International Equity Correlations, Integration and Contagion

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Abstract

This paper attempts to provide a comprehensive depiction of the dynamics of the correlation structure of international equity returns. In this pursuit, we employ a powerful yet parsimonious dynamic latent factor model with time-varying loadings and stochastic volatility. Such a specification allows us to account for the complex dynamics between international equity returns but is flexible enough to be estimated with a sample of daily data spanning over 20 years across a geographically diverse set of 15 major international markets. We first document that average global and regional correlations have risen steadily over the past two decades. Our main findings are that international equity returns have become increasingly exposed to common sources of variation, and that the entire low-frequency change in equity correlations is due to changing risk exposures rather than changing systematic risk. We also demonstrate significant financial contagion effects during the 1994 Mexican and 1997 Asian crises.

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The empirical characterization of time variation in international stock market correlations remains a largely unresolved issue in finance. While there exists a large literature studying the co-movements between stock returns, little agreement has been reached with regard to their basic time series properties. This paper attempts to provide a comprehensive depiction of the dynamics of the correlation structure of international equity returns. In doing so, we develop a basis for an inquiry into the issues of financial integration, interdependence and contagion.

In an increasingly integrated modern financial system, a proper understanding of the covariance structure of international equity returns is important for a number of reasons. First, international investors use the covariance between assets to guide efficient portfolio allocation and hedging decisions. A consequence of this is that the covariance structure sheds light on capital flows and investment and consumption decisions. In addition, an understanding of the covariance allows for analysis into the nature and extent of financial market integration. Finally, there are important policy implications related to the issue of financial contagion that the covariance structure can help uncover.

In exploring the linkages between international equity markets, we build upon an early literature that demonstrated the advantages of international portfolio diversification by documenting the existence of relatively low correlations between U.S. equities and many international markets (see, e.g., Grubel, 1968). According to more recent work by Gagnon and Karolyi (2006), these low correlations encouraged institutional investors to allocate increasing amounts of capital into foreign equity markets. Between 1977 and 2008, gross U.S. purchases of foreign stocks have grown from about $200 million to more than $450 billion. Also, net capital flows from the U.S. to foreign markets have increased dramatically from an average of about $230 million during the 1980s to approximately $5 billion during the 2000s (Treasury International Capital System, 2009). While real economic linkages and trade flows have also increased dramatically during this same time (see, e.g., Lane and Milesi-Ferretti, 2007), it is clear that these increasing capital flows are a primary source of growth in international financial linkages between the U.S. and the world.

An important consequence of these stronger economic and financial linkages is that financial markets are more interdependent and have the tendency to move together. As argued in Ripley (1973), covariation in international equity markets may reflect similarities or structural relationships between the markets, or a common covariance on another economic factor. Moreover, strong economic and financial linkages can also lead to common currency areas and similarities in income and trade flows, all of which contribute to greater co-movement in equity returns.

Attempts to understand international equity co-movements empirically have yielded only a limited set of stylized facts, namely, that the covariance structure of international equity returns is time-varying, and that correlations tend to increase during periods of high volatility and crisis. There is no consensus on whether the average correlation is increasing over time. There is further disagreement about how to properly classify the transmission of shocks from one market to another as indicative of either interdependence or contagion. A further limitation of existing studies is that they are typically focused on a restricted cross section of international markets over relatively short sample periods.

Our study makes a significant contribution to the literature by considering a sample of daily data spanning over 20 years, encompassing numerous financial crises and worldwide economic developments across a geographically diverse set of 15 major international stock markets. Moreover, we employ a flexible and parsimonious estimation framework in the form of a state-of-the-art dynamic latent factor model with time-varying loadings and stochastic volatility, which we estimate using Bayesian Markov chain Monte Carlo (MCMC) methods. Such a specification allows us to account for complex return co-movement dynamics and consequently a better understanding of financial integration and contagion.

Using our model, we characterize the commonalities between international stock markets with two factors and document that average cross-country equity return correlations exhibit a distinct upward trend over the sample period. Furthermore, we demonstrate that this average increase in correlation is not a result of increased factor variances but rather of rising factor loadings over time. This finding indicates that international stock markets have become increasingly exposed to common sources of variation. We also show that this is both a global and regional phenomenon. These empirical results taken together provide strong evidence of increased stock market integration over the past 20 years.

Our model also allows us a depiction of financial contagion. We adopt Bekaert, Harvey, and Ng (2005)'s definition of contagion as correlations between markets that are not explained by economic fundamentals. We derive these 'excess' correlations from the idiosyncratic residuals of the model, thus disentangling the underlying structural interdependence between markets from short periods of highly volatile co-movement. We then analyze these excess correlations in the context of the Mexican crisis of 1994 and the Asian crisis of 1997. In both instances, excess correlations between the countries involved exhibit significant spikes.

The rest of this paper is organized as follows. Section 1 overviews the relevant literature concerning the study of international equity co-movements and the econometric challenges involved. Section 2 describes the data we use in the estimation. Section 3 describes the statistical factor model, addresses questions of identification, and derives model-based equations of correlation. Section 4 reviews the estimation procedure and our choice of priors. Section 5 describes our main results and addresses the issues of integration and contagion. Section 6 concludes.

1 Literature review

A thorough survey of the literature regarding the transmission of prices and volatility between international markets is explored in Gagnon and Karolyi (2006). We briefly review the relevant literature here.

1.1 Early studies

The study of international equity co-movements has its origins in the portfolio allocation literature. In their early work, Grubel (1968), Levy and Sarnat (1970), Solnik (1974) and Lessard (1973, 1976) documented relatively low correlations between U.S. and international equity markets, and argued that an international investor can reduce his risk exposure significantly by diversifying his portfolio internationally. Motivated by this finding, researchers devised empirical studies to explore further the inter-relationships between international equity returns. In particular, Agmon (1972) estimated a linear factor model with a sample of monthly market indices and firm stock prices from the U.S., the U.K., Germany and Japan from the early 1960s, and found a significant contemporaneous relationship among the four markets in his sample. Similarly, Ripley (1973) employed factor analysis to monthly data on industrial stock price indices from 1960–1970 for a sample of 19 developed countries. He documented a high level of co-movement between the U.S. and Western Europe, and attributed this co-movement mainly to strong financial ties, open capital flows and strong trade linkages. In a more recent investigation, Eun and Shim (1989) estimated a vector autoregression (VAR) using daily data of nine major international markets from 1980–1985. They found statistical evidence of interdependence between the markets and discovered a particularly strong influence of the U.S. market on the foreign markets sampled.

Studies in this early literature have also investigated the time variation in correlations between international equity returns. Panton, Lessig, and Joy (1976) utilized the technique of cluster analysis to examine weekly data from 1963–1972 of 12 major international equity markets. They found the covariance structure between these nations to be quite persistent but did exhibit some variation over time. In another study, Kaplanis (1988) specifically tested the temporal stability of the covariance and correlation matrices using the Jennrich (1970) test on a sample of monthly international index returns for 10 developed nations between 1967–1982. As in the Panton et al. study, Kaplanis found statistical evidence of a gradual change of the covariance matrix over time.

The global stock market crash of October 1987 spurred a burst of research in international equity co-movements. Von Furstenberg and Jeon (1989) employed principal components analysis to compare the common sources of variation in the international equity returns before and after the 1987 crash. They found a significant increase in the amount of variation explained by the first principal component, a common factor they interpreted as capturing most global disturbances. The authors also calculated the correlations between the U.S., the U.K., Germany and Japan before and after the crash, and documented a dramatic post-crash rise in each pair-wise correlation. In another study, Koch and Koch (1991) investigated the lead-lag relationships between eight developed international markets using daily data for the three years 1972, 1980 and 1987. They argued that the financial markets in their sample have become more interdependent, especially those in the same geographical area with overlapping trading hours, confirming the earlier research by Hilliard (1979), who found statistical evidence of common factors within geographical regions. Additionally, Koch and Koch found that the covariance structure between these markets has changed over time, with higher correlations in recent years.

Another branch of the literature has explored the relative importance of industry factors and country factors in explaining international equity co-movements (see, e.g., Heston and Rouwenhorst, 1994). Recently, Baca, Garbe, and Weiss (2000), Cavaglia, Brightman, and Aked (2000) and Brooks and Del Negro (2004) asserted that global industry effects had largely been responsible for the increase in co-movement between international equity markets during the 1990s. In a more recent study, however, Bekaert, Hodrick, and Zhang (2008) argued that the increase in the importance of industry factors during the 1990s was short-lived and recently had declined in importance to country factors. With this result in mind, we elect not to include industry factors in this paper.

1.2 Spillovers

Although these early studies seem to indicate an increase in international equity co-movement after 1987 crash, a thorough understanding of why such an increase could happen so quickly and to such fundamentally different markets was lacking. King and Wadhwani (1990) addressed this question by constructing a theoretical framework with rational agents in which 'contagion' between markets can occur. Specifically, they developed a rational expectations equilibrium model that predicts market contagion as a result of market participants having differential access to information. King and Wadhwani then proceeded to empirically test the predictions of their model with respect to the 1987 crash with hourly data for the U.S., the U.K. and Japan between 1987–1988. They found that an increase in market volatility does tend to spillover to other markets, thus resulting in contagion.

The issue of volatility spillovers was investigated more fully in the work of Hamao, Masulis, and Ng (1990). Using daily and intra-daily data for the U.S., the U.K. and Japan between 1985–1988, these authors explored the co-movements of returns within the context of a lagged generalized autoregressive conditional heteroskedasticity (GARCH) model. They documented volatility spillovers in their sample by finding that higher current volatilities are associated with higher lagged volatilities, particularly from the U.S. and the U.K. to Japan. This disproportionate effect of the U.S. on foreign markets is consistent with the earlier results of Eun and Shim (1989). In another study of volatility spillovers, Theodossiou and Lee (1993) also estimated a lagged GARCH model and documented statistically significant spillover effects between a broader sample of international markets.

Research also developed to explore the dynamic aspects of these volatility spillovers. Karolyi and Stulz (1996) used daily and intra-daily stock prices for individual U.S. and Japanese firms between 1988–1992 to estimate

U.S.-Japan stock return co-movements in a constant conditional correlation multivariate GARCH (CCC-MGARCH) framework. They found that correlations and covariances are disproportionately high when markets are more volatile and that the covariance structure exhibits significant time variation. They also found that macroeconomic fundamentals explain very little of the covariation of returns. Ramchand and Susmel (1998a) analyzed a bivariate switching-ARCH model with weekly data for a broad sample of developed and developing international markets. They found mixed evidence of changing correlations through time but strong evidence that correlations increase a lot when the volatility of the U.S. market is high. Loretan and English (2000) also documented higher than average correlations during periods of higher than average volatility but cautioned against concluding that the correlation structure had changed.

In the literature exploring volatility spillovers, two recent papers have developed new statistics that compactly summarize the changing covariance structure through time. First, Chakrabarti and Roll (2002) constructed covariance and correlation indices by computing geometric means of absolute values of the elements of the covariance matrix. The authors recognized the necessary loss of information involved in reducing a higher dimensional space to a single number but argued that the indices are still meaningful because they are intended to summarize the covariance structure of a group of countries in a region and not individual pair-wise covariances. These indices can roughly capture the general level of regional covariance and thus can proxy for the level of volatility spillovers in that region. Chakrabarti and Roll computed the covariance index in a rolling six-month window for a sample of daily market indices for eight East Asian nations between 1994–1998. Using their covariance index, they demonstrated a clear and significant spike in volatility spillovers associated with the 1997 Asian crisis.

In another paper, Diebold and Yilmaz (2008) constructed a new statistic they call a 'spillover index' via the forecast error variance decompositions of VARs. They used real, weekly international equity returns for a broad sample of developed and developing nations, and constructed spillover indices for both equity returns and the volatility of returns. They documented that the return spillover index has steadily increased from 1992 to the present. Although they did not take a strong position on interpreting the result, they suggested that the greater spillover of international equity returns is consistent with the steady pace of globalization and financial integration. The authors also constructed a spillover index for the volatility of returns. Compared with the return spillover index, the volatility spillover index displays radically different behavior over the sample. It has no clear trend and exhibits large and significant spikes that can be associated with large market events, such as the 1997 Asian crisis, the September 11th terrorist attacks and the recent global financial crisis. These spillover indices present a compelling argument in favor of the changing interdependence and changing covariance structure of financial markets over the past 20 years.

1.3 Contagion

Several of the studies described above document an increase in correlation and co-movement when market volatility increases. A common interpretation of this effect is financial market contagion. While there are many possible mechanisms underlying financial contagion, one can imagine the pattern of contagion developing in the following manner: a negative shock in one nation causes returns to fall and domestic volatility to increase, which then spills over to a foreign market and 'infects' foreign returns. The foreign nation could then proceed to infect another nation, producing a cascade-like effect and potentially linking a number of countries together. The result of such contagion is typically depressed returns and a significant increase in volatility and correlation.

When considering financial contagion as an explanation to describe the co-movement of international equity returns during periods of stress, it is important to precisely define the notion of contagion and distinguish it from a general state of interdependence between the markets involved. Concerning the definition of contagion, Forbes and Rigobon (2002) argued that

> "...if two markets show a high degree of comovement during periods of stability, even if the markets continue to be highly correlated after a shock to one market, this may not constitute contagion. According to this paper's definition [i.e. Forbes and Rigobon], it is only contagion if cross-market comovement increases significantly after the shock. If the comovement does not increase significantly, then any continued high level of market correlation suggests strong linkages between the two economies that exist in all states of the world. This paper uses the term *interdependence* to refer to this situation." (p. 2224, emphasis theirs)

These authors assert that such a definition of contagion is reasonable and advantageous because it is a clear hypothesis that can be empirically tested by examining the time variation of the covariance structure.

A great deal of work has implicitly used a similar definition of contagion when concluding that the increase in correlations as a result of a financial shock represents a structural change. Many studies in this literature compare pre-crisis correlations to post-crisis correlations and use the change in correlation as evidence of a contagion-like effect (see, e.g., Von Furstenberg and Jeon, 1989; King and Wadhwani, 1990; Bertero and Mayer, 1990; Lee and Kim, 1993; Calvo and Reinhart, 1996). Forbes and Rigobon argued that such a 'contagion correlation test' is significantly upward biased due to heteroskedasticity and omitted variables, and developed a correction for the bias in the context of a linear model of returns. Using their corrected measure of correlation, they proceeded to find little statistical evidence of changing correlations through time and concluded the world is simply interdependent and has not suffered from contagion during recent periods of crisis.

This result contrasts with the conclusions of the literature regarding financial crises and volatility spillovers, thus motivating a fuller econometric analysis that explicitly takes the heteroskedasticity of returns into account. In fact, Corsetti, Pericoli, and Sbracia (2005) moved in this direction by generalizing the Forbes and Rigobon model to allow for a more general variance structure, nesting the Forbes and Rigobon model as a special case. They found that the Forbes and Rigobon conclusion of 'no contagion' is a bit too strong, as they did find evidence of contagion surrounding the 1997 Asian crisis, but their evidence on contagion was generally mixed.

It is also important to mention here that the Forbes and Rigobon bias correction is insufficient and must be used with caution since it can produce misleading results. Dungey and Zhumabekova (2001) argued that tests of changing correlation have very low statistical power in the context of financial crises. The central issue here surrounds the comparison of correlations during relative tranquil periods to periods of crisis. Naturally, the crisis periods are relatively short compared to the tranquil periods, resulting in far less data associated with crisis periods. The comparison of correlations is then made between two samples of potentially large differences in size, an example of selection bias. Dungey and Zhumabekova showed that "...the Forbes and Rigobon results consistently over-reject the hypothesis of contagion due in large part to the comparison of a large sample of non-crisis period data to a small sample of crisis period data" (p. 1). They proceeded to argue against the contagion correlation test in general because of its poorly understood biases and the inability to properly correct for them. This issue of selection bias with respect to tests of changing correlation was also explored in the work of Boyer, Gibson, and Loretan (1999).

The key insight obtained from this strand of literature is that the contagion correlation test is a poor measure of changing correlation and, as a result, a poor means of testing for the existence of contagion. An econometric analysis that explicitly models the time-variation of the covariance structure is necessary to avoid the problems inherent in these previous studies and perform a rigorous assessment for the presence of contagion.

It is important to mention that a few studies have attempted to directly test for time variation of the covariance matrix in the context of a more general econometric model. Longin and Solnik (1995) used monthly index returns of major international markets for the period 1960–1990 and estimated a constant conditional correlation bivariate GARCH model pair-wise between all countries in their sample. They developed a test to measure correlation changes, and found that international correlations have increased over their sample and tend to increase during periods of high conditional volatility. They also found that macroeconomic fundamentals can explain little of the variation in correlations. Longin and Solnik's analysis of time-varying correlations, however, is severely limited by the fact that they estimate a *constant* conditional correlation model. In more recent studies using both the constant and dynamic conditional correlation MGARCH models, Tse (2000) and Tse and Tsui (2002) found evidence of statistically significant changes in the covariance structure between a limited sample of Asian markets during the 1990s.

Another important issue to consider is that increased return volatility and increased correlation during periods of crisis are not necessarily evidence of contagion. In fact, in the context of a factor model, increases in correlation may simply be an artifact of higher factor loadings or factor volatilities. With this consideration in mind, we adopt in this paper the Bekaert, Harvey, and Ng (2005) definition of contagion as excess correlations, that is, correlations between the model residuals. This definition avoids the correlation corrections described above and is well-suited to disentangle the structural interdependence of markets, in the sense of Forbes and Rigobon, from financial contagion,

1.4 Econometric issues

Many of the empirical studies described above are limited due to the difficulty involved in estimating time-varying covariance matrices for a large set of assets. As the number of assets increases, the dimensionality of the covariance parameter space rapidly expands: in the absence of any structure, the estimation of a time-varying covariance matrix for n assets entails the computation of $n(n+1)/2$ distinct estimates at every point in time. Early approaches such as the vectorized conditional covariance (*vech*) model of Bollerslev, Engle, and Wooldridge (1988) reduced the immense dimension of this problem by parameterizing each element of the covariance matrix as a linear function of lagged squares and cross-products of errors, and lagged elements of the covariance matrix. While such a representation is quite general, it nevertheless requires the estimation of $O(n^4)$ parameters and thus is rarely feasible. For instance, in our application involving 15 assets, the *vech* model requires the estimation of 28,920 parameters. Moreover, positive definiteness of the covariance matrix is not guaranteed and additional restrictions are necessary to ensure this condition is satisfied. While these difficulties may be ameliorated somewhat by the imposition of diagonality on the parameter matrices in the equation governing the evolution of the covariance matrix (see, for example, the diagonal *vech* model or the BEKK model of Engle and Kroner, 1995), such restricted specifications still suffer from this curse of dimensionality, requiring $O(n^2)$ parameters to be estimated and are rarely performed with more than three or four assets.

To overcome the difficulty of maintaining positive-definiteness and the high level of parameterization encountered in the estimation of MGARCH models, Bollerslev (1990) developed a constant conditional correlation MGARCH model. Although this model is slightly more tractable, it still requires the estimation of $O(n^2)$ parameters. Moreover, subsequent work by Tsui and Yu (1999) and Tse (2000) rejected the assumption of constant conditional correlations across a range of equity and national stock market returns. The work of Tse and Tsui (2002) and Engle (2002) relaxed the assumption of constant correlations and presented MGARCH models with dynamic conditional correlation. Consistent with the earlier studies, Tse and Tsui also rejected the constant conditional correlation model in favor of the dynamic model. However, these papers imposed the restriction that all correlations be subject to the same dynamics, a restriction that becomes increasingly binding with a large number of variables. While this restriction may be relaxed somewhat via the imposition of a block diagonal structure on the coefficient matrices that describe the correlation dynamics (see Billio, Caporin, and Gobbo, 2006), such an approach requires *a priori* knowledge about asset groupings.

The most parsimonious MGARCH specifications utilize a factor structure to overcome the rapidly expanding parameter space. Diebold and Nerlove (1989) and King, Sentana, and Wadhwani (1994) developed latent factor models in which the factors are modeled as ARCH processes. Such models require only $O(n)$ parameters to be estimated. However, Pitt and Shephard (1999) and Engle and Sheppard (2001) argued that such models are very difficult to econometrically analyze from a likelihood perspective and typically perform poorly for less correlated systems such as single-name stocks. As a result of these shortcomings, the literature has not explored factor GARCH models quite as deeply in the pursuit of producing time varying estimates of covariances and correlations.

Multivariate models have also been recently explored in the stochastic volatility literature. The basic multivariate stochastic volatility model, developed by Harvey, Ruiz, and Shephard (1994), places restrictions on the time-varying covariance matrix in a similar way to the constant conditional correlation GARCH model of Bollerslev (1990). Like the CCC-MGARCH model described earlier, such a specification is rejected by the data and must be replaced by a more general specification. Furthermore, the basic model of Harvey et al. remains highly parameterized and requires the estimation of $O(n^2)$ parameters.

In their groundbreaking work, Pitt and Shephard (1999) presented a multivariate factor model with stochastic volatility and developed the econometric methodology to estimate the time-varying covariances. They applied their model to a sample of daily exchange rates of five major economies from 1981–1998. The model's factor structure is the key component that allows for a parsimonious and flexible solution to the problem of estimating time-varying covariances. Indeed, a particular advantage of the factor structure is that the number of parameters to be estimated is linear in the number of assets (i.e. $O(n)$). More recent work by Chib, Nardari, and Shephard (2006) and Yu and Meyer (2006) showed that factor models are also able to accommodate time-varying correlations. The model developed here in this paper builds upon and extends the basic structure of the Pitt and Shephard framework and utilizes the multitude of recent advances in estimating complex multivariate stochastic volatility models (see, e.g., Kim, Shephard, and Chib, 1998).

What is clear from the literature is that multivariate stochastic volatility factor models provide a powerful approach to estimating dynamic correlations and covariances. Such models circumvent the difficulties of high parameter dimensionality by imposing a common dynamic structure upon the set of returns that allows for a representation of the covariance matrix in terms of a smaller number of parameters. In doing so, factor models provide a parsimonious way of modeling financial return data while remaining flexible enough to adequately capture covariance dynamics. Standard dynamic factor models, however, typically assume both non-time-varying factor loadings and covariances and, as a result, do not adequately account for the well documented empirical features of heteroskedasticity and structural changes in equity returns. In order to account for these features of the data, we augment the standard factor model to allow for stochastic volatility and time-varying loadings. This extended specification allows us to fit the data well and produce the desired estimates of the evolution of the covariance matrix over time. This specification also allows us to properly investigate the issues of financial integration and contagion.

2 Data

The data consist of daily closing prices of national stock indices from a broad cross-section of international markets. We use the following countries (with specific national index in parentheses) in our estimation: United States (S&P 500), Mexico (IPC), Canada (TSX Composite), Argentina (Morgan Stanley Capital International (MSCI) Argentina in $U.S.), Brazil (MSCI Brazil in $U.S.), United Kingdom (FTSE 100), Germany (DAX 30), France (CAC 40), Sweden (OMX Stockholm 30), Japan (Nikkei 225), Hong Kong (Hang Seng), India (BSE 30), Malaysia (KLSE Composite), Singapore (STI) and Australia (All Ordinaries). The data cover a variety of both developed and developing nations, span geographically diverse locations and account for nearly 80% of global equity market capitalization as of January 2009 (World Federation of Exchanges, 2009). The indices are expressed in terms of U.S. dollars by means of daily foreign exchange rates where necessary. When closing price data for a given index does not exist for a specific day due to a holiday, the closing price of the index on the previous trading day is used. Returns are expressed as continuously compounded, daily percentage changes: $r_t = 100 \log(P_t/P_{t-1})$. The data begin on January 1, 1988 and end on March 9, 2009, covering 5527 days or about 21 years of data. All data are

Country	Index	Mean	Std.	Max	Min	Skew.	Kurt.
U.S.	S&P 500	4.59	17.78	10.96	-9.47	-0.34	10.27
Canada	TSX	3.98	18.13	11.93	-13.26	-0.92	17.12
Mexico	IPC	14.49	32.41	19.93	-25.20	-0.55	17.00
Brazil	MSCI	12.66	44.44	21.23	-26.35	-0.42	7.86
Argentina	MSCI	10.39	57.48	45.59	-92.70	-2.89	101.45
U.K.	FTSE 100	1.89	19.37	12.22	-10.54	-0.18	10.69
Germany	DAX 30	6.02	23.80	12.02	-12.91	-0.26	6.96
France	CAC 40	4.32	22.37	11.80	-11.67	-0.07	7.46
Sweden	OMX 30	6.00	25.99	14.63	-10.55	0.05	6.52
Japan	Nikkei 225	-4.14	25.51	12.39	-11.11	0.10	4.09
Hong Kong	Hang Seng	7.28	26.66	17.30	-24.87	-0.64	18.40
Malaysia	KLSE	3.60	25.18	24.28	-24.15	0.66	39.45
Singapore	STI	3.76	21.66	13.25	-10.39	-0.10	9.31
India	BSE 30	6.89	29.34	18.52	-19.13	-0.27	8.14
Australia	All Ords.	3.37	19.89	11.06	-13.98	-0.71	11.66

Table 1. Summary statistics of international equity returns. Means and standard deviations are expressed in annual percentage terms. Minima and maxima are expressed in daily percentage terms. Kurtosis is excess kurtosis. Daily data covers 5,527 days from January 1, 1988 to March 9, 2009. Price indices are expressed in U.S. dollars, and returns are 2-day moving averages of continuously compounded, daily percentage changes $r_t = 100 \log(P_t/P_{t-1})$.

from Datastream.

The summary statistics of the data are presented in table 1. The return statistics include the means and standard deviations, expressed in annual percentage terms, the minima and maxima, expressed in daily percentage terms, and the skewness and excess kurtosis. The developing markets typically have greater returns and greater volatility than do the developed markets. For example, the Latin American markets of Mexico, Brazil and Argentina all generated average annualized returns in excess of 10% over the past 21 years but exhibited volatilities roughly two to three times greater than the volatilities in developed markets. In addition, the skewness and excess kurotsis of the returns indicate the significant but expected departure from the normal distribution, as most returns are negatively skewed and all demonstrate fat tails.

The sample covariance and correlation matrix is presented in table 2. The covariances are expressed in daily percentage terms, and the correlations are denoted by italics and are in the upper triangular portion of the matrix. It is interesting to notice that, consistent with the idea of a world business cycle, every pair-wise correlation in our sample is positive. Moreover, strong trading partners and nations within similar geographical regions demonstrate particularly high correlations.

The use of daily data is important because it allows us to better capture correlation dynamics and intertemporal relationships between international stock markets during brief and turbulent market conditions that may be obscured in weekly or monthly data. During such periods, high frequency correlation and covariance estimates are especially important since they allow us to finely characterize effects such as volatility spillovers and market contagion. Furthermore, since our model specification is multivariate and includes many time-varying parameters, we must compute a large number of parameter estimates. Daily data provides a large enough sample to compute these estimates efficiently.

Daily data, however, also introduces the problem of non-synchroneity in the study of international equity return dynamics. Since we consider a variety of nations across a vast geographical area in many different time-zones, the trading hours of each international stock market are different. As a result, the closing prices in each market are not synchronous. Martens and Poon (2001) argued that the use of daily non-synchronous closing prices leads to an underestimation of the true contemporaneous correlations between stock markets, and consequently advocated the use of the non-synchroneity correction procedure developed in Burns, Engle, and Mezrich (1998), which modeled close-to-close returns as a first order moving average. However, the Burns et al. correction may introduce additional model specification bias, so we instead choose to follow the Forbes and Rigobon (2002) approach, which addressed the issue of non-synchroneity by computing returns as two-day moving averages of daily returns of each respective national index.

Finally, it is important to discuss our choice to express all international indices in terms of U.S. dollars. The primary motivation for this decision is to avoid the effects of massive changes in the local price levels on the national indices. For example, Argentina experienced severe inflation during the 1980s, averaging over 150% annually. Since our sample begins in 1988, it is particularly relevant to mention that the inflation rate averaged nearly 275% between 1988–1990 (Instituto Nacional de Estadística y Censos, 2009).

	U.S.	Can	Mex	Bra	Arg	U.K.	Ger	Fra	Swe	Jpn	H.K.	Mal	Sgp	Ind	Aus
U.S.	1.25	*0.63*	*0.49*	*0.35*	*0.19*	*0.40*	*0.41*	*0.39*	*0.35*	*0.06*	*0.14*	*0.04*	*0.16*	*0.10*	*0.07*
Canada	0.81	1.31	*0.42*	*0.37*	*0.23*	*0.50*	*0.46*	*0.48*	*0.47*	*0.18*	*0.24*	*0.12*	*0.26*	*0.16*	*0.26*
Mexico	1.11	0.99	4.17	*0.42*	*0.25*	*0.32*	*0.32*	*0.33*	*0.32*	*0.09*	*0.19*	*0.12*	*0.19*	*0.10*	*0.14*
Brazil	1.10	1.18	2.43	7.84	*0.21*	*0.31*	*0.29*	*0.31*	*0.30*	*0.10*	*0.18*	*0.10*	*0.20*	*0.13*	*0.17*
Argentina	0.78	0.97	1.85	2.16	13.1	*0.17*	*0.14*	*0.19*	*0.16*	*0.04*	*0.08*	*0.06*	*0.12*	*0.06*	*0.10*
U.K.	0.55	0.70	0.80	1.06	0.77	1.49	*0.66*	*0.75*	*0.65*	*0.24*	*0.31*	*0.17*	*0.31*	*0.17*	*0.32*
Germany	0.68	0.79	0.98	1.22	0.79	1.21	2.25	*0.78*	*0.68*	*0.25*	*0.32*	*0.17*	*0.32*	*0.15*	*0.29*
France	0.62	0.78	0.95	1.22	0.95	1.28	1.65	1.99	*0.71*	*0.25*	*0.29*	*0.15*	*0.31*	*0.16*	*0.29*
Sweden	0.65	0.87	1.08	1.38	0.94	1.31	1.66	1.64	2.68	*0.26*	*0.31*	*0.18*	*0.34*	*0.18*	*0.31*
Japan	0.10	0.33	0.30	0.47	0.23	0.48	0.61	0.57	0.68	2.58	*0.37*	*0.23*	*0.38*	*0.13*	*0.39*
Hong Kong	0.27	0.47	0.65	0.86	0.51	0.64	0.81	0.70	0.86	0.99	2.82	*0.38*	*0.57*	*0.22*	*0.47*
Malaysia	0.07	0.23	0.38	0.43	0.33	0.33	0.42	0.34	0.46	0.58	1.01	2.52	*0.49*	*0.13*	*0.29*
Singapore	0.25	0.40	0.53	0.75	0.57	0.52	0.66	0.59	0.76	0.83	1.32	1.05	1.86	*0.23*	*0.42*
India	0.20	0.33	0.39	0.66	0.38	0.37	0.42	0.43	0.54	0.39	0.67	0.37	0.59	3.42	*0.19*
Australia	0.10	0.38	0.36	0.60	0.44	0.49	0.54	0.51	0.64	0.78	0.99	0.58	0.71	0.43	1.57

Table 2. Sample covariance and correlation matrix of returns. Covariances are expressed in daily percentage terms. Correlations are denoted by italics and are in the upper triangular portion of the matrix.

Inflation of this magnitude had a significant impact on the national index for Argentina during this period. The local currency MSCI index for Argentina was equal to 100 at the start of 1988 but increased drastically to over 350,000 by the start of 1991, implying an average simple annual return of nearly 7000% over these three years. The MSCI index in U.S. dollars, however, documents an increase from 100 in 1988 to about 320 in 1991, an average simple annual return of about 50%. While this return is still unusually high, it is far more reasonable than the alternative and better reflects the true financial value.

We recognize that expressing all indices in terms of U.S. dollars introduces exchange rate fluctuations and that a better solution to the problem of changing price levels would be to express all indices in real terms in the local currencies. This, unfortunately, is not feasible with daily data. At best, price levels are estimated at a monthly frequency but may be available only at a quarterly frequency for many of the nations in our sample. Measurement error and deliberate misrepresentation is another significant issue with price level estimates, especially in times of economic distress or high inflation. The foreign exchange market, on the other hand, generates daily prices in a highly liquid market, and so is not subject to issues of measurement error. While exchange rate fluctuations are introduced by expressing the indices in U.S. dollars, we contend that it is a far better solution than to attempt to express the national indices in real, local terms.

3 Model

Our model specification is the dynamic, multivariate factor model developed in Del Negro and Otrok (2008). The model includes time-varying factors, time-varying factor loadings and stochastic volatilities, and incorporates these features in a manner that is scalable to a large number of assets. In our application, we estimate the model with data on 15 international equity indices, so the ability of the model to scale with the number of variables is particularly important. As argued earlier, such a large-scale estimation would be exceedingly difficult with a multivariate GARCH model that properly models time-varying covariances, but is feasible in the context of this factor model.

The factors, factor loadings and stochastic volatilities are all modeled as latent stochastic processes that must be filtered from the data. As a result, these objects are entirely statistical and have no direct economic analogues. The choice of modeling the factors in particular as latent statistical processes instead of defining them as financial or macroeconomic variables is primarily motivated by the earlier work of King et al. (1994), Longin and Solnik (1995), and Karolyi and Stulz (1996), who found that macroeconomic fundamentals explain very little of the covariation of returns. Since our primary goal is to specifically explain return covariance, we contend that it is more appropriate to model the factors as statistical processes.

While economists often do ascribe economic meaning to these statistical objects, it is important to mention there is no unambiguous economic interpretation. This caveat, however, only applies to interpreting the objects in isolation. For instance, we will show that the variances and covariances of the returns are described by functions of these underlying processes but are not subject to this issue of ambiguity. The economic interpretation of the covariance structure of returns is direct and valid.

The addition of time-varying factor loadings and stochastic volatility to the standard model also merits further discussion. The shared commonalities between international equity returns that are captured by the factors must necessarily be affected by the underlying financial, economic and regulatory conditions. As these conditions change over time and across countries, it is reasonable to postulate that the way in which each country's equity return relates to these commonalities must also change. It is for precisely this reason that we extend the standard factor model to include time-varying factor loadings.[1] In addition, time-varying volatility is a well established feature of financial time series, and we choose to model it as a latent stochastic volatility process with the interpretation of representing the new and uneven flow of information in the spirit of Clark (1973).

3.1 Model specification

Let $r_t = (r_{1t},\ r_{2t},\ \ldots,\ r_{nt})$ denote a vector of n returns observed at time t, and let $f_t = (f_{1t},\ f_{2t},\ \ldots,\ f_{kt})$ denote a vector of k unobservable factors at time t, where $t = 1 \ldots T$. As in the standard factor model, the returns are assumed to be determined by the k common latent factors and a vector of idiosyncratic shocks. However, as mentioned earlier, the model specified

[1]Time-varying factor loadings also have some prior empirical support in the literature. See, for example, Ramchand and Susmel (1998b), who found statistical evidence for time-varying loadings in the context of an international capital asset pricing model (ICAPM).

here generalizes the standard model and extends it to allow for time-varying factor loadings and stochastic volatilities. The precise specification assumed for return i is given by

$$\begin{aligned} r_{it} &= a_i + b_{i1t}f_{1t} + b_{i2t}f_{2t} + \cdots + b_{ikt}f_{kt} + \epsilon_{it} \\ &= a_i + \sum_{j=1}^{k} b_{ijt}f_{jt} + \epsilon_{it} \end{aligned} \tag{3.1}$$

where a_i is a constant term, f_{jt} is factor j at time t, b_{ijt} is the loading of return i on factor j at time t, and ϵ_{it} is the idiosyncratic term affecting return i at t.

As in the standard factor model, the factor loadings measure the degree by which a particular factor contributes to the overall return of an asset. Extending the model to include time-varying loadings allows the returns to exhibit varying sensitivity to the common factors across time. The factor loadings thus act as an kind of structural intermediary between the factors and the asset returns. With this interpretation in mind, we model the factor loadings as driftless random walks to capture permanent, structural changes (see also Cogley and Sargent, 2001, 2005):

$$b_{ijt} = b_{ijt-1} + \sigma_{\eta_{ij}}\eta_{ijt} \tag{3.2}$$

We model both the idiosyncratic terms ϵ_{it} and the factors f_{jt} as autoregressive (AR) processes, given the fact that many predictive economic variables exhibit some serial correlation:

$$\epsilon_{it} = \phi_{i1}\epsilon_{it-1} + \cdots + \phi_{ip_i}\epsilon_{it-p_i} + \sigma_i e^{h_{it}}u_{it} \tag{3.3}$$

$$f_{jt} = \varphi_{j1}f_{jt-1} + \cdots + \varphi_{jq_j}f_{jt-q_j} + e^{g_{jt}}v_{jt} \tag{3.4}$$

where the lag lengths p_i and q_j can differ by variable and by factor. Notice that both the processes for ϵ and f are modeled as having stochastic log-volatilities h and g. Since many financial time series exhibit heteroskedasticity, we intuitively expect the heteroskedasticity in the returns to be divided between the factors and the idiosyncratic terms in our model. The factors should exhibit heteroskedasticity because they are a major common source driving the returns. The heteroskedasticity of the idiosyncratic terms is harder to justify once we already assume heteroskedasticity in the factors, but King et al. (1994) documented in a multivariate factor model of international equity markets how the contribution of the idiosyncratic component to overall return volatility changes rapidly over time, especially for certain countries. This result motivates our choice to model the idiosyncratic terms as having stochastic volatility as well. As with the factor loadings, we model the stochastic volatilities as driftless random walks to capture permanent shifts in variance:

$$h_{it} = h_{it-1} + \sigma_{\zeta_i}\zeta_{it} \tag{3.5}$$

$$g_{jt} = g_{jt-1} + \sigma_{\xi_j}\xi_{jt} \tag{3.6}$$

We also assume that the stochastic volatilities h and g do not operate before our sample begins. That is, we assume that $h_{it} = g_{jt} = 0$ for all $t \leq 0$ and for all i and j. This assumption guarantees the existence of pre-sample stationary distributions of the f and ϵ, provided the AR coefficients ϕ and φ are also stationary. Lastly, all the error terms u, v, η, ζ and ξ in the above model equations are assumed to be i.i.d. $\mathcal{N}(0,1)$ across returns i, factors j and time t.

3.2 Identification

There are many identification issues present in this model. Some are common to factor models in general and some are specific to this particular specification. They are presented in detail in Del Negro and Otrok (2008) and will be reviewed briefly here.

The principal identification issue in this model is separately identifying the factors and the factor loadings. The factors are specifically modeled to capture the commonalities between the returns and, as a result, function as the vehicle by which returns co-move. It is precisely for this reason that we assume the stochastic processes for the factor loadings (eq. 3.2) are independent across returns i. This independence assumption guarantees that only the factors capture co-movement among the returns and is crucial for separately identifying the two processes.

It is important to also notice that we can multiply the loadings b by a constant c and divide the factors f by c and not change the product bf. Using this idea, we can recast the model in terms of $\tilde{b}_{ijt} = c\, b_{ijt}$ and $\tilde{f}_{jt} = f_{jt}/c$. We can then write the loading equation (3.2) and the factor equation (3.4) as

$$\begin{aligned} \tilde{b}_{ijt} &= \tilde{b}_{ijt-1} + \tilde{\sigma}_{\eta_{ij}}\eta_{ijt} \\ \tilde{f}_{jt} &= \varphi_{j1}\tilde{f}_{jt-1} + \cdots + \varphi_{jq_j}\tilde{f}_{jt-q_j} + e^{\tilde{g}_{jt}}v_{jt} \end{aligned}$$

where $\tilde{\sigma}_{\eta_{ij}} = c\ \sigma_{\eta_{ij}}$ and $\tilde{g}_{jt} = g_{jt} - \log c$. Notice also that we can write the stochastic volatility equation (3.6) in terms of $\tilde{g}_{jt}$:

$$\tilde{g}_{jt} = \tilde{g}_{jt-1} + \sigma_{\xi_j}\xi_{jt}$$

Without an additional restriction, this transformed model is observationally equivalent to our original specification and we cannot identify the parameters of the model. Recall, however, that we specified $g_{j0} = 0$ for all factors j. This restriction effectively determines the scale of the factors and thus allows for separate identification of b and f. A similar issue of indeterminate scale is present with respect to the idiosyncratic terms. In particular, notice that $\sigma_i e^{h_{it}} = c\,\sigma_i e^{h_{it}-\log c}$. As with the stochastic volatilities of the factors, since we require $h_{i0} = 0$ for all returns i, the scale of the idiosyncratic terms is determined and identification is obtained.

Since the loadings and the factors are both time-varying, it is also a concern that the rescaling described above could be time-varying and pose identification issues. In other words, there may exist a sequence of rescalings $\{c_t\}$ for all t that implicitly define $\tilde{b}_{ijt} = c_t\, b_{ijt}$ and $\tilde{f}_{jt} = f_{jt}/c_t$. Del Negro and Otrok also address this concern and argue that time-varying rescalings would not satisfy the loading and factor equations (3.2 and 3.4) and are thus not feasible.

Since our system specifically models multiple factors, another concern is separately identifying the different effects of each factor. In their work, Del Negro and Otrok model two factors and seek to interpret them as a 'world' factor and a 'European' factor. In this pursuit, they impose that the loading on the European factor is zero for any non-European country in their sample. Since we do not impose a specific interpretation on each factor, this restriction on the loadings is unnecessary. Identification between the factors is ensured by the assumption that the errors v in equation (3.4) are independent.

3.3 Variance and covariance

A primary goal of this research is to characterize the time variation of the covariances, variances and correlations of the returns. In particular, we are interested in computing estimates of the posterior, unconditional time t variances and covariances. Using the covariance estimates at each point in time, we can then directly compute estimates of the time-varying correlations. It is important to mention that, in the derivations that follow, the expectations and variances are taken with respect to the unconditional posterior distribution. In practical terms, these expectations and variances are computed for a given return i at time t using the draws from the posterior distribution generated by the Gibbs sampler described in section 4.2.

In the context of our model, the unconditional time t variance of return i is given by

$$\begin{aligned} V(r_{it}) &= V(a_i + \sum_{j=1}^{k} b_{ijt} f_{jt} + \epsilon_{it}) \\ &= V(a_i) + \sum_{j=1}^{k} V(b_{ijt} f_{jt}) + V(\epsilon_{it}) \end{aligned}$$

where for any factor j,

$$\begin{aligned} V(b_{ijt} f_{jt}) &= E[(b_{ijt} f_{jt})^2] - (E[b_{ijt} f_{jt}])^2 \\ &= E[b_{ijt}^2] E[f_{jt}^2] - E[b_{ijt}]^2 E[f_{jt}]^2 \end{aligned}$$

since the loadings, factors and idiosyncratic terms are independent processes. If the variance of the loading $V(b_{ijt})$ across MCMC draws at the given point in time is small, then $E[b_{ijt}^2] \approx E[b_{ijt}]^2$ and we can show that[2]

$$V(r_{it}) \approx V(a_i) + \sum_{j=1}^{k} \left\{ E[b_{ijt}]^2 \, V(f_{jt}) \right\} + V(\epsilon_{it}) \tag{3.7}$$

As for the covariance between returns i and s, we have

$$\begin{aligned} Cov(r_{it}, r_{st}) &= Cov\left(a_i + \sum_{j=1}^{k} b_{ijt} f_{jt} + \epsilon_{it},\ a_s + \sum_{j=1}^{k} b_{sjt} f_{jt} + \epsilon_{st} \right) \\ &= Cov(b_{i1t} f_{1t},\, b_{s1t} f_{1t}) + \cdots + Cov(b_{ikt} f_{kt},\, b_{skt} f_{kt}) \\ &= \sum_{j=1}^{k} Cov(b_{ijt} f_{jt},\, b_{sjt} f_{jt}) \end{aligned}$$

[2] Our estimates of the variance $V(b_{ijt})$ at each point in time are indeed small, so this approximation is quite good.

since the loadings, factors and idiosyncratic terms are independent and the only common elements between return i and return s are the factors. Notice that for any factor j,

$$
\begin{aligned}
Cov(b_{ijt} f_{jt},\ b_{sjt} f_{jt}) &= E[b_{ijt} b_{sjt} f_{jt}^2] - E[b_{ijt} f_{jt}] E[b_{sjt} f_{jt}] \\
&= E[b_{ijt}] E[b_{sjt}] \left(E[f_{jt}^2] - E[f_{jt}]^2 \right) \\
&= E[b_{ijt}] E[b_{sjt}]\ V(f_{jt})
\end{aligned}
$$

Thus we have

$$
Cov(r_{it}, r_{st}) = \sum_{j=1}^{k} E[b_{ijt}] E[b_{sjt}]\ V(f_{jt}) \tag{3.8}
$$

The correlation is then simply

$$
Corr(r_{it}, r_{st}) = \frac{Cov(r_{it}, r_{st})}{\sqrt{V(r_{it})\ V(r_{st})}}
$$

$$
\approx \frac{\sum_{j=1}^{k} E[b_{ijt}] E[b_{sjt}]\ V(f_{jt})}{\sqrt{V(a_i) + \sum_{j=1}^{k} E[b_{ijt}]^2 V(f_{jt}) + V(\epsilon_{it})} \sqrt{V(a_s) + \sum_{j=1}^{k} E[b_{sjt}]^2 V(f_{jt}) + V(\epsilon_{st})}} \tag{3.9}
$$

It is illustrative to use equation (3.9) to explore how the correlation between two assets changes in response to changes in the volatilities of the underlying parameters. In particular, does the correlation between return i and return s increase as the return volatility $V(r_{it})$ increases? Notice from equation (3.7) that, all else being equal, return volatility $V(r_{it})$ is an increasing function of both factor volatility $V(f_j)$ and idiosyncratic volatility $V(\epsilon_{it})$. If return volatility increases because factor volatility increases, equation (3.9) implies that correlation can either increase or decrease, depending on the other parameter values. However, if an increase in idiosyncratic volatility causes the increase in return volatility, then the correlation between returns always decreases.

As Chakrabarti and Roll (2002) argued in the appendix of their paper, there consequently is no necessary connection between an increase in return volatility and an increase in correlation in a linear factor model. In the context of financial crises, it is therefore important to understand how the volatilities of the factors and the idiosyncratic terms change relative to one another. Only then is it possible to explore the relationship between changes in correlation and financial crises or to make claims about financial contagion.

4 Estimation

An important issue we consider prior to estimating our model is the number of factors to include in our specification. Typically the number of factors is either assumed *ex ante* by the researcher or determined by an underlying economic model, such as the capital asset pricing model (CAPM). Since we do not make an explicit link between our international equity returns and a distinct set of economic variables, we need a systematic way of inferring the appropriate number of factors from the data. To accomplish this, we employ the statistical criterion developed by Bai and Ng (2002). Unlike the Akaike and Bayesian information criteria, an advantage of the criterion devised by Bai and Ng is that it does not impose any restrictions between the number of variables n and the time series length T. The Bai and Ng criterion function specifically is computed as the addition of the sum of squared residuals associated with a given number of factors, and a penalty function constructed using the number of factors and the dimensions (n, T) of the sample. If more factors are included in the model, the fit improves but efficiency is lost as additional factor loadings must also be estimated. The criterion function therefore quantifies the trade-off between goodness-of-fit and model parsimony. Applying this metric to our sample of returns, we determine the optimal number of factors is 3. We must mention, however, that the Bai and Ng criterion is based on a factor model with *non*-time-varying loadings. As a result, when applied to a model with time-varying loadings, this procedure generates an upper bound on the optimal number of factors since dynamic loadings will provide an additional source of variation in the model. Given our specification includes time-varying loadings, we let the number of factors k in this paper be equal to 2. This is consistent with other empirical studies using factor models (e.g. Bekaert, Harvey, and Ng, 2005).

4.1 Priors

We assume prior distributions on the non-time-varying parameters of the model, and so the estimation procedure is Bayesian. We adopt a Bayesian framework to give the estimation procedure some discipline, especially concerning the volatility parameters σ, σ_η, σ_ζ and σ_ξ. These parameters govern the scale and time variation of the factors, factor loadings and stochastic volatilities. Since the primarily goal of this paper is to study the time-varying co-movements of international equity returns, these volatility parameters and the respective prior distributions over them are of central importance.

In many Bayesian applications, variance parameters are often assigned inverse gamma priors since the inverse gamma distribution has the support of the positive real line and is conjugate to the normal distribution. Since the volatility parameters σ, σ_η, σ_ζ and σ_ξ in this model represent standard deviations, we thus assume a *square root* of an inverse gamma prior for them. The square root of an inverse gamma is also conjugate to the normal, so the posterior distributions of the volatilities are distributed according to the square root of an inverse gamma.

To remain relatively agnostic regarding the prior distributions of these volatility parameters, we assume that each is distributed with mean 0.01 and standard deviation 0.01. While this may seem to be a very tight prior specification, it does not restrict the volatility parameters much during the actual estimation. For example, the volatilities often become as large as 1,000 or as small as 0.0001 during the estimation procedure as the parameters explore the parameter space. A primary motivation for these priors is computational in nature. Specifically, the numerical procedure to estimate this model becomes unstable when the volatilities become very small or very large. These priors, while not excessively restricting the parameters, act to mitigate this numerical instability quite well and keep the parameter values in economically reasonable ranges.

The remaining priors to be specified are the priors on the constants a and the autoregressive coefficients ϕ and φ. We assume a normal prior with mean 0 and standard deviation 0.05 for the constant term a_i of each return series. Since we express returns in daily percentage terms, this prior specifies the constants are centered at 0 with daily standard deviations of 5 basis points. Regarding the AR coefficients, we assume 2 lags in each idiosyncratic equation (3.3) and 2 lags in each factor equation (3.4). In other words, we assume $p_i = 2$ and $q_j = 2$ for all returns i and factors j. For every autoregressive coefficient, we assume a normal prior with mean 0 and standard deviation 0.25. Moreover, we assign zero prior probability mass on the combinations of AR coefficients ϕ and φ such that the idiosyncratic or factor equations (3.3 and 3.4) are not stationary. That is, we do not accept any draws from the conditional distributions of ϕ or φ that have non-stationary roots. Table 3 summarizes the prior distributions.

An issue related to the specification of the priors concerns the initial values of the parameters that we use to start the Markov chain in our Gibbs sampling procedure. To construct these initial values, we perform a rough

	Dist.	Mean	Std. Dev.
σ_i	$\mathcal{SIG}$	0.01	0.01
$\sigma_{\eta_{ij}}$	$\mathcal{SIG}$	0.01	0.01
σ_{ζ_i}	$\mathcal{SIG}$	0.01	0.01
σ_{ξ_j}	$\mathcal{SIG}$	0.01	0.01
a_i	$\mathcal{N}$	0	0.05
ϕ_i	$\mathcal{N}$	0	0.25
φ_j	$\mathcal{N}$	0	0.25

Table 3. Prior distributions of the non-time-varying parameters for all returns i and factors j. $\mathcal{N}$ denotes the normal distribution and $\mathcal{SIG}$ denotes the square root of an inverse gamma distribution.

preliminary analysis of the data. First, we extract the time series of the first two principal components of our sample of returns and use these components as rough initial values for our two factors f. While we understand that principal components are not unique and that any orthonormal transformation will generate another set of valid components, we argue that these non-rotated principal components are a reasonable starting place for the factors. Then, using these as factors, we compute a series of linear regressions of equation (3.1) on a moving window of data to obtain a rough idea of the time-varying factor loadings b and their respective volatilities σ_η. Next, we compute the residuals of these regressions and use a basic GARCH model to estimate the AR coefficients ϕ, scale volatilities σ, time-varying idiosyncratic volatilities h, and the volatilities σ_ζ of h. Applying a similar GARCH analysis to the factors, we estimate the AR coefficients φ, time-varying factor volatilities g, and the volatilities σ_ξ of g. The results of this preliminary analysis form the initial values of the Markov chain in our estimation. The actual values that these initial values take are economically reasonable and consistent with our prior distributions specified above.

4.2 Estimation procedure

Our model specification requires us to estimate the latent factors, loadings and stochastic volatilities at every point in time, in addition to the non-time-varying parameters. While the joint distribution of all the parameters is intractable, we can decompose it into a set of conditional distributions that have analytic representations. We then employ the Gibbs sampler to exploit this decomposition and provide a natural and efficient means of estimating our model and obtaining draws from the full joint distribution.

The estimation procedure described in this section is entirely based on the methodology of Del Negro and Otrok (2008). While specific details of the procedure can be found both in their paper and in the appendix to this paper, the estimation generally proceeds as follows. First, the parameters are divided into the following groups or blocks: (i) non-time-varying parameters, (ii) time-varying factors, (iii) time-varying factor loadings, and (iv) stochastic volatilities. The Gibbs sampler completes one 'sweep' or 'link' of the Markov chain by sequentially sampling from the conditional distributions of all four blocks of parameters.

In the first block, we sample from the distribution of the non-time-varying parameters, conditioning on all the other parameters in the model. We can derive analytic expressions for these conditional distributions by applying the approach described in Chib and Greenberg (1994) to transform our model into a single linear regression through a variety of algebraic and matrix manipulations. In the second and third blocks, we obtain draws of the time-varying factors and time-varying factor loadings, again conditioning on the other parameters. This is accomplished by transforming the model equations into state-space form and then applying the simulation smoother of Durbin and Koopman (2002). In the fourth block, we sample the conditional stochastic volatilities by utilizing the methodology described in Kim, Shephard, and Chib (1998) to approximate our model with a conditionally Gaussian model. Estimation of the stochastic volatilities h and g requires an approximation because they are modeled as log-volatilities, implying that the normally distributed shocks ζ and ξ in respective equations (3.5) and (3.6) are related to the returns via a logarithmic transformation. This transformation produces a linear but non-Gaussian state-space form. Kim et al. approximated this non-Gaussian error by a mixture of normal random variables, thereby producing a conditionally Gaussian system that approximated the true system quite well.[3] Using this conditionally Gaussian system, we sample the conditional stochastic volatilities through another application of the Durbin and Koopman simulation smoother. Finally, we must also sample over the precise mixture of normals used in the approximation.

[3]The mixture of normals approximation was later refined in the work of Omori, Chib, Shephard, and Nakajima (2007) in the context of a stochastic volatility model with leverage. We utilize this refined mixture of normals in this paper.

We use this Gibbs sampler to produce 15,000 draws from the posterior distribution. We save one in every 5 draws to reduce the serial correlation of the Markov chain and discard the initial 500 draws, leaving a final sample of 2,500 draws. While it may seem that the initial 15,000 or the final 2,500 draws is a relatively small amount in an MCMC routine, it is important to remember that the Gibbs sampler is typically far more efficient than a general Metropolis-Hastings sampler since every draw is accepted. Furthermore, the multi-move sampler utilized here to draw the time-varying parameters is very efficient. Kim et al. (1998), Chib, Nardari, and Shephard (2002) and Omori, Chib, Shephard, and Nakajima (2007) documented that the multi-move sampler was between 2 and 5 times more efficient than a single-move sampler. They subsequently argued that only 5,000 to 20,000 draws were necessary to properly estimate these models. While we use a smaller final sample in this paper, it is still on the same rough order of magnitude as these amounts.

The estimation procedure is also relatively quick. Our full sample of 21 years of daily data for 15 countries takes about 8 hours to estimate. The primary computational limitation is memory. Excluding the memory requirements of auxiliary variables, storing a *single* draw of the Markov chain, including all non-time-varying and time-varying parameters, requires about 2.2 megabytes of memory in double precision. Consequently, storing the final 2,500 draws of the chain requires 5.5 gigabytes of memory. While we can reduce this sizeable memory burden by periodically saving the draws to the hard drive, certain statistical operations such as computing percentiles requires all the draws for a particular parameter to be loaded into memory at one time. This is the primary reason that we do not use a larger number of draws. Lastly, it is important to mention that, with a less efficient sampling procedure, far more draws would be necessary and these memory limitations would become even more severe, thereby rendering this estimation problem practically infeasible on most computational platforms.

5 Results

This section describes our estimation results. Table 4 describes the posterior estimates of the non-time-varying parameters specific to the returns: the constants a, AR coefficients ϕ_1 and ϕ_2, idiosyncratic scale volatilities σ, volatilities σ_η of the factor loadings, and the volatilities σ_ζ of the idiosyncratic terms. Recall that we include 2 factors in our model and specify 2 lags for each of the idiosyncratic and factor autoregressive equations (3.3 and 3.4). Medians and standard deviations are listed for each parameter for all countries.

The median estimates of the constants a, while in daily percentage terms, imply in annual terms quite different values from the sample means listed in table 1. The median estimates of all the idiosyncratic AR coefficients ϕ have complex characteristic roots, implying that the idiosyncratic terms exhibit stochastic cycles that typically last about 6 days. Furthermore, the scale volatilities σ tend to be relatively low, a reasonable result given that we explicitly model stochastic volatility. The other volatilities σ_η and σ_ζ indicate that the factor loadings and the idiosyncratic volatilities both exhibit a relatively large amount of variation. Notice also that the standard deviations of the estimates are all quite small, indicating that the parameters are tightly estimated.

Table 5 describes the non-time-varying parameters specific to the factors: the AR coefficients φ_1 and φ_2, and the volatilities σ_ξ of the factor volatilities. Similarly, medians and standard deviations are listed for each parameter and factor. This table indicates that the median estimates of the factor AR coefficients φ also have complex characteristic roots and have average stochastic cycles of about 7 days. The volatilities σ_ξ of the factor volatilities are roughly an order of magnitude smaller than the volatilities σ_ζ of the idiosyncratic volatilities. Since we specify the factors to represent the structural commonalities between the returns and since we expect structural changes to be more persistent, it is reasonable that the volatilities of the factor volatilities are smaller.

The estimates of the factors are illustrated in figure 1. This figure shows the medians and 90% confidence bands computed at each point in time across MCMC draws. The confidence bands are quite narrow and indicate that the factors are tightly estimated. In addition, the factors are stationary and exhibit a clear pattern of volatility clustering around notable market events such as the Asian crisis of 1997–1998 and the current global financial crisis. The average correlations between the returns and the medians of the first and second factors are 0.33 and 0.06, respectively, and the maximum correlation between either factor and any country is 0.43. This suggests that the factors reflect global economic forces and that it is not sufficient to proxy for either of the factors by using a major stock market such as the U.S. Furthermore, the second factor is more correlated with Europe, with a correlation of 0.17. This

	a		ϕ_1		ϕ_2		σ		σ_{η_1}		σ_{η_2}		σ_ζ	
	Med.	Std.	Med.	Std.	Med.	Std.	Med.	Std.	Med.	Std.	Med.	Std.	Med.	Std.
U.S.	0.040	0.010	0.808	0.044	-0.570	0.012	0.061	0.003	0.278	0.043	0.445	0.081	2.389	0.039
Canada	0.068	0.025	0.873	0.059	-0.463	0.024	0.035	0.003	0.287	0.045	0.414	0.068	2.909	0.051
Mexico	0.049	0.004	0.782	0.015	-0.477	0.020	0.036	0.002	0.568	0.107	0.723	0.111	3.438	0.059
Brazil	-0.083	0.032	0.761	0.004	-0.397	0.005	0.016	0.004	0.869	0.156	1.094	0.160	4.545	0.144
Argentina	0.057	0.019	0.571	0.021	-0.375	0.023	0.045	0.003	0.685	0.170	1.139	0.174	3.734	0.075
U.K.	-0.172	0.028	1.068	0.074	-0.749	0.091	0.028	0.005	0.368	0.062	0.454	0.071	2.873	0.050
Germany	-0.024	0.008	0.835	0.026	-0.564	0.040	0.114	0.005	0.352	0.069	0.469	0.078	1.883	0.035
France	-0.108	0.006	0.974	0.073	-0.642	0.076	0.037	0.004	0.387	0.071	0.479	0.080	2.802	0.045
Sweden	-0.160	0.053	0.849	0.075	-0.562	0.066	0.023	0.004	0.491	0.093	0.627	0.113	3.460	0.073
Japan	-0.176	0.010	0.876	0.042	-0.472	0.037	0.047	0.003	0.536	0.084	0.840	0.126	3.089	0.048
Hong Kong	-0.060	0.035	0.740	0.019	-0.388	0.025	0.018	0.003	0.473	0.073	0.727	0.114	3.819	0.096
Malaysia	0.042	0.005	0.739	0.002	-0.365	0.002	0.015	0.004	0.390	0.060	0.535	0.086	3.998	0.174
Singapore	0.034	0.013	0.701	0.008	-0.378	0.003	0.024	0.003	0.408	0.068	0.571	0.092	3.556	0.083
India	-0.107	0.027	0.771	0.010	-0.399	0.013	0.033	0.002	0.706	0.103	0.848	0.112	3.768	0.060
Australia	0.175	0.018	0.597	0.007	-0.271	0.006	0.035	0.003	0.439	0.075	0.611	0.089	3.446	0.068

Table 4. Posterior estimates of non-time-varying parameters for all returns i for the 2-factor model with 2 lags for each of the idiosyncratic and factor autoregressive equations. Parameters are expressed in terms of daily percentage changes. Medians and standard deviations are listed for all parameters. Posterior draws are obtained by using the Gibbs sampler to produce a chain of 15,000 draws. We save one in every 5 draws and discard the initial 500 draws, leaving a final sample of 2,500 draws.

	φ_1		φ_2		σ_ξ	
	Med.	Std.	Med.	Std.	Med.	Std.
Factor 1	0.887	0.015	-0.455	0.021	0.127	0.022
Factor 2	0.810	0.022	-0.468	0.019	0.079	0.020

Table 5. Posterior estimates of non-time-varying parameters for all factors j. Medians and standard deviations are listed for all parameters.

suggests that the first factor may be more of a global factor while the second factor may be slightly more of a European factor. It is also noteworthy that the correlation between the second factor and Argentina is -0.34 and that India is the least correlated with the factors of any country, with respective correlations of 0.09 and 0.05.

Figure 2 illustrates the stochastic volatilities g of the factors. The factor volatilities clearly reflect the volatility clustering present in the factors through increases in volatility during significant market events. They also exhibit no discernible trends but are quite persistent. In fact, the factor volatilities are far more persistent than the idiosyncratic volatilities, which are not shown but demonstrate a far greater amount of variation (evident also by comparing σ_ζ and σ_ξ).

Since we are primarily interested in studying the time-varying co-movements of equity returns, it is essential that our model generates correlation estimates that are comparable to the data before we can proceed to make any further claims. Figure 3 illustrates both the sample average world correlation and the model-based estimate of average world correlation. The sample correlations are computed by using a 6-month moving window for each country. The model estimates of correlation are quite volatile, so they are passed through a 6-month moving average filter to extract the longer term behavior. The average world correlations are then computed as the equally-weighted average of the correlations between all pair-wise combinations of countries in our sample.

As can be seen in this figure, the sample world correlation and the model estimate of world correlation are quite similar and clearly demonstrate a high degree of covariation (correlation is 83%), though the model estimate of world correlation does tend to be a little larger than the sample correlation. Since our estimation procedure is likelihood based and thus does not try to explicitly match any particular moments, it is noteworthy that our model generates a similar time series of world average correlation. It is also impor-

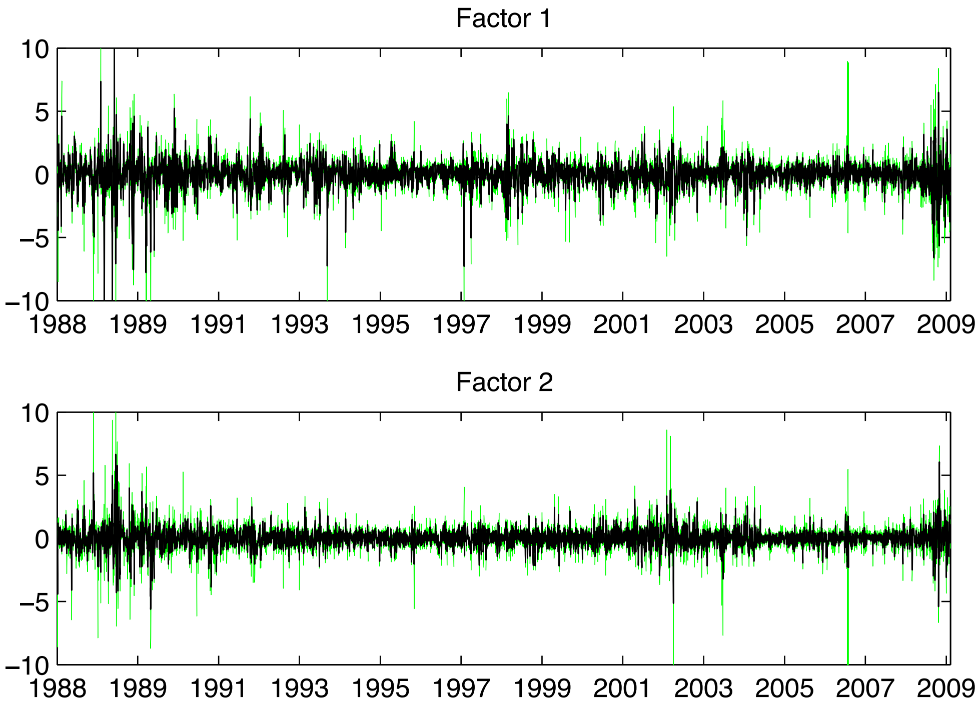

Figure 1. Posterior estimates of factors. This figure illustrates the medians and 90% confidence bands computed at each point in time across MCMC draws for each factor. The medians are depicted by thick black lines, and the confidence bands are depicted by thin green lines.

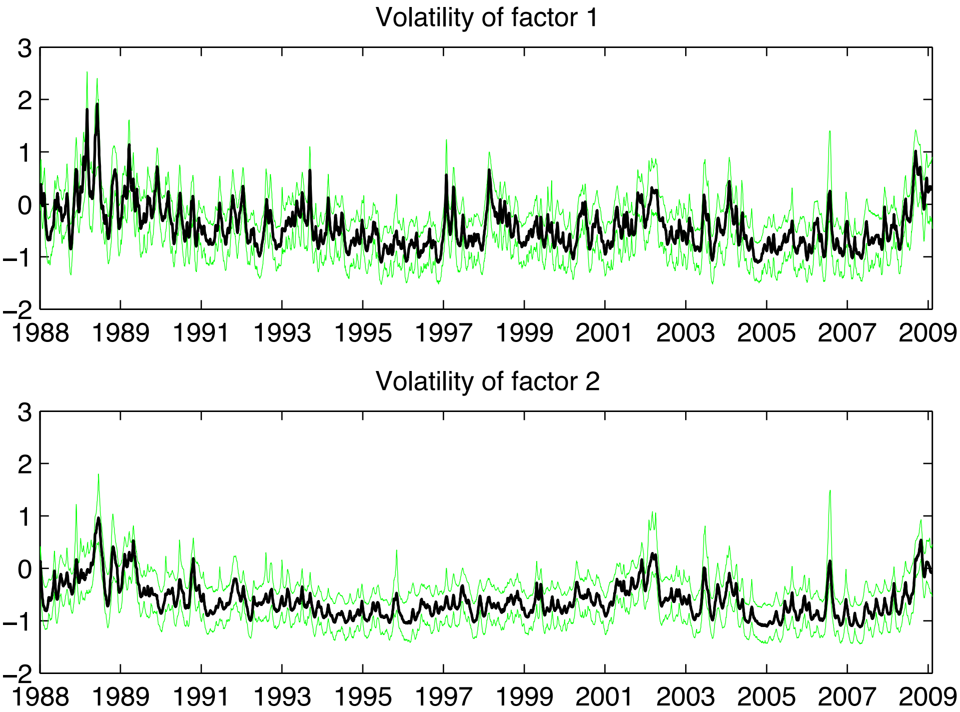

Figure 2. Posterior estimates of factor volatilities. This figure illustrates the medians and 90% confidence bands computed at each point in time across MCMC draws for the stochastic volatility g of each factor. The medians are depicted by thick black lines, and the confidence bands are depicted by thin green lines.

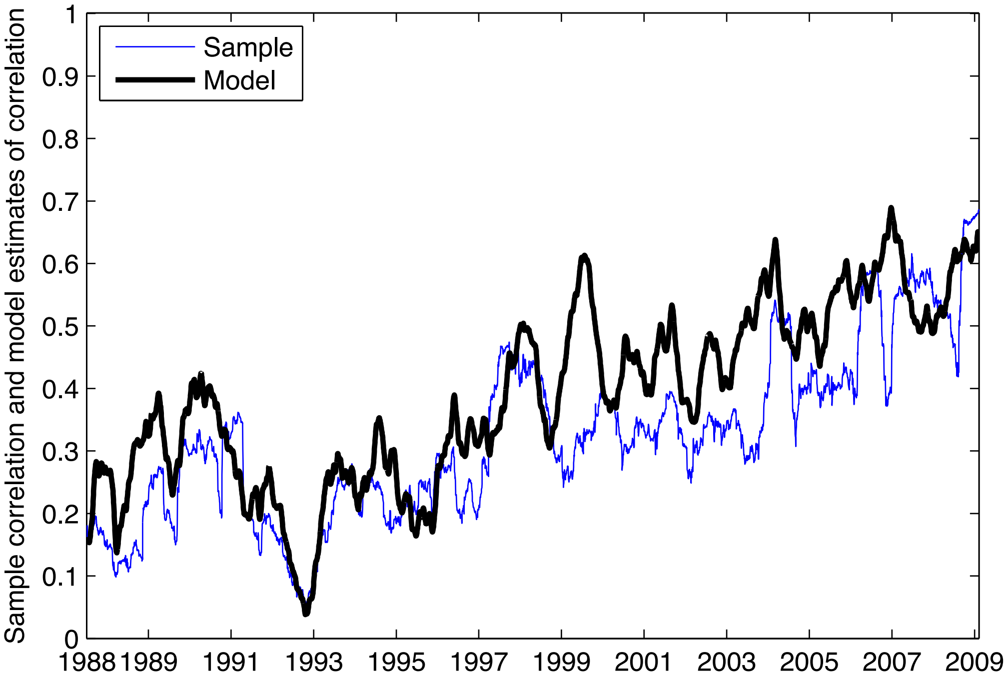

Figure 3. Average world correlation between 1988 and 2009. This figure illustrates both the 6-month moving average of the model-based estimate of average world correlation, and the 6-month moving average of the sample average world correlation. Average world correlation is computed as the equally-weighted average of the correlations between all pair-wise combinations of countries in our sample.

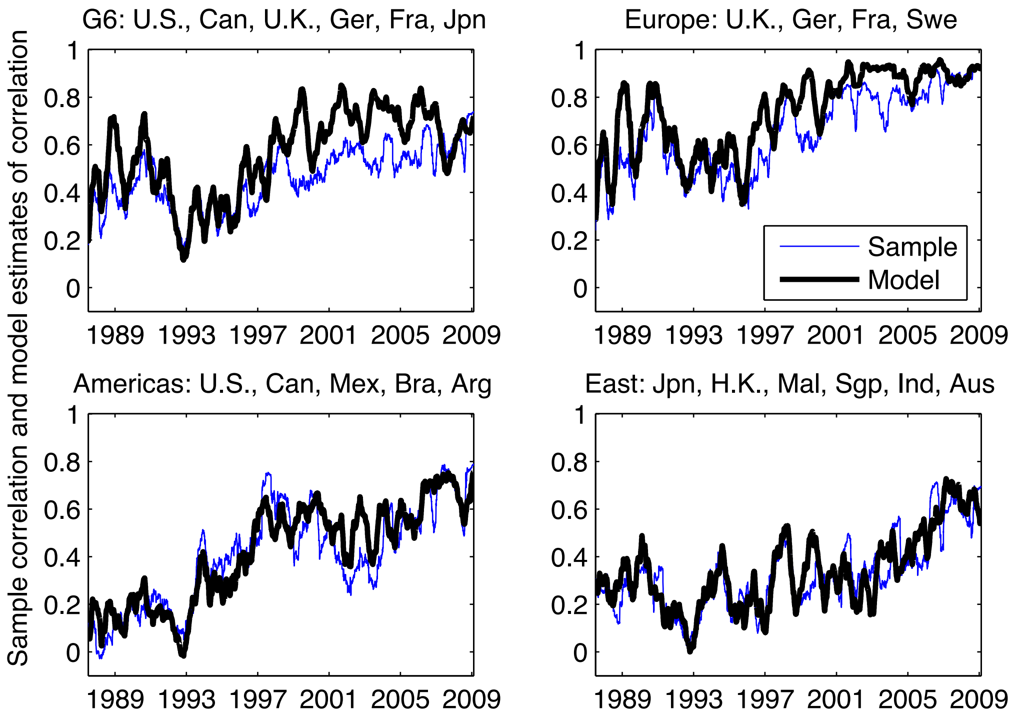

Figure 4. Average regional correlations between 1988 and 2009. This figure illustrates both the 6-month moving averages of the model-based estimates of average regional correlations, and the 6-month moving averages of the sample average regional correlations. Average regional correlation is computed as the equally-weighted average of the correlations between all pair-wise combinations of countries in that particular region. The regions are the G6 (U.S., Canada, U.K., Germany, France and Japan), Europe (U.K., Germany, France and Sweden), the Americas (U.S., Canada, Mexico, Brazil and Argentina) and the East (Japan, Hong Kong, Malaysia, Singapore, India and Australia).

tant to mention that the sample correlation does not necessarily represent the 'true' correlation, but we do expect and are reassured to see a great deal of overlap.

Similarly, figure 4 illustrates both the sample average correlations and the model-based estimates of average correlations between countries in four different regions. The regions are the G6 (U.S., Canada, U.K., Germany, France and Japan), Europe (U.K., Germany, France and Sweden), the Americas (U.S., Canada, Mexico, Brazil and Argentina) and the East (Japan, Hong Kong, Malaysia, Singapore, India and Australia). As with the world correlations, this figure also illustrates a very similar fit between the model estimates of correlation and the sample correlations, particularly for the Americas and the East.

These figures 3 and 4 suggest that our model fits the data well and can generate reasonable patterns of equity co-movements. Also regarding the fit of our model, we compute an average R^2 across countries of 75%. This statistic indicates that our model can account for a significant amount of the variation in returns.

5.1 Integration

Since our model seems to fit the data quite well, we proceed in this section to investigate the model's implications concerning financial integration. The correlations illustrated in figures 3 and 4 demonstrate that international equity correlations have trended upward during the past 21 years. To properly understand this increase in correlation with respect to our model, we explore the role of the factor loadings. Figure 5 depicts 6-month moving averages of our estimates of the average world factor loadings for each factor. The average world factor loadings are computed as the equally-weighted averages of the mean factor loadings for each factor and all countries.

While there is some variation, the average world loadings for each factor demonstrate a clear upward trend throughout our sample. This pattern is evident not only in the average world loadings but also in the average regional loadings. Figure 6 depicts 6-month moving averages of our estimates of the average regional factor loadings for each factor. As before, we consider the G6, Europe, the Americas and the East as the four regions.

These figures indicate that the consistent increase in the average factor loadings is both a global and regional phenomenon. As a result, national stock markets are loading more heavily on the common factors and are thus

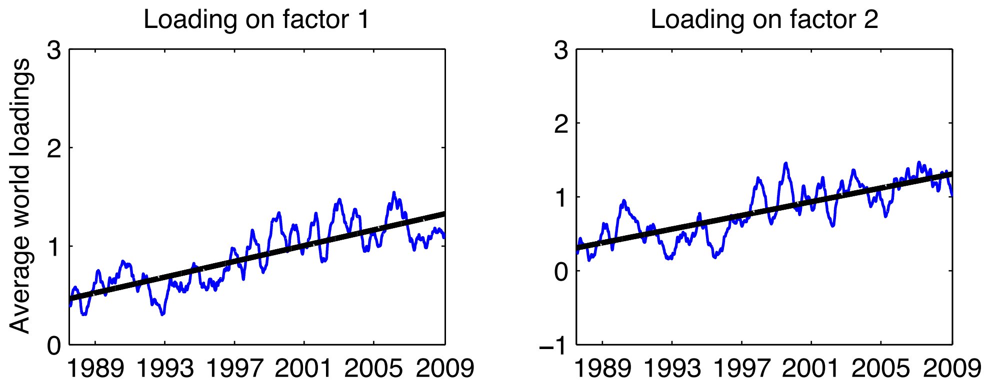

Figure 5. Average world factor loadings between 1988 and 2009. This figure illustrates 6-month moving averages of the model-based estimates of the average world factor loadings for each factor. The average world factor loadings are computed as the equally-weighted averages of the mean factor loadings for each factor and all countries. The simple linear trends are also illustrated.

becoming more exposed to common sources of variation. As these common factors account for a greater proportion of the variation of returns, we expect the proportion of variation explained by the idiosyncratic terms to decrease, and this is precisely what has happened both globally and regionally. Figures 7 and 8 illustrate the 6-month moving averages of the proportion of return variation explained by the idiosyncratic terms ϵ. These figures document a consistent downward trend of the role of idiosyncratic variation during our sample.

We have shown that the loadings on each factor display a clear upward trend and the proportion of variation explained by the idiosyncratic terms exhibits a downward trend. Each of these trends contributes to rising correlations during the past 21 years, but they are not two distinct phenomena. All else being equal, greater loadings on common factors imply a decline in the variation explained by the idiosyncratic terms. In other words, when the correlation between international equity returns increases and there is no clear trend in return volatility, the role of idiosyncratic variation must decline. Consequently, these findings are both the manifestation of an empirical regularity that we view as a central contribution of our paper: over the course of our sample, international stock market returns have become increasingly exposed to common sources of variation. Since the factor volatilities demon-

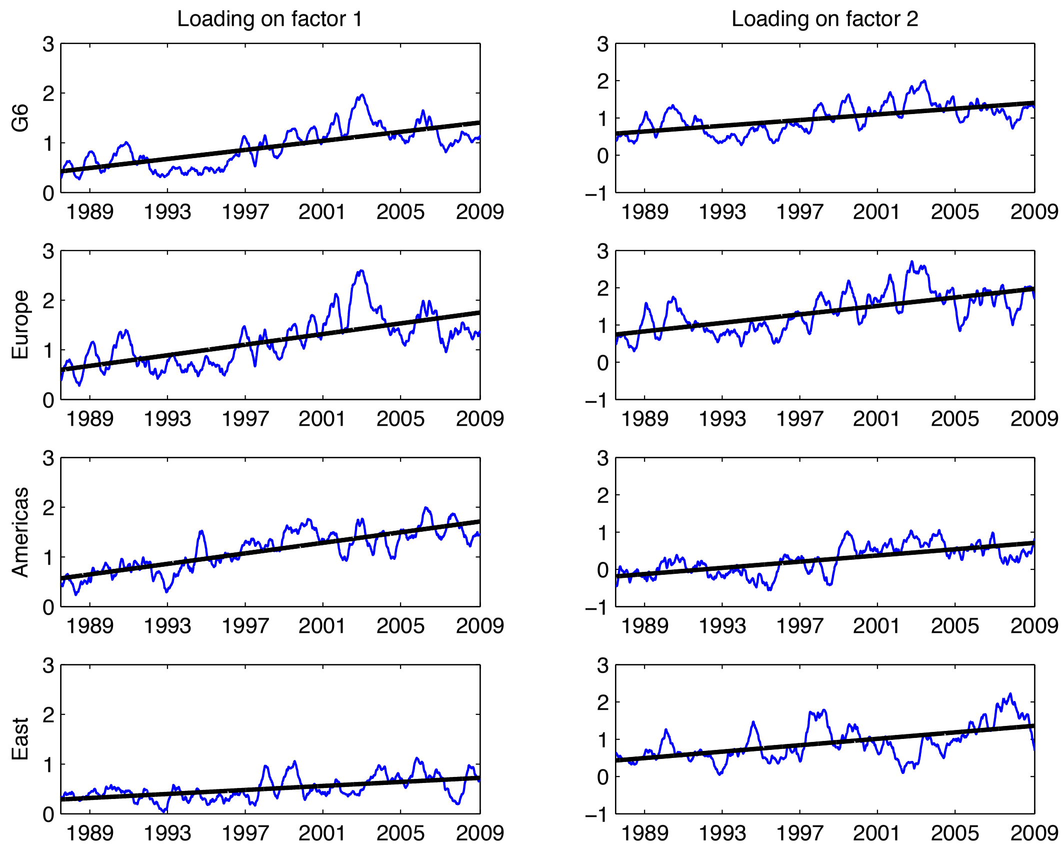

Figure 6. Average regional factor loadings between 1988 and 2009. This figure illustrates 6-month moving averages of the model-based estimates of the average regional factor loadings for each factor. The average regional factor loadings are computed as the equally-weighted averages of the mean factor loadings for each factor for all the countries in that particular region. The regions are the G6 (U.S., Canada, U.K., Germany, France and Japan), Europe (U.K., Germany, France and Sweden), the Americas (U.S., Canada, Mexico, Brazil and Argentina) and the East (Japan, Hong Kong, Malaysia, Singapore, India and Australia). The simple linear trends are also illustrated.

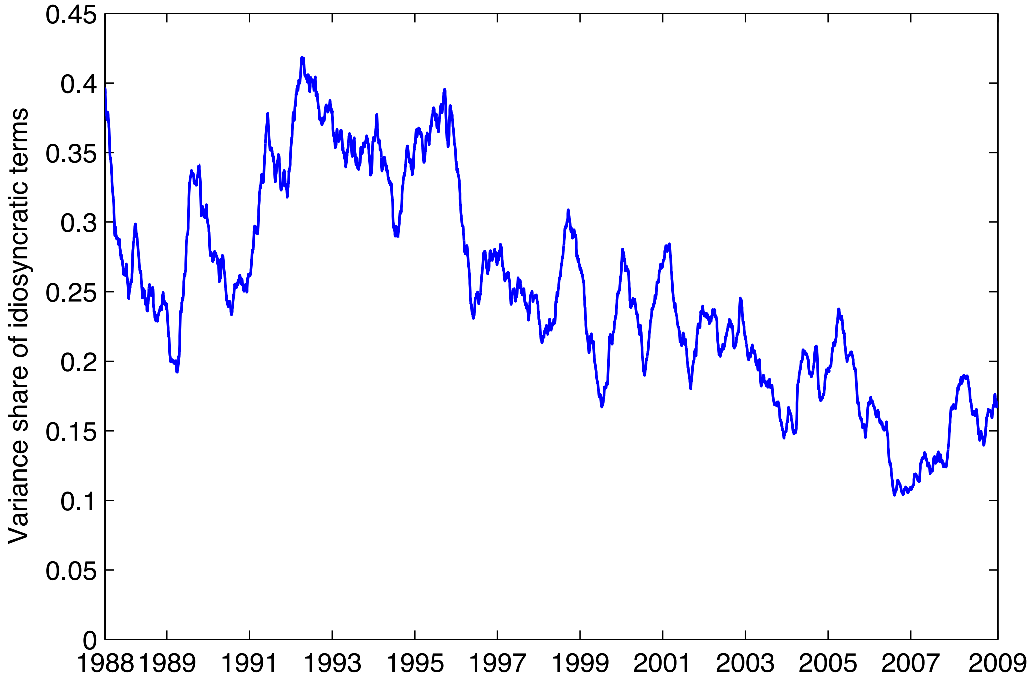

Figure 7. Average world variance share of idiosyncratic terms between 1988 and 2009. This figure illustrates 6-month moving average of the model-based estimate of the average world variance share of the idiosyncratic terms. The variance share of the idiosyncratic terms is the proportion of return i variation that is explained by the idiosyncratic term ϵ_i. The average world variance share is then the average of these shares at each given time across all countries.

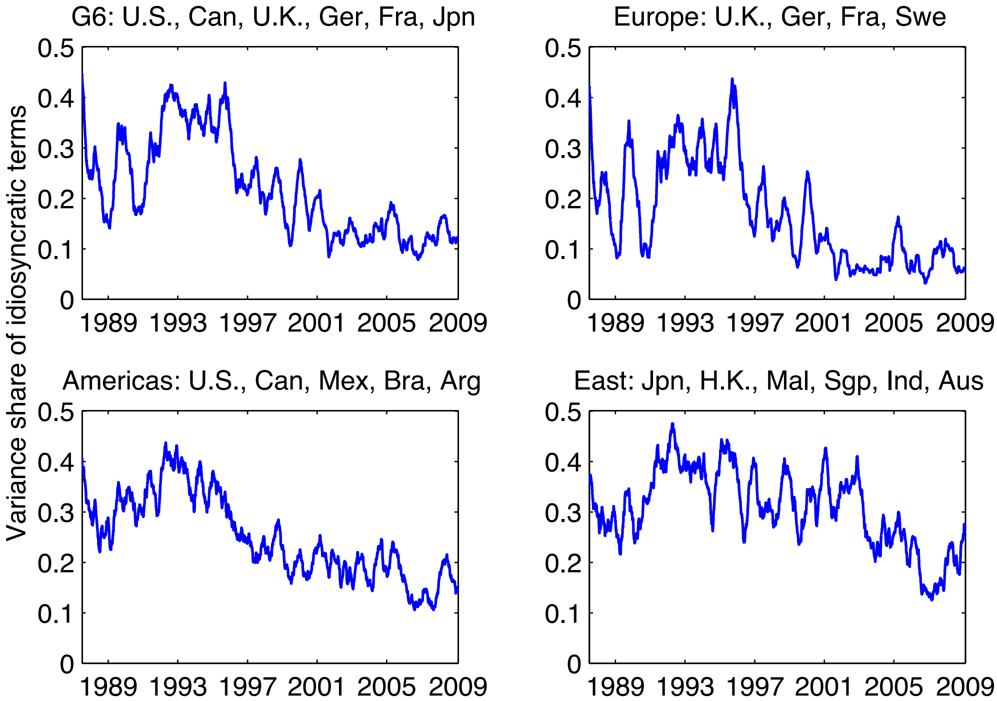

Figure 8. Average regional variance shares of idiosyncratic terms between 1988 and 2009. This figure illustrates 6-month moving averages of the model-based estimates of the average regional variance shares of the idiosyncratic terms. The variance share of the idiosyncratic terms is the proportion of return i variation that is explained by the idiosyncratic term ϵ_i. The average regional variance share is then the average of these shares at each given time across all countries in that particular region. The regions are the G6 (U.S., Canada, U.K., Germany, France and Japan), Europe (U.K., Germany, France and Sweden), the Americas (U.S., Canada, Mexico, Brazil and Argentina) and the East (Japan, Hong Kong, Malaysia, Singapore, India and Australia).

strate no clear trend, the entire low-frequency change in equity correlations is due to changing factor loadings. This finding has significant implications for economic modeling. In particular, the systematic risk that is embodied in the factor volatilities is not what is driving correlations. Rather, to understand the changes in correlation, it is necessary to understand why the risk exposures (i.e. loadings) have changed.

5.2 Contagion

In addition to investigating financial integration, we use our model to shed light on issues of contagion. Financial contagion can describe the co-movement of international equity returns during periods of crisis, but, as argued in the literature review, such co-movements may also reflect a general state of interdependence between the markets involved. To properly investigate the presence of contagion, we must precisely define contagion with respect to our model and be able to differentiate it from interdependence.

Recall that Forbes and Rigobon (2002) defined contagion as any significant increase in cross-market co-movements after a shock. This definition, however, is not sufficient in the context of our model. Since we explicitly model time-varying correlations, an increase in correlation may simply represent a structural increase in factor volatility or factor loadings and not represent evidence of contagion. Instead, we adopt the convention of Bekaert, Harvey, and Ng (2005) and define contagion as correlation between markets that cannot be explained by economic fundamentals, that is, 'excess' correlation. Specifically, we define contagion between markets i and s as correlation between the model residuals ϵ_{it} and ϵ_{st}. This definition differentiates the structural interdependence between markets that is captured by the time-varying factors and loadings from financial contagion that is captured by co-movements of the idiosyncratic residuals. While Bekaert et al. used this definition of contagion in the context of a factor model where the two factors were actual market returns, such a definition is also appropriate for our model with statistical factors since we interpret our factors as capturing global economic and financial commonalities.

Defining contagion as excess correlation has intuitive appeal, but it is important to mention that excess correlation may also represent model misspecification. That is, there may be other factors or different mechanisms that are important in explaining the covariation of equity returns that we have neglected. Though this is a possibility, we argue that our dynamic model utilizes the appropriate number of factors, fits the data well and captures many of the salient characteristics of returns.

Since financial contagion is intimately connected with instances of financial crisis, we briefly investigate two crises with respect to our model in the remainder of this section. In particular, we consider the Mexican crisis of 1994 and the Asian crisis of 1997.

5.2.1 Mexican crisis of 1994

We first turn our attention to the Mexican crisis of 1994, the so-called 'Tequila' crisis. As described in Forbes and Rigobon (2002), the Mexican government, in response to a balance of payments crisis, abandoned its exchange rate regime for the peso on December 19, 1994. This policy shift quickly lead to the devaluation of the peso and a steep drop in the Mexican stock market, which then spilled over and began to affect many other Latin American markets. Argentina and Brazil were hit particularly hard by the situation in Mexico, as explained by Calvo and Reinhart (1996):

> "In Latin America, Argentina and Brazil came under the most severe pressures. Between December 1994 and March 1995, Argentina's banking system lost 18 percent of its deposits and about one-half of its foreign exchange reserves... At the height of the crisis, Brazil was compelled to implement measures to stimulate capital inflows by reducing or eliminating existing taxes on foreign purchases of stocks and bonds." (p. 151)

The significant effect of the Mexican crisis on the equity markets of Argentina and Brazil is clearly evident in figure 9, which shows that the markets of Argentina and Brazil lost about 50% of their value in the span of the three months following December 1994. The U.S. market index is also plotted for comparison. Although the Latin American markets were still depressed, many economists consider the Mexican crisis to end in April 1994.

To properly address the claim of financial contagion between Mexico and Argentina and Brazil, we examine the pair-wise excess correlations between these markets between January 3, 1994 to April 30, 1996. Notice that we examine approximately 1 year before and after the duration of the Mexican crisis to put the changes of the excess correlation in perspective. Figure 10 depicts the excess correlations between Mexico and Argentina, Mexico and Brazil, Mexico and the U.S., and the average excess correlation between

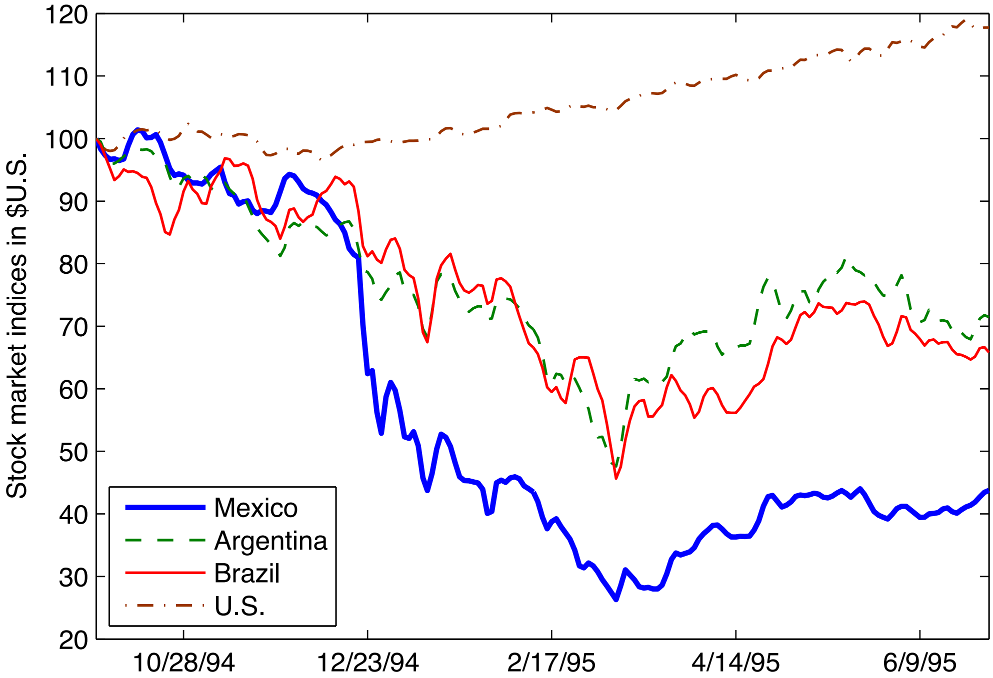

Figure 9. Stock market indices during the 1994 Mexican crisis. This figure illustrates stock market indices for Mexico, Argentina, Brazil and the U.S. around the time of the December 1994 crash in the Mexican market. Indices are set to 100 on October 3, 1994, and are based on U.S. dollar values.

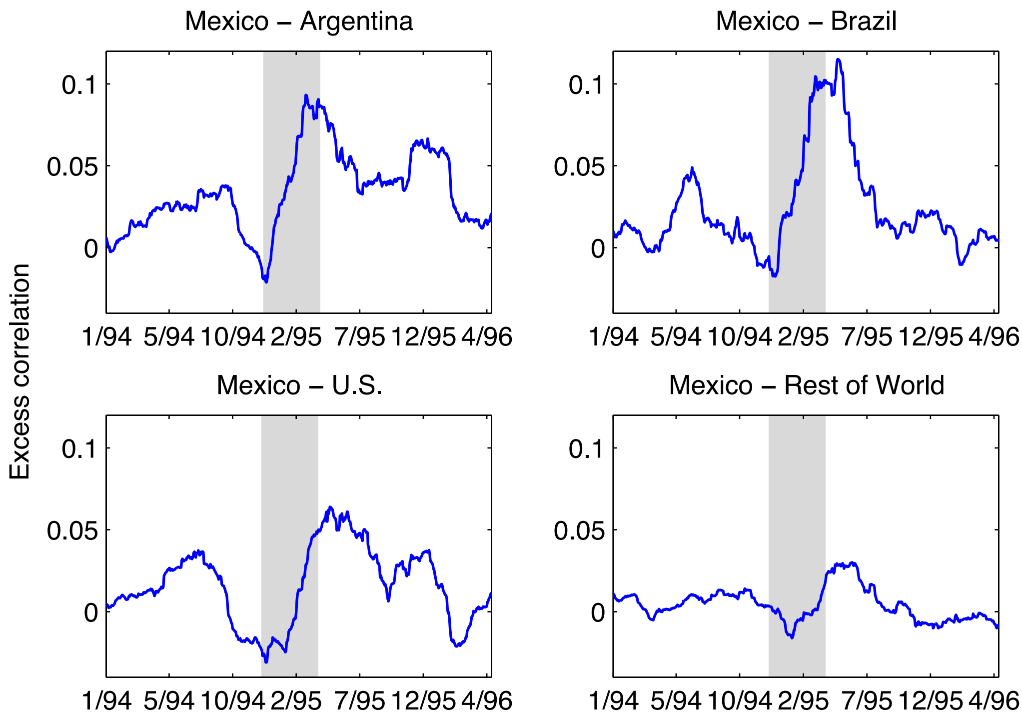

Figure 10. Excess correlations during the 1994 Mexican crisis. This figure illustrates 3-month moving averages of the excess correlations between Mexico and Argentina, Mexico and Brazil, Mexico and the U.S., and Mexico and the rest of the world. The shaded regions indicate the duration of the Mexican crisis from December 1994 to April 1995.

Mexico and all the other markets in our sample besides Argentina, Brazil and the U.S. The excess correlations plotted in this figure are 3-month moving averages to accentuate the trends in the high frequency excess correlation estimates from the model.

As is clearly evident in figure 10, the excess correlations between all the markets examined increase significantly during the crisis period in question, despite the slight lag introduced by the 3-month moving average. Since our factor model specifically captures systematic time variation in correlations, this increase in excess correlation documents the existence of additional spillovers, particularly between Mexico and Argentina and between Mexico and Brazil. It is also important to notice that the excess correlation between Mexico and the rest of the world increased much less than that of Argentina and Brazil. This finding supports the claim in the literature that financial contagion affects nearby markets more strongly than distant markets (see, e.g., Calvo and Reinhart, 1996).

In summary, our estimates document a significant contagion effect between Mexico and Argentina and Mexico and Brazil, and a smaller contagion effect between Mexico and the U.S. and the rest of the world. Our findings also lend weight to the importance of the geographical region in the event of financial contagion.

5.2.2 Asian crisis of 1997

In this section, we explore the role of contagion in the 1997 Asian crisis. In late 1997, after experiencing a decade of explosive economic growth and sharply rising asset values, the economies of South-East Asia experienced a particularly severe and systematic financial crisis, leading to capital flight, disrupted credit allocation, dramatic currency devaluations and steep declines in equity prices. Subsequent research (e.g. Moreno et al., 1998; Lindgren et al., 1999; Mishkin, 1999) has indicated the cause and extent of the crisis to be largely the result of pervasive financial and corporate sector weaknesses and macroeconomic vulnerabilities. Large capital inflows helped fuel rapid credit expansion, lowering the quality of credit and leading to asset price inflation. These inflated asset prices encouraged further capital inflows and lending, often by weakly supervised non-bank financial institutions, which allowed excessive risk taking and further inflated asset prices.

The crisis was triggered by the floating and subsequent devaluation of the Thai currency in July 1997, which lead to sharp depreciations of most

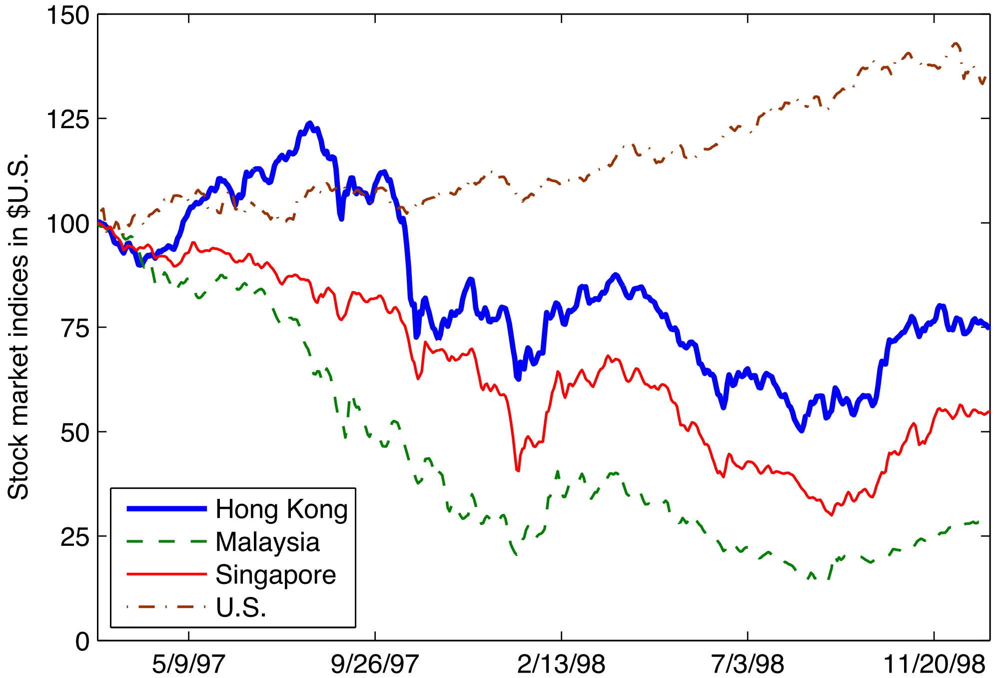

Figure 11. Stock market indices during the 1997 Asian crisis. This figure illustrates stock market indices for Hong Kong, Malaysia, Singapore and the U.S. around the time of the October 1997 crash in the Hong Kong market. Indices are set to 100 on March 3, 1997, and are based on U.S. dollar values.

currencies in the region. This in turn lead to bank runs, rapid withdrawals of foreign private capital, and severe stock market declines. Although Thailand is not specifically in our sample, we can see the significant effect of the Asian crisis on the regional stock markets in figure 11. This figure shows that the markets of Hong Kong, Malaysia and Singapore lost between 25% and 75% of their value in the year following the start of the crisis in July 1997. Although the Asian markets were still quite depressed, many economists consider the Asian crisis to have ended by roughly the end of 1998.

As in our analysis of the 1994 Mexican crisis, we investigate the existence of financial contagion during the 1997 Asian crisis by examining excess correlations between these markets. Figure 12 depicts the excess correlations between Hong Kong and Malaysia, Hong Kong and Singapore, Malaysia and Singapore, and these South-East Asian markets (Hong Kong, Malaysia and

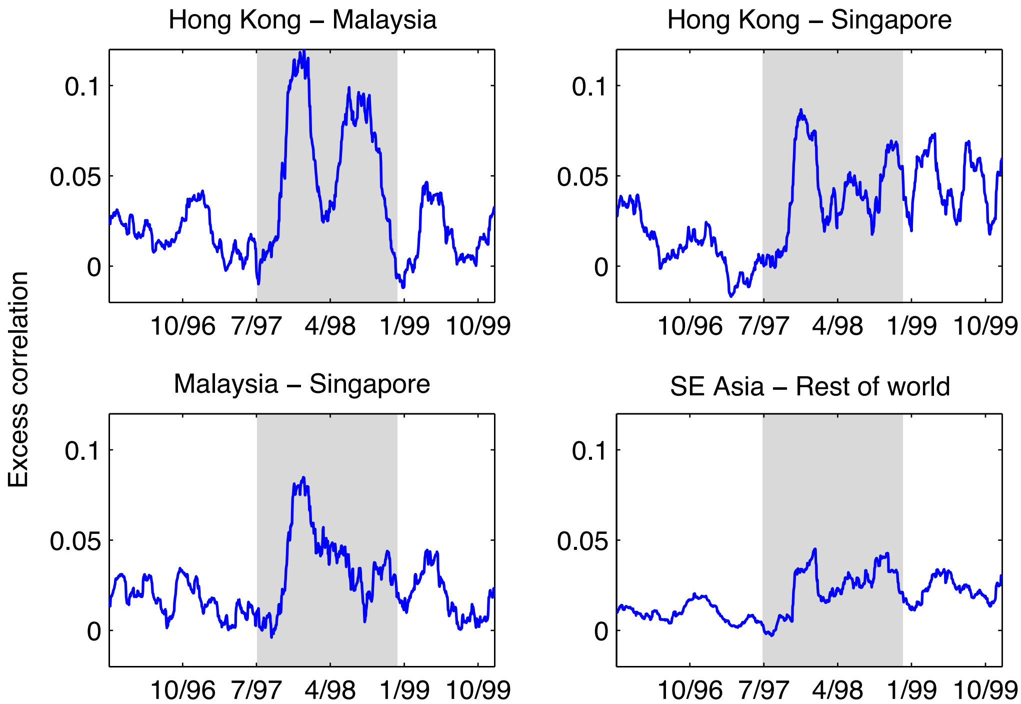

Figure 12. Excess correlations during the 1997 Asian crisis. This figure illustrates 3-month moving averages of the excess correlations between Hong Kong and Malaysia, Hong Kong and Singapore, Malaysia and Singapore, and these South-East Asian markets (Hong Kong, Malaysia and Singapore) and the rest of the world. The shaded regions indicate the duration of the Asian crisis from July 1997 to the end of 1998.

Singapore) and the rest of the world between January 1, 1996 and December 31, 1999. Notice again that we include approximately 1 year before and after the duration of the Asian crisis to put the changes in excess correlation in perspective.

Examining figure 12 of all the regional excess correlations, we notice a distinct spike in October 1997. During this month, stock market indices across the region suffered dramatic declines as bank-lending rates soared to fend off speculative currency attacks. As can be seen in figure 11, the effect on the Hong Kong market was particularly severe, as the Hang Seng index lost about 25% of its value in October alone. These precipitous declines in the regional equity markets correspond to significant increases in excess correlations, indicating the presence of financially substantial spillovers between these markets during the period of crisis. As the crisis waned, the excess correlations generally decreased and resumed pre-crisis levels. This pattern is especially clear between Hong Kong and Malaysia and between Malaysia and Singapore. The excess correlation between Hong Kong and Singapore, however, indicates a far more persistent increase in excess correlation that takes much longer to die down. Lastly, it is important to notice that the excess correlation between South-East Asia and the rest of the world increased much less than the intra-regional correlations, lending further support to the claim that financial contagion is largely a regional phenomenon.[4]

We may possibly attribute the post-crisis decrease in excess correlations to the efforts of national governments in the region to establish state controlled entities to purchase and restructure non-performing assets and re-capitalize banks. Such institutions, in conjunction with policies required by the International Monetary Fund, may have helped to reduce the systemic regional exposure to external shocks and may partially explain the drop in excess correlations.

[4]It is worth noting that the 1997 Asian crisis had a significant effect on the Brazilian market, as it lost nearly 20% during October of 1997. However, the excess correlation between Brazil and South-East Asia (not shown) does not indicate the significant increase that we observe between the countries within South-East Asia. This finding suggests that the impact on Brazil was evidence primarily of financial and economic interdependence and not of contagion as it is defined here.

6 Conclusion

Our study employs a dynamic, multivariate factor model with time-varying factor loadings and stochastic volatility to study the time variation of correlations between 15 major international stock indices. The approach that we adopt has numerous advantages and allows us to produce an empirical characterization of international stock return co-movements that is superior in scope and detail compared to existing studies.

The model specification is quite parsimonious as it utilizes just two factors to capture the commonalities that exist across a diverse sample of equity returns. Despite the relatively small number of factors, the inclusion of time-varying factor loadings and stochastic volatility allows us to account for a wide range of dynamics not captured by more restrictive models. Furthermore, although our model requires the estimation of latent time-varying factors, time-varying factor loadings and stochastic volatilities across a relatively large cross-section of assets, the Bayesian Markov chain Monte Carlo estimation technique that we employ circumvents the curse of dimensionality typically encountered by standard likelihood based methods and is thus well suited for our task.

Our model estimates reveal several interesting empirical facts. First, we show that average global and regional correlations have risen steadily over the past 21 years. We also observe a similar upward trend in the factor loadings and a corresponding downward trend in the role of idiosyncratic volatility, both at the global and regional levels. We argue that these findings provide strong evidence of greater stock market interdependence as international stock market indices have become increasingly exposed to common sources of variation.

Our model estimates also yield insights into the existence and characterization of financial contagion. We define contagion between two markets in our model as excess correlation, that is, co-movement between the idiosyncratic terms of the respective markets. This definition is well-suited to disentangle the structural interdependence of markets, in the sense of Forbes and Rigobon (2002), from financial contagion. Using this definition, we investigate the existence of contagion in the context of two major financial crises: the Mexican crisis of 1994 and the Asian crisis of 1997. We document significant increases in excess correlations during both of these financial crises that generally dissipate as the crises end. The magnitudes of these excess correlation spikes suggest there exists a substantial amount of contagion during the crises, especially region-wide.

In characterizing and providing evidence of these important empirical phenomena, we see avenues for further interesting research. One extension of our analysis would involve the application of the model to a portfolio choice problem. The computation of robust and accurate variance-covariance matrices between assets is a vital component of any investors decision-making process. Within the particular context of international equity markets, a proper understanding of correlation dynamics is important because international investors often invest in foreign assets to diversify risk away from the domestic market. Indeed, the past has shown that many firms without quality correlation estimates have suffered catastrophic losses during periods of crisis. As argued in Bookstaber (1997) and Greenspan (1999), the benefits of international diversification may be significantly reduced during periods of crisis as all correlations tend to increase. Since this model can produce quality estimates of time-varying correlations between assets during periods of financial crisis, it is a potentially successful candidate in a portfolio choice application. Further research is also required to further discern the underlying sources of stock market integration and contagion.

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