
- US Federal funds rate

Money Supply:
- European M3
- US M1
- US M2

Real Activity:
- Brazillian industrial production (IP)
- Canadadian IP
- European employment
- European IP
- European leading indivator (LEAD)
- French IP
- G7 employment
- G7 IP
- German IP
- Japanese IP
- Mexican IP
- South Korean IP
- United Kingdom IP
- United States (US) capacity utilisation
- US coincident indicator
- US employment
- US IP
- US lagging indicator
- US LEAD
- US manufacturing volume
- US retail trade

Spot Exchange Rates:
- European trade-weighted-index
- Euro / US dollar (USD)
- Brazillian real / USD
- Chinese Yuan / USD
- Indian rupee / USD
- USD / Russian ruble / USD
- South African rand / USD

Data source. Inet Bridge.

Figure 1. Shares of world market capitalisation for strategic market indices

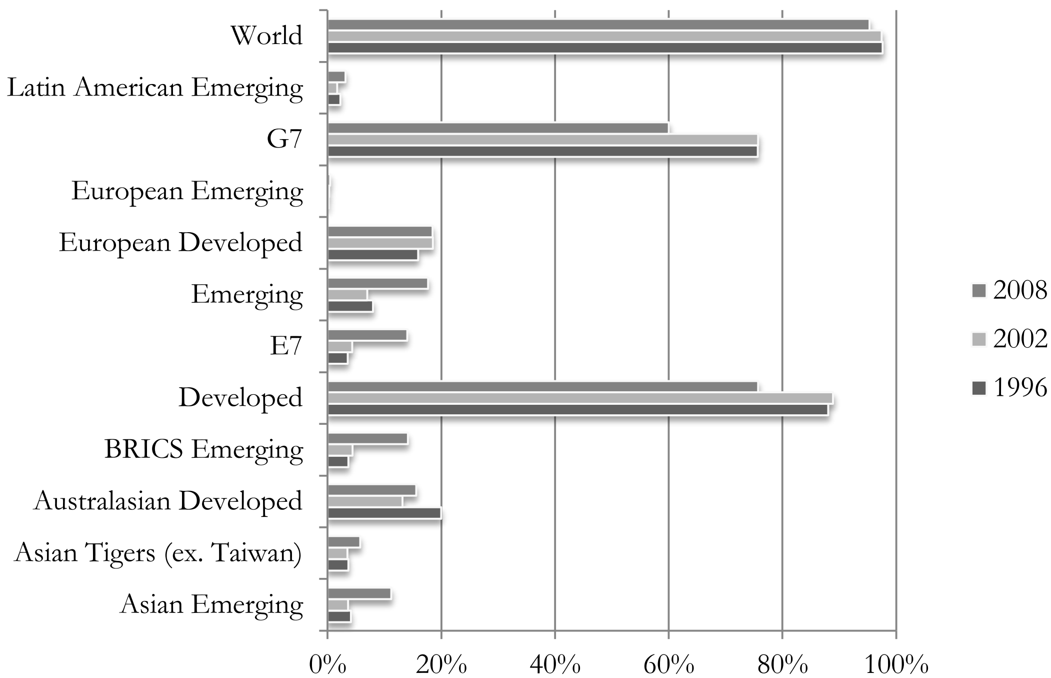

Figure 2. Volatility plots for strategic market indices

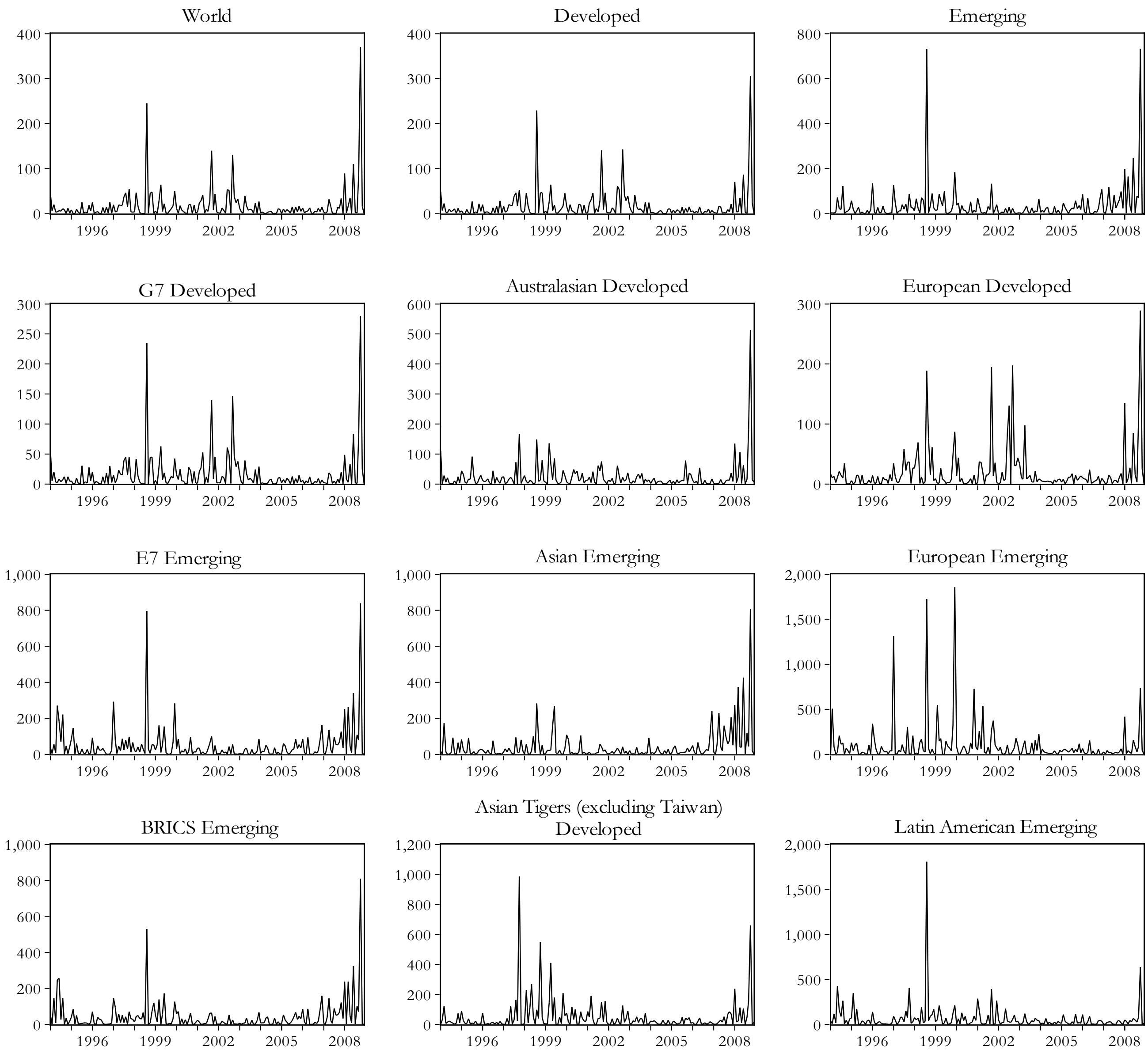

Figure 3. Volatility comovement in developed equity markets

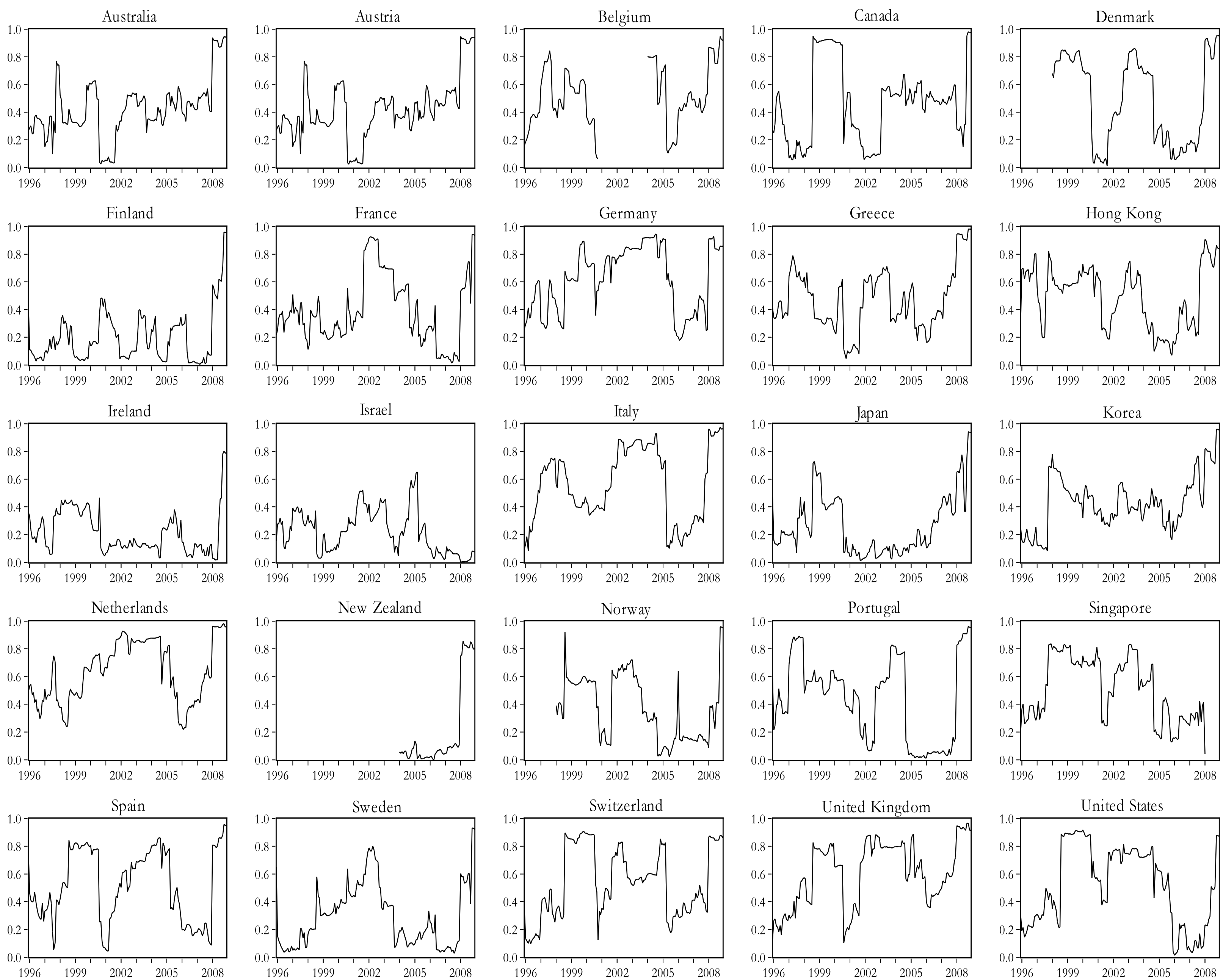

Figure 3 (continued). Volatility comovement in emerging equity markets

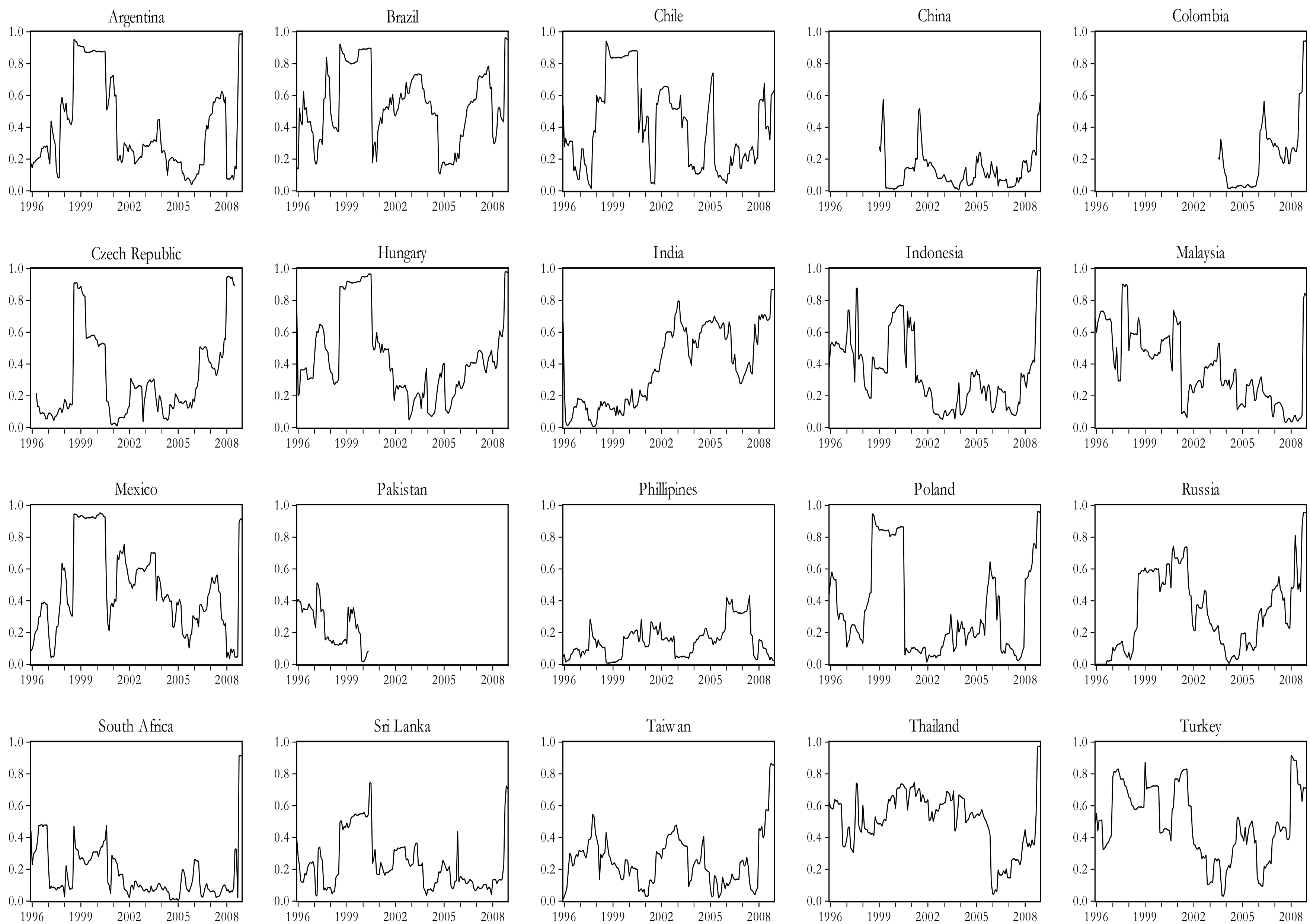

Figure 4. Volatility comovement for developed, emerging, and world indices

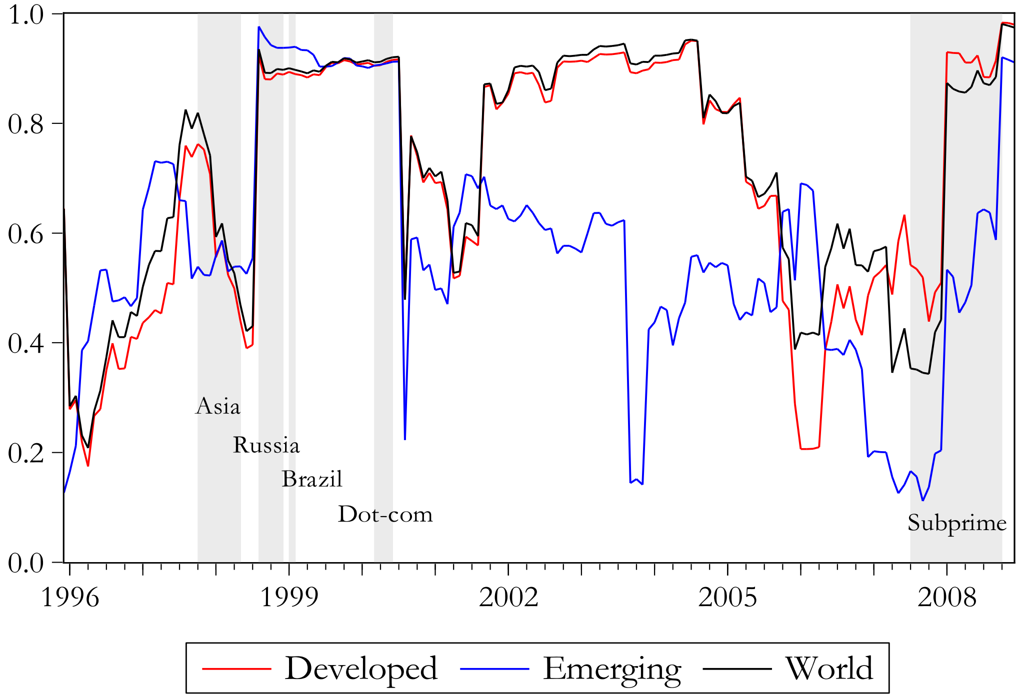

Figure B.1. Volatility comovement for regional strategic market groupings