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Contagion: An Empirical Test

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Abstract: Using the conditional Capital Asset Pricing Model (CAPM), this paper tests for the existence and pattern of contagion and capital market integration in global equity markets. *Contagion* is defined as significant excess conditional correlation among different countries' asset returns above what could be explained by economic fundamentals (systematic risks). *Capital market integration* is defined as the situation in which only systematic risks are priced. The paper uses a panel of sixteen countries, divided into three blocs: Asia, Latin America, and Germany-U.K.-U.S., for the period from 1990 through 1999. The results show evidence of contagion and capital market integration. In addition, contagion is found to be a regional phenomenon.

Keywords: contagion, CAPM, excess correlation

JEL classification: G12, G14, G15, F30

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1 Introduction

The occurrence of several major financial crises in the late 1990s had large effects on economic performance, asset valuation, and the efficiency of the global financial markets in sharing risk. As a result policy makers, the media, and academics have increasingly focused their attention on the spread of crises (shocks) from country to country. This phenomenon is often called (sometimes somewhat loosely) *contagion*.

Although interest in contagion has never been higher, there is still no generally accepted definition of contagion[1], let alone understanding of the phenomenon. Contagion is sometimes referred to as co-movements among countries that cannot be explained by *economic fundamentals* (Masson (1998)). This concept is similar to the notion of excess co-movements in Pindyck and Rotemberg (1990). In this paper I follow this definition, and more specifically, define *contagion* as significant excess conditional correlations among countries asset returns beyond what could be explained by *economic fundamentals* or *systematic risks*. With this definition, I test both for the existence and pattern of contagion in global equity markets.

Empirical studies of contagion have exploded in the past few years, with each study using different testing methodologies and data samples.[2] Despite the differences in methodologies, most studies have two controversial features in common. The first feature is that the proxies for economic fundamentals are not defined with reference to a theory. From the way we define contagion, its existence depends on the economic fundamentals used. Most empirical studies tend to choose fundamentals somewhat arbitrarily, using macroeconomic variables, dummies for important events, and time trends (e.g., Valdes (1997) and Baig and Goldfajn (1999)). The cost of not appropriately controlling for economic fundamentals is that we might pick up

[1]See Masson (1998) and Rigobon (2002) for detail discussion. Calvo and Reinhart (1996), Park and Song (2001), and Forbes and Rigobon (2002) refer to contagion as significant increases in asset returns co-movements, while Valdes (1997), Baig and Goldfajn (1999), Connolly and Wang (2002), and Bekaert, Harvey, and Ng (2003) refer to it in a narrower definition as significant increases in asset co-movement that cannot be explained by economic fundamentals. Edwards and Susmel (2001, 2003) refer to contagion as asset volatility co-movements. In addition, Sachs, Tornell, and Velasco (1996), Eichengreen, Rose, and Wyplosz (1996), Gregorio and Valdes (2001), and Kaminsky and Reinhart (2000) define contagion as a situation in which a crisis in one country lead to a higher probability of a crisis occurring in another country.

[2]See Claessens, Dornbusch, and Park (2001) for a comprehensive review of the literature.

spurious relationships that are thought to be evidence of contagion. For example, a change in the U.S. monetary policy may induce equity markets in other countries to react in the same way. Masson (1998) provides detail discussion on this issue.

To provide a framework to control for economic fundamentals, I rely on the Capital Asset Pricing Model (CAPM). The economic fundamental under the CAPM is the world market portfolio. Evidence of contagion is the significance conditional correlations of idiosyncratic risk–the part that cannot be explained by the world market portfolio.

The second feature of these studies relates to the modeling of economic time-series. It is well known that most economic time-series exhibit time dependencies in the second moment (Mandelbrot (1963); Fama (1965)). As an illustration of time dependency, Figure 1 shows plots of rolling cross country correlations in equity markets. It is evident from the figure that equity returns exhibit time-varying correlations. Therefore, in order to make sense of the empirical results, it is important that we properly take this property into account.[3] In this paper I use a multivariate General Autoregressive Conditional Heteroscedastic (GARCH) model, an extension of work developed by Engle (1982) and Bollerslev (1986), to model the conditional covariance matrix of idiosyncratic risks jointly with a univariate GARCH model for the market portfolio volatility. With a complete statistical model of the conditional covariance matrix of asset returns–the world market portfolio and idiosyncratic parts, I test for contagion jointly among different countries.[4]

Another possible problem relating to the use of the CAPM to price assets for all countries is the assumption of capital market integration. *Capital market integration* is defined as a situation in which only systematic risks are priced (King, Sentana, and Wadwani (1994);

[3]In empirical studies of contagion, Boyer, Gibson, and Loretan (1999), Forbes and Rigobon (2002), Rigobon (2002), Edwards and Susmel (2001, 2003), and Bekaert, Harvey, and Ng (2003) recognize heteroscedasticity in economic time-series and take this property into account when they perform the test.

[4]To my knowledge, this is the first paper to attempt to test for contagion jointly for a large number of countries (16). The multivariate GARCH model that I estimate has 313 parameters. The estimation is performed in Fortran 90 with NPSOL optimizer (Gill, Murray, Saunders, and White (1983)). A closely related, contemporaneous, paper is Bekaert, Harvey, and Ng (2003). They extend the world CAPM by decomposing the world market portfolio into the U.S. and regional returns. Unlike this paper, they do not model the conditional correlation of idiosyncratic risks directly and they perform the test in two steps, which is less efficient than the one-step test performed in this paper.

Bekaert and Harvey (1995)). I implicitly assume that capital markets are fully integrated. Figure 2 illustrates the relationship between contagion and capital market integration concepts. Under the CAPM, evidence of capital market integration is the significance of only the world market portfolio risk in the asset return equation. To test this hypothesis, I test for the significance of constant terms and idiosyncratic volatilities in the return equation. Under the null hypothesis of capital market integration, all those terms should be insignificant.

Using the conditional CAPM and properly modeling the time-series dependencies of equity returns, I test for the existence and pattern of contagion for sixteen countries, covering three country blocs for the period from 1990 through 1999. I find evidence for contagion and capital market integration. In addition, contagion is found to be a regional phenomenal. The results on capital market integration are robust to several specification tests.

The remainder of the paper is organized as follows. Section 2 describes the setup and methodology of the tests. Empirical results are discussed in Section 3. Diagnostic tests of the model are presented in Section 4. Finally, Section 5 presents conclusions.

2 Model Setup and Methodology

2.1 Asset Excess Return

From the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Black (1972), asset risk premium is proportional to the covariance of asset return and the market portfolio return. This framework is appropriated to analyze cross-sectional asset returns at any given point in time. Since we live in a dynamic world, it would be more realistic to assume that the CAPM holds conditionally period by period (Jagannathan and Wang (1996)). Under this framework, asset excess returns can be postulated as

$$Z_t = B_{t-1}E_{t-1}(z_t^m) + B_{t-1}\{z_t^m - E_{t-1}(z_t^m)\} + \epsilon_t, \tag{1}$$

$$E_{t-1}(\epsilon_t) = 0,$$

$$E_{t-1}(\epsilon_t z_t^m) = 0,$$

where Z_t is an $N \times 1$ vector of asset excess returns (asset return minus risk free rate), B_{t-1} is an $N \times 1$ vector of asset conditional beta given the information at time $t-1$, z_t^m is market portfolio excess return, ϵ_t is an $N \times 1$ vector of idiosyncratic risks, N is the number of assets, and $E_{t-1}(\cdot)$ denotes the mathematical expectation conditional on the information available at time $t-1$. It should be noted that the CAPM does not impose any restriction on the second moment of the idiosyncratic risks (ϵ_t). They are allowed to be correlated across assets.

The time-variation of asset conditional beta (B_{t-1}) is modeled as

$$B_{t-1} = b_0 + b_1 J_{t-1}, \tag{2}$$

where b_0 is an $N \times 1$ vector of constants, b_1 is an $N \times K$ matrix of coefficients, J_{t-1} is an $K \times 1$ vector of information variables known at time $t-1$, and K is the number of information variables. This specification includes the usual static CAPM when $b_1 = 0$. In general, the time-variation of B_{t-1} can be modeled as any function of information variables known at time $t-1$, but for simplicity I assume the function to be linear.

Given the CAPM specification in (1) and (2), the conditional covariance matrix of asset excess returns is

$$V_{t-1}(Z_t) = B_{t-1}\sigma_{m,t}^2 B_{t-1}^{'} + \Omega_t, \tag{3}$$

where $V_{t-1}(Z_t)$ denotes an $N \times N$ matrix of the conditional covariance of asset excess returns at time t given the information at time $t-1$, $\sigma_{m,t}^2$ denotes the conditional variance of market portfolio excess return at time t given the information at time $t-1$, and Ω_t denotes an $N \times N$ matrix of the conditional covariance of the idiosyncratic risks at time t given the information at time $t-1$.

The above setup shares many similarities with the Arbitrage Pricing Theory (APT) of Ross (1976) and Chamberlain and Rothschild (1983), for the case in which market portfolio is the only factor. The extension of this idea to estimate the asset conditional covariance matrix is the Factor-Autoregressive Conditional Heteroscedastic (Factor-ARCH) model.[5] There are

[5] The major works in this literature are Diebold and Nerlove (1989), Engle, Ng, and Rothschild (1990), Ng, Engle, and Rothschild (1992), Engle and Kozicki (1993), Engle and Susmel (1993), King, Sentana, and Wadwani (1994), and Demos and Sentana (1998).

two key differences between the model in this paper and the Factor-ARCH model.

The first issue is the theoretical restriction on the idiosyncratic risks (ϵ_t). The Factor-ARCH model is derived from the APT, which implies that the conditional covariance matrix of the idiosyncratic risks (Ω_t) cannot have all off-diagonal elements be non-zero. However, from the derivation of the CAPM, the only restriction on the idiosyncratic risks is that they are orthogonal to the market portfolio. Therefore, in this paper I do not impose any restriction on the idiosyncratic risks conditional covariance matrix. This implication will be of interest in testing for contagion. However, how can I interpret a non-diagonal covariance matrix? From the standpoint of the APT, a non-diagonal covariance matrix means that I do not have enough relevant factors. On the contrary, since I rely on the maintain hypothesis, this result is interpreted as evidence of contagion based on the CAPM model.

The second issue relates to the implementation issue. In most of the APT and Factor-ARCH studies, factors are often obtained from statistical methods–factor analysis or principal component analysis–which have no economic interpretation. However, in this paper I rely on the CAPM; therefore, the economic fundamental in this case is the market portfolio.

2.2 Market Portfolio Expected Return and Volatility

From the CAPM, the market portfolio expected return has a linear relationship with its volatility. I model the time varying market portfolio excess return volatility with a GARCH(1,1)-in-mean as in Bollerslev, Engle, and Wooldridge (1988),

$$z_t^m = \alpha_1 \sigma_{m,t}^2 + \eta_t, \tag{4}$$

where η_t is the innovation of the market portfolio excess return. The conditional variance of the market portfolio return is defined as

$$\sigma_{m,t}^2 = \gamma_0 + \gamma_1 \eta_{t-1}^2 + \gamma_2 \sigma_{m,t-1}^2, \tag{5}$$

where γ_0, γ_1, and γ_2 are parameters.

2.3 Idiosyncratic Risks Covariance Matrix

In modeling the conditional covariance matrix, many methodologies can be employed. The conditional covariance matrix can be modeled as parametric functions, such as with the GARCH model (Bollerslev, Engle, and Wooldridge (1988)) and with some functions of information variables (Harvey (1991)).

I model the conditional covariance matrix with a multivariate GARCH model. However, within the GARCH framework, there are many specifications that I can employ such as the Diagonal VECH model of Bollerslev, Engle, and Wooldridge (1988), the Factor-ARCH model of Engle, Ng, and Rothschild (1990), the Constant Conditional Correlation (CCORR) model of Bollerslev (1990), the BEKK model of Engle and Kroner (1995), the Generalized Dynamics Covariances (GDC) model of Kroner and Ng (1998), the R-GARCH model of Gallant and Tauchen (1998), the decentralized estimation of Ledoit, Santa-Clara, and Wolf (2002), the time-varying conditional correlation of Tse and Tsui (2002), and the Dynamic Conditional Correlation (DCC) model of Engle (2002). In selecting an appropriate model for this paper, the necessary conditions are as follows. First, the conditional covariance matrix should be positive semi-definite. Second, the matrix should be symmetric. Third, the matrix should be suitable for parameterizing the covariance to be zero while maintaining the variance to be positive.

Under these requirements, the candidate models are the Diagonal VECH, the GDC, and the R-GARCH models. The Factor-ARCH and BEKK models cannot parameterize the covariances to be zero while maintaining positive variances.[6] The CCORR restricts the conditional correlation to be constant over time. The decentralized estimation, the DCC, and the time-varying conditional correlation model are nice ways to estimate a large conditional covariance matrix; however, they do not have a clean way to impose parametric restrictions so that conditional covariance equals zero.

I choose the R-GARCH(1,1) model for the following reasons: first, the R-GARCH(1,1) allows for richer dynamics as compared to the Diagonal VECH and second, the R-GARCH(1,1)

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[6]The Factor-ARCH is a special case of the BEKK model.

requires a smaller number of parameters as compared to the GDC. The R-GARCH(1,1) specification is

$$\Omega_t = R_t R_t^{'}, \tag{6}$$

$$vech(R_t) = \rho + P|\epsilon_{t-1}| + diag(G)vech(R_{t-1}), \tag{7}$$

where R_t is an $N \times N$ upper triangular matrix, ρ is an $N(N+1)/2 \times 1$ vector of constants, P is an $N(N+1)/2 \times N$ matrix of coefficients, G is a diagonal $N(N+1)/2 \times N(N+1)/2$ matrix of the coefficients, and *diag* represents the diagonal part of a matrix. The R-GARCH(1,1) is similar to the GARCH(1,1) model, but instead of parameterizing the variance, R-GARCH parameterizes the standard deviation.

One drawback of the R-GARCH model, also with other multivariate GARCH models in general, is the large number of parameters that need to be estimated. For R-GARCH(1,1) of N assets, there are $N(N+1)(N+2)/2$ parameters. For example, a system with 16 assets requires 2,448 parameters. To make the estimation feasible, I impose some restrictions on the P matrix. These restrictions are shown in the Appendix. The number of parameters under the restricted R-GARCH(1,1) of N assets is $2N(N+1) - N$. In the case of 16 assets, this reduces the number of parameters to 528. A drawback to this specification is that it is sensitive to the ordering of assets.[7]

2.4 Estimation Method

The estimation is conducted by Quasi-Maximum Likelihood Estimation (QMLE). The robust standard errors are calculated from $H^{-1}SH^{-1}$, where H is the Hessian and S is the outer product of the gradients (Bollerslev and Wooldridge (1992)). The log-likelihood of the sample is

$$L = -\frac{NT}{2} ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} ln|\Sigma_t| - \frac{1}{2}\sum_{t=1}^{T} \Upsilon_t^{'}\Sigma_t^{-1}\Upsilon_t, \tag{8}$$

where L is the log-likelihood, T is the number of observations per asset,

$$\Upsilon_t = \begin{bmatrix} Z_t - C - B_{t-1}E_{t-1}(z_t^m) \\ z_t^m - \alpha_0 - \alpha_1\sigma_{m,t}^2 \end{bmatrix}, \tag{9}$$

[7] In Section 4, I test this sensitivity by estimating the model by changing the order of country returns.

and

$$\Sigma_t = \begin{bmatrix} B_{t-1} \\ 1 \end{bmatrix} \sigma^2_{m,t} \begin{bmatrix} B'_{t-1} & 1 \end{bmatrix} + \begin{bmatrix} \Omega_t & 0 \\ 0 & 0 \end{bmatrix}. \qquad (10)$$

It should be noted that I also estimate the intercept terms in the mean equation, C and α_0. Theoretically, the intercept terms should be zero.

Alternatively, I can jointly model market portfolio and asset idiosyncratic risks conditional covariance matrix as one multivariate GARCH model, Σ_t (Bollerslev, Engle, and Wooldridge (1988)), as opposed to modeling Ω_t and $\sigma^2_{m,t}$ separately. However, if I model Σ_t jointly, restriction of the zero idiosyncratic risk covariance will be non-parametric. The results would rely on the assumption of a distribution of Υ_t, which is hard to justify in a multivariate setting. In the contrast, the parameterization I use in this paper does not rely on the distributional assumption on Υ_t.

2.5 Hypothesis Testing

The contagion hypothesis tests the significance of the conditional correlations among asset excess returns after accounting for the CAPM systematic risk, market portfolio excess return. This hypothesis is equivalent to testing the significance of the conditional covariances of the idiosyncratic risks (Ω_t). However, in testing for contagion, we are implicitly assuming that the capital market in each country is fully integrated.[8] In other words, we are assuming that the world CAPM can price all assets. Therefore, to make sense of the result of the contagion test, I first test for capital market integration. I then proceed to test for contagion.

The hypothesis for capital market integration is that if the capital market is fully integrated, then only systematic risk (market portfolio excess return) is priced. This implies a joint test on all intercepts in each country's mean equation (C). The evidence for capital market integration is the insignificance of C. The test is performed by a robust Wald (W) test. Later in Section 4, I also use different parametric test by testing whether the idiosyncratic risk volatility is priced or not.

[8]See Figure 2 for a conceptual relationship between contagion and capital market integration.

The hypothesis for contagion is to test for the significance of the conditional covariances in the idiosyncratic risks (Ω_t). I pursue the test by using a robust Lagrange Multiplier (LM) test. The parametric restrictions on the general model is in the Appendix. The test starts from the most restricted model. If that model is rejected, the model is then expanded, and this process repeats until the model cannot be rejected.

The test for contagion begins from the null hypothesis of no contagion. I restrict the idiosyncratic conditional covariance matrix to be diagonal

$$\Omega_t = \begin{bmatrix} \omega_{11,t} & 0 & ... & 0 \\ 0 & \omega_{22,t} & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \omega_{NN,t} \end{bmatrix},$$

where $\omega_{ij,t}$ is the idiosyncratic conditional covariance at time t between country i and j. Under this null hypothesis, the co-movements among countries can all be explained by systematic risk. If the model is rejected, I then test for contagion within a specific group. The grouping criteria are, for example, economic similarity, trading partners, common lenders, and geographic region. With this hypothesis, there is contagion within a group but not across groups. To illustrate the restrictions, consider contagion within the group for two groups of countries. The idiosyncratic covariance would be restricted to have the following structure:

$$\Omega_t = \begin{bmatrix} \omega_{11,t} & \omega_{12,t} & 0 & ... & 0 \\ \omega_{21,t} & \omega_{22,t} & 0 & ... & 0 \\ 0 & 0 & \omega_{33,t} & ... & \omega_{3N,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \omega_{N3,t} & ... & \omega_{NN,t} \end{bmatrix}.$$

I then test for the restrictions. If the model is rejected, I relax more restrictions on the covariance matrix until it cannot be rejected. Specifically, I allow for more non-zero covariance terms. Once the model fails to reject, the structure from the grouping criterion is the pattern of contagion. It is worth mentioning that the most general model is the one that has contagion across all countries–which allows all covariance terms to be non-zero.

3 Empirical Results

3.1 Data Description

The data series for equity market indices (total market return in U.S. dollars) are from Datastream Global Indices, except in the cases of Argentina and Brazil, for which the data series are from International Finance Corporation (IFC) Global indices.[9] The series are mid-week (Wednesdays) on a weekly frequency from April 11, 1990 through September 15, 1999–a total of 493 observations. The sample includes four groups of countries as follows: South East Asia (Indonesia, Malaysia, The Philippines, Singapore, and Thailand), East Asia (Hong Kong, Japan, South Korea, and Taiwan), Latin America (Argentina, Brazil, Mexico, and Chile), and Germany, the U.K., and the U.S. Equity excess returns are computed as ex-post gross return minus ex-post one-month Euro dollar interest rate.

Information variables to capture the time variation of beta (matrix J from equation(2)) include the world market dividend yield in excess of the risk free interest rate (DY), the change in the term structure spread (U.S. 10-year bond yield minus U.S. 3-month treasury bill: TERM), and the default spread (Moody's Baa minus Aaa bond yields: DEF).[10]

Table 1 shows summary statistics on excess return for each country. The last three columns report Ljung-Box statistics, Q12, QAR(3)12, and QSAR(3)12, for excess returns, innovations of excess returns from an autoregressive model with three lags (AR(3)), and squared innovations of excess returns from an AR(3), respectively. The test statistic (Q12) indicates that returns are highly serially correlated. In order to identify the ARCH effect, I take out the effect of autocorrelation in excess returns by using an AR(3) model. The innovation from the AR(3) shows no indication of autocorrelation, while the squared innovation indicates a strong degree of autocorrelation, providing evidence of an ARCH effect. Therefore, it is appropriate to model the dependency of the second moments of asset returns.

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[9]Datastream does not cover Brazil and their data for Argentina starts in August 1993. Morgan Stanley Capital International (MSCI) is another major alternative data source for equity market indices. I choose Datastream over MSCI because MSCI only has market total return on a monthly basis. IFC data only cover emerging markets.

[10]Bekaert and Harvey (1995), Jagannathan and Wang (1996), and Ferson and Harvey (1999) advocated using these information variables to capture the world business cycle.

Tables 2 and 3 show the unconditional correlation and covariance matrix. It is interesting to note that the correlations within each region are much stronger than the correlations across the regions. Also, the Philippines and Taiwan have very low correlations with the rest of the world and have negative correlations with the world market portfolio.

3.2 Capital Market Integration and Contagion Hypotheses

In this section, I test for capital market integration and contagion in equity markets under the assumption that beta is time-varying (Bollerslev, Engle, and Wooldridge (1988); Harvey (1989); Ferson and Harvey (1991)). The time-variation of beta is assumed to be a linear function of lagged information variables (equation 2).

I begin by testing the hypothesis of no contagion, which implies that the conditional correlations after accounting for the world market portfolio excess return are zero. In other words, it implies that all co-movements can be explained by economic fundamentals, represented by the world market portfolio. This approach is equivalent to testing for the diagonality of the idiosyncratic risk conditional covariance matrix. As discussed in the previous section, this test implicitly assumes that capital markets are fully integrated. Therefore, I start with the test for capital market integration under the restricted model of no contagion. Figures 3 and 4 show the structure of and restrictions on the Ω_t and R_t matrices. I call this hypothesis *No Contagion*.

Table 4 shows results for the test of capital market integration. The robust Wald statistic is 19.24. The statistic fails to reject the null hypothesis of capital market integration, given the 95% critical value of 26.30 for χ^2_{16}. This result is not surprising, as it is well known that, during the 1990's, most countries liberalized their capital accounts. This finding is consistent with the results in Bekaert and Harvey (1995), Bekaert, Harvey, and Lumsdaine (2002), Bekaert and Harvey (2000), and Henry (2000), which all test for capital market integration in emerging markets. The test of contagion is performed with the robust LM statistic. (See the Appendix for the benchmark model.) The robust LM statistic is 1085.35 which rejects the null hypothesis of no contagion at the 95% confidence level given the critical value of 532.08 for χ^2_{480} .

Given that the *No Contagion* hypothesis is rejected, I then test for contagion within a group of countries. I group countries by geographic regions. The rationale for using this criterion is, as shown in Kaminsky and Reinhart (2000), that grouping countries by geographic region (Gregorio and Valdes (2001)), economic similarities (Sachs, Tornell, and Velasco (1996)), trade with common third parties (Glick and Rose (1999)), and common lenders (Rijckeghem and Weder (2001, 2003)) all yield a similar set of countries. I divide the countries into four groups: South East Asia, East Asia, Latin America, and Germany-U.K.-U.S. This hypothesis is called *Regional Contagion I.* Figures 5 and 6 illustrate the grouping of countries and parametric restrictions on Ω_t and R_t. Table 4 shows that the hypothesis of capital market integration can not be rejected at the 95% confidence level. The contagion hypothesis is also rejected at 95% confidence level.

In the next step, I test for contagion within a region by treating South East Asia and East Asia as one block, which I refer to as *Asia.* This hypothesis is termed *Regional Contagion II.* Figures 7 and 8 illustrate the grouping of countries and parametric restrictions on Ω_t and R_t. The result for capital market integration is similar to that of the previous case, as shown in Table 4. As for the contagion hypothesis, the result shows that the hypothesis cannot be rejected. In other words, I find evidence for contagion within a group of countries but not across groups. The results show that from the standpoint of the CAPM model there is evidence of capital market integration and contagion within a geographic region. This result is similar to the findings in Bekaert, Harvey, and Ng (2003).

To test the evidence of time-varying beta, I employ a robust Wald test on b_1 for the *Regional Contagion II* model. The robust Wald statistic is 75.26. The test statistic is distributed as χ^2_{48} and the critical value at the 95% confidence level is 65.17. The test rejected the null hypothesis for time-invariant beta.

The ability of the *Regional Contagion II* model to capture properties of returns series are shown in Table 5. I employ a test on the standardized residuals ($U_t^{-1}\Upsilon_t$). The standardization is based on a Cholesky decomposition ($U_t U_t^{'} = \Sigma_t$). If the model is correctly specified, the standardized residuals should be independently identically distributed (i.i.d). Table 5 shows test statistics for skewness, kurtosis, and 12th-order serial correlation (Ljung-

Box statistics: QZ12) and for squared 12th-order serial correlation (QZS12). The result indicates some degrees of dependency in the first moment. However, the *Regional Contagion II* model appears to capture dependencies in the second moment fairly well for all countries except Germany and the U.S.

3.3 Contribution of Market Portfolio to the Conditional Correlation

The main objective of this paper is to test for contagion. Under the CAPM, contagion is defined as significant conditional correlations after accounting for the world market portfolio. The results from time-varying beta indicates that there is evidence of regional contagion. Therefore it is of interest to investigate the extent to which the market portfolio can explain intra-regional conditional correlations.

Figure 9 compares the conditional correlations implied from the CAPM with time-varying beta under the *Regional Contagion II* model (solid line) and the conditional correlation computed from a rolling window (dashed line). This comparison offers evidence that conditional correlations implied from the model are smoother than the rolling correlation. The contribution of the world market portfolio (solid line) to the total conditional correlation (dashed line) is shown in Figure 10. It is interesting to note that the market portfolio can capture the variation but fails to capture the level of correlation. However, in the case of Latin America, market portfolio can capture neither the variation nor the level.

4 Diagnostic Test

4.1 Market Portfolio Volatility

It is often noted that equity returns have thick tail distribution, which the normal distribution cannot be able to capture. In testing for contagion in this paper, the estimates of the conditional volatility of the market portfolio play an important part. Although this paper uses QMLE and robust standard errors, which should give consistent estimates for both the parameters and standard errors, in practice the estimates could be different under different error distributions.

Thus, I estimate market portfolio volatility under the alternative t-distribution. Table 6 shows parameter estimates of the market portfolio volatility. The second and third columns show the estimates from the *Regional Contagion II* model with time-invariant and time-varying beta, respectively. The fourth column shows the parameter estimates of market volatility under the assumption of t-distribution with 5 degrees of freedom. The parameter estimates on the volatility equation are very close. Figure 11 shows the plot of the market portfolio volatility. It is evident that the estimates of volatility are almost the same. It is interesting to see that the volatility from the *Regional Contagion II* model is always of the same magnitude as that under the t-distribution.

4.2 Idiosyncratic Covariance Matrix

As mentioned in the previous section, one drawback of the restricted R-GARCH specification is the sensitivity of the estimates to the ordering of assets. To check for the robustness, I estimate the *Regional Contagion II* model again by changing the orders of countries within each group. It turns out that the LM test of the model under the null hypothesis of regional contagion cannot be rejected at the 95% confidence interval.

4.3 Asymmetric Variance and Covariance

In modeling the volatility of equity returns, many authors, including Nelson (1991), Glosten, Jagannathan, and Runkle (1993), Bekaert and Wu (2000), find evidence of asymmetric volatility. However, the evidence of asymmetric volatility in the emerging markets is mixed, as shown in Bekaert and Harvey (1997) and Lundblad (2000). The findings are very puzzling, because most people attribute asymmetric volatility to the leverage effect (Christie (1982)), which of course is a wide-spread phenomenon in the emerging markets.

I employ an LM test for asymmetric volatility. To account for asymmetry, the R-GARCH is modified to include ζ_{t-1} which is to capture an addition impact of negative innovation beyond the same size positive innovation on returns conditional variance-covariance matrix. The modified R-GARCH specification is

$$\Omega_t = R_t R_t^{'}, \tag{11}$$

$$vech(R_t) = \rho + P|\epsilon_{t-1}| + diag(G)vech(R_{t-1}) + D|\zeta_{t-1}|, \tag{12}$$

where D and P are $N(N+1)/2 \times N$ matrix of coefficients and ζ_{t-1} is defined as

$$\epsilon_{t-1} = \begin{pmatrix} \epsilon_{1,t-1} \\ \vdots \\ \epsilon_{N,t-1} \end{pmatrix}, \ \zeta_{t-1} = \begin{pmatrix} \zeta_{1,t-1} \\ \vdots \\ \zeta_{N,t-1} \end{pmatrix}, \ \zeta_{i,t-1} = \begin{cases} \epsilon_{i,t-1} & \text{if } \epsilon_{i,t-1} < 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall i.$$

The restrictions on the D matrix are the same as those for the P matrix. It is interesting to note that under the modified R-GARCH, this specification can capture the asymmetry both in variance and covariance. The null hypothesis of no asymmetry in both the variance and covariance of idiosyncratic risks implies the parametric restriction $D = 0$ (under the three-block diagonal, *Regional Contagion II* model). The robust LM test statistic for equity markets under the *Regional Contagion II* model is 120.78. The test statistic is distributed as χ^2_{106} and the critical value at the 95% confidence level is 131.03. The result indicates that we fail to reject the null hypothesis of no asymmetry at 95%.

4.4 Capital Market Integration

From the test of contagion, I implicitly assume that capital markets are fully integrated. The test for capital market integration is to test whether only systematic risk is priced. I implemented the test in the previous section by testing the significance of the intercept in the mean equations (C). This test is only one of various tests under the definition of capital market integration. To check for the robustness of the result, I test whether idiosyncratic volatility is priced. The model specification is

$$Z_t = C + B_{t-1}E_{t-1}(z_t^m) + B_{t-1}\{z_t^m - E_{t-1}(z_t^m)\} + \epsilon_t + diag(A)\, diag(\Omega_t), \tag{13}$$

where A is a diagonal $N \times N$ matrix of coefficients and *diag* represents the diagonal terms of a matrix.

The null hypothesis of capital market integration implies parametric restriction $C = 0$ and $A = 0$. Due to the computational time, I use the estimates from the *Regional Contagion II* model, which also includes C, and apply an LM test for the significance of A. The robust LM test statistic is 24.25. The test statistic is distributed as χ^2_{16} and the critical value at the

95% confidence level is 26.30. The result indicates that we fail to reject the null hypothesis of capital market integration at 95%.

5 Conclusions

This paper tests for contagion and capital market integration in equity markets using the conditional CAPM. The paper offers a systematic way to test for contagion by using economic theory as a guide for which economic fundamentals belong in the empirical model and by recognizing and modeling the properties of economic time-series. The paper finds evidence of regional contagion and capital market integration in equity markets.

The findings have several important implications. First, regulators should pay more attention to developments in both domestic and world financial markets since there might be contagion across markets. Second, the evidence of regional contagion might imply regional factors that are not priced in world equity markets but that systematically affect all equity markets in the region. Therefore, if we can identify these regional factors, we might be able to hedge these risks.

An extension of this work would be to explain regional contagion. This can be pursued in several directions. For example, it would be interesting to investigate whether currency markets can explain regional contagion. Another issue worth investigating is to study the effect of information asymmetry on contagion (e.g., Calvo and Mendoza (2000); Kyle and Xiong (2001); Kodres and Pritsker (2002)).

Appendix

A Restrictions on the R-GARCH specification

The idiosyncratic conditional covariance matrix is modeled as R-GARCH(1,1). The model is

$$\Omega_t = R_t R_t',$$

$$vech(R_t) = \rho + P|\epsilon_{t-1}| + diag(G)vech(R_{t-1}),$$

where Ω_t is an $N \times N$ conditional covariance matrix, R_t is an $N \times N$ upper triangular matrix, ρ is an $N(N+1)/2 \times 1$ vector of constants, P is an $N(N+1)/2 \times N$ matrix of coefficients, G is a diagonal $N(N+1)/2 \times N(N+1)/2$ matrix of the coefficients, and N is the number of countries. The number of parameters for this covariance matrix is $N(N+1)(N+2)/2$. When $N = 16$, the number of parameters is 2,448. Under the restricted model (*Regional Contagion II*), the number of parameters is 585, which is a large number of parameters as compared to the data. The ratio of data per parameter is 13.

To overcome this over parameterizing problem, I impose restrictions on the structure of the P matrix. The diagonal element of R is assumed to only depend on its own innovation and the off-diagonal is assumed to depend on its covariate. To illustrate the restrictions, consider a case in which $N = 4$. The R matrix is

$$R_t = \begin{bmatrix} r_{11,t} & r_{12,t} & r_{13,t} & r_{14,t} \\ 0 & r_{22,t} & r_{23,t} & r_{24,t} \\ 0 & 0 & r_{33,t} & r_{34,t} \\ 0 & 0 & 0 & r_{44,t} \end{bmatrix}.$$

The variance-covariance matrix can be written in term of r's as

$$\Omega_t = \begin{bmatrix} r_{11,t}^2 + r_{12,t}^2 + r_{13,t}^2 + r_{14,t}^2 & r_{12,t}r_{22,t} + r_{13,t}r_{23,t} + r_{14,t}r_{24,t} & r_{13,t}r_{33,t} + r_{14,t}r_{34,t} & r_{14,t}r_{44,t} \\ r_{12,t}r_{22,t} + r_{13,t}r_{23,t} + r_{14,t}r_{24,t} & r_{22,t}^2 + r_{23,t}^2 + r_{24}^2 & r_{23,t}r_{33,t} + r_{24}r_{34} & r_{24,t}r_{44,t} \\ r_{13,t}r_{33,t} + r_{14,t}r_{34,t} & r_{23,t}r_{33,t} + r_{24}r_{34} & r_{33,t}^2 + r_{34,t}^2 & r_{34,t}r_{44,t} \\ r_{14,t}r_{44,t} & r_{24,t}r_{44,t} & r_{34,t}r_{44,t} & r_{44,t}^2 \end{bmatrix}$$

$$vech(R_t) \equiv \begin{bmatrix} r_{11,t} \\ r_{12,t} \\ r_{22,t} \\ r_{13,t} \\ r_{23,t} \\ r_{33,t} \\ r_{14,t} \\ r_{24,t} \\ r_{34,t} \\ r_{44,t} \end{bmatrix} = \begin{bmatrix} \rho_{11} \\ \rho_{12} \\ \rho_{22} \\ \rho_{13} \\ \rho_{23} \\ \rho_{33} \\ \rho_{14} \\ \rho_{24} \\ \rho_{34} \\ \rho_{44} \end{bmatrix} + \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \\ p_{51} & p_{52} & p_{53} & p_{54} \\ p_{61} & p_{62} & p_{63} & p_{64} \\ p_{71} & p_{72} & p_{73} & p_{74} \\ p_{81} & p_{82} & p_{83} & p_{84} \\ p_{91} & p_{92} & p_{93} & p_{94} \\ p_{101} & p_{102} & p_{103} & p_{104} \end{bmatrix} \begin{bmatrix} |\epsilon_{1,t-1}| \\ |\epsilon_{2,t-1}| \\ |\epsilon_{3,t-1}| \\ |\epsilon_{4,t-1}| \end{bmatrix} +$$

$$\begin{bmatrix} g_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & g_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & g_{33} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & g_{44} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & g_{55} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & g_{66} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & g_{77} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & g_{88} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & g_{99} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & g_{1010} \end{bmatrix} \begin{bmatrix} r_{11,t-1} \\ r_{12,t-1} \\ r_{22,t-1} \\ r_{13,t-1} \\ r_{23,t-1} \\ r_{33,t-1} \\ r_{14,t-1} \\ r_{24,t-1} \\ r_{34,t-1} \\ r_{44,t-1} \end{bmatrix}.$$

It can be seen that the diagonal terms in the R_t matrix only enter the diagonal part of Ω_t. With that observation, I restricted the diagonal terms in the R_t to only depend on its own innovation, e.g., $p_{12} = p_{13} = p_{14} = 0$. As for the covariance term, consider that $r_{12,t}$ enters in $\omega_{11,t}$ and $\omega_{12,t}$. I restricted $r_{12,t}$ to only depend on the innovation of the first and second countries ($\epsilon_{1,t-1}$ and $\epsilon_{2,t-1}$). With the same logic, the P matrix for $N = 4$ is restricted to be

$$P = \begin{bmatrix} p_{11} & 0 & 0 & 0 \\ p_{21} & p_{22} & 0 & 0 \\ 0 & p_{32} & 0 & 0 \\ p_{41} & 0 & p_{43} & 0 \\ 0 & p_{52} & p_{53} & 0 \\ 0 & 0 & p_{63} & 0 \\ p_{71} & 0 & 0 & p_{74} \\ 0 & p_{82} & 0 & p_{84} \\ p_{91} & 0 & p_{93} & p_{94} \\ 0 & 0 & 0 & p_{104} \end{bmatrix}.$$

The number of parameters under the restricted R-GARCH(1,1) of N assets is $2N(N+1)-N$. In the case of 16 assets, this reduces the number of parameters to 528. One drawback to this specification is that it is sensitive to the ordering of assets.

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Table 1: Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis	Q12	QAR(3)12	QSAR(3)12
Indonesia	-0.1321	6.1544	0.1504	10.0148‡	26.9040*	19.4110+	363.0800*,+
Malaysia	0.1183	5.0967	0.1198	13.8291‡	30.5650*	16.1410	135.9100*
The Philippines	0.1732	4.3569	0.0213	7.1782‡	29.1620*	14.0270	39.4110*
Singapore	0.0773	2.9369	-0.2358	5.6633‡	27.1220*	20.9610	164.8400*
Thailand	0.0639	5.6514	0.4363	5.4148‡	22.2570*	12.1950	161.6700*
Hong Kong	0.3250	3.6015	-0.4457†	4.4370‡	21.6910*	15.8660	80.9110*
Japan	0.0022	3.2168	0.4926†	4.8681‡	16.0680	12.2330	48.9670*
South Korea	0.1040	5.3440	-0.0017	7.9034‡	36.7000*	12.0270	326.5200*
Taiwan	-0.0029	5.3339	0.5648	7.4728‡	21.8950*	7.8276	181.6500*
Argentina	0.4818	5.8000	0.6577	7.3420‡	20.0370	10.3880	52.9650*
Brazil	0.5868	7.1693	0.2764	3.8078‡	9.8103	9.8169	78.7890*
Chile	0.3166	3.2048	0.2716	4.9267‡	36.5490*	9.8608	58.0340*
Mexico	0.3891	4.5220	-0.3665	5.7502‡	21.5800*	9.7475	88.9730*
Germany	0.1021	2.3370	-0.4477†	4.3681‡	30.4990*	14.8020	155.7000*
The U.K.	0.2072	2.0953	0.0911	4.2607	13.8590	7.5134	28.0050*
The U.S.	0.2618	1.9313	-0.4684†	4.7691‡	29.3430*	11.2250	114.8100*
World	0.1387	1.7439	-0.2918	4.4503‡	26.4870*	20.0870	147.7900*
Default	0.0147	0.0036	1.3788	4.8605			
Term	0.0000	0.0025	0.2896	4.0813			
Dividend	-0.0596	0.0259	0.2346	2.6866			

The table shows summary statistics for weekly excess returns (in weekly percentages). The data are from Datastream Global Indices, except Argentina and Brazil, which are from the International Finance Corporation (IFC) Global indices. Total Market Return indices are in U.S. dollars. Excess return is calculated by (1) calculating the arithmetic return for each country's stock index and (2) subtracting the one-month Euro dollar interest rate from the market return. The last three rows show information variables. *Default* is the lag of Moody's Investor Service spread returns between Moody's bond rating Baa and Aaa. *Term* is lag of the changes in the spread of treasury bill yield between 10-year and 3-month maturies. *Dividend* is lag of world market dividend yield in excess of one-month Euro dollar interest rate. All series are from 11 April 1990 through 15 September 1999 for a total of 493 observations. The fourth and fifth columns show the skewness and kurtosis, respectively. † indicates the skewness is significantly different from normal distribution at the 95% confidence interval. ‡ indicates the kurtosis is significantly different from normal distribution at the 95% confidence interval. These two statistics are computed from GMM moment conditions with Newey and West (1987) standard errors. The last three columns show Ljung-Box test statistics for 12th-order serial correlation of the weekly excess returns (Q12), residual from an AR(3) model of weekly excess return (QAR(3)12), and residual squared from an AR(3) of weekly excess return (QSAR(3)12). The $\chi^2(12)$ critical values are 18.5493 (10%), 21.0261 (5%), and 26.2170 (1%). * indicates the coefficient is significant at the 95% confidence interval. + indicates the statistics from an AR(6) model.

Table 2: Correlation Matrix

	ID	MY	PH	SG	TH	HK	JP	KO	TA	AR	BR	CL	MX	BD	UK	US	WD
ID	1.00	0.43	0.05	0.41	0.45	0.38	0.16	0.21	0.02	0.09	0.12	0.13	-0.01	0.16	0.10	0.14	0.23
MY		1.00	0.02	0.60	0.48	0.45	0.19	0.23	0.00	0.06	0.01	0.14	0.00	0.24	0.23	0.21	0.31
PH			1.00	-0.07	-0.01	-0.06	-0.07	-0.05	0.02	0.02	0.03	-0.08	-0.01	0.02	-0.07	-0.11	-0.11
SG				1.00	0.57	0.56	0.31	0.27	0.00	0.09	0.02	0.18	0.03	0.33	0.36	0.31	0.47
TH					1.00	0.46	0.17	0.32	-0.01	0.14	0.12	0.20	-0.01	0.29	0.26	0.26	0.34
HK						1.00	0.23	0.31	0.03	0.11	0.02	0.27	-0.02	0.36	0.41	0.38	0.48
JP							1.00	0.26	0.02	-0.04	-0.02	0.07	0.03	0.37	0.36	0.23	0.70
KO								1.00	0.04	-0.04	-0.04	0.15	-0.06	0.20	0.21	0.22	0.33
TA									1.00	0.03	0.00	-0.04	-0.11	-0.13	-0.07	-0.02	-0.02
AR										1.00	0.30	0.24	-0.09	-0.06	0.00	0.08	0.02
BR											1.00	0.18	-0.08	0.03	0.07	0.06	0.05
CL												1.00	-0.03	0.15	0.20	0.24	0.26
MX													1.00	-0.03	-0.05	0.03	0.01
BD														1.00	0.61	0.47	0.69
UK															1.00	0.50	0.71
US																1.00	0.77
WD																	1.00

The table shows the correlation matrix of equity excess returns. The country codes are as follows: ID = Indonesia, MY = Malaysia, PH = The Philippines, SG = Singapore, TH = Thailand, HK = Hong Kong, JP = Japan, KO = South Korea, TA = Taiwan, AR = Argentina, BR = Brazil, CL = Chile, MX = Mexico, BD = Germany, UK = United Kingdom, US = United States of America, and WD = World. The correlation is computed from 11 April 1990 through 15 September 1999 for a total of 493 observations.

Table 3: Covariance Matrix

	ID	MY	PH	SG	TH	HK	JP	KO	TA	AR	BR	CL	MX	BD	UK	US	WD
ID	37.80	13.31	1.37	7.48	15.63	8.32	3.09	6.91	0.53	3.15	5.13	2.50	-0.33	2.30	1.35	1.70	2.47
MY		25.92	0.45	8.98	13.93	8.16	3.18	6.18	0.12	1.83	0.47	2.31	0.05	2.91	2.41	2.10	2.79
PH			18.94	-0.85	-0.34	-0.94	-0.97	-1.18	0.35	0.44	0.90	-1.13	-0.25	0.17	-0.66	-0.92	-0.85
SG				8.61	9.41	5.95	2.90	4.30	0.05	1.54	0.45	1.70	0.43	2.29	2.20	1.74	2.40
TH					31.87	9.43	3.08	9.72	-0.34	4.52	4.97	3.62	-0.30	3.88	3.03	2.79	3.37
HK						12.94	2.63	5.95	0.60	2.29	0.53	3.06	-0.26	3.01	3.06	2.60	3.02
JP							10.33	4.47	0.42	-0.67	-0.36	0.73	0.45	2.76	2.41	1.42	3.93
KO								28.50	1.15	-1.13	-1.58	2.50	-1.33	2.46	2.32	2.29	3.04
TA									28.39	0.81	0.05	-0.71	-2.61	-1.57	-0.73	-0.16	-0.16
AR										33.57	12.39	4.48	-2.37	-0.87	-0.06	0.88	0.25
BR											51.29	4.08	-2.62	0.53	1.09	0.84	0.67
CL												10.25	-0.48	1.10	1.37	1.46	1.43
MX													20.41	-0.34	-0.46	0.30	0.04
BD														5.45	2.99	2.10	2.82
UK															4.38	2.04	2.59
US																3.72	2.59
WD																	3.04

The table shows the covariance matrix of equity excess returns. The country codes are as follows: ID = Indonesia, MY = Malaysia, PH = The Philippines, SG = Singapore, TH = Thailand, HK = Hong Kong, JP = Japan, KO = South Korea, TA = Taiwan, AR = Argentina, BR = Brazil, CL = Chile, MX = Mexico, BD = Germany, UK = United Kingdom, US = United States of America, and WD = World. The covariance is computed from 11 April 1990 through 15 September 1999 for a total of 493 observations.

Table 4: Capital Market Integration and Contagion Hypotheses Tests

Hypothesis	No Contagion	Regional Contagion I	Regional Contagion II
Capital Market Integration	Failed to Reject (W = 19.2437) ($\chi^2_{16,0.95} = 26.2962$)	Failed to Reject (W = 18.6342) ($\chi^2_{16,0.95} = 26.2962$)	Failed to Reject (W = 20.1045) ($\chi^2_{16,0.95} = 26.2962$)
Contagion	Rejected (LM = 1085.3471) ($\chi^2_{480,0.95} = 532.0754$)	Rejected (LM = 719.8412) ($\chi^2_{380,0.95} = 426.4537$)	Failed to Reject (LM = 310.5128) ($\chi^2_{300,0.95} = 341.3951$)

The table shows test statistics for the capital market integration and contagion hypotheses. The null hypothesis for capital market integration is that the intercepts in the mean asset excess returns equation are equal to zero, $C = 0$. The test is performed by a robust Wald test. The statistics are distributed Chi-square with 16 degree of freedom (χ^2_{16}). *No Contagion* is the restricted model under the hypothesis of no contagion (See Figures 3 and 4). *Regional Contagion I* is the restricted model under the hypothesis of Regional Contagion I (See Figures 5 and 6). *Regional Contagion II* is the restricted model under the hypothesis of Regional Contagion II (See Figures 7 and 8). The test of the significance of time-varying beta from the *Regional Contagion II* model is performed by a robust Wald test. The statistic rejected the insignificance of the information variables at the 95% confidence interval ($W = 75.2641$ with $\chi^2_{48,0.95} = 65.1708$). All robust standard errors are calculated from $H^{-1}SH^{-1}$, where H is the Hessian and S is the outer product of the gradients (Bollerslev and Wooldridge (1992)).

Table 5: Residual Diagnostic

	Skewness	Kurtosis	QZ12	QZS12
Indonesia	-0.1502	3.9951	20.2487	7.1637
Malaysia	0.0811	5.9328	7.9994	16.4642
The Philippines	0.0058	7.0881	21.2241*	9.3204
Singapore	-0.1112	6.7947	6.0906	9.4237
Thailand	0.3837	4.7586	8.1127	10.2757
Hong Kong	-0.4917	3.9000	25.2641*	12.6672
Japan	0.4112	4.0790	17.7374	12.8364
South Korea	0.3959	6.2182	21.0784*	12.1812
Taiwan	0.1330	4.1144	32.7031*	20.2043
Argentina	0.3267	4.8636	17.2749	12.5983
Brazil	-0.0973	3.7207	13.9712	10.9624
Chile	0.1034	3.9489	42.8892*	16.0026
Mexico	-0.3479	5.4702	15.8771	15.9115
Germany	-0.4945	4.8430	17.7358	46.5423*
U.K.	0.0156	4.7310	13.5782	20.9752
U.S.	-0.6058	4.9795	28.5025*	42.8582*

The table shows test statistics for standardized residual implied from the conditional CAPM model with time-varying beta (*Regional Contagion II*). Standardized residual is computed from $U_t^{-1}\Upsilon_t$, where $U_t U_t^{'} = \Sigma_t$. U_t is an upper triangular matrix and Σ_t is the covariance matrix. All series are from 11 April 1990 through 15 September 1999 for a total of 493 observations. The last two columns show Ljung-Box test statistics for 12th-order serial correlation of standardized residual (QZ12) and standardized residual squared (QZS12). The $\chi^2(12)$ critical values are 18.5493 (10%), 21.0261 (5%), and 26.2170 (1%). * indicates the coefficient is significant at the 95% confidence interval.

Table 6: Estimates of the GARCH(1,1)-M for the World Market Portfolios

$$z_t^m = \alpha_0 + \alpha_1 \sigma_{m,t}^2 + \eta_t$$

$$\sigma_{m,t}^2 = \gamma_0 + \gamma_1 \eta_{t-1}^2 + \gamma_2 \sigma_{m,t-1}^2$$

	Time-Invariant	Time-Varying	t-Dist. ($\nu = 5$)
α_0	0.1716	0.1156	0.0414
	(0.1723)	(0.1462)	(0.1741)
α_1	0.0433*	0.0394*	0.0575*
	(0.0145)	(0.0124)	(0.0314)
γ_0	0.1650*	0.1457*	0.2355*
	(0.5170)	(0.0497)	(0.0647)
γ_1	0.1898*	0.1784*	0.1546*
	(0.0414)	(0.0378)	(0.0254)
γ_2	0.7460*	0.7714*	0.7689*
	(0.0427)	(0.0394)	(0.0378)
Skewness	-0.0431	-0.4468	-0.4342
Kurtosis	4.0362	4.0368	3.9122
QZ12	15.2254	15.0791	14.6522
QZS12	12.4223	11.4934	12.6377

The table shows estimates of the market portfolio equation. The equation is estimated via Quasi-Maximum Likelihood (QMLE). The robust standard errors are in parentheses. Robust standard errors are computed from $H^{-1}SH^{-1}$, where H is the Hessian and S is the outer product of the gradients. *Time-Invariant* shows results from the *Regional Contagion II* model with time-invariant beta. *Time-Varying* column shows results from the *Regional Contagion II* model with time-varying beta. *t-Dist* column shows results from an univariate estimation of the market portfolio volatility under the assumption that η_t has a conditional t-distribution with 5 degrees of freedom ($\nu = 5$). Skewness and Kurtosis show the estimates of skewness and kurtosis of the standardized residuals. QZ12 and QZS12 show Ljung-Box test statistics for 12th-order serial correlation of the residual and residual squared, respectively. The $\chi^2(12)$ critical values are 18.55(10%), 21.03(5%), and 26.22(1%). * indicates the coefficient is significant at the 95% confidence interval.

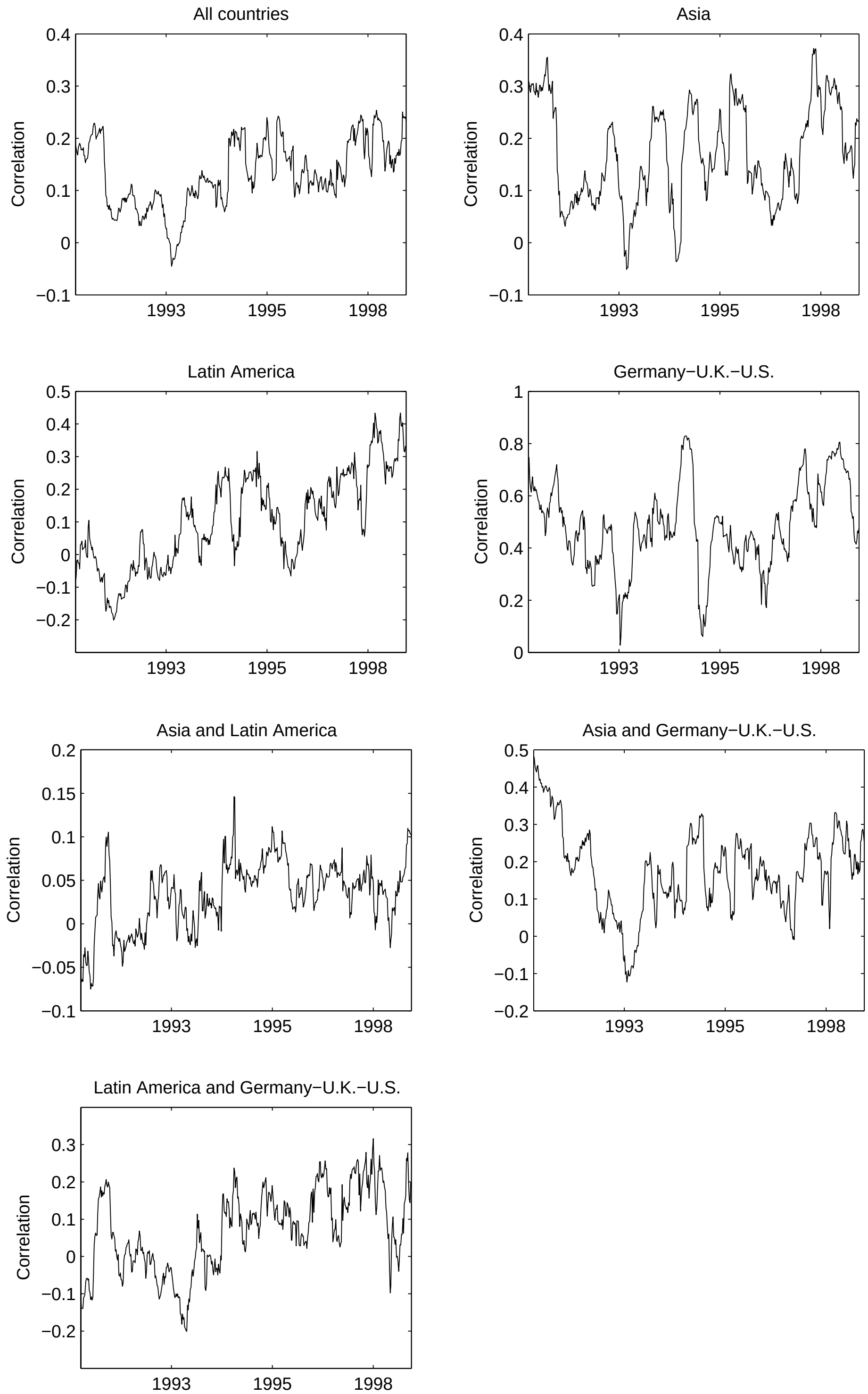

Figure 1: Equally-weighted average of cross-country correlations

The figure shows equally-weighted average excess return rolling cross-country correlations. The rolling window is 24 weeks. The name on top of each figure indicates the equally-weighted average correlations in that group of countries. *All countries* consists of Asia, Latin America, and Germany-U.K.-U.S.. *Asia* includes Indonesia, Malaysia, The Philippines, Singapore, Thailand, Hong Kong, Japan, South Korea, and Taiwan. *Latin America* includes Argentina, Brazil, Chile, and Mexico.

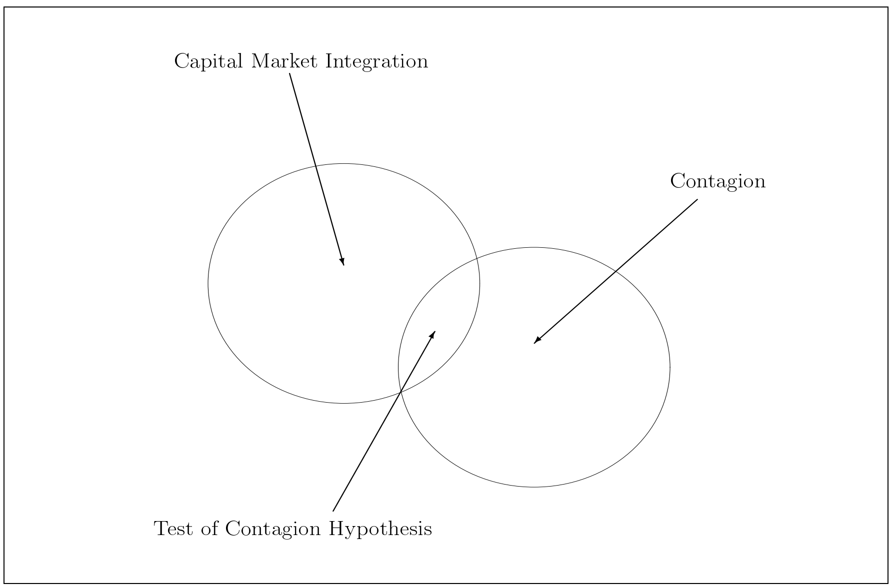

Figure 2: Relationship between Capital Market Integration and Contagion

The figure shows relationships between Capital Market Integration and Contagion concepts. This paper tests for contagion under the assumption of capital market integration (*Test of Contagion Hypothesis*).

$$\Omega_t = \begin{bmatrix} \boxed{\text{ID}} &&&&&&&&&&&&&&& \\ & \boxed{\text{MY}} &&&&&&&&&&&&&& \\ && \boxed{\text{PH}} &&&&&&&&&&&&& \\ &&& \boxed{\text{SG}} &&&&&&&&&&&& \\ &&&& \boxed{\text{TH}} &&&&&&&&&&& \\ &&&&& \boxed{\text{HK}} &&&&&&&&&& \\ &&&&&& \boxed{\text{JP}} &&&&&&&&& \\ &&&&&&& \boxed{\text{KO}} &&&&&&&& \\ &&&&&&&& \boxed{\text{TA}} &&&&&&& \\ &&&&&&&&& \boxed{\text{AR}} &&&&&& \\ &&&&&&&&&& \boxed{\text{BR}} &&&&& \\ &&&&&&&&&&& \boxed{\text{CL}} &&&& \\ &&&&&&&&&&&& \boxed{\text{MX}} &&& \\ &&&&&&&&&&&&& \boxed{\text{BD}} && \\ &&&&&&&&&&&&&& \boxed{\text{UK}} & \\ &&&&&&&&&&&&&&& \boxed{\text{US}} \end{bmatrix}$$

Figure 3: Idiosyncratic conditional covariance matrix: *No Contagion*

$$R_t = \begin{bmatrix}
r_{1,1(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & r_{2,2(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & r_{3,3(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & r_{4,4(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & r_{5,5(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & r_{6,6(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & r_{7,7(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{8,8(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{9,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{10,10(t)} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{11,11(t)} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{12,12(t)} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{13,13(t)} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{14,14(t)} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{15,15(t)} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{16,16(t)}
\end{bmatrix}$$

Figure 4: Restrictions on the idiosyncratic conditional covariance matrix ($\Omega_t = R_t R_t'$): *No Contagion*

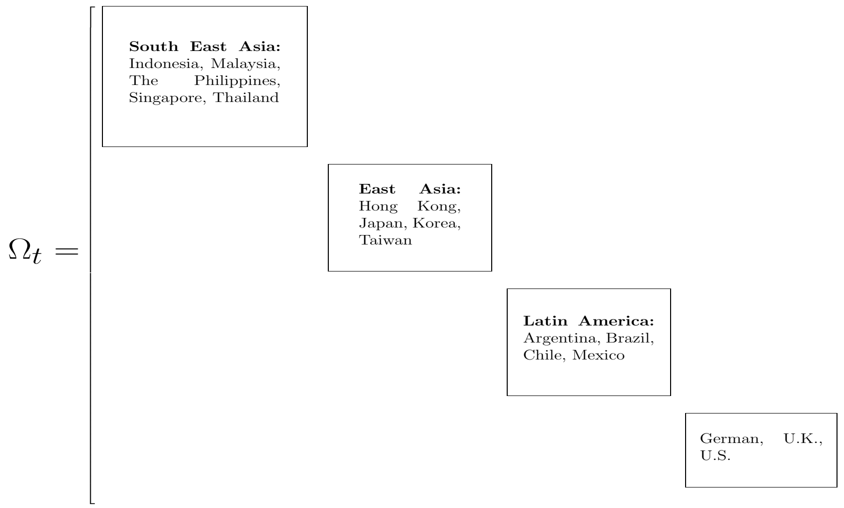

Figure 5: Idiosyncratic conditional covariance matrix: *Regional Contagion I*

$$R_t=\begin{bmatrix}
r_{1,1(t)} & r_{1,2(t)} & r_{1,3(t)} & r_{1,4(t)} & r_{1,5(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & r_{2,2(t)} & r_{2,3(t)} & r_{2,4(t)} & r_{2,5(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & r_{3,3(t)} & r_{3,4(t)} & r_{3,5(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & r_{4,4(t)} & r_{4,5(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & r_{5,5(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & r_{6,6(t)} & r_{6,7(t)} & r_{6,8(t)} & r_{6,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & r_{7,7(t)} & r_{7,8(t)} & r_{7,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{8,8(t)} & r_{8,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{9,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{10,10(t)} & r_{10,11(t)} & r_{10,12(t)} & r_{10,13(t)} & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{11,11(t)} & r_{11,12(t)} & r_{11,13(t)} & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{12,12(t)} & r_{12,13(t)} & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{13,13(t)} & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{14,14(t)} & r_{14,15(t)} & r_{14,16(t)}\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{15,15(t)} & r_{15,16(t)}\\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{16,16(t)}
\end{bmatrix}$$

Figure 6: Restrictions on the idiosyncratic conditional covariance matrix ($\Omega_t = R_t R_t^{'}$): *Regional Contagion I*

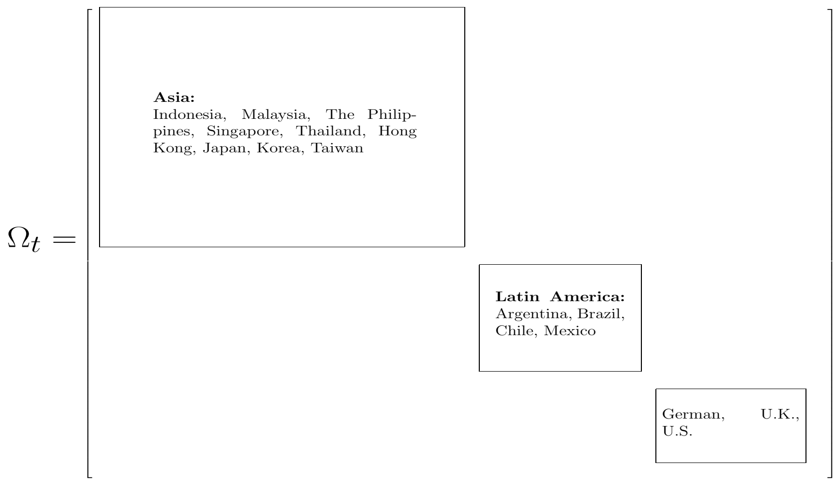

Figure 7: Idiosyncratic conditional covariance matrix: *Regional Contagion II*

$$R_t=\begin{bmatrix}
r_{1,1(t)} & r_{1,2(t)} & r_{1,3(t)} & r_{1,4(t)} & r_{1,5(t)} & r_{1,6(t)} & r_{1,7(t)} & r_{1,8(t)} & r_{1,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & r_{2,2(t)} & r_{2,3(t)} & r_{2,4(t)} & r_{2,5(t)} & r_{2,6(t)} & r_{2,7(t)} & r_{2,8(t)} & r_{2,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & r_{3,3(t)} & r_{3,4(t)} & r_{3,5(t)} & r_{3,6(t)} & r_{3,7(t)} & r_{3,8(t)} & r_{3,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & r_{4,4(t)} & r_{4,5(t)} & r_{4,6(t)} & r_{4,7(t)} & r_{4,8(t)} & r_{4,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & r_{5,5(t)} & r_{5,6(t)} & r_{5,7(t)} & r_{5,8(t)} & r_{5,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & r_{6,6(t)} & r_{6,7(t)} & r_{6,8(t)} & r_{6,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & r_{7,7(t)} & r_{7,8(t)} & r_{7,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{8,8(t)} & r_{8,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{9,9(t)} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{10,10(t)} & r_{10,11(t)} & r_{10,12(t)} & r_{10,13(t)} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{11,11(t)} & r_{11,12(t)} & r_{11,13(t)} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{12,12(t)} & r_{12,13(t)} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{13,13(t)} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{14,14(t)} & r_{14,15(t)} & r_{14,16(t)} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{15,15(t)} & r_{15,16(t)} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & r_{16,16(t)}
\end{bmatrix}$$

Figure 8: Restrictions on the idiosyncratic conditional covariance matrix ($\Omega_t = R_t R_t'$): *Regional Contagion II*

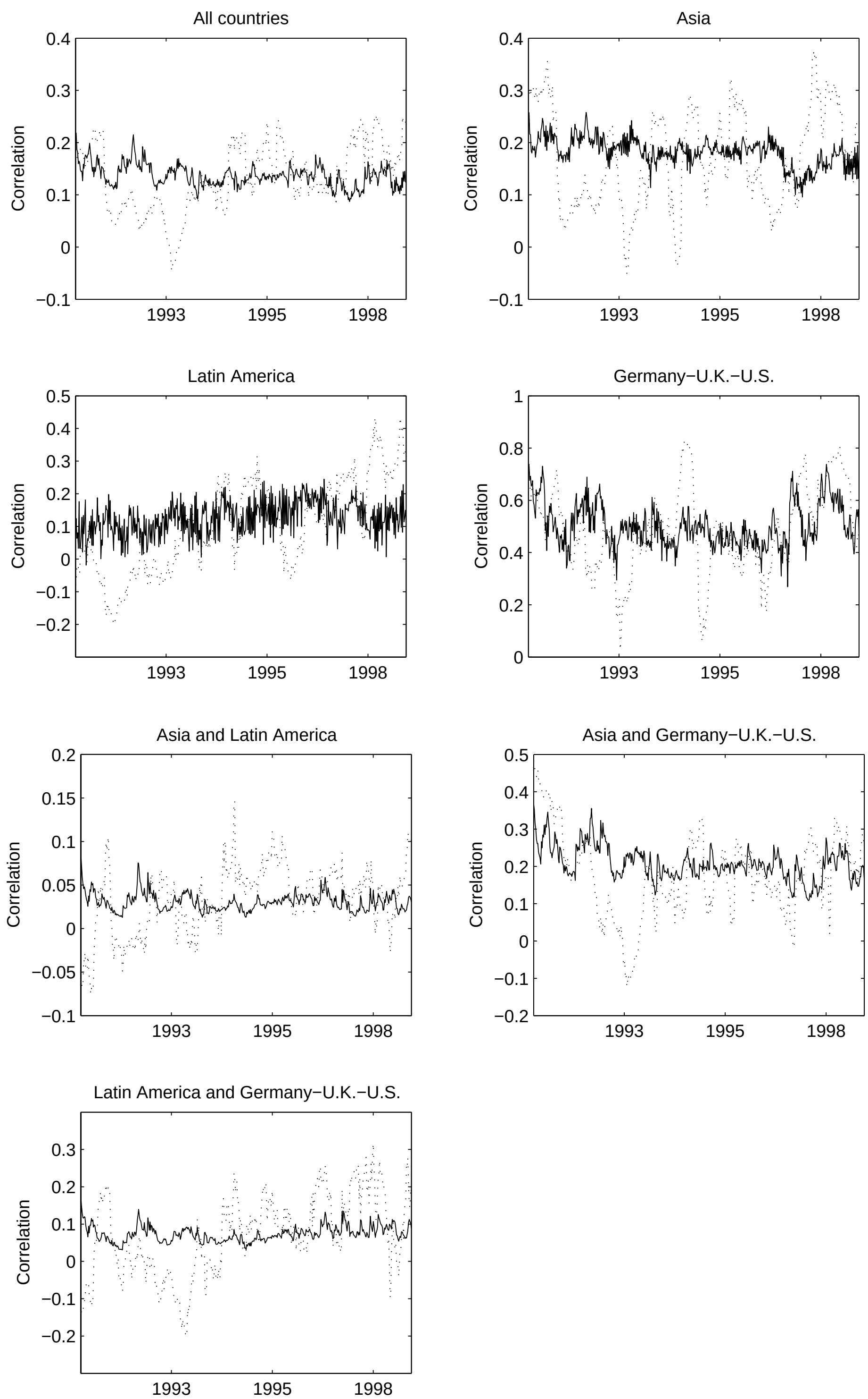

Figure 9: Conditional correlations implied from the CAPM: *Regional Contagion II*

The figure shows both equally-weighted average conditional correlations implied from the conditional CAPM with time-varying beta under the *Regional Contagion II* model (solid line) and shows the equally-weighted average rolling cross-country correlations (dashed line). The rolling window is 24 weeks. The name on top of each figure indicates the equally-weighted average correlations in that group of countries. See description in Figure 1 for the notation of each group.

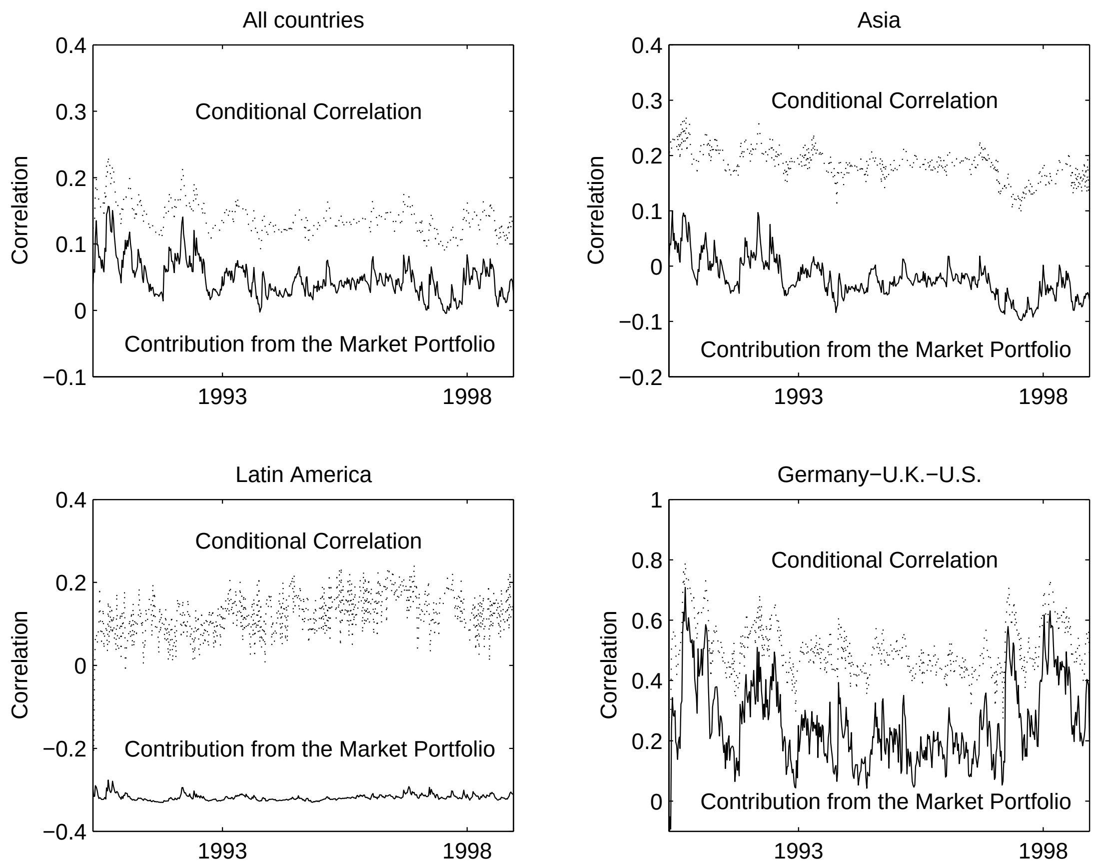

Figure 10: Contribution of the World Market Portfolio to the conditional correlation: *Regional Contagion II*

The figure shows the contribution of the World Market Portfolio to the conditional correlation (solid line). Correlations are equally-weighted average conditional correlations implied from the conditional CAPM with time-varying beta under the *Regional Contagion II* model (dashed line). The name on top of each figure indicates the equally-weighted average correlations in that group of countries. See description in Figure 1 for the notation of each group.

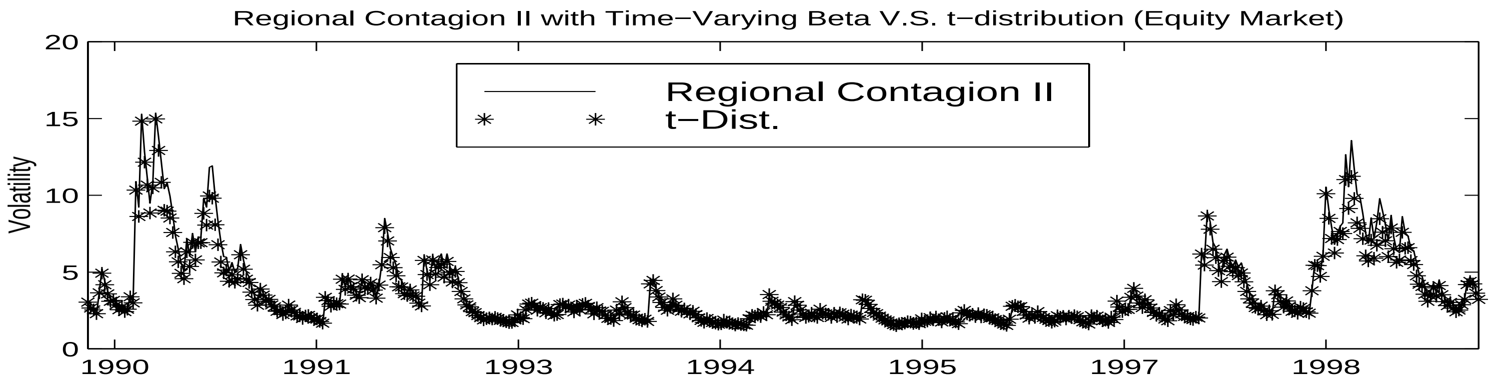

Figure 11: The World Market Portfolio Volatility