Contagion and Industry Risk

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Introduction

The financial crisis of East Asia in 1997 was largely unanticipated and was characterized by sharp falls in currency values and stock prices in several countries simultaneously. A number of complex factors trigged the financial crisis in Asia, but, fundamentally, unbridled expansion and subsequent contraction of banking lending played a leading role. One of the biggest challenges facing scholars studying the East Asian financial crisis is to explain this contagion in which crisis emanating from one country soon swept across all countries in the region.

There are number of reasons why banking centers may add to financial contagion. They can be classified into two types of financial contagion (see Van Rijckeghem and Weder (1999)). The first has been called the "common bank lender channel." Due to the increasing cross-border integration among banks, a common lender can be the main source of funds for several countries. But, competition for funds from the same bank might become a problem. For example, consider the case in which the firms from two countries A and B borrow from the same banking system (say, country C). When a crisis hits A, banks from C may face defaults on loans to A. To restore capital adequacy ratios, country C can provoke a credit crunch in country B by calling in the loans. Thus, the productive sector of country B comes under pressure and eventually the whole country may face a crisis. In this case, even if B's economy is not directly linked to A's, the presence of a third party C makes the crisis spread from one country to the other. The second kind of contagious response also leads to outflows but, in contrast with the common lender channel there is no need for a real linkage through losses. In other words, even if banks had no exposure in the primary crisis country they might still react with a generalized reduction of credit to other countries, due to revisions of expected returns in this asset class or a generalized increase in risk-aversion. This financial contagion due to common bank lenders will not be considered as "pure contagion effect" according to Masson (1999). Instead, it will be categorized as "spillover effect" due to financial interdependence. However, the second type of financial contagion can be qualified as the pure contagion effect because the transmission of financial crises is not due to financial interdependence and neither can it be explained by changes in fundamentals.

In this paper, I examine whether there are pure contagion effects in both conditional means and volatilities of four developed markets' bank stock returns, namely Germany, Japan, the United Kingdom, and the U.S. during the 1997 Asian crisis. There are a number of reasons why negative events relating to the Asian financial crisis might be expected to have a negative effect on the financial markets of non-crisis countries. Firstly, as financial markets become more integrated, shocks can be transmitted quickly between them. To the extent that financial crises in some countries result in a generalized increase in uncertainty in world financial markets, we should expect increased volatility in financial markets in non-crisis countries. Secondly, some market participants might have factored in some possibility that contagion of the crisis could have spread as far as, for example, the U.S., perhaps due to financial institutions' debt exposures to the crisis countries as discussed earlier. Finally, even if financial market participants do not expect that those developed countries will experience financial crisis, they may expect that portfolio rebalancing behavior could result in sharp

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declines in asset prices in countries with unrelated fundamentals (see Kaminsky and Schmukler (1999)).

By using an asymmetric Multivariate General Autoregressive Conditional Heteroscedastic in Mean (MGARCH-M) approach to model the conditional mean and asymmetric volatility spillovers during the crisis period, I find strong evidence of contagion effects in the conditional means of bank stock returns after systematic risks have been accounted for. Specifically, the lead/lag relationships appear to be multidirectional since the return shocks originating in any one of the markets tend to spill over to the other markets. As for the contagion-in-volatility effects, they are not significant. In addition, the global industry risk priced, suggesting the importance of incorporating the industry risk into the conditional ICAPM.

The remainder of the paper is organized as follows. Section one presents the theoretical asset pricing model used to control for systematic risks, and the econometric methodology employed to estimate the model. Several test hypotheses are presented in Section two. Section three describes the data and empirical results are reported in Section four. Some conclusions are offered in the final section.

The Model and Econometric Methodology

We know that the first-order condition of any consumer-investor's portfolio optimization problem can be written as:

$$E[M_t R_{i,t} \mid \Omega_{t-1}] = 1,\ \forall i \qquad (1)$$

where M_t is known as a stochastic discount factor (SDF) or an intertemporal marginal rate of substitution (IMRS); $R_{i,t}$ is the gross return of asset i at time t and Ω_{t-1} is market information known at time $t-1$. Without specifying the form of M_t, equation (1) has little empirical content since it is easy to find some random variable M_t for which the equation holds. Thus, it is the specific form of M_t implied by an asset pricing model that gives equation (1) further empirical content. In empirical tests, the SDF is projected onto two factors: the world market and industry factors. The selection of these two factors is theoretically justified based on the intertemporal CAPM (ICAPM) of Merton (1973). In particular, the conditional two-factor ICAPM model is specified as,

$$r_{i,t} = \lambda_{mkt,t-1} Cov(r_{i,t}, r_{mkt,t} \mid \Omega_{t-1}) + \lambda_{ind,t-1} Cov(r_{i,t}, r_{ind,t} \mid \Omega_{t-1}) + \varepsilon_{i,t}\ \ \forall i \qquad (2)$$

where "mkt" denotes world market risk and "ind" is the global industry risk.

The conditional ICAPM in equation (2) has to hold for every asset. However, the model does not impose any restrictions on the dynamics of the conditional second moments. Several multivariate GARCH (MGARCH) models have been proposed to model the conditional second moments, such as the diagonal VECH model of Bollerslev, Engle, and Wooldridge (1988), the constant correlation (CCORR) model of Bollerslev (1990), the factor ARCH (FARCH) model of Engle, Ng, and Rothschild (1990), and the BEKK model of Engle and Kroner (1995). Among these four popular MGARCH models, the BEKK model is better suited for the purpose of this paper because it not only guarantees that the covariance matrices in the system are positive definite, but also allows the conditional variances and covariances of different markets to influence each other, which is very important for testing contagion in this paper. As a result, a BEKK structure with asymmetric volatility effects is selected over the other MGARCH specifications to model the conditional second moments of bank stock returns and to test contagion effects among those banks. Specifically, the dynamic process for the conditional variance-covariance matrix of stock returns is specified as:

$$\begin{aligned} H_t &= C'C + A' \cdot H_{t-1} \cdot A + B' \cdot \varepsilon_{t-1}\varepsilon_{t-1}' \cdot B + D' \cdot \eta_{t-1}\eta_{t-1}' \cdot D \\ &+ G' \cdot \psi_{t-1}\psi_{t-1}' \cdot G + K' \cdot \xi_{t-1}\xi_{t-1}' \cdot K + L' \cdot \mu_{t-1}\mu_{t-1}' L + M' \cdot \nu_{t-1}\nu_{t-1}' \cdot M + N' \cdot \theta_{t-1}\theta_{t-1}' \cdot N \\ &+ P' \cdot \varsigma_{t-1}\varsigma_{t-1}' \cdot P + Q' \cdot \tau_{t-1}\tau_{t-1}' \cdot Q + S' \cdot \upsilon_{t-1}\upsilon_{t-1}' \cdot S + V' \cdot \zeta_{t-1}\zeta_{t-1}' \cdot V + Y' \cdot \rho_{t-1}\rho_{t-1}' \cdot Y \end{aligned} \quad (3)$$

where H_t is 6×6 time-varying variance-covariance matrix of asset returns; C is restricted to be a 6×6 upper triangular matrix and A, B, D, G, K, L, M, N, P, Q, S, V, and Y are diagonal matrices whose general form, X, is given by:

$$X = \begin{bmatrix} x_{GM} & 0 & 0 & 0 & 0 & 0 \\ 0 & x_{JP} & 0 & 0 & 0 & 0 \\ 0 & 0 & x_{UK} & 0 & 0 & 0 \\ 0 & 0 & 0 & x_{US} & 0 & 0 \\ 0 & 0 & 0 & 0 & x_{Bank} & 0 \\ 0 & 0 & 0 & 0 & 0 & x_{World} \end{bmatrix} \quad (4)$$

The 6×1 vector, η_{t-1}, captures the asymmetric impact that the vector of past negative shocks has on the conditional covariance matrix in a manner similar to that of Glosten et al. (1993). The effects of past shocks of other markets on a market's conditional variance or conditional covariances (volatility spillovers) are captured by the vectors ψ_{t-1}, ξ_{t-1}, μ_{t-1}, ν_{t-1}, and θ_{t-1}. Several papers in the literature show that volatility spillovers between markets are asymmetric in the sense that negative innovations in a market increase volatilities in other markets more than do positive innovations in that market. Consequently, it will be interesting to see whether such asymmetric volatility spillovers do occur during the *crisis*. The vectors ς_{t-1}, τ_{t-1}, υ_{t-1}, ζ_{t-1}, and ρ_{t-1} capture this asymmetry. The difference between the first set of innovation vectors (ψ_{t-1}, ξ_{t-1}, μ_{t-1}, ν_{t-1}, θ_{t-1}) and the second set of innovation vectors (ς_{t-1}, τ_{t-1}, υ_{t-1}, ζ_{t-1}, ρ_{t-1}) is that the first set captures overall volatility spillovers during the *entire* sample period, while the second set captures the asymmetric volatility spillovers during the *crisis* period. By including vectors ς_{t-1}, τ_{t-1}, υ_{t-1}, ζ_{t-1}, and θ_{t-1}, I can then test the incremental influences of volatility shocks on the banking sectors, which is a true test of contagion-in-volatility. In this model, for example, the conditional variance of excess German bank stock returns, $h_{GM,t}$, depends on its past conditional variance, $h_{GM,t-1}$, through the parameter, a_{GM}, its own past shocks, $\varepsilon_{GM,t-1}$, through the parameter, b_{GM}, and past shocks of the other markets through the parameters, g_{GM}, k_{GM}, l_{GM}, m_{GM}, and n_{GM}. This conditional variance also depends on its own past negative shocks through the parameter, d_{GM}, and on past negative shocks of the other markets through the parameters, p_{GM}, q_{GM}, s_{GM}, v_{GM}, and y_{GM} during the crisis. Here, these parameters measure the incremental amounts by which bad news in one market at time $t-1$ affect the conditional variance of excess German bank stock returns at time t.

Under the assumption of conditional normality, the log-likelihood to be maximized can be written as:

$$\ln L(\varpi) = -\frac{TN}{2}\ln 2\pi - \frac{1}{2}\sum_{t=1}^{T}\ln|H_t(\varpi)| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t(\varpi)'\ H_t(\varpi)^{-1}\varepsilon_t(\varpi) \qquad (5)$$

where ϖ is the vector of unknown parameters in the model. Since the normality assumption is often violated in financial time series, I use quasi-maximum likelihood estimation (QML) proposed by Bollerslev and Wooldridge (1992) which allows inference in the presence of departures from conditional normality. Under standard regularity conditions, the QML estimator is consistent and asymptotically normal and statistical inferences can be carried out by computing robust Wald statistics. Optimization is performed using the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm.

Hypothesis Testing

Testing Time-varying Risk Premium

Many empirical studies have shown that the prices of risks are time-varying. (e.g., De Santis and Gerard (1997, 1998), among others.) This time-varying price of risk is economically appealing in the sense that investors use all available information to form their expectations about future economic performance, and when the information changes over time, they will adjust their expectations and thus their expected risk premia when holding different risky assets. Therefore, to test time-varying risk premium hypothesis, I allow not only the conditional second moments (covariance risks) to change over time, but also the prices of covariance risks to be time-varying (equation (2)).

The dynamic of price of world market risk is chosen according to the theoretical asset pricing model developed by Merton (1980). In his model, the price of world market risk is the coefficients of risk aversion of risk averse investors, and thus should be positive. Consequently, similar to De Santis and Gerard (1997, 1998), an exponential function is used to model the dynamic of $\lambda_{mkt,t-1}$ and for the dynamic of $\lambda_{ind,t-1}$, a linear specification is adopted because the model does not restrict the price of industry risk to be positive.

$$\lambda_{mkt,t-1} = \exp(\varphi_{mkt}' z_{t-1}) \qquad (6)$$

$$\lambda_{ind,t-1} = \varphi_{ind}' z_{t-1} \qquad (7)$$

where Z_{t-1} is a vector of information variables observed at the end of time $t-1$ and φ's are time-invariant vectors of weights. Thus, the price of global industry risk is assumed to be a linear function of the information variables in Z_{t-1}, and the price of world market risk is assumed to be an exponential function of information variables in Z_{t-1}. Given the dynamics of prices of risks, I can then test the whether the world prices of market and industry risks are significantly priced and change over time by testing whether the information variables in Z_{t-1} are significant in addition to significant GARCH parameters.

Testing Contagion in Mean and Volatility

To test whether a country's past idiosyncratic shocks have significant impact on the other countries' condition returns (contagion-in-mean) during the Asian crisis, I incorporate past country-specific innovations into equation (2). Specifically, the equation (2) can be modified as:

$$r_{i,t} = \lambda_{mkt,t-1} Cov(r_{i,t}, r_{mkt,t} \mid \Omega_{t-1}) + \lambda_{ind,t-1} Cov(r_{i,t}; r_{ind,t} \mid \Omega_{t-1}) + \sum_{i,j} \phi_{ij} \varepsilon_{j,t-1} + crisis(\sum_{i,j} \omega_{ij} \varepsilon_{j,t-1}) + \varepsilon_{i,t} ; \forall i, j \quad (8)$$

where "*crisis*" is a dummy variable, which is equal to one during the crisis period (07/04/1997 – 12/25/98) and zero otherwise. In testing the contagion-in-mean effects, I allow the past country-specific innovations to affect bank stock returns in the *entire* sample period, and then test whether there are any incremental influences of past innovations on these returns during the *crisis* period. Thus, the contagion-in-mean hypothesis can be examined by testing whether the coefficients, $\omega_{ij} (i \neq j)$, are individually or jointly significant after the systematic risks have been accounted for.

Data and Summary Statistics

Weekly observations of bank stock total return indices from Germany (GM), Japan (JP), the United Kingdom (UK), and the U.S. (US) are examined. Datastream world total bank ($Bank$) and market return indices ($World$) are used to proxy global industry and market risks, respectively. 7-day Eurodollar interest rate is used as conditionally risk-free rate to compute excess returns on all indices.

I select a set of conditioning variables that have been widely used in the international asset pricing literature (e.g., De Santis and Gerard (1997, 1998), among others). They are excess dividend yield measured by the dividend yield on $World$ in excess of the 7-day Eurodollar interest rate (DIV), the change in the U.S. term premium, measured by the first difference of the yield difference between 10-year Treasury constant maturity rate and 7-day Eurodollar rate ($\Delta USTP$), the U.S. default premium, measured by the yield difference between Moody's Baa-rated and Aaa-rated U.S. corporate bonds ($USDP$), the lagged excess return on $World$, and a constant ($CONSTANT$).

The weekly data ranges from April 6, 1990 to March 23, 2001, which is a 573-data-point series. However, I work with rates of return and use the first difference of conditioning variables, and finally all the conditioning variables are used with a one-week lag, relative to the excess return series; that leaves 571 observations expanding from April 20, 1990 to March 23, 2001. All the data are extracted from Datastream.

Table 1 presents summary statistics of the continuously compounded stock returns. As can be seen from panel A, among all the return series UK has the highest weekly mean returns, 0.273%, and JP, on the other hand, performs worst with a return of -0.219% per week and a standard deviation of 4.237%. Table 1 also reports Bera-Jarque and Ljung-Box statistics. Bera-Jarque test rejects normality for all return series. The Ljung-Box test statistics for raw returns ($LB(20)$) are only significant at the 5% level in two markets: GM and JP, implying that linear dependencies are not very strong in the sample. However, for squared returns, $LB^2(20)$ is significant at the 1% level for all series except UK, indicating strong nonlinear dependencies in the sample. This is consistent with the volatility clustering observed in most stock markets, suggesting that the use of a conditional heteroscedasticity model is advisable. The unconditional correlation coefficients for the conditioning variables are reported in panel B of Table 1. The correlation coefficients are pretty small, and none of them are statistically significant, indicating that the selected conditioning variables contain sufficiently orthogonal information.

Empirical Evidence

The quasi-maximum likelihood estimation of the conditional ICAPM (equation (8)) is reported in Table 2. The hypothesis tests regarding the prices of risks and the predictability of conditioning variables are presented in Table 3. The hypothesis tests concerning the contagion in mean are shown in Table 4.

The evidence of time-varying risk premia

First, consider the test results for the existence of time-varying risk premia for global industry and market risks, the joint hypothesis of zero prices of industry and market risks is strongly rejected by Wald statistic ($Wald$ = 586.387) with a p-value nearly zero. The joint hypothesis of constant prices of industry and market risks is also rejected ($Wald$ = 67.374). Next, the joint hypothesis of constant price of industry risk is strongly rejected by Wald test ($Wald$ = 25.388), and the joint hypothesis of constant price of market risk is also rejected ($Wald$ = 24.758). These test results imply that both industry and market risks are not only priced but also time varying. The conditioning variables useful in predicting the dynamics of the risk prices include excess dividend yield (DIV) and lagged excess return on world market portfolio ($World$) as evidenced from the hypothesis tests (#7 and #10) reported in Table 3.

Evidence of Mean Spillover and Contagion in Mean

After controlling the systematic industry and market risks, I can then test contagion-in-mean effects among four banking sectors. However, before that, I need to control for the overall mean spillovers in the entire sample period, so any incremental mean spillover effects can be tested during the crisis period. It can be seen from Table 4 that the hypothesis of no mean spillover (#1 - #4) is rejected at the 1% level for GM and UK. To find out the sources of mean spillover for these two markets, one can check statistical significance of individual mean spillover parameter, ϕ, reported in Table 2. Table 2 indicates that the source of mean spillover for GM comes from JP, and for UK, the sources are from JP and US. However, JP appears to be the major market in generating return shocks for the other markets based on the Wald statistic ($Wald$ = 37.561) for the hypothesis test (#10) reported in Table 4.

Now, considering the test results of contagion in mean effects, as shown in Table 4, these effects are statistically significant at the 1% level for all markets. For example, the joint hypothesis of no contagion in return shocks for GM ($H0: \omega_{GM,j} = 0; \forall j = JP, UK, US$) during the crisis is strongly rejected by the Wald statistic ($Wald$ = 14.771) at the 1% level. The same rejection also applies to JP, UK, and US. To find out the sources of contagion in return shocks for GM, one can again examine the individual significance of contagion-in-mean parameter, $\omega_{JP,j}$, reported in Table 2 based on robust standard errors. Basically, the current returns in GM are affected by past return shocks in JP ($\omega_{GM,JP}$= -0.052) and UK ($\omega_{GM,UK}$= 0.109). The current return shocks in JP are due to the past return shocks in the other three markets in addition to its own past return shocks. That is the contagion-in-mean parameters for JP, $\omega_{JP,j}$, are all significant. Similarly, the current return shocks for UK and US are also affected by the other three markets. By examining the significance of these individual contagion-in-mean parameters, one can conclude that basically the lead/lag relationships appear to be multidirectional since return shock originated from any one of the markets tend to spill over to the other three markets, and this conclusion has been confirmed by the hypothesis tests (#13 - #16) reported in Table 4. However, Germany and U.K. appear to be the major markets in generating those contagion effects because the Wald test statistics for the hypotheses of no contagion in return shocks from GM and UK (#13 and #15) are significant higher than those for JP and US.

Evidence of Volatility Spillover and Contagion in Volatility

Turning to volatility spillovers and contagion effects on the conditional variances of excess stock returns, it can be seen from Table 2 that none of the volatility spillover parameters is statistically significant except $m_{World,US}$, implying that there is no volatility spillover among the four banking sectors in the entire sample period. It will be interesting to examine next where the dynamics of conditional variances of these bank stock returns behave differently during the crisis. In particular, I test whether countries' negative idiosyncratic shocks become contagious during the crisis after controlling the overall volatility spillovers in the entire sample period. That is, I test contagion-in-volatility hypothesis. As shown in Table 2, none of the contagion-in-volatility parameters is statistically significant, suggesting that there is no volatility spillover even during the crisis period. Finally, in addition to the volatility spillover and contagion-in-volatility parameter estimates shown in Table 2, Table 2 also reports the estimates for GARCH and ARCH parameters (a_i, b_i) and own asymmetric volatility shock parameters, d_i. The GARCH parameters are all significant at the 1% level, implying that all the conditional variance processes are highly persistent. However, none of the parameters, d_i, is significant, suggesting that asymmetries are not present in the bank stock returns.

Summary and Concluding Remarks

This paper tests whether contagion can occur at the industry level, in particular the banking industry. Previous studies on contagion have failed to take into account the important distinction between the two concepts of interdependence and contagion. Specifically, in this paper I define 'contagion' as significant spillovers of country-specific idiosyncratic shocks during the crisis after economic fundamentals or systematic risks have been accounted for. To control for the economic fundamentals, I rely on the ICAPM, which provides me a theoretical basis in selecting the economic fundamentals. The economic fundamentals under ICAPM are world market and industry risks, so the evidence of contagion is based on testing whether idiosyncratic risks - the part that cannot be explained by the world market and industry risks, are significant in describing the dynamics of conditional mean and volatility of bank stock returns during the 1997 Asian crisis.

The empirical results indicate strong contagion effects in the conditional means of bank stock returns after systematic risks have been accounted for. Specifically, the lead/lag relationships appear to be multidirectional among four banking sectors since the return shocks originating in any one of the markets tend to spill over to the other three markets. As for the contagion-in-volatility effects, they are not significant. In addition, the global industry risk is significantly priced, suggesting the importance of incorporating the industry risk into the conditional ICAPM.

Table 1

Panel A: Summary statistics of bank and world stock returns

	GM	*JP*	*UK*	*US*	*Bank*	*World*
Mean (%)	0.011	-0.219	0.273	0.249	0.030	0.066
Std. Dev. (%)	3.021	4.237	3.465	2.999	2.365	1.866
Minimum (%)	-13.135	-15.322	-10.260	-10.079	-9.076	-9.127
Maximum (%)	14.091	19.402	17.413	16.041	10.272	7.608
$B-J$	115.818**	110.780**	46.418**	105.358**	82.657**	164.580**
$LB(20)$	37.357*	37.438*	19.194	23.331	20.468	15.972
$LB^2(20)$	141.468**	63.099**	27.877	208.999**	153.123**	118.952**

Panel B: Unconditional correlation of conditioning variables

	DIV	$\Delta USTP$	*USDP*	*World*
DIV	1			
$\Delta USTP$	0.087**	1		
USDP	-0.031	0.058	1	
World	0.034	-0.031	0.015	1

* and ** denote statistical significance at the 5% and 1% level, respectively.

Table 2

Quasi-Maximum Likelihood estimation of the conditional ICAPM

Panel A: Conditional mean process

	World prices of market and industry risks				
	CONSTANT	*DIV*	$\Delta USTP$	*USDP*	*World*
φ_{mkt}	1.512	0.979	0.736	4.383	-31.405
	(1.384)	(1.657)	(1.676)	(10.012)	(7.184)**
φ_{ind}	6.766	9.227	-9.047	23.768	65.063
	(0.906)**	(2.017)**	(46.252)	(18.669)	(82.563)
	Mean spillovers				
	$j=GM$	$j=JP$	$j=UK$	$j=US$	
$\phi_{GM,j}$	-0.002	0.069	-0.006	0.055	
	(0.030)	(0.023)**	(0.024)	(0.029)	
$\phi_{JP,j}$	-0.016	-0.010	0.027	-0.025	
	(0.021)	(0.024)	(0.022)	(0.035)	
$\phi_{UK,j}$	-0.019	-0.081	-0.192	0.099	
	(0.023)	(0.018)**	(0.021)**	(0.033)**	
$\phi_{US,j}$	0.021	-0.017	0.002	-0.065	
	(0.024)	(0.021)	(0.022)	(0.020)**	
	Contagion in mean				
	$j=GM$	$j=JP$	$j=UK$	$j=US$	
$\omega_{GM,j}$	0.043	-0.052	0.109	-0.051	
	(0.055)	(0.026)*	(0.040)**	(0.066)	
$\omega_{JP,j}$	-0.271	-0.305	0.247	-0.132	
	(0.024)**	(0.011)**	(0.022)**	(0.028)**	
$\omega_{UK,j}$	-0.119	0.128	-0.083	0.123	
	(0.030)**	(0.038)**	(0.025)**	(0.054)*	
$\omega_{US,j}$	0.250	0.098	-0.158	0.002	
	(0.059)**	(0.046)*	(0.063)*	(0.072)	

Panel B: Conditional variance process						
	$i = GM$	$i = JP$	$i = UK$	$i = US$	$i = Bank$	$i = World$
a_i	0.963 (0.018)**	0.953 (0.021)**	0.949 (0.020)**	0.955 (0.017)**	0.955 (0.017)**	0.956 (0.016)**
b_i	0.177 (0.065)**	0.275 (0.078)**	0.217 (0.070)**	0.274 (0.071)**	0.251 (0.049)**	0.221 (0.048)**
d_i	0.903 (1.879)	0.156 (0.788)	-1.665 (2.223)	0.846 (1.892)	0.457 (1.295)	1.550 (1.627)
Volatility spillovers [a]						
	$i = GM$	$i = JP$	$i = UK$	$i = US$	$i = Bank$	$i = World$
$j = GM$		-0.004 (0.025)	-0.002 (0.057)	0.009 (0.035)	0.001 (0.016)	-0.003 (0.011)
$j = JP$	0.034 (0.058)		0.018 (0.026)	0.001 (0.036)	0.000 (0.003)	0.003 (0.006)
$j = UK$	0.118 (0.072)	0.005 (0.037)		0.004 (0.058)	0.010 (0.010)	0.003 (0.005)
$j = US$	-0.035 (0.054)	-0.053 (0.064)	0.076 (0.101)		0.003 (0.006)	0.062 (0.014)**
$j = Bank$	0.033 (0.100)	0.008 (0.050)	-0.086 (0.054)	-0.056 (0.094)		0.009 (0.016)
$j = World$	0.034 (0.116)	-0.005 (0.095)	-0.002 (0.086)	0.004 (0.126)	0.006 (0.045)	
Contagion in asymmetric volatility [a]						
	$i = GM$	$i = JP$	$i = UK$	$i = US$	$i = Bank$	$i = World$
$j = GM$		0.333 (2.341)	0.584 (1.997)	0.291 (1.084)	-0.005 (0.395)	0.310 (0.817)
$j = JP$	0.185 (0.985)		-0.195 (0.926)	0.041 (0.362)	-0.005 (0.181)	0.000 (0.158)
$j = UK$	0.019 (2.288)	-3.707 (3.794)		-0.016 (1.411)	0.158 (0.887)	0.090 (0.309)
$j = US$	0.647 (2.403)	0.292 (5.364)	-0.817 (4.167)		-0.376 (1.234)	0.010 (0.682)
$j = Bank$	1.882 (4.422)	-2.834 (4.779)	-0.120 (2.379)	1.489 (2.215)		-0.087 (1.687)
$j = World$	-3.670 (11.101)	-4.978 (11.979)	1.415 (10.962)	-0.087 (3.948)	0.073 (3.087)	

[a] The reported parameter estimates for both the volatility spillover and contagion-in-asymmetric-volatility coefficients can be interpreted as follows. For example, if x_{ij} represents the volatility spillover coefficient from market j to market i, then the volatility spillover coefficient estimate from JP to GM is 0.034, which corresponds to $g_{GM,JP}$ in matrix G in the variance-covariance matrix in equation (3). Similarly, the volatility spillover coefficient estimate from UK to GM is 0.118, which corresponds to $k_{GM,UK}$ in matrix K in the variance-covariance matrix in equation (3), and so on. The reported parameter estimates for the contagion-in-asymmetric-volatility coefficients have the same interpretation as those for volatility spillover coefficients. Robust standard errors are given in parentheses. * and ** denote statistical significance at the 5% and 1% level, respectively.

Table 3
Hypothesis tests: prices of risks and predictability of conditioning variables

Null Hypothesis	Wald	d.f.	P-Value
1. Are the prices of industry and market and risks equal to zero? $H0: \varphi_{ind} = \varphi_{mkt} = 0; Z_{t-1} = \{CONSTANT, DIV, \Delta USTP, USDP, World\}$	586.387	10	0.000
2. Are the prices of industry and market risks constant? $H0: \varphi_{ind} = \varphi_{mkt} = 0; Z_{t-1} = \{DIV, \Delta USTP, USDP, World\}$	67.374	8	0.000
3. Is the price of industry risk equal to zero? $H0: \varphi_{ind} = 0; Z_{t-1} = \{CONSTANT, DIV, \Delta USTP, USDP, World\}$	203.462	5	0.000
4. Is the price of industry risk constant? $H0: \varphi_{ind} = 0; Z_{t-1} = \{DIV, \Delta USTP, USDP, World\}$	25.388	4	0.000
5. Is the price of market risk equal to zero? $H0: \varphi_{mkt} = 0; Z_{t-1} = \{CONSTANT, DIV, \Delta USTP, USDP, World\}$	90.205	5	0.000
6. Is the price of market risk constant? $H0: \varphi_{mkt} = 0; Z_{t-1} = \{DIV, \Delta USTP, USDP, World\}$	24.758	4	0.000
7. Is there no predictability from excess dividend yield? $H0: \varphi_{ind,k} = \varphi_{mkt,k} = 0; \forall k = DIV$	21.308	2	0.000
8. Is there no predictability from the change in term premium? $H0: \varphi_{ind,k} = \varphi_{mkt,k} = 0; \forall k = \Delta USTP$	0.198	2	0.905
9. Is there no predictability from the U.S. default premium? $H0: \varphi_{ind,k} = \varphi_{mkt,k} = 0; \forall k = USDP$	2.325	2	0.312
10. Is there no predictability from the world market portfolio? $H0: \varphi_{ind,k} = \varphi_{mkt,k} = 0; \forall k = World$	19.141	2	0.000

Table 4
Hypothesis tests: mean spillover and contagion in mean

Null Hypothesis	Wald	d.f.	P-Value
1. Is there no mean spillover for GM **?** $H0:\phi_{GM,j}=0;\forall j=JP,UK,US$	11.618	3	0.000
2. Is there no mean spillover for JP **?** $H0:\phi_{JP,j}=0;\forall j=GM,UK,US$	3.057	3	0.382
3. Is there no mean spillover for UK **?** $H0:\phi_{UK,j}=0;\forall j=GM,JP,US$	31.557	3	0.000
4. Is there no mean spillover for US **?** $H0:\phi_{US,j}=0;\forall j=GM,JP,UK$	1.538	3	0.673
5. Is there no contagion in return shocks for GM **?** $H0:\omega_{GM,j}=0;\forall j=JP,UK,US$	14.771	3	0.002
6. Is there no contagion in return shocks for JP **?** $H0:\omega_{JP,j}=0;\forall j=GM,UK,US$	214.791	3	0.000
7. Is there no contagion in return shocks for UK **?** $H0:\omega_{UK,j}=0;\forall j=GM,JP,US$	30.687	3	0.000
8. Is there no contagion in return shocks for US **?** $H0:\omega_{US,j}=0;\forall j=GM,JP,UK$	30.205	3	0.000
9. Is there no mean spillover from GM **?** $H0:\phi_{i,GM}=0;\forall i=JP,UK,US$	2.183	3	0.535
10. Is there no mean spillover from JP **?** $H0:\phi_{i,GM}=0;\forall i=JP,UK,US$	37.561	3	0.000
11. Is there no mean spillover from UK **?** $H0:\phi_{i,UK}=0;\forall i=GM,JP,US$	1.605	3	0.658
12. Is there no mean spillover from US **?** $H0:\phi_{i,US}=0;\forall i=GM,JP,UK$	14.664	3	0.002
13. Is there no contagion in return shocks from GM **?** $H0:\omega_{i,GM}=0;\forall i=JP,UK,US$	312.761	3	0.000
14. Is there no contagion in return shocks from JP **?** $H0:\omega_{i,JP}=0;\forall i=GM,UK,US$	21.364	3	0.000
15. Is there no contagion in return shocks from UK **?** $H0:\omega_{i,UK}=0;\forall i=GM,JP,US$	137.002	3	0.000
16. Is there no contagion in return shocks from US **?** $H0:\omega_{i,US}=0;\forall i=GM,JP,UK$	35.453	3	0.000

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