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EXCESS RETURNS AND SYSTEMIC RISK FOR CHILE AND MEXICO*

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Abstract

This paper is concerned with excess returns in the equity markets and the evolution of systemic risk in Chile and Mexico during the years 1989-1998, a period of financial openness, policy reform and crisis. A time varying generalised autoregressive conditional heteroscedastic in mean framework is used to estimate progressively more complex models of risk. They include the univariate own volatility models, the bivariate market pricing model, and the trivariate intertemporal asset pricing model. The results show no evidence of a significant reduction in systemic risk rather excess returns have remained volatile for both countries. For Chile, excess returns are significantly related to own lagged levels, while for Mexico excess returns are significantly related to own lagged variances. The influence of global factors are relatively minimal compared to potential home factors.

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I. Introduction

This paper examines time-varying risk premia (defined as excess returns inclusive of currency risk) for the Chilean and Mexican stock markets, since 1989, a period of financial openness and reform, but also a period of turbulence and stress. We are particularly interested in the ability of various risk models to explain the systemic component of excess returns.

In the early 1990's, both Chile and Mexico were model "policy reformers" among the Latin American countries. Mexico's reputation was bolstered by the ratification of the North American Free Trade Agreement in 1993. Chile was waiting to be next in line for a NAFTA expansion to be renamed Free Trade Agreement for the Americas. Not surprisingly, Chile[1] and Mexico[2] are countries which have attracted considerable research interest during the past two decades.

An underlying issue for both of these countries is the role of "globalization" of securities and equity markets. Are the risk premia in both of these countries related more to international or US factors, such as the sharp drop in US inflation, or are they home-country phenomena? In this important respect, Chile has had markedly different policies from Mexico. From the beginning of its reform process, until the aftermath of the 1997 Asian crisis, Chile maintained special taxes on short-term capital inflows. In particular, foreigners had to pay a tax of 30 percent on all investments less than two years in duration.[3] Mexico, on the other hand, had a virtually free and open market for short-term flows.[4]

The particular aim of the paper is to examine the evolution of "systemic risk" in these two countries. Rather than examine directly the policy variables, capital flows, and terms of trade developments in these countries, we analyze excess returns in the equity markets to learn about the behavior of systemic risk during this period of time.

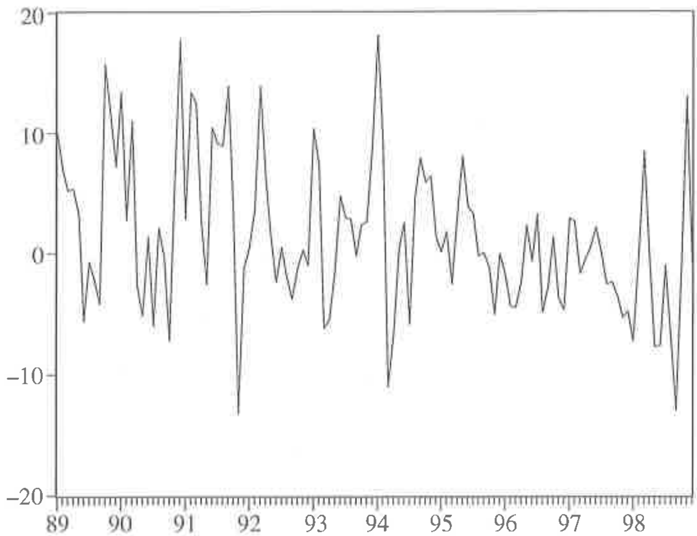
Figure 1 shows the evolution of the monthly changes in the share prices of Chile and Mexico. While both series show a similar pattern, the Mexican volatility is by far the larger throughout most of the period. Moreover, the Mexican series show two sharp falls – late 94-early 95 and mid-98. The first fall relates to the Mexican peso crisis and the second relates to spillovers in Mexico of the Asian crisis which began in 1997.

The aim of this paper is to explore models that offer some explanation of the link between the measure of risk premia and the volatility present in the excess return data for Chile and Mexico during the past decade. Alternatives to simple linear models are considered.

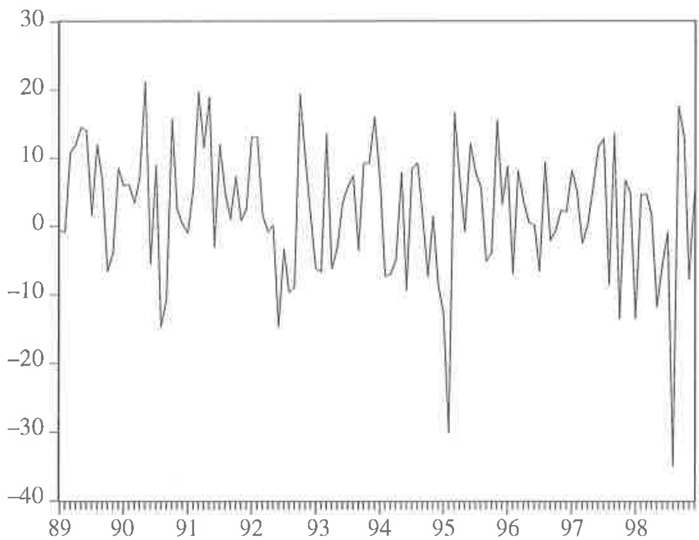
Two alternatives are readily available –Kalman filtering and neural network approximation methods. The Kalman filter is a model of learning behavior, in which the coefficients change, or are updated, as new observations become available. Parameters of the model adjust as the economic transactors learn from previous forecast errors of the excess returns. The Kalman filter is thus akin to an "error-correction" model, but the "correction" takes place in "parameter space" rather than in the "dependent variable" space.

FIGURE 1

MONTHLY RETURNS (%)



Chile



Mexico

Sargent (1998) has recently shown that the Kalman filter represents "learning behavior" under assumptions of "bounded rationality"[5]. The insight of the Sargent "bounded rationality" learning is that economic agents "learn" from their errors, in the sense that they update their coefficients of their incorrectly specified models, based on the previous period forecast errors. A drawback is that such learning is spread out over the entire parameter space. Bounded rationality learning does not imply any restrictions on the parameter "learning space". Would it not be more plausible if participants adjust some parameters more readily than others, in response to forecast errors? If so, which ones, and why? Learning models based on the Kalman filter do not give a clue for answering this question.[6]

Analogous approaches are polynomial and neural network approximations.[7] In this case the "learning" is about the proper function form of relation between excess returns and the explanatory variables. Alternative polynomial expansions (of progressive higher degree), and more extensive neural networks, approximate diverse and increasingly complex functional relationships.

The problem with these approximation methods is that there is no *a priori* restriction on the degree of the polynomial expansion or the number of neurons, and thus the number of parameters, of the approximation. Mindful of the Lucas' warning to "beware of economists bearing free parameters", most researchers have been slow to take up this approach.

More fundamentally, polynomial and neural network approximations are forms of semi-non-parametric statistics. By altering either the degree of polynomial expansion or the number of neural network coefficients, one is searching over a "function space", since both approximate unknown functional forms linking the exogenous variables to the dependent variable.

However, when one models risk and its effects on excess-return data, more restricted and more commonly defined families of probability distributions usually come to mind, at least for a first attempt to explain the evolution of the data. Approximation methods, by contrast, are not restricted to any functional form or family of distributions of the excess-return data.

For this reason, we confine our investigation to the univariate and multivariate generalized autoregressive conditional heteroskedastic in mean (M-GARCH-M) framework to estimate progressively more complicated versions of risk premia or excess return models. These approaches also increase the number of parameters to be estimated, but the parameters are defined in terms of the evolution of variances and covariances of the error processes. Thus, the distributions are normal, conditional on the time-varying mean and variance, and the optimization process for finding the best set of coefficients are predicated on a Gaussian likelihood function.

The ARCH model proposed by Engle (1982), and the GARCH model generalized by Bollerslev (1986), have been used extensively to model the behavior of volatility over time.[8] In particular, the GARCH-M model of Engle, Lilien and Robbins (1987) explicitly links the conditional variance to the conditional mean of the returns and hence is the ideal framework to study the relationship between measures of risk and volatility. In this paper, the M-GARCH-M framework is applied to estimate all three models –starting from the univariate own volatility in mean model, to the bivariate model linking risk premia to market volatility, to the trivariate model which includes a role for inflation volatility.

Like the Kalman filter, there are time varying parameters, specifically the conditional variances or conditional covariances, which affect the mean of the dependent variable. The conditional variances and covariances, in turn, adjust to previous period "forecast errors", and thus may represent "bounded rationality" learning behavior. But in the case of this framework the "parameter learning space" is restricted to the effects of the conditional variances and covariances on the dependent variable.

Like polynomial and neural network approximations, the GARCH approach takes seriously the non-linear processes in the underlying evolution of the excess return data. However, in contrast to the neural network, both the number of parameters and the functional form of time-varying distribution are well specified in a conditional variance and covariance framework. Thus, one is not left to search through and approximate a wide variety of perhaps idiosyncratic probability distributions to explain the data.

The approach of this paper thus tries to combine the best of the Kalman filtering and neural network approaches. Some parameters do indeed adjust through time, since there are time-varying variances and covariances which affect the mean. Secondly, a non-linear process, relating the exogenous variables to "excess returns", through "risk", is approximated, but with a restricted number of parameters and a well-defined function form. Much in the spirit of Marcet and Nicolini (1998), our venture into the "jungle" of bounded rationality and non-linearity is with a well-specified map!

We apply the univariate GARCH-M and multivariate GARCH-M to explain excess returns and risk in the variety of ways described in the recent literature. Specifically, we examine three different types of risk modelling: (1) those which relate risk directly to own volatility;[9] (2) those which explain risk in terms of the capital asset-pricing framework;[10] and (3) those which parameterize relative risk aversion in an intertemporal general equilibrium model.[11]

The paper is structured as follows. Section II contains a brief discussion of the theoretical background to the models estimated. It shows that the three models examined –the model which focuses on own volatility as a determinant of systemic risk, the model which focuses on time-varying betas, and the model which focuses on the role of the risk aversion parameter– can all be viewed as variations of the Euler condition derived from the dynamic general equilibrium intertemporal consumption portfolio model.

Section III presents results for all three approaches estimated within the M-GARCH-M framework. While the own and capital-asset pricing models have been popularly estimated as univariate and bivariate GARCH systems respectively, the intertemporal model has been usually estimated by the generalized method of moments.

We show how the general equilibrium model can also be set up as a trivariate GARCH system. Hence we present a unified framework for estimating all three models. Section III applies these methods to the Chilean and Mexican excess returns in equity markets. Results are presented for the in-mean variance, the time-varying beta and the risk aversion coefficient approaches to the modelling of systemic risk. The last section IV concludes.

II. Theoretical Framework

The general equilibrium approach for explaining risk in financial markets is inspired by the two-country complete markets model of Lucas (1982). In this framework, asset prices are determined from the Euler condition for an intertemporal choice problem of an investor who can trade freely in asset j, and who maximizes the expectation of a time-separable utility function. The Euler condition is:

$$\frac{U'(C_t)}{P_t} = \delta E_t\left[R_t^j \frac{U'(C_{t+1})}{P_{t+1}}\right] \tag{1}$$

where δ is the time preference parameter and C_t is real consumption, $U'(C)$ denotes the marginal utility of consumption, P_t is the price index. R_t^j is the one-period gross nominal return on asset j; $R_t^j = (1 + r_t^j)$. This expression is more often presented as:

$$E_t\left[R_t^j Q_{t+1}\right] = 1 \tag{2}$$

where Q_{t+1} is the intertemporal marginal rate of substitution:

$$Q_{t+1} = \delta \frac{U'(C_{t+1})}{U'(C_t)} \frac{P_t}{P_{t+1}} \tag{3}$$

To derive the measure of excess returns, first recognize that the Euler equation for the riskless asset is:

$$R_t^f = \frac{1}{E_t[Q_{t+1}]} \tag{4}$$

and the equivalent first-order condition for asset j is:

$$E_t\left[Q_{t+1}, R_t^j\right] = 1 \tag{5}$$

From equation (4) and the definition of covariance applied to (5) we obtain the standard excess returns result:

$$E_t\left[R_t^j - R_t^f\right] = -R_t^f Cov_t\left[Q_{t+1}, R_t^j\right] \tag{6}$$

Since Q is not observable, additional assumptions are needed to obtain a testable version. A typical assumption is to re-express equation (6) in terms of a benchmark portfolio on the conditional mean-variance frontier. The benchmark portfolio has gross return R^m, which can be written as a linear combination of the minimum variance portfolio nominal return (which is perfectly correlated with Q) and the risk-free return, R^f. The equilibrium return on asset j can then be expressed as the conditional beta CAPM model:

$$E_t\left(R_t^j - R_t^f\right) = \frac{Cov_t\left[R_t^j, R_t^m\right]}{Var_t\left[R_t^m\right]} E_t\left(R_t^m - R_t^f\right) \tag{7}$$

Another version of the first order condition is based on the assumption that $q_{t+1} = \log(Q_{t+1})$ and $r_t^j = \log\left(R_t^j\right)$ are conditional joint lognormally distributed.[12] Hence an alternative expression for excess returns is:

$$E_t\left[r_t^j - r_t^f\right] = -\frac{Var_t\left(r_t^j\right)}{2} - Cov_t\left(r_t^j, q_{t+1}\right) \tag{8}$$

where $Var_t\left(r_t^j\right)$ is the conditional variance of r_t^j, and $Cov_t\left(r_t^j, q_{t+1}\right)$ is the covariance between r_t^j and q_{t+1}. If the covariances are assumed to be negligible, we have the own volatility in mean model:

$$E_t\left[r_t^j - r_t^f\right] = -\frac{Var_t\left(r_t^j\right)}{2} \tag{9}$$

Another common way to derive an empirically tractable equation of excess returns, is to assume a time-separable power utility function:

$$U(C_t) = \frac{C_t^{1-\gamma} - 1}{1-\gamma} \tag{10}$$

where γ is the coefficient of relative risk aversion.[13]

This implies a first-order condition of form:

$$E_t\left[\delta R_t^j\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left(\frac{P_t}{P_{t+1}}\right)\right]=1 \tag{11}$$

which gives a general volatility-in-mean expression:

$$E_t\left[r_t^j-r^f\right]=-\frac{Var_t\left(r_t^j\right)}{2}-Cov_t\left(r_t^j,\pi_{t+1}\right)+\gamma Cov_t\left(r_t^j,c_{t+1}\right) \tag{12}$$

where $\pi_{t+1}=\log\ (P_{t+1}/P_t)$, $c_{t+1}=\log\ (C_{t+1}/C_t)$. $Cov_t\left(r_t^j,\pi_{t+1}\right)$ and $Cov_t\left(r_t^j,c_{t+1}\right)$ are the conditional covariances. An estimate of γ can be obtained if consumption data is available.

However, high frequency data on consumption are generally unavailable. Instead, approximating nominal consumption growth with the return on the equilibrium portfolio, gives:

$$E_t\left[R_t^j\left(R_t^m\right)^{-\gamma}\left(\frac{P_t}{P_{t+1}}\right)^{1-\gamma}\right]=1 \tag{13}$$

Again assuming joint log normality, the expression for excess returns becomes a function of second moments of asset returns:

$$E_t\left[r_t^j-r_t^f\right]=-\frac{Var_t\left(r_t^j\right)}{2}+\gamma Cov_t\left(r_t^j,r_t^m\right)+(1-\gamma)Cov_t\left(r_t^j,\pi_{t+1}\right) \tag{14}$$

where $Cov_t\left(r_t^j,r_t^m\right)$ is the conditional covariance of the return on asset j with the return on the market portfolio.

The advantage of equation (14) is that it allows direct estimation of the coefficient of relative risk aversion parameter γ. It is appealing as a model of risk premium because it includes the three main explanators of excess returns: own volatility, co-variability of the return rate with the world return and co-variability of the return rate with inflation. The major weakness is that it is derived from a specific type of utility function.

III. Empirical Analysis

3.1 Data

Figure 2 shows the evolution of the risk premia in the equity markets from investing in Chile or Mexico from the perspective of an international investor. In this regard, the risk premia (*RP*) is defined inclusive of the currency risk:

$$RP_t^j = \left(r_t^j - r_t^f\right) + \left(s_{t+1} - s_t\right)$$

where s_t is the log of the spot rate, defined as the units of foreign currency per domestic currency. The risk-free rate is the US treasury-bill rate. The frequency is monthly covering the period 1989: 01 to 1998: 12.

The top panel in Figure 2 shows the excess returns (domestic return less risk-free rate, $r_t^j - r_t^f$), the second panel shows the changes in the exchange rates $(s_{t+1} - s_t)$ and the third panel shows the combined effects – the risk premia from the perspective of an international investor, RP_t^j from investing in Chile and Mexico. As shown in Figure 2, with the exception of two periods in Mexico, the excess returns for Chile and Mexico are within the $\pm 20\%$ range. With respect to the exchange rate changes, variations in the bilateral $USD/Chilean peso are comparatively small with the exception of two periods in 1992, shortly after the transition to democracy, and in 1995, at the time of the Mexican crisis, known in other countries as the "tequila effect". The bilateral $USD per Mexican peso, on the other hand, suffered a massive depreciation in late 1994, and its exchange rate has been volatile while floating, since then. Since this paper is not concerned with "jumps" in the data, we have included two regime dummies in the empirical study and they are:

$$\begin{aligned} dum\_chi &= 1;\ \ 1992{:}\,02,\ 1995{:}\,04,\ 1995{:}\,05 \\ &= 0;\ \ otherwise \end{aligned}$$

$$\begin{aligned} dum\_mex &= 1;\ \ 1994{:}\,12,\ 1995{:}\,01,\ 1995{:}\,02,\ 1998{:}\,08 \\ &= 0;\ \ otherwise \end{aligned}$$

Table 1 presents some descriptive statistics. For Chile, the mean excess return is non-zero but the distribution of risk premia is normal. For Mexico, the properties of the excess returns are clearly dominated by the two masive depreciations of the currency. Removing the effect of these changes, we generated excess returns that have a non-zero mean, but where the distribution of the risk premia is normal.[14]

FIGURE 2

COMPONENTS OF RISK

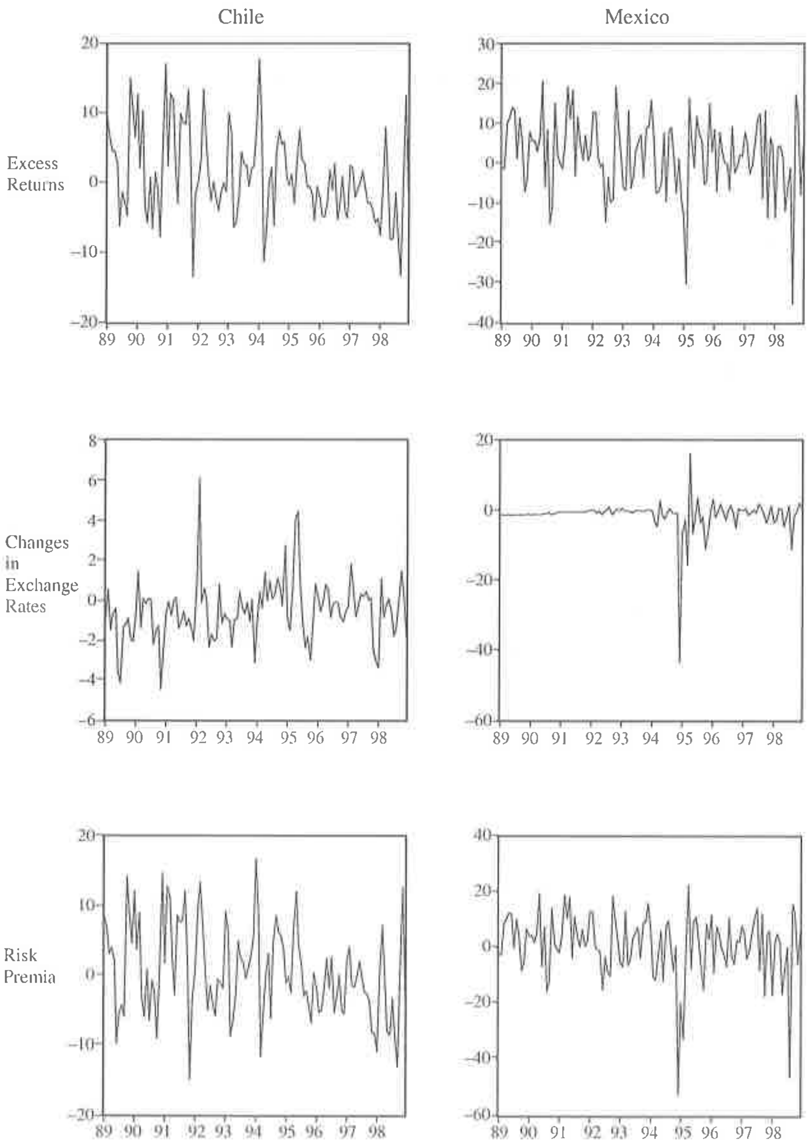


TABLE 1

DESCRIPTIVE STATISTICS*

Chile	$(r^c - r^f)$	$(s_{t+1} - s_t)$	RP	RP^2
Mean	1.009	−0.548	0.461	0.222
Maximum	17.866	6.103	16.764	16.764
Minimum	−13.574	−4.496	−15.012	−15.012
Std. Deviation	6.243	1.509	6.506	6.345
Skewness	0.424	0.842	0.260	0.308
Kurtosis	3.056	6.646	2.674	2.858
JB test[1]	(0.165)	(0.000)	(0.390)	(0.368)

Mexico	$(r^m - r^f)$	$(s_{t+1} - s_t)$	RP	RP^2
Mean	2.008	−1.220	0.788	2.054
Maximum	20.638	16.422	22.685	22.685
Minimum	−35.395	−43.409	−52.566	−17.508
Std. Deviation	9.532	4.890	11.585	9.062
Skewness	−0.751	−5.376	−1.525	−0.145
Kurtosis	4.574	49.338	7.713	2.450
JB test[1]	(0.000)	(0.000)	(0.000)	(0.380)

* The risk premia is $RP = (r^j - r^f) + (s_{t+1} - s_t)$; $j = c$ (Chile), $j = m$ (Mexico).

1 p-values of the Bera-Jarque (1980) test for normality.

2 The residuals from the OLS regression of the Chilean risk premia series on the dummy variable which yielded a coefficient of 9.420 (0.011).

3 The residuals from the OLS regression of the Mexican risk premia series on the dummy variable which yielded a coefficient of −37.972 (0.000).

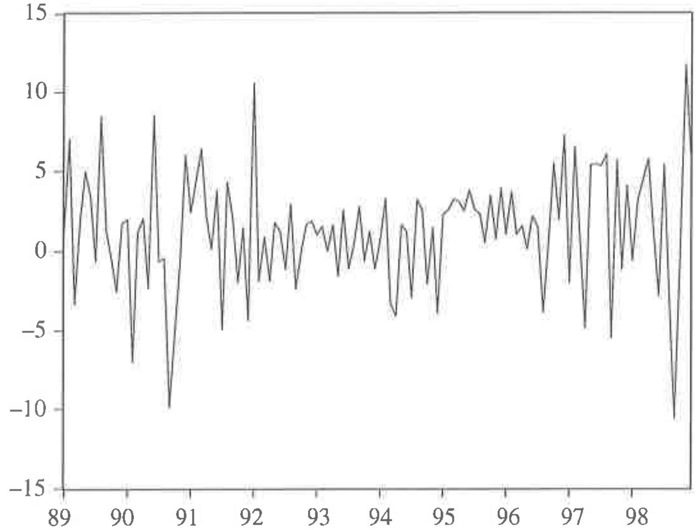
The aim of the paper is to examine the evolution of the risk premia to assess the extent to which it can be related systemically to global factors, in particular as represented by the US economy. The top panel in Figure 3 shows the volatility in the US returns while the second panel shows the US inflation volatility. To what extent can the volatility in Chilean and Mexican risk be related to its own past volatility and to what extent can these variables be related to these international (US) factors?

3.2 The M-GARCH-M Framework

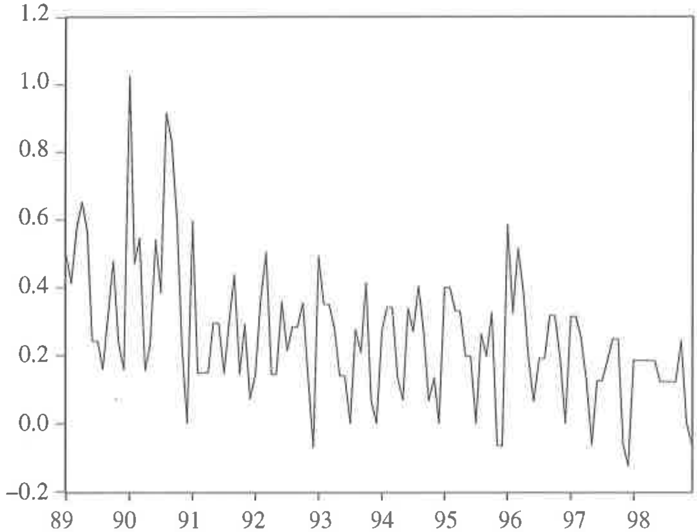
All models were estimated by maximum likelihood methods for the GARCH (1,1) case. Furthermore, we report heteroskedastic-consistent estimates of the standard error based on the Hessian matrices. Bollerslev and Wooldridge (1988), for example, have shown that asymptotically valid inference may be based on a quasi maximum likelihood procedure, when a robust covariance matrix for the parameters is calculated from $H^{-1}(GG')H^{-1}$, where H is the Hessian, and G is the outer product of the gradients.

FIGURE 3

US MONTHLY RETURNS AND INFLATION RATES (%)



Monthly Returns



Inflation Rates

3.2.1 *Own-Volatility Model*

Baillie and Bollerslev (1990) argue that the covariances in excess return equations are negligible. So the simplest version of risk model relates the excess returns to the square root of the conditional variance, and this may be set up as a univariate GARCH-M model. For this application, the model is as follows:[15]

$$RP_t = \alpha RP_{t-1} + \gamma\sqrt{h_t} + \varepsilon_t$$

$$\varepsilon_t \left| I_{t-1} \right. \sim N(0, h_t)$$

$$h_t = c + a\varepsilon_{t-1}^2 + gh_{t-1}$$

where RP_t is the risk premia comprising excess returns and currency risk. With these models, the conditional mean and volatility of the series are assumed to be predictable using past available information on returns and volatility measures.[16]

Table 2 presents the results of the GARCH-in-Mean model for the two countries. The error diagnostics indicate that the mean equation is adequately specified (no further evidence of autocorrelation or ARCH) and that the conditional variances specification also satisfy the Pagan-Sabau tests for consistency.

TABLE 2

OWN VOLATILITY MODEL*

		Chile		Mexico	
RP_{t-1}:	α	0.415	(0.000)	−0.133	(0.073)
$\sqrt{h_t}$:	γ	−0.024	(0.778)	0.226	(0.020)
$dummy_t$:	ϕ	8.779	(0.742)	−42.216	(0.000)
c		2.284	(0.499)	8.092	(0.084)
a		0.099	(0.159)	−0.133	(0.056)
g		0.838	(0.000)	1.029	(0.000)
R^2		0.227		0.396	
PS test[1]		−1.189	(0.117)	0.121	(0.548)
Q (1)		0.729	(0.393)	0.726	(0.394)
Q^2 (1)		1.582	(0.208)	0.673	(0.412)
JB test		5.592	(0.061)	3.029	(0.219)

* The terms in parenthesis are p-values.

1 Pagan-Sabau (1992) tests for consistency.

The results show that there are significant GARCH processes. But the interesting result is that the Chilean risk premia can be explained by its own lagged level of the risk premia, whereas the Mexican risk premia is significantly related to its own lagged variance of the risk premia. This suggests that subjective "risk" or "expectational measures" of volatility are more important for Mexican excess returns, while observable lagged risk premia are more important for Chile.

A plausible partial explanation for this phenomenon is that the Chilean economy for most of the estimation period was subject to partial capital controls. All short-term foreign investors were required to deposit 30 percent of their funds in a non-interest bearing account for a period of two years. Later, in the mid-90's, this practice was changed, and foreign investors were simply allowed to pay a tax of 30 percent of their returns in domestic markets. Finally, in 1998, at the time of the Asian crisis, this tax on foreign capital inflows was dropped. Given this tax on foreign flows, the Chilean stock market may display greater "inertia" or backward looking autoregressive effects than the relatively less regulated Mexican market.[17]

3.2.2 *Market Volatility Model*

In the partial equilibrium models of asset pricing, Adler and Dumas (1983) were the first to show that the "market return" in the international CAPM model should generalize across many countries. The international capital asset pricing model evaluates the risk and return of an asset j relative to a benchmark return and risk; specifically the ICAPM postulates that the equilibrium excess return on any asset j, is related to the excess returns from a benchmark portfolio. In the context of this study, the model is as follows:

$$RP_t = \frac{h_t^{12}}{h_t^{22}} E_{t-1}\left[r_t^m - r_t^f\right] + \varepsilon_{1t}$$

$$\left[r_t^m - r_t^f\right] = \delta\left[r_{t-1}^m - r_{t-1}^f\right] + \varepsilon_{2t}$$

$$\varepsilon_t' = \left[\varepsilon_{1t}, \varepsilon_{2t}\right];\ \varepsilon_t' \middle| I_{t-1} \sim N(0, H_t)$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + G'H_{t-1}G$$

$$H = \begin{bmatrix} h^{11} & h^{12} \\ h^{12} & h^{22} \end{bmatrix}; \qquad C = \begin{bmatrix} c^{11} & c^{12} \\ 0 & c^{22} \end{bmatrix};$$

$$A = \begin{bmatrix} a^{11} & a^{12} \\ a^{12} & a^{22} \end{bmatrix}; \qquad G = \begin{bmatrix} g^{11} & g^{12} \\ g^{12} & g^{22} \end{bmatrix};$$

where h_t^{22} is the conditional variance of the benchmark portfolio and h_t^{12} is the conditional covariance between the risk premia of the Chilean or Mexican asset and the benchmark (US) portfolio. We have used the Morgan Stanley Capital International US equity index as the appropriate benchmark portfolio to compute the market return, R_t^m.[18] In this model, beta is not a constant but is conditional on the covariance between the asset and market returns relative to the variance of the market return.

The ICAPM time-varying beta model makes use of GARCH-in-mean estimation, and the vector of errors ε_t' is assumed to have a conditional bivariate normal distribution with zero mean and conditional covariance matrix defined by the Engle and Kroner (1995) BEKK form, where C, is an upper triangular matrix and A and G are symmetric matrices of parameters.[19]

The results from estimating the constant beta and the time-varying beta models appear in Table 3 and Table 4 respectively. From the constant beta model, we note that excess market returns are insignificant in explaining the risk premia for Mexico, whereas excess market returns have an influence in the Chilean case.

From the time-varying beta model, the first point to note is that most of the coefficient estimates are significant, and that the conditional variances satisfy the Pagan-Sabau tests for error consistency (at the 1% level of significance). The average betas are also consistent with the constant beta OLS results. However, from the error diagnostics for the mean equation, we note again in the Chilean case, the role of own lagged risk premia. For completeness, we have included results for the market model with a lagged risk premia.

TABLE 3

CONSTANT CAPITAL ASSET PRICING MODEL

		Chile		Mexico
$(r^m - r^f)_t$:	β	0.424 (0.006)	0.373 (0.007)	0.106 (0.640)
$dummy_t$:	ϕ	9.081 (0.012)	8.461 (0.010)	−37.865 (0.000)
RP_{t-1}:	α		0.406 (0.000)	
R^2		0.108	0.275	0.358
Q_1 (1)		23.059 (0.000)	0.960 (0.327)	0.053 (0.818)
Q_1^2 (1)		0.598 (0.439)	0.979 (0.322)	0.028 (0.867)
JB test		2.877 (0.237)	3.377 (0.185)	1.881 (0.390)

TABLE 4

TIME-VARYING CAPM

	Chile		Mexico
$(r^m - r^f)_{t-1}: \delta$	–0.075 (0.241)	–0.064 (0.296)	–0.024 (0.401)
$dummy_t$: ϕ	8.842 (0.000)	8.170 (0.000)	–33.339 (0.000)
RP_{t-1} : α		0.408 (0.000)	
c_{11}	3.027 (0.000)	2.553 (0.003)	6.112 (0.000)
c_{12}	2.751 (0.000)	1.518 (0.176)	–0.391 (0.389)
c_{22}	0.000 (0.500)	2.079 (0.000)	3.291 (0.000)
a_{11}	–0.309 (0.021)	–0.275 (0.130)	–0.188 (0.169)
a_{12}	0.178 (0.030)	0.066 (0.392)	0.150 (0.116)
a_{22}	0.408 (0.003)	0.330 (0.004)	0.035 (0.446)
g_{11}	0.830 (0.000)	0.858 (0.000)	–0.734 (0.000)
g_{12}	–0.009 (0.456)	0.131 (0.179)	–0.101 (0.099)
g_{22}	–0.449 (0.006)	–0.649 (0.006)	–0.173 (0.353)
average beta	0.356	0.312	0.153
R^2	0.060	0.226	0.351
PS_h^{11}	–0.256 (0.399)	–0.551 (0.291)	–0.662 (0.254)
PS_h^{12}	–1.322 (0.093)	1.682 (0.954)	0.480 (0.684)
PS_h^{22}	–2.020 (0.022)	–0.060 (0.476)	–0.466 (0.320)
Q_1 (1)	17.536 (0.000)	0.481 (0.488)	0.007 (0.935)
Q_1^2 (1)	0.162 (0.687)	1.782 (0.182)	0.186 (0.667)
Q_2 (1)	0.214 (0.643)	0.239 (0.625)	0.324 (0.569)
Q_1^2(1)	0.879 (0.348)	0.504 (0.478)	0.034 (0.854)

3.2.3 *Model with own, market and inflation volatility*

The generalized method of moments (GMM) has been used to estimate the "deep parameters" such as the coefficient of risk aversion in the representative agent's utility function, which ultimately determine excess returns under efficient markets.[20] However, to allow for time-varying conditional variances and covariances, the general model underlying the intertemporal asset pricing model[21] is estimated as a trivariate GARCH-M system allowing for own, market and inflation volatility as follows:[22]

$$RP_t = \gamma_1 h_t^{11} + \gamma_2 h_t^{12} + \gamma_2 h_t^{13} + \varepsilon_{1t}$$

$$r_t^m = \delta_1 r_{t-1}^m + \varepsilon_{2t}$$

$$\pi_t = \delta_2 \pi_{t-1} + \varepsilon_{2t}$$

$$\varepsilon_t' = [\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}];\ \varepsilon_t' \big| I_{t-1} \sim N(0, H_t)$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}' A + G' H_{t-1} G$$

This framework has the same structure as previous models and has the advantage of allowing for time-varying variances and covariances.

The results are presented in Table 5. The first point to note is that the diagnostics indicate that the model mean and conditional variance equations are adequately specified (at the 1% level). However, there is again evidence of autocorrelation in the residuals for the Chilean case.

The results show that US inflation volatility is not a significant determinant of Chilean and Mexican risk premia. Instead the results are consistent with previous models, namely that the significant determinant of Chile's risk premia is its own lag in the levels while the significant determinant of Mexico's risk premia is its own lag in the variance.

TABLE 5

TRIVARIATE GARCH_M: CCAPM

		Chile		Mexico	
r^m_{t-1}:	δ_1	−0.001	(0.496)	0.060	(0.246)
π_{t-1}:	δ_2	0.729	(0.000)	0.760	(0.000)
h_t^{11}:	γ_1	−0.065	(0.271)	0.256	(0.009)
h_t^{12}:	γ_2	0.061	(0.322)	3.143	(0.393)
h_t^{13}:	γ_3	92.512	(0.408)	13.033	(0.418)
$dummy_t$:	ϕ	8.173	(0.000)	−40.410	(0.000)
R^2		0.081		0.402	
PS_h^{11}		−1.801	(0.036)	−0.176	(0.430)
PS_h^{12}		−1.236	(0.108)	0.354	(0.638)
PS_h^{13}		0.104	(0.541)	0.947	(0.829)
PS_h^{22}		−2.023	(0.021)	−1.086	(0.139)
PS_h^{33}		−0.540	(0.294)	−0.269	(0.394)
Q_1 (1)		10.367	(0.001)	0.216	(0.642)
Q_1^2 (1)		1.145	(0.285)	0.003	(0.957)
Q_2 (1)		1.366	(0.242)	1.553	(0.213)
Q_1^2 (1)		2.156	(0.142)	0.186	(0.666)
Q_3 (1)		0.329	(0.566)	1.563	(0.211)
Q_3^2 (1)		0.050	(0.822)	0.126	(0.722)

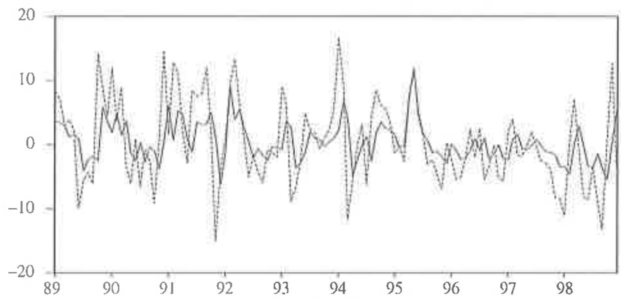
IV. Conclusion

This paper has been concerned with understanding the determinants of the risk premia for Chile and Mexico and in particular, how it has responded to lower global inflation and increased globalization of financial markets. To this end, three models with a focus on own volatility, market volatility and inflation volatility were estimated using the M-GARCH-M technique.

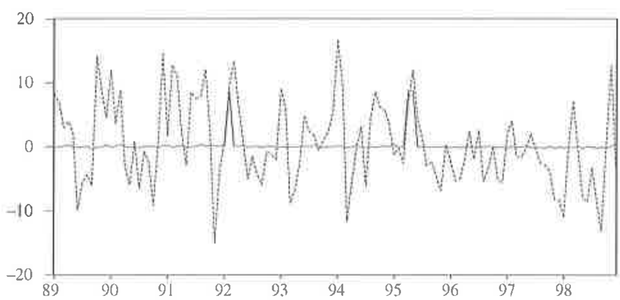
As a means of comparison, the in-sample forecasts and actual risk premia are plotted in Figure 4 (for Chile) and Figure 5 (for Mexico). From the results reported, for Chile, the preferred model is the constant coefficient model where the risk premia is a function of own lag, the market return and the dummy variable (see Table 3).

FIGURE 4

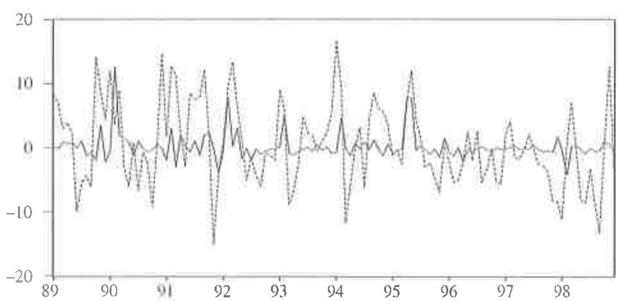
ACTUAL (DOTTED LINE) AND PREDICTIONS (SOLID LINE) - CHILE



Own Volatility



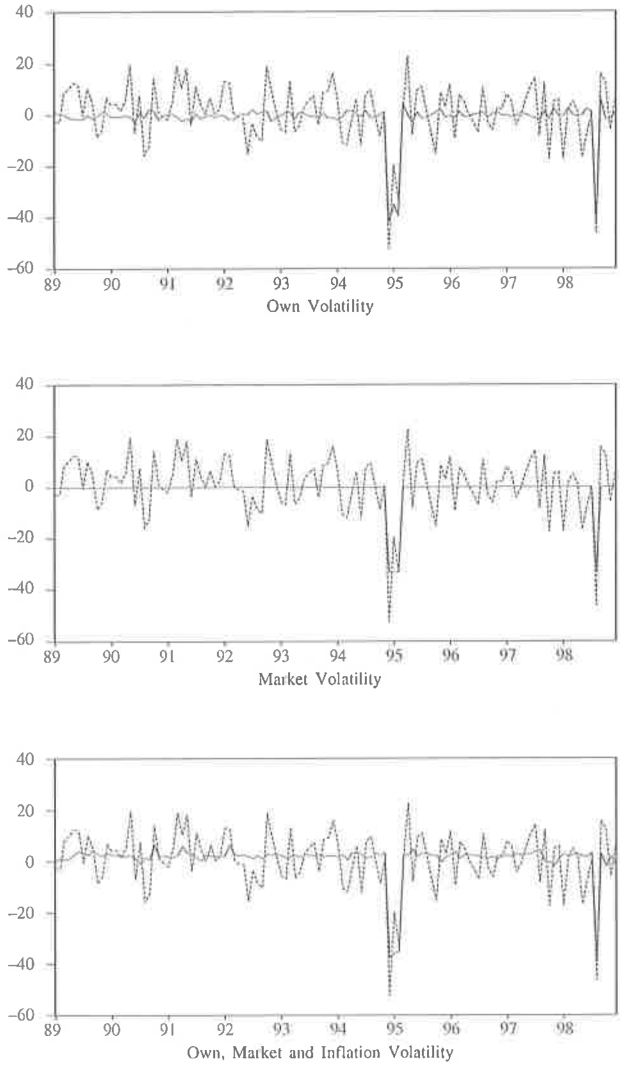
Market Volatility



Own, Market and Inflation Volatility

FIGURE 5

ACTUAL (DOTTED LINE) AND PREDICTIONS (SOLID LINE) - MEXICO



For Mexico, the preferred model is the time-varying own volatility model (see Table 2). These results suggest that these markets are not well integrated into the global financial system. Specifically, for Chile, excess returns are a function of own lagged excess returns, while for Mexico, excess returns are a function of own lagged variance.

The finding in this paper is perhaps not too surprising. The risk models studied are benchmark models formulated under the assumption of arbitrage in competitive, sophisticated financial markets. Given the emerging market status of the Chilean and Mexican markets, the nature of the financial markets and the data examined may not adequately capture the inherent risks in the system; hence not surprisingly the results provide little support for the risk prediction models examined. Nevertheless, these results suggest that future research could be productively directed at a better understanding of home, rather than global factors, for explaining the evolution of excess returns in these two countries.

Notes

[1] Edwards (1986) and Edwards and Edwards (1987) drew attention to the monetarist and trade liberalization experiments in Chile in the 1970's. Corbo (1985) and Corbo and Matte (1984) analyzed the effects of capital account liberalization on monetary policy and the real exchange rate. McNelis and Schmidt-Hebbel (1993) showed that the rapid Chilean financial liberalization shifted the burden of adjustment from the domestic interest rate to the real exchange rate. More recently, Calvo and Mendoza (1998) analyzed the implications of the Chilean "success story" as a policy-reform model for other Latin American countries. They conclude that our "understanding of the Chile's experience is limited", that there is "little formal evidence linking Chile's stabilization policy framework to the gradual deceleration of inflation", and that "little is known is known about the extent to which the cyclical performance of the economy was influenced by important exogenous developments" (Calvo and Mendoza (1998): p. 2). They use a vector autoregression technique with recursive identification to argue that the growth of the Chilean economy was mainly due to unusually favorable terms of trade and surge in capital inflows (Calvo and Mendoza (1998): p. 28).

[2] Dornbusch and Reynoso (1989) analyzed Mexico's experience of financial liberalization and fiscal deficits leading up to the debt crisis in the early 1980's. Dornbusch and Warner (1994) drew attention to the role of the over-valued real exchange rate and current account problems in Mexico in the early 1990's. In contrast to Dornbusch and Warner, Calvo and Mendoza (1996) pointed to the currency and liquidity "mismatch" in the structure of Mexico's assets and liabilities prior to the exchange-rate crisis of 1994 and 1995. Kamin and Rogers (1996) analyzed the response to monetary policy to external shocks, and the failure of the central bank to tighten sufficiently, in the period leading up to the same currency crisis. Finally, Cole and Kehoe (1996) analyzed the Mexican crisis as an example of "sunspots" in a model of multiple equilibria.

[3] The original decree imposing a tax on short-term foreign investment, *Decreto Ley 824, Titulo IV art. 59, Nº 1*, was suspended this year by a series of decrees by the Central Bank of Chile. Detailed information is available on these decisions in the web page, *www.bcentral.cl*

Edwards (1999), pages 71-72, gives a detailed description of the working of Chilean controls since the late 1970's.

[4] See Edwards (1999), p. 68. He points out that Mexico had "for all practical purposes" free capital mobility.

[5] Specifically, in the Sargent model, the central bank incorrectly uses a Keynesian Phillips curve to forecast either inflation or unemployment while the true rate of inflation is generated by a "natural rate" model. The private sector also watches the central bank and forecasts inflation by a simply vector autoregression of inflation on lagged inflation and unemployment. In this framework, there are shocks to both inflation and unemployment.

The insight of the Sargent "bounded rationality" learning is that the central bank, and the public, "learn' from their errors, in the sense that they update their coefficients of their incorrectly specified models, based on the previous period forecast errors. Within a very short time, the model converges to a long-run "low inflation" Ramsey equilibrium, even though the central bank is using the "wrong" model.

6 In practice too, while this approach is certainly an attactive option, there are a large number of "wrong models" to choose from, when modelling financial markets! Sargent's focus is on the Federal Reserve's conquest of inflation, in which there is the correct "natural rate" model and the incorrect Keynesian Phillips curve model. In financial markets, there are a multiplicity of "incorrect" models to choose, depending on one's perspective, from "chartist" models to sunspots.

7 Lim and McNelis (1998) applied a modified neural network approach to forecasts of returns in the Australian share market, based on a time-zone trading model of the network "neurons".

8 For a review of the numerous applications of the GARCH framework for estimating volatility, see Bollerslev, Chou and Kroner (1992).

9 See Bollerslev (1990), Baillie and Bollerslev (1990), Dukas, Fatemi and Lai (1993).

10 For examples, see McCurdy and Morgan (1991), Malliaropulos (1997).

11 For example, see Ayuso and Restoy (1996).

12 See Campbell, Lo, and MacKinlay (1997), various sections, for a discussion of the following substitutions.

13 In this setting, risk premia critically depend on the specification of the underlying utility function. Mark (1985) has found that the parameter of risk aversion in a constant relative risk aversion specification of the utility function has to be quite large (in the range 12 to 20) to explain the variability of excess returns. Cumby (1988) suggested that the non-separability over time of the utility function in t may account for the failure of the general equilibrium models to explain speculative returns.

14 While this practice may appear to be ad-hoc, in semi-non-parametric methods such as neural network approximation, outliers in the data are usually "squashed" by stepwise function, in which variables greater than a prespecified level simply take on maximum values. We are thus filtering the data, with the assumption that the crisis periods do not represent normal processes in the excess return data.

15 In a related model by Dukas, Fatemi, and Lai (1993), the variable s_t is modeled as a random walk process and the currency risk is hypothesied to be related to the conditional variance of the exchange rate, h_t^s which follows the GARCH process.

16 See McCurdy and Stengos (1992) for a comparison of parametric versus non-parametric conditional mean estimators. Their results show that a parametric specification of the GARCH process avoids the problem of over-fitting.

17 This possibility is consistent with the estimation results obtained by Edwards (1999) which suggest that "the policy of restricting capital inflows helped Chile reduce stock market instability" (p. 79).

18 For the benchmark world portfolio, McCurdy and Morgan (1991) included a moving average component, to reflect the effects of non-synchronized trades of the components of the world index. Since this study is based on monthly data, non-synchronicity is not an issue.

19 For an alternative parametrization, see Malliaropulos (1997) application of Bollerslev (1990) model which assumes a constant conditional correlation while allowing the conditional variances and covariances to vary over time.

20 The GMM method is due to Hansen (1982). For applications in this area see Bodurtha and Mark (1991), Ayuso and Restoy (1996).

21 In many other empirical studies, such as those of Lewis (1988) and Engel and Rodriguez (1989), the relative risk aversion coefficient is not significantly different from zero. A larger class of dynamic asset pricing models has recently been studied by Bakshi and Naka (1997). They note that stochastic discount factors that incorporate habit forming behaviour are better at explaining the empirically observed asset prices. For these reasons, a general rather than specific form of the intertemporal asset pricing model has been estimated.

22 For an earlier work on a tri-variate CAPM model, see Bollerslev, Engle and Wooldridge (1988), their work also suggest potential role for consumption shocks. See Bekaert (1995) for a combined VAR-GARCH model.

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