

Volatility Dynamics of World Stock Returns

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Abstract:

In this paper, a dynamic factor model is designed to decompose stock return volatility into three orthogonal factors: world factor, region factor and local factor (idiosyncratic component), which are assumed to capture all variation of volatility in stock markets. Fourteen countries are included in the empirical study in order to cover both developed stock markets and emerging stock markets. Stock return volatility is measured as log variance of log return based on historical stock index price levels over period 1993 to 2009. All parameters and unobserved factors in the model are estimated by Markov Chain Monte Carlo methods. Empirical results show that common factors are able to account for more than 50% variation of volatility for most of countries. World factor seems to be significant for North America and Latin America, nevertheless region factor is more important for Europe and Asia. Spillover effects across stock markets and impact of financial integration on world stock market are also investigated.

Key words: volatility dynamics, stock return, stock volatility, dynamic factor model, spillover effects, financial globalization, MCMC

JEL classification codes: G10, G15

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1 Introduction

Understanding the transmission mechanisms linking international equity markets is important for not only policymakers but also fund managers in terms of risk diversification. Based on finance theory, it is believed that there are potential gains from international portfolio diversification of returns from investment in different national stock markets which are not perfectly correlated and the correlation structure is stable. This has led economists and finance specialists to investigate the contagion and interdependencies among international equity market.

Change in stock market volatility can have important effects on capital investments, consumption, and other business cycle variables. Some papers have related stock market volatility to the time-varying volatility of a variety of economic variables. Stock volatility reflects uncertainty about the future course of the economy, which shows up later in the realized growth rates of nonfinancial macroeconomic variables such as the money supply, consumption, and investment. In reverse, expectation of future macroeconomic behavior also contributes into change in stock volatility. Due to closer economic connection among countries all over the world, international stock market appears to be more contagious and interdependent.

Besides economic connections, it is widely accepted that some linkage channels are thought to arise from information shocks which result in interdependent equity markets moving in harmony with each other. The remarkable technological advances in the computer and communication industries have made it much easier for large numbers of people to learn about and react to information very quickly. They have also made it possible for financial markets to provide liquidity for investors around the world. As a

consequence, there are large incentives for investors to get and act on new information. Because new information spreads more quickly, the rate at which prices change in response to information has also accelerated. More recently, linkage originating from unanticipated shocks in a particular country or group of countries, which spread to international equity markets, has a large impact on international markets even where there are no strong economic linkages connecting the economies.

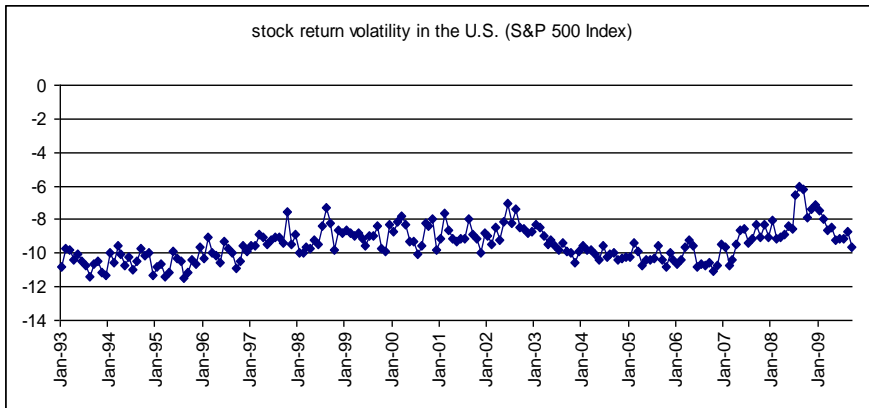
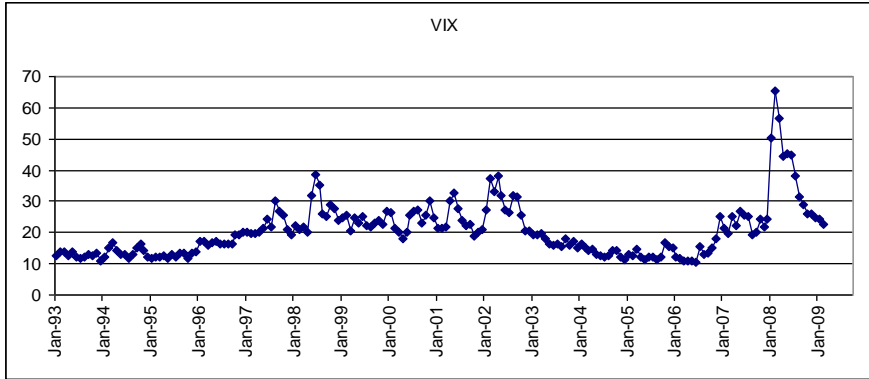
Previous empirical studies of the interrelationship of the major world stock indexes have not provided consistent results. King, Sentana and Wadhvani (1994) investigate the time-variation in the covariances between stock markets and assess the extent of capital market integration. They conclude that the global stock markets are not integrated and “unobservable” factors have historically been more important in explaining stock returns than the macroeconomic variables. Bekaert and Harvey (1997) examine 20 emerging stock markets volatility dynamics and Angela Ng (2000) writes a paper on volatility spillover effects from Japan and the US to the Pacific-Basin. Most research has concentrated on mature and developed stock markets. There are comparatively few studies on emerging stock markets. Bekaert, Hodrick and Zhang(2009) study the comovements between the returns for 23 countries during 1980-2005. A simple linear factor model is adopted to capture international asset return comovements. But they fail to find evidence of a trend in country return comovement and the globalization process has not yet led to large, permanent changes in the correlation structure across international stocks.

In this paper, we investigate dynamics of stock indexes return volatility to capture comovement across world stock market. A dynamic factor model is designed to

decompose stock return volatility into three orthogonal factors: world factor, region factor and local factor, which are assumed to capture all variation of volatility. Fourteen countries are included in our empirical study in order to cover both developed stock markets and emerging stock markets. These countries belong to four regions: North America, Europe, Asia and Latin America. The goal is to examine considerable volatility comovement across stock markets and explain how much of the comovement can be accounted for by world factor, region factor and local factor in each country. We also check spillover effects among national stock markets and impact of financial globalization on the world stock market.

When it comes to measuring volatility, VIX (Chicago Board Options Exchange Market Volatility Index) is a popular measure of the implied volatility of S&P 500 index options. It was first introduced by Robert E. Whaley (1993) and first-ever traded on March 26, 2004 on CBOE Future Exchange. The formula to calculate VIX uses a kernel-smoothed estimator that takes as inputs the current market prices for all out-of-the-money calls and puts for the front month and second month expirations. The goal is to estimate the implied volatility of the S&P 500 index over the next 30 days. Over its history, VIX has acted reliably as a fear gauge. High levels of VIX are coincident with high degrees of market turmoil, whether the turmoil is attributable to stock market decline, the threat of war, unexpected change in interest rates, or any number of other newsworthy events.

In this paper, we use log variance of log return based on historical stock indexes prices as the measure of stock return volatility. To compare with VIX, following plots are drawn over the same period 1993 to 2009. Correlation between VIX and our measure of volatility is around 0.66.



Methodology implemented in this paper is dynamic factor model. Stock return volatility is decomposed into three orthogonal factors: world factor, region factor and local factor (idiosyncratic component), which are designed to capture all fluctuation of volatility. Otrok and Whiteman (1998) design a Bayesian dynamic latent factor model to analyze business cycle. Posterior distributions of parameters and latent factors are analyzed by Markov Chain Monte Carlo methods. We apply the similar methodology to estimate unobserved factors and all parameters for our model.

We successfully capture common factors which are able to account for more than 50% variation of volatility for most of countries. World factor seems to be significant for North America and Latin America, nevertheless region factor is more important for Europe and Asia. It shows that when volatility becomes high, the world factor turns to be

more important in explaining interdependence and comovement among stock markets over the world. We modify the model by adjusting transition equations to investigate spillover effect of one country or a group of countries on other countries. But little evidence of significant spillover effects has been found. Furthermore, we analyze financial integration effect on world stock market by extending time horizon to 1967 and cutting down to 9 countries due to lack of data for some countries.

The remainder of this paper is organized as follows. Section 2 reviews literature on the relevant topics. Section 3 describes empirical framework which includes model setup, computation techniques, data structure details and classification of sample countries. Empirical results are demonstrated in section 4. Section 5 gives brief conclusion.

2 Literature review

There has been a large amount of literature on international transmission of stock returns and volatility. On the study of return and volatility spillover effect across international equity market, most of existing literature focuses on applying GARCH and SV models to capture feature of returns and volatilities.

One of the most important contributions toward a better understanding of international stock returns comovements is King, Sentana and Wadhvani (1994). The paper was published in *Econometrica*, named “Volatility and Links between National Stock Markets”. The paper investigates the time-variation in the covariances between stock markets and assesses the extent of capital market integration. They use data on sixteen national stock markets over the period 1970-1988 to estimate a multivariate factor model in which the time-varying volatility of returns is induced by changing volatility in the underlying factors. They assume that excess returns depends both on innovations in observable economic variables and on unobservable factors. They allow the conditional variances of the underlying factors to vary over time and parameterize this in terms of GARCH processes. Their theoretical model can be understood as a dynamic version of the Arbitrage Pricing Theory. They reach the conclusion that the global stock markets are not integrated. They are able to reject the null hypotheses that idiosyncratic risk is not priced, and that the “price of risk” associated with the relevant factors is the same across countries. In addition, “unobservable” factors have historically been more important in explaining stock returns than the “observable” factors.

Another interesting paper “Emerging equity market volatility”, written by Bekaert and Harvey (1997), provides an approach that allows the relative importance of world and

local information to change through time in both the expected returns and conditional variance processes. They apply GARCH model with world factor to 20 emerging markets over the period 1976-92. They claimed that decomposition of the sources of variation in volatility sheds light on how each market is affected by world capital markets and on how this impact varies over time. The evidence in this paper suggests that volatility decreases in most countries that experience liberalization. There is a sharp drop in volatility in five countries in their 20 emerging markets sample. Even after controlling for all of the potential influences on the time-series and cross-section of volatility, they find that capital market liberalizations significantly decrease volatility in emerging markets.

Angela Ng (2000) wrote a paper on volatility spillover effects from Japan and the US to the Pacific-Basin. The author constructs a volatility spillover model which allows the unexpected return of any particular Pacific-Basin market be driven by a local idiosyncratic shock, a regional shock from Japan and a global shock from the US. Particular interest of this paper is the impact of capital market liberalization on volatility spillovers. The tests in this study are based on the ARCH family of models. The major findings in this paper are threefold. First, both regional and world factors are important for market volatility in the Pacific-Basin region, although the world market influence tends to be greater. Second, the relative importance of the regional and world market factors is influenced by important liberalization events. Third, the proportions of the Pacific-Basin market volatility captured by the regional and world factors are generally small.

Francis X. Diebold and Kamil Yilmaz (2009) investigate equity market spillovers in the Americas. Five equity markets in the Americas are chosen: Argentina, Brazil, Chile,

Mexico and the U.S. They explore study in both non-crisis and crisis episodes, 1992-2008, including spillover cycles and bursts. They claim that they find striking evidence of divergent behavior in the dynamic of return spillovers and volatility spillovers: return spillover effects display gradually evolving cycles but no burst, whereas volatility spillovers display clear bursts that correspond closely to economic events.

Most of literature discussed above only focuses on volatility dynamics and transmission in one region. A more recent paper published in *The Journal of Finance* was titled “International Stock Return Comovements”, written by Bekaert, Hodrick and Zhang. They study the comovements between the returns on country-industry portfolios and country-style portfolios for 23 countries, 26 industries, and nine styles during 1980-2005. A simple linear factor model is adopted to capture international asset return comovements. The factor structure and the risk loadings on the factors are allowed to change every half year, so the model is claimed to be general enough to capture time-varying market integration and to allow for risk sources other than the market. Little evidence of a trend in country return correlations is found, except within Europe. Second, the globalization process has not yet led to large, permanent changes in the correlation structure across international stocks.

Corradi, Distaso and Fernandes (2009) propose a framework to gauge the degree of volatility transmission among international stock markets by deriving tests for conditional independence among daily volatility measures. They investigate volatility spillovers between the stock markets in China, Japan, and the U.S. from 2000 to 2005. The testing procedure involves two steps. In the first stage, they estimate the integrated variance using return data by means of realized measures so as to avoid misspecification risks. In

the second step, they then test for conditional independence between the resulting realized measures. The empirical study evinces that volatility transmission between Japan and US runs in both directions, whereas they find stronger evidence of spillovers running from China to either Japan or US than vice-versa.

Other than ARCH family of models and SV models, we investigate dynamic factor model to see if it's a good fit for decomposition of volatility. Dynamic factor model can cope with many variables without running into scarce degrees of freedom problems. In addition, idiosyncratic movements which possibly include measurement error and local shocks can be eliminated. Dynamic factor model has been successfully used in research on international business cycle with large dataset.

One of the most important contributions into the study on international business cycle by using dynamic factor model is Christopher Otrok and Charles H. Whiteman (1993). This paper designs and implements a Bayesian dynamic latent factor model for a vector of data describing economy. Posterior distributions of parameters and the latent factor are analyzed by Markov Chain Monte Carlo methods, and coincident and leading indicators are computed by using posterior mean values of current and predictive distributions for the latent factor. They provide feasible computation techniques for our empirical study to handle large time series dataset in application of dynamic factor model.

In 2008, Marco Del Negro, Christopher Otrok develop dynamic factor model to measure changes in international business cycle by making parameters time-varying. This paper develops and estimates a dynamic factor model with time-varying factor loadings and stochastic volatility in the innovations to both the common factors and idiosyncratic components. The model is used as measurement tool to characterize the evolution of

international business cycle since 1970. Their model, which explicitly allows for changes in factor loadings, is a natural framework to analyze recent policy debates on the supposed decoupling of emerging markets economies. They also claim that the model can be applied to the forecasting literature and literature for both pricing asset and for portfolio allocation.

3 Empirical Framework

3.1 Model setup

We apply dynamic multi-factor model to decompose volatility of stock returns in 14 countries into independent factors. We assume that there are K dynamic, unobserved factors which are well suited to capture variation of returns in world stock market. The dependent variable is volatility of stock indices returns in N countries. For N observables at time t :

$$y_t = A + \Lambda f_t + u_t$$

$\begin{matrix} N \times 1 & (N \times 1) & (N \times K) & (K \times 1) & (N \times 1) \end{matrix}$

Subject to:

$$f_t = \Phi_1 f_{t-1} + \Phi_2 f_{t-2} + \dots + \Phi_q f_{t-q} + \varepsilon_t$$

$\begin{matrix} (K \times 1) & (K \times K) & (K \times 1) & (K \times K) & (K \times 1) & \dots & (K \times K) & (K \times 1) & (K \times 1) \end{matrix}$

$$u_t = \Psi_1 u_{t-1} + \Psi_2 u_{t-2} + \dots + \Psi_p u_{t-p} + e_t$$

$\begin{matrix} (N \times 1) & (N \times N) & (N \times 1) & (N \times N) & (N \times 1) & \dots & (N \times N) & (N \times 1) & (N \times 1) \end{matrix}$

$$\begin{bmatrix} e_t \\ \varepsilon_t \end{bmatrix} : \left(0, \begin{bmatrix} \Sigma_{ee} & 0 \\ 0 & \Sigma_{\varepsilon\varepsilon} \end{bmatrix} \right)$$

$\begin{matrix} (N \times 1) & (K \times 1) \end{matrix}$

Where, y_t represents volatility of stock indices in N countries discussed above. f_t indicates unobserved factors which are suited to capture the variation of volatility in world stock market. Λ stands for the factor loading matrix. u_t is idiosyncratic components (or error term) for all observables. Factors and idiosyncratic components follow autoregressive processes of order p and q . Additionally, Ψ, Φ are both diagonal

which indicates all factors and idiosyncratic components only depend on its own lagged value. A is intercept matrix.

For instance, there are two unobserved factors: world factor and regional factor and all 14 countries belong to two regions, additionally first 4 countries belong to the first regional factor and last 10 countries belong to the second regional factor, then $K=3$ and

$$\Lambda_{(14 \times 3)} = \begin{bmatrix} \cdot & \lambda^d_{(4 \times 1)} & \cdot & \mathbf{0}_{(4 \times 1)} \\ \lambda^w_{(14 \times 1)} & \cdot & \cdot & \cdot \\ \cdot & \mathbf{0}_{(10 \times 1)} & \cdot & \lambda^e_{(10 \times 1)} \end{bmatrix}$$

3.2 Methodology

Otrok and Whiteman(1998) used a method based on development in the Bayesian literature on missing data problems. Simple structure can be used to determine the conditional (normal) distribution of the factors given the data and the parameters of the model. Then it is straightforward to generate random samples from this conditional distribution, and such samples can be employed as stand-ins for the unobserved factors. Because the full set of conditional distributions is known-parameters given data and factors, factors given data and parameters-it is possible to generate random samples from the unknown parameters and the unobserved factor using a Markov-Chain Monte Carlo (MCMC) procedure. This sequential sampling of the full set of conditional distribution is known as "Gibbs sampling" (Siddhartha Chib and Edward Greenberg, 1996; John Geweke, 1996, 1997).

The practical benefit of this procedure is that it can easily be applied to a large cross section of countries. Classical maximum likelihood methods generally do not so decompose, and are difficult to apply to a problem with large dimension.

However, the difficulty with sampling from the conditional distribution of the factor arises because of a long time series. In our particular case, given monthly volatility in 14 countries from 1993 to 2009, it is difficult to handle the computation burden. Therefore, we turned to use Kalman Filter to estimate unobserved factors and keep using Gibbs-sampling for estimating parameters.

For generating Ψ for each country i , we know that

$$y_t = \Lambda f_t + u_t$$

$$u_{it} = \psi_{i1} u_{i,t-1} + \psi_{i2} u_{i,t-2} + e_{it}$$

So, in matrix notation, we can get

$$\tilde{u}_{iT} = U_i \tilde{\psi}_i + \tilde{e}_{iT}, \quad \tilde{e}_{iT} \square N(0, \sigma_i^2 I_T)$$

Prior distribution is assumed to be $\tilde{\psi}_i \square N(a_i, b_i)$.

Posterior distribution can be calculated as

$$\tilde{\psi}_i | \Lambda_i, \sigma_i^2, f_i, y_i \square N(a_i^*, b_i^*)$$

where

$$a_i^* = (b_i^{-1} + \sigma_i^{-2} U_i' U_i)^{-1} (b_i^{-1} a_i + \sigma_i^{-2} U_i' \tilde{u}_{iT})$$

$$b_i^* = (b_i^{-1} + \sigma_i^{-2} U_i' U_i)^{-1}$$

For generating Φ , we have

$$f_t = \Phi_1 f_{t-1} + \Phi_2 f_{t-2} + \varepsilon_t$$

Prior distribution: $\tilde{\phi}_i \square N(c_i, d_i)$

Posterior distribution:

$$\tilde{\phi}_i | f_i, y_i \square N(c_i^*, d_i^*) \quad i=1,2,3$$

where

$$c_i^* = (d_i^{-1} + F_i' F_i)^{-1} (d_i^{-1} c_i + F_i' f_{iT})$$

$$d_i^* = (d_i^{-1} + F_i' F_i)^{-1}$$

For generating σ_i^2 , we know from above

$$\tilde{u}_{iT} = U_i \tilde{\psi}_i + \tilde{e}_{iT}, \quad \tilde{e}_{iT} \square N(0, \sigma_i^2 I_T)$$

Prior distribution is $1/\sigma_i^2 \square \Gamma(\frac{v_i}{2}, \frac{w_i}{2})$

Posterior distribution is

$$1/\sigma_i^2 | \tilde{\psi}_i, \Lambda_i, f_i, y_i \square \Gamma\left(\frac{v_i + (T-2)}{2}, \frac{w_i + (\tilde{u}_{iT} - U_i \tilde{\psi}_i)'(\tilde{u}_{iT} - U_i \tilde{\psi}_i)}{2}\right)$$

For generating Λ , we need to do some adjustment. Substitute $y_t = A + \Lambda f_t + u_t$

into $u_t = \Psi_1 u_{t-1} + \Psi_2 u_{t-2} + e_t$. Take $i=1$ for example,

$$y_{1t} = \lambda_{11} f_t^w + \lambda_{12} f_t^d + u_{1t}$$

$$u_{1t} = \psi_{11} u_{1,t-1} + \psi_{12} u_{1,t-2} + e_{1t}$$

Then, we can get

$$y_{1t} - \lambda_{11} f_t^w + \lambda_{12} f_t^d = \psi_{11} (y_{1,t-1} - \lambda_{11} f_{t-1}^w + \lambda_{12} f_{t-1}^d) + \psi_{12} (y_{1,t-2} - \lambda_{11} f_{t-2}^w + \lambda_{12} f_{t-2}^d) + e_{1t}$$

$$y_{1t} - \psi_{11} y_{1,t-1} - \psi_{12} y_{1,t-2} = \lambda_{11} (f_t^w - \psi_{11} f_{t-1}^w - \psi_{12} f_{t-2}^w) + \lambda_{12} (f_t^d - \psi_{11} f_{t-1}^d - \psi_{12} f_{t-2}^d) + e_{1t}$$

$$y_{1t}^* = \lambda_{11} f_{1t}^{w*} + \lambda_{12} f_{1t}^{d*} + e_{1t}$$

By using the same method of generating Φ , we can get the sampling for Λ .

For estimating unobserved factors, we rewrote the model into state space pattern and Kalman Filter can also be applied to achieve the estimate of factors.

It's important to monitor the convergence of the computation. We did so in a number of ways. First, we restarted the computation from a number of different initial values, and the procedure always converged to the same results. Second, we discarded first 5,000 drawings and took the next 15,000 drawings. We tried more drawings and the results were the same.

3.3 Data

The raw data employed are daily stock indices price in terms of US dollars from Datastream. The indices used are from 14 countries over period 1993-2009: U.S. (S&P 500), Canada (S&P/TSX), UK(FTSE ALL SHARE), Germany (DAX 30 PERFORMANCE), France (S&P FRANCE BMI), Italy (S&P ITALY BMI), HongKong (HANG SENG), South Korea (KOREA SE COMPOSITE), Taiwan (TAIWAN SE WEIGHTED), Singapore (FTSE ST ALL SHARE L), Argentina (ARGENTINA MERVAL), Brazil (BRAZIL BOVESPA), Chile (CHILE GENERAL (IGPA)) and Mexico (MEXICO IPC (BOLSA)). Monthly log returns are used to calculate volatility to avoid the problems of nonsynchronous trading and the day-of-the-week effects. Volatility is calculated as monthly log variance of daily log return.

3.4 Classification

We explore 14 countries in the world stock market. All 14 countries belong to four regions. Hence, there are one world factor and four regional factors obtained in the model.

The following is classification of countries:

Table 1: Classification of countries

World	Region	Country
Common	North America	
		US
		Canada
	Europe	
		UK
		Germany
		France
		Italy
	Asia	
		Hong Kong
		South Korea
		Taiwan
		Singapore
	Latin America	
		Argentina
		Brazil
		Chile
		Mexico

4 Empirical Results

4.1 Model estimation

We first follow existing work by decomposing stock returns into unobserved factors. The result is consistent with other literature that proportions of stock returns comovement captured by world and regional factor are very small. The study on stock returns dynamics fail to explain comovement and contagion across world stock markets. Since stock returns are relatively volatile, estimated unobserved factors in return model turn out to be also volatile. There does not exist clear trend of movement in the world factor and region factors. Figure 1 is the world factor obtained in return model.

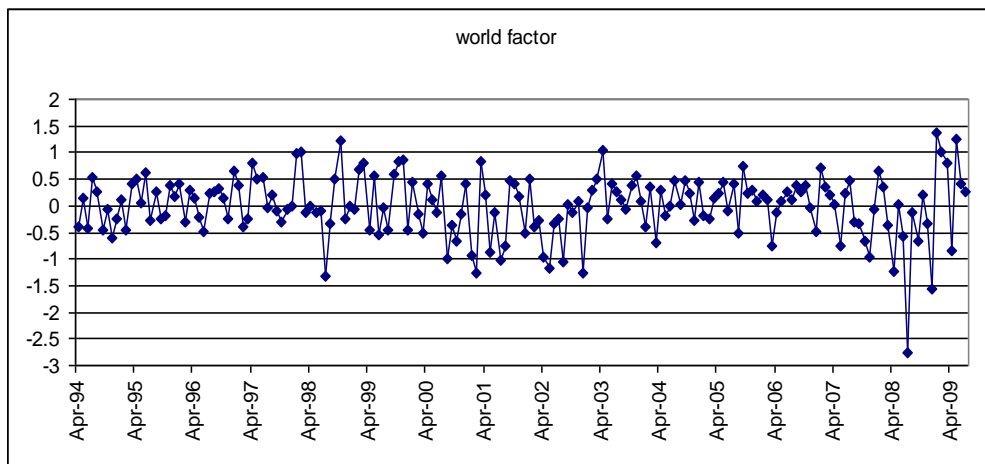


Figure 1. World factor for stock indices returns

Other than stock returns, main interest of this paper is to decompose volatility based on historical data into unobserved independent factors. Volatility is relatively persistent and widely believed to be predictive. Volatility evolves over time in a continuous manner and it does not diverge to infinity. Statistically speaking, volatility is often stationary. But

the topic on performance of volatility forecasting models still remains inconclusive. We only focus on volatility dynamic based on historical stock indices data to investigate if common factors are able to capture large proportion of volatilities in the world stock market. Figure 2 describes world factor obtained in volatility model.

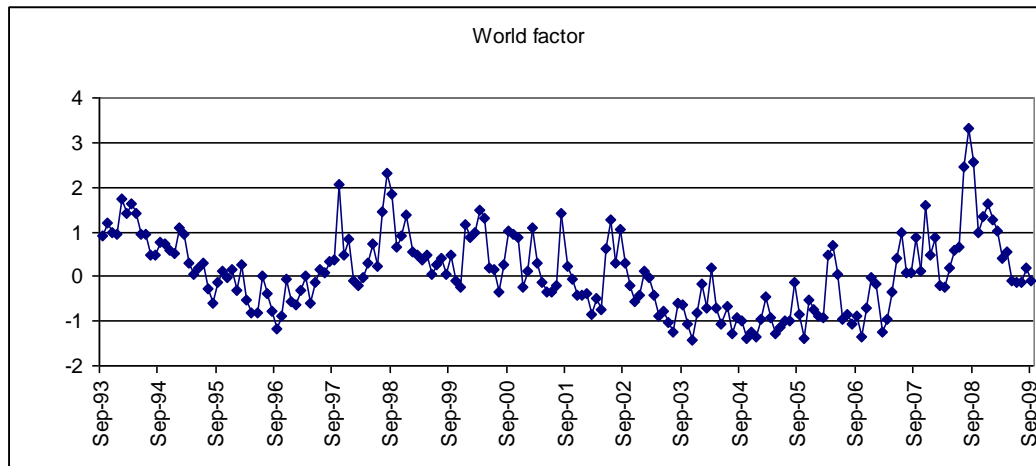


Figure 2. World factor for stock indices volatilities

Estimate of world factor is a good fit for worldwide variation in world stock market. It captures extreme cases happened in history, like Asia crisis in 1997-98 and financial crisis around 2008. Unlike returns model, world factor obtained from stock volatility is able to explain a big proportion of volatility comovement in world stock market.

4.2 Conditional variance decomposition

Since dynamic factor model is designed to decompose observed variable into several orthogonal factors, variance of the observed variable is the sum of variance of all factors including error term (or idiosyncratic component). The ratio of variance of each factor to

variance of the observed variable can be explained as shares by which such factor is attributable to variation of the observed variable.

On research of international business cycle, variance decomposition is explored to measure the relative contributions of the world, regional factors to variation of uncertainty in each country by estimating the share of the variance to each factor. With the assumption of orthogonal factors, the fraction of variation due to the factor would be:

$$\frac{\lambda_{ij}^2 \text{var}(f_j)}{\text{var}(y_i)} \quad \text{where } \lambda \text{ is factor loading, } f \text{ is factor and } y \text{ is observables.}$$

$i=1,2,\dots,N$, denotes countries. $j=1$, represents world or regional factors. For instance, λ_{11} means world factor loading for country 1. With this way to calculate variance decomposition, it is only able to provide constant share of the variance for each factor.

In this paper, we implement conditional variance decomposition in order to achieve time-varying variance share. Variance of factors is replaced by conditional variance and the rest of formula remains the same.

In the U.S. stock market, world factor is able to account for roughly 30% of variation and the rest of proportion is explained by idiosyncratic component. Figure 3 describes shares of variation explained by each factor over time in the U.S. stock market. When stock market is experiencing high volatility, like financial crisis, world factor becomes more important in explaining comovement. With the effect of Asia crisis happened around in 2008 and global financial crisis occurred in 2008, the world factor gets to account for about 40% of variation of volatility in the U.S. stock market.

Region factor in the U.S. and Canada fail to capture comovement of stock volatility. The reasonable interpretation is that the U.S. and Canada stock markets have high

correlation which contributes to the world factor. In other words, world factor gets to explain comovement between U.S. and Canada stock markets and therefore region factor can not explain much in contagion between those two countries.

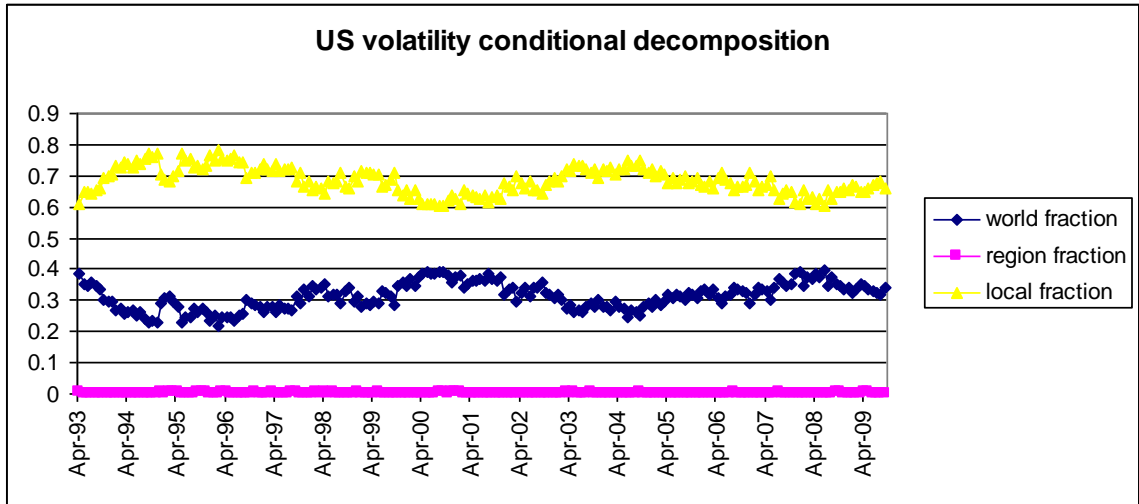


Figure 3. Conditional variance decomposition for the U.S.

In the European stock market, shares of variation accounted by each factor are quite different than in the U.S. market. Figure 4. gives results on conditional variance decomposition in European stock market.

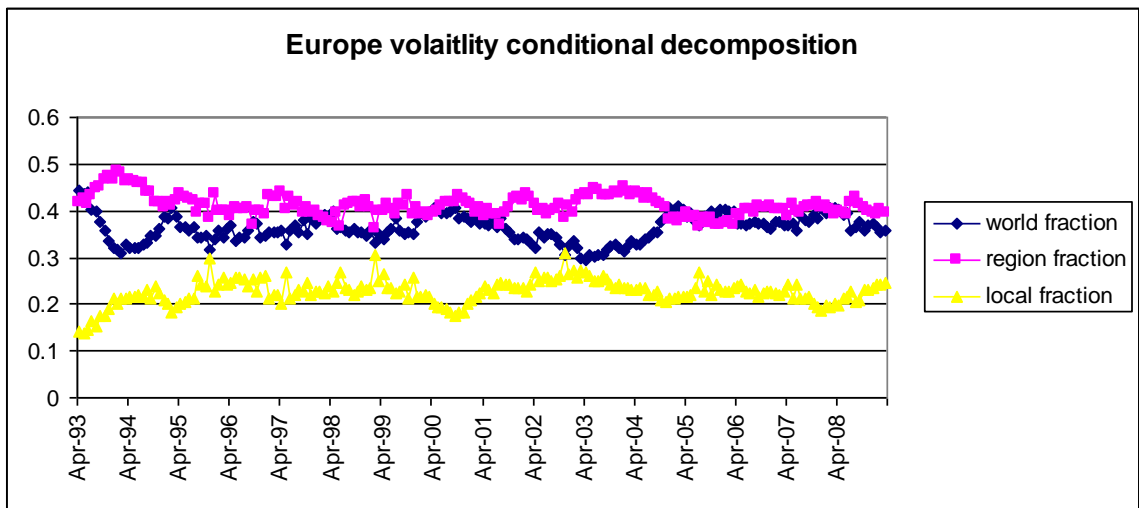


Figure 4. Conditional variance decomposition for Europe.

In Europe, world factor is still able to accounts for approximately 40% of variation of stock volatility. Unlike the U.S. stock market, regional factor plays an important role to explain variation of volatility in European market. It means stock markets in Europe are highly correlated with each other and such regional correlation does not spread out to outside markets as a worldwide common factor. The main reasons of high regional correlation in Europe are threefold. First, the introduction of the euro improved transparency, standardized the pricing in financial markets and reduced investors' transaction and information costs. Secondly, with no change in domestic law, it nullified various legal restrictions within the EU on the foreign currency composition of assets held by institutional investors, like pension funds. Third, the introduction of a single currency eliminated intra-European currency risk and, to the extent that currency risk was priced, reduced the overall exchange rate exposure of European stocks.

Figure 5. shows conditional variance decomposition for Asian stock market volatility.

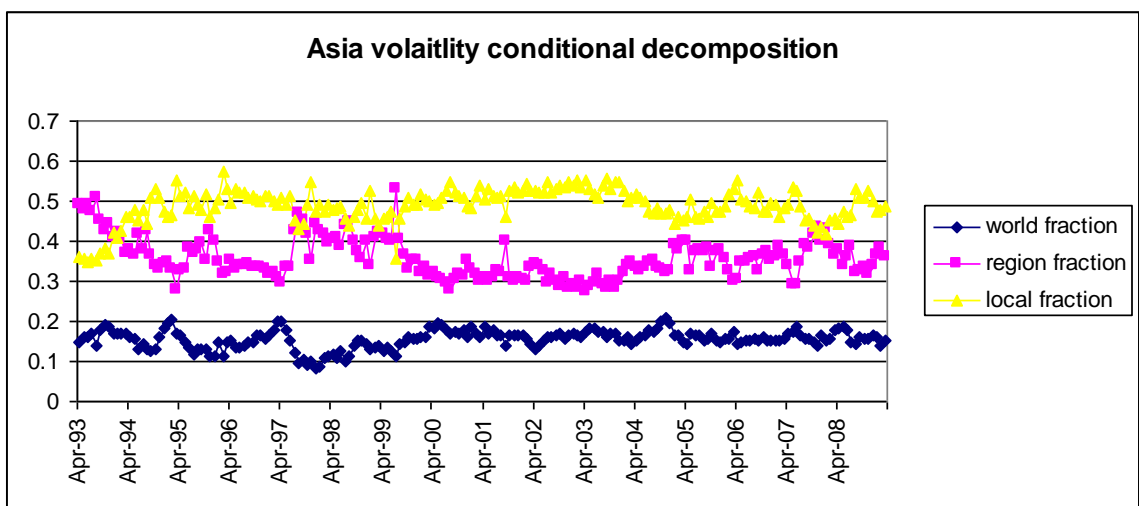


Figure 5. Conditional variance decomposition for Asia.

Compared to world factor, comovement in Asian stock market is driven more by regional factor. Some studies on this issue have been done to achieve the conclusion that Asian stock market fluctuations are mainly due to intra-regional contagion effects. It is partly because of the growing share of intra-regional trade and investment in this Asian belt in recent years. Moreover, greater linkages among these Asian markets are also partly accounted for by the more common monetary policy followed, particularly since the crash occurred in 1987. All these countries in Asian region have the U.S. as one of their major trading partners and most of their currencies are tied to the US dollar. Since the exchange rate pegging became much stronger after the crash, the standard deviation of the exchange rate among Asian countries' currencies fell by a substantial amount.

In Latin American stock market, results are consistent with existing studies that major proportion of stock index variance is contributed by foreign stock markets. In figure 6, it demonstrates that world factor contributes roughly 35% of variation and regional factor only explains 20%.

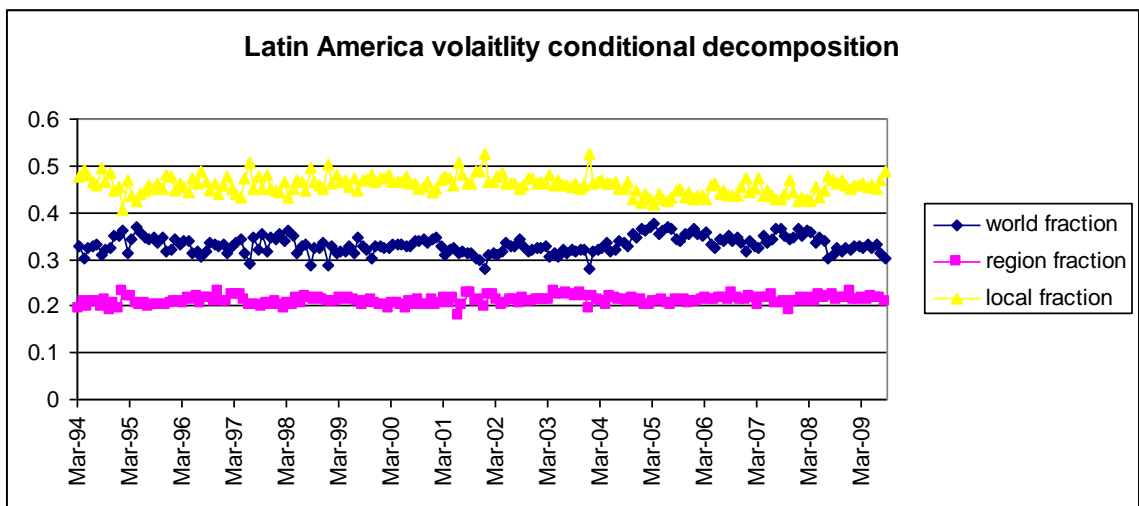


Figure 6. Conditional variance decomposition for Latin America.

To sum up, world factor plays an important role to explain variation of volatility in world stock markets. For developed stock markets, like North American and European stock markets, world factor accounts for around 40% of variation. When the stock markets are experiencing high volatility, world factor becomes more important in explaining volatility fluctuation. For region factor, it turns out to be relatively important for European and Asian stock markets due to intra-regional trade and investment effects. Latin American stock markets rely more on foreign developed markets than intra-regional markets.

4.3 Spill-over effect analysis

4.3.1 U.S. dominant model

In the section 4.2, it shows that world factor plays an important role in each country's stock market. A natural question to be asked is what becomes the driving force of world factor. The purpose of this section is to investigate if the world factor is dominated by the U.S. stock index volatility.

The model is modified as follows:

$$y_t = A + \Lambda f_t + u_t$$

$\begin{matrix} N \times 1 & (N \times 1) & (N \times K) & (K \times 1) & (N \times 1) \end{matrix}$

Subject to:

$$f_t^w = \phi_1 f_{t-1}^w + \phi_2 f_{t-2}^w + \phi_3 f_{t-1}^{us} + \phi_4 f_{t-2}^{us} + \varepsilon_t^w$$

$$f_t = \Phi_1 f_{t-1} + \Phi_2 f_{t-2} + \dots + \Phi_q f_{t-q} + \varepsilon_t$$

$\begin{matrix} (K \times 1) & (K \times K) & (K \times 1) & (K \times K) & (K \times 1) & \dots & (K \times K) & (K \times 1) & (K \times 1) \end{matrix}$

$$u_t = \Psi_1 u_{t-1} + \Psi_2 u_{t-2} + \dots + \Psi_p u_{t-p} + e_t$$

$\begin{matrix} (N \times 1) & (N \times N) & (N \times 1) & (N \times N) & (N \times 1) & \dots & (N \times N) & (N \times 1) & (N \times 1) \end{matrix}$

Note that all parts of the model remain the same except for autoregressive process of world factor, which now not only depends on its own lagged value but also U.S. volatility (or called US factor).

Results show that coefficient of US factor, ϕ_3, ϕ_4 are both statistically insignificant at 5% significance level with value of 0.0939 and 0.0039. Little evidence is found that the U.S. dominates world stock market over period 1993-2009.

4.3.2 U.S. influence developing stock markets model

Since we fail to prove that the U.S. dominates world stock market by influencing world factor, some interest is then focused on impact of U.S. volatility on Asian and Latin American regional factors.

For instance, the model can be modified to structure U.S.-influence-Asian as follows:

$$f_t^A = \phi_1 f_{t-1}^A + \phi_2 f_{t-2}^A + \phi_3 f_{t-1}^{US} + \phi_4 f_{t-2}^{US} + \varepsilon_t^A$$

Other parts of baseline model keep the same.

In this exercise, we still fail to capture statistically significant coefficients of the US factor on both modified models for Asian and Latin American markets.

4.3.3 Asia influences Latin America and Latin America influences Asia model

In order to test that if there exists significant linkage between developing stock markets, we reset the model to satisfy this assumption:

$$f_t^A = \phi_{A1}f_{t-1}^A + \phi_{A2}f_{t-2}^A + \phi_{A3}f_{t-1}^{LA} + \phi_{A4}f_{t-2}^{LA} + \varepsilon_t^A$$

$$f_t^{LA} = \phi_{L1}f_{t-1}^{LA} + \phi_{L2}f_{t-2}^{LA} + \phi_{L3}f_{t-1}^A + \phi_{L4}f_{t-2}^A + \varepsilon_t^{LA}$$

Other parts of baseline model remain unchanged.

We are still not able to obtain significant coefficients of LA factor and Asian factor.

Spillover effect investigation remains lack of evidence for conclusion.

4.4 Financial globalization effect on world stock market

Financial globalization is widely recognized to take place since middle of 1980's. In order to address the issue on impact of financial globalization on world stock market, we need to extend time series back to 1970's. Due to lack of data from Datastream for all 14 countries back to 1970's, we cut sample countries down to 9 countries. Reclassification of countries is adjusted as follows:

World	Region	Country	
Common	North America	US	
		Canada	
	Europe	UK	
		Germany	
		Austria	
		Belgium	
		Asia	Hong Kong
			South Korea
			Taiwan

Table 2: Classification of 9 countries

We estimate the baseline model for two time periods: 1976-85 and 1986-2009. Table 3 gives the variance decomposition results for each country during different time periods.

	1976-1985 Share contributed by word factor	1976-1985 Share contributed by region factor	1986-2009 Share contributed by word factor	1986-2009 Share contributed by region factor
US	64.54%	0.27%	25.46%	5.96%
Canada	69.36%	6.02%	32.89%	8.27%
UK	6.70%	1.51%	75.29%	3.77%
Germany	10.55%	46.36%	42.15%	24.83%
Austria	1.95%	76.76%	5.88%	2.81%
Belgium	8.69%	13.68%	42.61%	15.55%
Hong Kong	38.84%	4.43%	23.72%	18.25%
South Korea	5.72%	0.92%	6.91%	36.27%
Taiwan	1.43%	1.16%	4.59%	34.78%

Table 3: Variance decomposition for 9 countries

In North America, averagely around 65% of variation of stock volatility used to be explained by the world factor before financial globalization. It demonstrates that the U.S. and Canada acted as a driving force of fluctuation in world stock market in pre-1985. After financial integration took place since 1986, world factor becomes much less important in accounting for stock variation in North American market. In other words, dominance of the U.S. is getting weaker as financial integration becomes stronger. Regional factor turns to contribute very small proportion of stock variation in North American market. The U.S. and Canada's stock markets have been highly correlated, but

such high correlation is absorbed by world common factor which led region factor to capture no more than 6% of stock variation on average in North American stock market.

In Europe, region factor used to account for a large proportion of variation of stock volatility except for UK before financial globalization. It was due to standardized equity pricing system and similar domestic laws on equity investments within European stock markets. Since 1986 when financial globalization was believed to take effect, European stock markets start acting like a main force to influence world stock market. World factor becomes capable of explaining 42% of variation of stock volatility in Germany and Belgium and 75% in UK. The importance of world factor for European stock market has exceeded that for North America after financial integration. Regional factor turns to be less important when world factor becomes more important accounting for variation in European stock market. The reason we believe is that partial regional comovement within European stock market is explained by world factor after financial integration.

For Asian stock market, region factor is able to account for much bigger proportion of stock variation after 1986. Since the crash occurred in 1987, Asian stock markets follow more common monetary policy and intra-regional trade and investment in recent years are growing fast. World factor appears to be losing importance in Asian markets, especially in Hong Kong since international financial market becomes more integrated. In pre-1985, 39% of stock variation in Hong Kong stock market was explained by world factor, whereas it dropped to 24% after 1986. It means that Asian markets rely less on mature and developed stock markets over time and it starts to become an important influence in world stock market.

5 Conclusion

Study on comovement and contagion in world stock markets has been a popular topic for years. Conclusions reached in existing literature are threefold. First, macroeconomic variables fail to explain much comovement in international stock markets whereas unobserved common factors turn to be important in accounting for stock variation. Second, stock returns decomposition fails to capture large proportion of variation in world stock market. Lastly, little evidence of significant impact of financial globalization on stock markets has been found.

Based on existing literature, the purpose of our research is to capture unobserved common factors which are able to explain large proportion of variation in world stock market and investigate if there exists significant spillovers across national stock markets. The other interest of our paper is to explore the impact of financial globalization on world stock market.

In this paper, we investigate dynamics of stock indexes return volatility to capture comovement across world stock market. A dynamic factor model is designed to decompose stock return volatility into three orthogonal factors: world factor, region factor and local factor, which are assumed to capture all variation of volatility. Fourteen countries are included in our empirical study in order to cover both developed stock markets and emerging stock markets.

We successfully capture common factors which are able to account for more than 50% variation of volatility for most of countries. World factor seems to be significant for North America and Latin America, nevertheless region factor is more important for Europe and Asia. It shows that when volatility becomes high, the world factor turns to be

more important in explaining interdependence and comovement among stock markets over the world. We modify the model by adjusting transition equations to investigate spillover effect of one country or a group of countries on other countries. But little evidence of significant spillover effects has been found.

Furthermore, we analyze impact of financial integration on world stock market by extending time horizon to 1967 and cutting down to 9 countries due to lack of data for some countries. The results show that the dominance of the U.S. stock market in world stock market has been weaker as international financial market is getting more integrated. Emerging stock markets becomes more independent of developed and mature stock markets after financial globalization. Region factor started playing an important role in Asian stock markets due to fast growing intra-regional trade and investment.

For future research, extending time horizon and adjusting sample countries to investigate spillovers across national stock markets could be a good direction to go in order to capture significant spillover effects before and after financial globalization. Another interesting extension is to decompose stock return and volatility together into several orthogonal factors, in which way relation between stock return and volatility can be investigated. We can address the problem that how much variation of stock return is determined by volatility common factors, which can be described as price of risk.

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