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Contagion
How to Measure it?

Roberto Rigobon

6.1 Introduction

The issue of contagion has been one of the most debated topics in international finance since the Asian crises. One interesting aspect of this discussion is the strong agreement among economists about which events have constituted instances of contagion: the debt crises in 1982, the Mexican Tequila effect in December 1994, the Asian "flu" in the last half of 1997, the Russian "cold" in August 1998 (including the long-term capital management [LTCM] crisis), the Brazilian "sneeze" in January 1999, and the Nasdaq "rash" in April 2000. Paradoxically, however, there is no consensus on what contagion means.

This paper deals with the question of how to measure contagion. Therefore, instead of providing a list of all its possible definitions and the procedures to measure it, this paper concentrates on the two most frequently asked questions raised by applied papers in this area: First, what are the channels through which shocks are propagated from one country to the other? In other words, is it trade, macrosimilarities, common lenders, learning, or market psychology that determines the degree of contagion? Second, is the transmission mechanism stable through time? Or more specifically, does it change during a crisis?

Answering either of the previous two questions encounters important

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econometric limitations. Contagion has been associated with high-frequency events; hence, it has been measured on stock market returns, interest rates, exchange rates, or linear combinations of these. These data are plagued by simultaneous equations, omitted variables, conditional and unconditional heteroskedasticity, serial correlation, nonlinearity, and nonnormality problems. Unfortunately, no procedure can handle all these problems at the same time; therefore, the literature has been forced to take short cuts.

This paper evaluates the performance of some of those techniques. Obviously, there is not enough space to study all the possible empirical procedures nor all the problems. Thus, the paper discusses the most widely used methodologies in the contagion literature (linear regressions, logit-probit regressions, and tests based on principal components and correlation coefficients[1]) and concentrates on the three main problems exhibited by the data: simultaneous equations, omitted variables, and heteroskedasticity. Issues related to serial correlation, nonnormality, and nonlinearity are left out of the analysis.

The paper briefly examines two new procedures that are robust to the problems studied here: one designed to test for the stability of parameters, and the second one designed to solve the problem of identification. In each case, the assumptions underlying the methodologies and the circumstances in which they can be used are reviewed.

The paper is organized as follows: Section 6.2 introduces the statistical models used in the discussions. Section 6.3 investigates the problems surrounding the second question concerning contagion: how to test for changes in the propagation mechanism. The paper analyzes this question first because the limitations of the standard techniques become evident in simple models. Section 6.3 studies alternative corrections for the standard tests and the conditions under which they can be used. Finally, the section summarizes a new procedure to test for parameter stability under simultaneous equations, omitted variables, and heteroskedasticity, and points out the assumptions required for its use.

Section 6.4 considers the more complicated issue: the measurement of the transmission channels. Several Monte Carlo simulations are presented to illustrate the problems in the interpretation of the results when the propagation channel is measured by probit, ordinary least squares, or principal components methods. At the end of the section, a new procedure to esti-

1. I am leaving important aspects of the measurement of contagion out of this analysis, mainly measures based on autoregressive conditional heteroskedasticity (ARCH) models (see Edwards and Susmel 2000), cointegration (see Cashin, Kumar, and McDermott 1995 and Longuin and Slonick 1995), switching regimes (again, see Longuin and Slonick 1995). There are two other techniques that have not yet been used: factor regression models (see Sentana and Fiorentini 1999 for problems of estimation in these models when the factors are heteroskedastic) and limited dependent models under heteroskedasticity (see Chen and Kahn 1999 and Klein and Vella 2000 for estimation problems in these models).

mate the contemporaneous interrelationship across countries is reviewed. This procedure is robust to the data problems emphasized here.

Section 6.5 applies the two new techniques to measure contagion in Latin American and Southeast Asian countries. First, the test on stability of parameters across time is implemented; second, the transmission mechanism is estimated. Section 6.6 explores avenues for future research. Section 6.7 concludes.

6.2 The Models

Several simple models are used to discuss the problems involved in the measurement of contagion. Even though true description of the world is probably the union of these particular pieces, the paper uses minimal statistical frameworks to highlight the problems there more easily.

The country variables of interest are denoted by x_t and y_t. They reflect either stock market returns, exchange rates, interest rates, or combinations of these. Without loss of generality, assume that x_t and y_t have been demeaned and are serially uncorrelated. Common unobservable shocks are denoted by z_t. These should be interpreted as liquidity shocks, risk preferences, investor's sentiments, etc. All the idiosyncratic innovations are denoted by ε_t and η_t. It is assumed that they are independent, with mean zero, and independent from the common shocks as well. The models concentrate on the bivariate case, although most of the results can be easily extended to larger setups.

When the paper focuses on the problems of simultaneous equations, the following model (model 1) to describe the interrelationship between the countries is used:

$$y_t = \beta x_t + \varepsilon_t$$

$$x_t = \alpha y_t + \eta_t$$

where $E(\varepsilon_t) = 0$, $E(\eta_t) = 0$, and $E(\varepsilon_t \eta_t) = 0$, and their variances are denoted by σ_ε and σ_η. When the problem of omitted variables is contemplated, model 2 is used:

$$y_t = \beta x_t + \gamma z_t + \varepsilon_t$$

$$x_t = z_t + \eta_t$$

where, in addition to the previous moment restrictions, it is assumed that $E(\varepsilon_t z_t) = 0$, and $E(\eta_t z_t) = 0$. The variance of the common shock is σ_z.

In all these models, the parameter of interest is β (or whether it has shifted). It is assumed that the equation to be fitted is the following:

$$y_t = \beta x_t + \nu_t \tag{1}$$

Due to the problems of simultaneous equations and omitted variables, it is well known that this equation cannot be consistently estimated without further information. Formally, $E(x_t \nu_t)$ is different from zero (the "identification condition") for both model 1 and model 2, which implies inconsistent estimates.

One solution is to find valid instruments. However, for the purpose of the paper, it is assumed that those instruments do not exist. Nevertheless, there are circumstances in which it could be claimed otherwise. For example, it is possible to assume, on the basis of large-economy arguments, that Organization for Economic Cooperation and Development (OECD) countries are unaffected by emerging markets. This would motivate an exclusion restriction, $\alpha = 0$. Even though this assumption might be appealing, it raises important questions of why, during both the Hong Kong and Russian crises, the U.S. and European stock markets were so heavily influenced. In fact, part of the FED's motivation to lower interest rates at the end of 1998 was based on the stability of world markets. Similarly, it is possible to argue that proxies for the common shocks exists. However, most of these measures are, at best, derived from the same prices and volumes the model is explaining. In this paper, it is assumed that the instruments are weak (whenever they exist), and that the problems persist.

To tackle the question on the measurement of the channels of contagion, the statistical framework must be slightly more general. Most of the theories of contagion imply that the transmission of shocks across countries is a function of the strength of the contagion channel. Therefore, a reduced form of the return of country $x_{i,t}$ would be described by a latent factor model as follows:

$$\begin{aligned} x_{i,t} = {} & \alpha_1 X_{\sim i,t} + \alpha_2 \mathbf{TRADE}_{\boldsymbol{i,\sim i}} \boldsymbol{X_{\sim i,t}} + \alpha_3 \mathrm{MACRO}_{i,\sim i} X_{\sim i,t} + \alpha_4 \mathrm{REGION}_{i,\sim i} X_{\sim i,t} \\ & + \ldots + \beta_{1,i} \mathrm{LIQUIDITY}_t + \beta_{2,i} \mathrm{RISK}_t + \ldots + \varepsilon_{i,t} \end{aligned}$$

where $x_{i,t}$ is the ith country return; $\varepsilon_{i,t}$ is the idiosyncratic shock to country i's fundamentals; $X_{\sim i,t}$ are the returns of the rest of the countries; $\mathbf{TRADE}_{\boldsymbol{i,\sim i}}$ is the vector that measures trade between country i and other countries; $\mathrm{MACRO}_{i,\sim i}$ is the degree of macrosimilarities across the countries; and $\mathrm{REGION}_{i,\sim i}$ captures regional characteristics (similarly for other channels of contagion not included in the specification). Common unobservable shocks also affect country returns, and in this example, liquidity shocks and shifts in risk preferences have been modeled. Other shocks could be incorporated.

Each country satisfies an analogous equation, which conforms a system of equations

$$\begin{aligned} & A_1 X_t + A_2(\mathrm{TRADE}) X_t + A_3(\mathrm{MACRO}) X_t + A_4(\mathrm{REGION}) X_t + \ldots \\ & \qquad = B_1 \mathrm{LIQUIDITY}_t + B_2 \mathrm{RISK}_t + \ldots + \varepsilon_t, \end{aligned}$$

which can be rewritten as

$$(2) \qquad AX_t = BZ_t + \varepsilon_t$$
$$A = A_1 + A_2(\text{TRADE}) + A_3(\text{MACRO}) + A_4(\text{REGION}) + \dots$$
$$B = (B_1, B_2, \dots)$$
$$Z_t = (\text{LIQUIDITY}_t, \text{RISK}_t, \dots)'.$$

This model is too complex to analyze. Therefore, it is simplified it in two directions. First, model 3 concentrates on the omitted variable problems with multiple regressors. Therefore, A is assumed to be triangular, and B is assumed to be different from zero and nontriangular. In particular, the model with three countries (model 3) is

$$y_t = \beta x_{1,t} + z_t + \varepsilon_t,$$
$$x_{1,t} = \gamma_1 z_t + \eta_{1,t},$$
$$x_{2,t} = \gamma_2 z_t + \eta_{2,t},$$

where y_t and z_t are as before and $x_{i,t}$ are two other countries. The idiosyncratic shocks are assumed to be independent.

In this model, $x_{2,t}$ does not enter the structural equations of y_t. The only relationship between these variables arises from the omitted common shock. The main question is how well the standard procedures capture the true underlying structure of the model.

Second, model 3a focuses on simultaneous equations problems. The common shocks are shut down ($B = 0$), and the three country returns are determined by

$$A \begin{bmatrix} y_t \\ x_{1,t} \\ x_{2,t} \end{bmatrix} = \begin{bmatrix} \varepsilon_t \\ \eta_{1,t} \\ \eta_{2,t} \end{bmatrix},$$

where A is non-block diagonal. Again, the question in this model is related to the identification of matrix A.

These models are (in general) estimated using three procedures: OLS, probit, and principal components. When OLS is used, it is assumed that the research fits the following equation:

$$(3) \qquad y_t = \beta_1 x_{1,t} + \beta_2 x_{2,t} + \nu_t$$

It is well known that β_1 and β_2 will be biased, but the question is the size and direction of it.

There is another important strand of the contagion literature that estimates models 3 and 3a using probit (logit or multinomial) setups. The equation fitted is

$$(4) \qquad y_t^* = 1(c + \beta_1 x_{1,t} + \beta_2 x_{2,t} > \tilde{y}).$$

Again, where c is the constant, the question is the bias of β_1 and β_2.

Finally, the last technique used to determine the importance of the contagion channels is based on principal components estimation on the multivariate system.

6.3 Testing for Changes in the Propagation Mechanism

A large applied literature defines *contagion* as a shift in the transmission channel. Hence, testing for the existence of contagion is implemented as a test for parameter stability.

The most widely used procedures are based on OLS estimates (including generalized least squares [GLS] and feasible generalized least squares [FGLS]), principal components, and correlation coefficients. The objective of the tests is to determine whether there is a change in the coefficients across two different samples, usually crisis and tranquil periods.

As will become clear below, if the data suffer from heteroskedasticity and either of the other two problems (simultaneous equations or omitted variables), then most of the standard techniques are inappropriate to test for the stability of the parameters.

It is important to note that the standard techniques are inappropriate only if all problems are present. For example, if the data are homoskedastic, then the tests for parameter stability are consistent even in the presence of simultaneous equations and omitted variables. In other words, if the structural change test is rejected, then it must be explained by parameter instability. The test result does not indicate which one has changed, nor in which equation, but at least it indicates that a shift has occurred. On the other hand, if there is only heteroskedasticity, then procedures exist to correct all the traditional tests and achieve consistency. It is the interaction between the heteroskedasticity and the other problems what creates the inconsistency in the tests.

The intuition explaining this case is simple: both the endogenous and the omitted variable biases depend on the relative variances. If the data exhibit heteroskedasticity, then the biases shift across the sample. Therefore, it is possible to reject the hypothesis that the estimates are stable because of the change in the biases, and not because of a shift in the underlying parameters.

The objective of this section is to show these results formally. It is organized as follows: First, it analyzes each of the procedures and their problems. Second, it summarizes some of the adjustments that can be introduced to (partially) solve them. In certain cases, exact corrections exist; however, these adjustments are not general and often only approximations can be used. Finally, this section reviews a new test that is robust to the presence of all three problems, indicating the situations in which the test can be used and what assumptions are needed.

6.3.1 Testing Using OLS

The OLS estimates of the first equation in model 1 and model 2 are

$$\hat{\beta}_{\mathrm{Mod1}} - \beta = \alpha(1 - \alpha\beta)\frac{\sigma_\varepsilon}{\alpha^2\sigma_\varepsilon + \sigma_\eta}, \tag{5}$$

$$\hat{\beta}_{\mathrm{Mod2}} - \beta = \gamma\frac{\sigma_z}{\sigma_z + \sigma_\eta}, \tag{6}$$

respectively. Note that the bias (in both cases) depends on the relative variances of disturbances.

Assume that the question of interest is whether the parameters are stable along the sample. In general, the structural change test takes two forms; either it estimates a β in the two subsamples and performs a comparison, or it introduces a dummy in one of the subsamples and tests for its significance. Independently of the setup, however, the results indicated below are the same. For simplicity in the exposition, it is assumed that the sample is split and two separate regressions are run.

RESULT 1. *When there is no heteroskedasticity, then regardless of the simultaneous equations or omitted variables problems, the test for structural change is consistent.*

This results comes from the fact that the biases under the null hypothesis are the same in both subsamples. Formally, the difference in the estimates is

$$(\hat{\beta}_{\mathrm{Mod1},s1} - \beta_{s1}) - (\hat{\beta}_{\mathrm{Mod1},s2} - \beta_{s2}) = -\frac{\alpha^2}{\alpha^2 + \dfrac{\sigma_\eta}{\sigma_\varepsilon}}(\beta_{s1} - \beta_{s2})$$

in model 1 and

$$(\hat{\beta}_{\mathrm{Mod2},s1} - \beta_{s1}) - (\hat{\beta}_{\mathrm{Mod2},s2} - \beta_{s2}) = \frac{1}{1 + \dfrac{\sigma_\eta}{\sigma_z}}(\gamma_{s1} - \gamma_{s2})$$

in model 2, where $s1$ and $s2$ stand for each subsample.

Under the null hypothesis that α, β, and γ are constant across samples, the difference in the estimates is zero; it is proportional to the change in the parameters. Thus, the rejection occurs only if the parameters have shifted.

RESULT 2. *When the data have heteroskedasticity along with either simultaneous equations or omitted variables problems, the test for stability is inconsistent.*

If there is heteroskedasticity in the sample, the test for stability can be rejected under two cases: (1) if the parameters have changed, or (2) if the variances (and hence the biases) have shifted. To exemplify this point, assume there is heteroskedasticity and that the parameters are constant. The difference in the estimates is

$$\hat{\beta}_{\mathrm{Mod1},s1} - \hat{\beta}_{\mathrm{Mod1},s2} = \alpha(1-\alpha\beta)\left[\frac{1}{\alpha^2 + \left(\frac{\sigma_\eta}{\sigma_\varepsilon}\right)_{s1}} - \frac{1}{\alpha^2 + \left(\frac{\sigma_\eta}{\sigma_\varepsilon}\right)_{s2}}\right]$$

in model 1 and

$$\hat{\beta}_{\mathrm{Mod2},s1} - \hat{\beta}_{\mathrm{Mod2},s2} = \gamma\left[\frac{1}{1 + \left(\frac{\sigma_\eta}{\sigma_z}\right)_{s1}} - \frac{1}{1 + \left(\frac{\sigma_\eta}{\sigma_z}\right)_{s2}}\right]$$

in model 2.

The biases across the samples cancel each other out if there is homoskedasticity or if the heteroskedasticity implies a proportional increase in the variance of all shocks ($\sigma_\eta/\sigma_\varepsilon$ or σ_η/σ_z are invariant). Otherwise, the estimates are different even though the underlying parameters are constant.[2] Moreover, this problem cannot be solved by estimating the parameters using GLS or FGLS.

In conclusion, when there are problems of specification, the test for stability (based on a version of the Chow test) is implicitly testing against the joint alternative hypothesis: the stability of parameters and the homoskedasticity of the residuals. In the particular case of contagion, it is important to remember that the data are characterized by large shifts in second moments. Thus, making any inference about the stability of parameters in the linear regression context is complicated; the test does not provide the reason for the rejection.

6.3.2 Testing Using Principal Components

Principal components is a technique designed to find common factors for a set of time series. The objective of the methodology is well summarized by Kaminsky and Reinhart (2000), who state that "in the case where the original series are identical, the first Principal Component explains 100 percent of the variation in the original series. Alternatively, if the series are orthogonal to one another, it would take as many Principal Components as there are series to explain all the variance in the original series. In that case, no advantage would be gained by looking at common factors, as none exist."[3]

Formally, assume there are K variables each with n observations. Denote the sample data as X and their covariance matrix as Ω. The first component explains the K series as well as possible. Thus, it minimizes the discrepancies of

2. Obviously, the changes in parameters and heteroskedasticity exactly cancel each other out and make the test equal to zero. This means that the test has no power against such a set of parameters.

3. See Theil (1971) for a formal derivation.

$$X - a'p$$

where p is the principal components and a' is a matrix of scalars. The variable p is identified only up to a constant, and therefore some normalization is imposed (usually $p'p = 1$ or the diagonal of the p matrix is equated to 1). It can be shown that the first component corresponds to the eigenvector of the largest eigenvalue of Ω. The components of p are known as the loading and reflect the importance of a particular variable in explaining the rest.

Principal components have been widely used to test for the stability of the propagation mechanism because their estimates are consistent even if the data have simultaneous equations and omitted variables problems.[4] This aspect of the measurement is perhaps the greatest advantage of using principal components.

RESULT 3. *When there is no heteroskedasticity, tests of stability based on principal components are consistent.*

The intuition of the structural change test based on principal components is that if the loadings in the first component change, then the parameters underlying the statistical model have shifted as well. Model 1 implies a covariance matrix equal to[5]

$$\Omega = \frac{1}{(1 - \alpha\beta)^2} \begin{bmatrix} \beta^2\sigma_\eta + \sigma_\varepsilon & \beta\sigma_\eta + \alpha\sigma_\varepsilon \\ \beta\sigma_\eta + \alpha\sigma_\varepsilon & \sigma_\eta + \alpha^2\sigma_\varepsilon \end{bmatrix}.$$

The eigenvalues are given by

$$\frac{1}{2}\sigma_\varepsilon\left(\Theta_1 \pm \sqrt{\Theta_2}\right),$$

where

$$\Theta_1 = 1 + \alpha^2 + (1 + \beta^2)\theta,$$

$$\Theta_2 = (1 + \beta^2)^2\theta^2 - 2[(1 - \beta^2)(1 - \alpha^2) - 4\alpha\beta]\theta + (1 + \alpha^2)^2,$$

$$\theta = \frac{\sigma_\eta}{\sigma_\varepsilon}.$$

The eigenvector of the first eigenvalue (the largest one) is

$$\begin{bmatrix} \frac{1}{2}\frac{\sigma_\varepsilon}{\alpha + \beta\theta}(\Theta_3 + \sqrt{\Theta_2} \\ 1 \end{bmatrix}, \tag{7}$$

4. See Calvo and Reinhart (1995), Kaminsky and Reinhart (2000), and Masson (1997) for applications in the contagion literature.

5. In this section only the case under endogenous variables is studied; the results are qualitatively the same under omitted variables.

where

$$\Theta_3 = 1 - \alpha^2 - (1 - \beta^2)\theta.$$

Note that the eigenvalues and eigenvectors depend only on the parameters (α and β) and the relative variance of the idiosyncratic shocks (θ).

Therefore, under the assumption of homoskedasticity, a change in the loadings of the principal component indeed implies a shift in the parameters (α and β). This property of the principal components is what grants its usefulness in testing for parameter stability. However, as before, this result holds only in the lack of heteroskedasticity.

RESULT 4. *Tests of parameter stability based on principal components are inconsistent in the presence of heteroskedasticity.*

This result is stronger than the one stated for the OLS case. It says that even in the absence of simultaneous-equation and omitted-variable problems, the tests of structural change based on principal components are inconsistent if the residuals are heteroskedastic. Hence, as oppose to the OLS or the correlation case (see below), there is no procedure that can deal with the existence of heteroskedasticity alone. A shift in the relative variances (θ) alters the loadings, even if α or β is equal to zero.[6]

Again, the fact that contagion is accompanied by large shifts in second moments implies that comparisons of principal components across samples are inadequate as an indication of parameter stability.

6.3.3 Testing Using the Correlation

The first paper (to my knowledge) to test for changes in the propagation mechanism using correlation measures was the influential contribution by King and Wadhwani (1990). The intuition of their test is that changes in the underlying coefficients imply a shift in the correlation coefficients as well. This test has been widely used in the literature because of its simplicity and intuitive implications.

However, the conditions under which a change in correlations implies a shift in the underlying parameters are restrictive. Ronn (1998) shows that increases in variance implies a rise in the correlation.[7]

For instance, assume that the problem of endogenous variables does not exist (make $\alpha = 0$ in model 1). The correlation between x_t and y_t is

$$\rho = \frac{\beta\sigma_\eta}{\sqrt{\sigma_\eta(\sigma_\varepsilon + \beta^2\sigma_\eta)}} = \frac{\beta}{\sqrt{\dfrac{1}{\theta} + \beta^2}},$$

which is a function of θ.

6. This result should be intuitive. By the definition of principal components, movements in the relative variances, in the end, must reflect changes in the loadings because the common component is shifting. This should be true in almost any model.

7. See Boyer, Gibson, and Loretan (1999), Forbes and Rigobon (1999), and Loretan and English (2000) for generalizations of Ronn's result.

Shocks to the variance of x_t imply an increase in θ, which causes the absolute value of the correlation to rise as well. In the limit, when shocks to country x_t are infinitely large, the idiosyncratic shocks to y_t are negligible and the correlation between the two variables is 1. On the other hand, when the variance of η_t goes to 0, the correlation is 0. Note that the correlation moves from 0 to 1 and that the parameter β remains the same.[8]

RESULT 5. *Tests of parameter stability based on (unadjusted) correlation coefficients are inconsistent if the data are heteroskedastic.*

The result is stated on *unadjusted* correlation because there are some cases in which the bias can be corrected. This adjustment was first proposed by Ronn (1998) in the bivariate setting.[9] The main assumptions required are that there are no problems of simultaneous equations or omitted variables and that the heteroskedasticity is fully explained by shifts in η_t and not in ε_t. In this case, the data provide a measure of the change in θ (which is given by the increase in the variance of x_t), and the "unconditional" correlation can be computed where it can be compared across samples, and its stability is consequential for tests of structural change.

The procedure is as follows. Assume the variance of x_t increases in δ; then the correlation in that subsample is given by

$$\rho_c = \frac{\beta}{\sqrt{\dfrac{1}{\theta(1+\delta)} + \beta^2}}.$$

The implied unconditional correlation is the one that would have prevailed if the errors were homoskedastic. Hence, it is given by

$$\rho_u = \frac{\beta}{\sqrt{\dfrac{1}{\theta} + \beta^2}};$$

Solving for the implied unconditional correlation (ρ_u) as a function of the conditional correlations and the shift in the volatility, the following adjustment is found:

$$\rho_c = \rho_u \sqrt{\frac{1+\delta}{1+\delta\rho_u^2}}$$

The ρ_u's can be compared across samples. Under the assumptions stated in this derivation, if they change it is the case that the β's have also shifted. The two main advantages of this procedure are: First, δ can be estimated directly

8. See Rigobon (1999) and Forbes and Rigobon (2000) for a simple example highlighting the biases induced by using correlation coefficients.

9. For applications of these corrections, see also Baig and Goldfjan (2000), Gelos and Sahay (2000), and Favero and Giavazzi (2000).

from the sample by looking at the shift in the variance of x_t. This makes the adjustment very simple. Second, there is no need to estimate β to perform a test of its stability.

However, as was mentioned before, this adjustment can be used only if there are no simultaneous equations and omitted variables issues.[10] In fact, in this situation there is no problem using OLS, and thus no need to estimate the correlation coefficient in the first place. This is the main weakness of using correlation coefficients to indicate the stability of a model; the setting under which the change in the correlation coefficient (or its adjustment) is meaningful generally justifies the implementation of other methodologies.

6.3.4 New Procedure

The previous discussion clearly indicates that the empirical question of the stability of parameters across countries faces tremendous econometric difficulties. The properties of the data make procedures designed to cope with one of the empirical issues inappropriate when all the problems are present.

This section describes a new methodology to test for structural change under simultaneous equations, omitted variables, and heteroskedasticity problems. It is a simplified version of Rigobon (2000b). This procedure is based on the assumptions that (1) the country generating the crisis is known, and (2) the changes in the variance of the rest of the countries is explained, at least in the short run, by the country under crisis and not by other idiosyncratic shocks.

The first assumption is relatively uncontroversial. However, it is important to highlight that in several events, this information is unavailable. For example, during the European Monetary System (EMS) crises, which country is to be blamed for the increase in volatility? The second assumption is perhaps the most difficult one to acknowledge. It is a crucial assumption but one that in the contagion literature is reasonable; and, indeed, it is testable. In the discussion below, this property of the test is explored more carefully.

10. However, as is claimed in Forbes and Rigobon (1999), if the adjustment is practiced using only the country generating the crisis, then it is still possible to get a good approximation of the unconditional correlation based on "near identification" arguments (see Fisher 1976) where "near-identification" refers to the condition that exists when the variance of the shock in one of the equations is significantly larger than the variance of the shocks in the other equations. In this case, as can be seen in equation (5), the biases tend toward zero in both the simultaneous equations and the omitted variable cases. The estimates get closer to the one in which $\alpha = 0$ or $\gamma = 0$. The periods of crisis closely follow this description. For example, during the Mexican crisis in 1994, the variance of the Mexican stock market increased by fifteen times following the devaluation in December. One limitation of this approach is that the adjustment can be performed only in pair-wise comparisons in which the variable x_t always corresponds to the country under crisis. Hence, the stability of parameters between two countries that are not the originators of the crisis cannot be tested. The procedure proposed by Boyer, Gibson, and Loretan (1999) has the same characteristics as the one indicated in Forbes and Rigobon and therefore can be applied in the same conditions.

Assume the variables are described by model 1.[11] Additionally, assume that it is known that in a subsample the variances of x_t and γ_t rise because the variance of η_t increases, while the variance of ε_t remains constant. In this case, two covariance matrices can be computed, one for the low-volatility period (L) and one for the high-volatility period (H):

$$\Omega^L = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \beta^2\sigma_\eta^L + \sigma_\varepsilon & \beta\sigma_\eta^L + \alpha\sigma_\varepsilon \\ \beta\sigma_\eta^L + \alpha\sigma_\varepsilon & \sigma_\eta^L + \alpha^2\sigma_\varepsilon \end{bmatrix}$$

$$\Omega^H = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \beta^2\sigma_\eta^H + \sigma_\varepsilon & \beta\sigma_\eta^H + \alpha\sigma_\varepsilon \\ \beta\sigma_\eta^H + \alpha\sigma_\varepsilon & \sigma_\eta^H + \alpha^2\sigma_\varepsilon \end{bmatrix}$$

Note that the change in the covariance matrix is given by

$$\Delta\Omega = \frac{\Delta\sigma_\eta}{1-\alpha\beta}\begin{bmatrix} \beta^2 & \beta \\ \beta & 1 \end{bmatrix},$$

which has a determinant equal to zero. In fact, proposition 1 in Rigobon (2000b), applied to the case studied here, states that:

RESULT 6. *The determinant of the change in the covariance (DCC) matrices is zero if the parameters are stable and if the heteroskedasticity is explained by the shift in the variance of only one of the shocks.*

In other words, if the parameters shift or if the two variances change, then the determinant of the difference of the covariance matrices is not zero. The model can have both common shocks and simultaneous equations and this result will still hold.[12]

Two remarks about the test are worth highlighting. First, the test is rejected in two situations: when the parameters shift (which is the interesting case) and when there is heteroskedasticity in more than two idiosyncratic shocks (which is uninteresting for the purposes of studying contagion). Second, the test requires the knowledge of the country generating the increase in volatility, as well as the timing of the volatility. Even though the country producing the crisis can be pointed out in some cases, the tranquil and crisis periods might not be as easy to determine.

These two weaknesses deserve further discussion.

Two Alternative Hypotheses

First, there is no procedure to disentangle the two alternative hypotheses thus far. However, an advantage of the test is that if there is no rejection,

11. The omitted variables case produces identical results.

12. Conversations with Giancarlo Corsetti helped me generalize that the test can be applied to models as complicated as the following: $A\binom{x_t}{y_t} = \Gamma z_t + B\binom{\varepsilon_t^1}{\boldsymbol{\eta}_t^1} + \binom{\varepsilon_t^2}{\boldsymbol{\eta}_t^2}$, where A, Γ, and B are nondiagonal matrices and where the vectors of idiosyncratic shocks ε_t^1 and $\boldsymbol{\eta}_t^1$ is transmitted across countries with higher intensity than the other vectors of idiosyncratic shocks, ε_t^2 and $\boldsymbol{\eta}_t^2$. In this model, it is still the case that if the heteroskedasticity in a subsample is explained by the shift in the variance of one of the shocks, then the change in the covariance matrix is not full rank. I thank Giancarlo Corsetti for all his comments.

then the assumption of stability (and on the particular form of the heteroskedasticity) are accepted. It is only when the test is rejected that the assumption about the form of the heteroskedasticity becomes crucial for the interpretation of the results.

The question, then, is one of the power of the test. Rigobon (2000c) studies the power against two possible alternative hypotheses: (1) a change in β, and (2) shifts in the two variances. The main conclusions of that exercise is that, with sample sizes around sixty observations, if the parameters are not too large (α and β should be smaller than 0.8) and if the observed heteroskedasticity of x_t and y_t is relatively large (the variances increase by at least five times), then the power of the test against both alternative hypotheses is better than 10 percent.

In applications of contagion, both conditions are generally satisfied. First, concerning the shift in variance, finding changes of the order of ten times are common in stock markets, domestic interest rates, exchange rates, and Brady bond returns. Second, estimates larger than 0.8 imply extremely high interrelationships not found even in Brady bond markets. Moreover, straight OLS regression estimates are generally smaller than 0.8. Due to the endogenous biases it should be expected that these estimates are upwardly biased, suggesting that the true parameters are smaller than 0.8.

Definition of the Periods

The second question is related to the definition of the periods of high and low volatility. One important result of this test is that the determinant of the change in the covariance is consistent even if the windows are misspecified. This implies that the test is robust to badly stipulated periods. This is a major advantage of the test because, in most of the contagion events, the beginnings of the crises are relatively clear but their ends are not. On the other hand, the cost of the misspecification is that the test loses power; thus it is more likely not to find a rejection.

The intuition of the consistency of the test is the following: If the periods are misspecified, the estimated covariance matrices are linear combinations of the true underlying matrices. The difference between the misspecified ones is also a linear combination of the difference of the true ones. If the original change in matrices is less than full rank, the linear combination would be so too. Hence, consistency is assured. The loss in power is also understood from this intuition because the linear combination reduces the difference across the samples by averaging the underlying matrices.

It is impossible, in practice, to define the crisis period precisely. Hence, robustness of the results when the window is modified should be studied.[13]

13. See Rigobon (2000b) for an application to test the stability of the international propagation of shocks across stock markets.

When To Use the Test

The traditional techniques testing for structural change, in general, are not appropriate as tests for contagion because the data have simultaneous equations, omitted variables, and heteroskedasticity problems. Some adjustments might reduce the biases, but in fact, there is no guarantee that those corrections improve the test. More important, the conditions under which principal components and correlations estimates can be adjusted are those under which OLS could (and should) be estimated.

The test summarized in this section deals with some of the problems of the data. Obviously, it depends on another important assumption: namely, that the heteroskedasticity must be explained by a subset of the idiosyncratic shocks. This is the major assumption (and therefore a weakness) of the procedure and should be made cautiously.

For example, the application of this methodology during the Mexican crisis satisfies the premises in the test. It is difficult to claim that the increase in the volatility of the other Latin American stock markets (following two weeks after the 19 December 1994 devaluation) is explained by shocks to those particular countries, and was not a direct consequence of Mexican problems. In fact, as is shown in the empirical section, the stability is not rejected for this crisis.

However, using the same procedure to test for stability of parameters during the EMS or Korean crises is more difficult. Which country should be blamed for the increase in volatility during the collapse of the EMS? One, two, or all of them? Indeed, if the test is applied to the EMS and Korean crises, it would be easy to reject that the determinant is zero. For the EMS it is clear that no single country can be pointed out as the source of the heteroskedasticity. For the Korean crisis, there does not exist a period of ten consecutive days without a crisis in another Southeast Asian country. By the characteristics of these two crises, a rejection should be expected. However, claiming that the crisis is due to parameter instability is impossible. Again, this is a case in which the rejections are uninteresting.

In the implementation of this methodology, the two main questions should be: first, whether the data are heteroskedastic, and whether they are large enough. This is the precondition for the second question: can the data be described by shifts in the variances of a subset of the idiosyncratic shocks? If so, then the procedure described here is a valid test of parameter stability. Most of the contagion events, however, can answer both questions affirmatively.

6.4 Measuring the Channels of Contagion

The second question tackled by most empirical applications of contagion is the measurement of the different channels through which shocks are propagate across countries.[14] Regardless of the channels, from the empirical point of view there exist essentially three approaches to measure them: probit, OLS, and principal components.

6.4.1 Measuring Using Probit-Logit

One of the first empirical papers in the contagion literature was Eichengreen, Rose, and Wyplosz (1996). They considered the probability that country y will face a speculative attack, given that country x is suffering one. Their interpretation of contagion is natural and appealing.

To implement their test, they take three steps. First, they define an index (capturing the strength of an speculative attack); second, they characterize a crisis as large movements in such indexes; and third, they compute the interrelationship across countries estimating a probit.[15] In order to test for the importance of the different channels of contagion, they interacted the right-hand side crisis indexes with measures of trade, country similarities, etc. The interpretation of their results are undoubtedly engaging. However, this model encounters two problems, one that occurs when the residuals are heteroskedastic, and one that occurs when there are omitted variables and simultaneous equations problems.

Heteroskedasticity in y_t*'s Residuals*

One of the most difficult problems to solve in limited dependent variable regressions is the consistency of the estimates when the residuals of the selection equation are heteroskedastic. Several procedures have been developed to deal with this issue: maximum score (see Manski 1985; Horowitz 1992, 1993) and symmetric trimming (see Powell 1986; Honore 1992; and Honore, Kyriazidou, and Udry 1997). These methodologies are able to handle the estimation biases. Nevertheless, they have not yet been used in contagion applications. On the other hand, the lack of control for heteroskedasticity significantly affects the estimates. This is the discussion highlighted in this section.

A Monte Carlo simulation is run to quantify the bias. Assume that the returns are described by model 3a, in which the matrix A is given by

$$A = \begin{bmatrix} 1 & -\alpha & -\alpha \\ -\alpha & 1 & -\alpha \\ -\alpha & -\alpha & 1 \end{bmatrix}.$$

14. These channels are based on a large theoretical literature and they usually include trade, country similarities, common lender, learning, liquidity, distance, and so forth. See Goldstein, Kaminsky, and Reinhart (2000) and the references therein for a survey of the models.

15. Other papers have also used probit regressions to measure contagion. See Eichengreen et al. (1996) in the context of measuring the probability of issuing foreign debt. See also Bae, Karolyi, and Stulz (2000) for an application using multinomial regressions.

Table 6.1 **Probit Estimates of Both Coefficients for Different Values of α and Different Degrees of Heteroskedasticity**

	First Coefficient: $\hat{\beta}_1$				Second Coefficient: $\hat{\beta}_2$			
	Point Estimate	Diff.	Std. Dev. Diff.	t-stat.	Point Estimate	Diff.	Std. Dev Diff.	t-stat.
			True α = *0.1*					
Homoskedasticity	0.1897				0.1887			
Increase in variance								
2	0.1927	–0.0030	0.0071	0.42	0.1567	0.0145	0.0319	2.20
5	0.1965	–0.0067	0.0124	0.55	0.1241	0.0259	0.0646	2.50
10	0.1977	–0.0080	0.0160	0.50	0.1093	0.0311	0.0794	2.55
			True α = *0.2*					
Homoskedasticity	0.3465				0.3493			
Increase in variance								
2	0.3624	–0.0159	0.0123	1.28	0.2875	0.0199	0.0617	3.11
5	0.3762	–0.0297	0.0205	1.45	0.2292	0.0323	0.1200	3.72
10	0.3825	–0.0360	0.0252	1.43	0.2042	0.0374	0.1450	3.88
			True α = *0.3*					
Homoskedasticity	0.4728				0.4711			
Increase in variance								
2	0.5037	–0.0310	0.0225	1.38	0.3918	0.0329	0.0793	2.41
5	0.5320	–0.0592	0.351	1.69	0.3188	0.0444	0.1523	3.43
10	0.5429	–0.0702	0.0408	1.72	0.2956	0.0511	0.1755	3.43

Notes: For each simulation 500 draws are computed. The tranquil sample and the high-volatility sample contain 500 observations each.

Assume that the third shock ($\eta_{2,t}$) is the only one that suffers from heteroskedasticity.

The Monte Carlo simulation consists of 500 random-independent draws of the three shocks, with sample size of 1,000 observations each. The sample of $\eta_{2,t}$ is split in two and the second half is assumed to have higher variance. Three different degrees of heteroskedasticity—increases by two, five, and ten times—are studied, as well as three different values of α (0.1, 0.2, and 0.3).

The variables y_t, $x_{1,t}$, and $x_{2,t}$ are computed for each realization. The variable $y_t^* = 1(y_t > 0)$ is calculated afterward, and the probit regression (equation [4]) is estimated: $y_t^* = 1(c + \beta_1 x_{1,t} + \beta_2 x_{2,t})$. The objective of the exercise is to compare the estimates of the coefficients (β_1 and β_2) with and without heteroskedasticity. The results are shown in table 6.1; here, the results for the first coefficient ($\hat{\beta}_1$) are summarized in the first four columns and for the second coefficient ($\hat{\beta}_2$) in the next four columns. The first four rows are the estimates when $\alpha = 0.1$, the next four rows are the estimates when $\alpha = 0.2$, and the last four are the results for $\alpha = 0.3$. For the four rows present for each value of α, the first row holds the results under homoskedasticity, which is the benchmark for comparison; the next three rows are the three heteroskedasticities studied.

For each coefficient, the first column shows the point estimates.[16] The second column is the difference between the estimates with heteroskedasticity and the respective ones under homoskedasticity. The third column shows the computed standard deviation of the difference, which was obtained from the bootstrapping. The fourth column calculates the *t*-statistic.

Regarding the first coefficient, three remarks can be extracted from the table. First, an increase in the heteroskedasticity of $\eta_{2,t}$ biases the estimates of $x_{1,t}$ upward. Second, the larger the heteroskedasticity, the larger its bias. Third, the larger the true coefficient (α), the higher the relative impact of the heteroskedasticity. Nevertheless, even though these patterns are quite strong, statistically it is impossible to reject the hypothesis that all coefficients are the same as those under homoskedasticity.

The results on the second coefficient are different from those of $\hat{\beta}_1$. First, the bias is downward, as oppose to upward. Second, the patterns of the heteroskedasticity effects and α size on the bias are the same as before. Third, changes in volatility on the order of ten times imply coefficients that are almost half the size of those under homoskedasticity. Fourth, and more important, the differences are statistically significant.

The last exercise performed is the comparison of the $\hat{\beta}_1$ and $\hat{\beta}_2$ estimates for the same set of parameters. By construction (of matrix A), they should be the same; in fact, under homoskedasticity the estimates are almost identical. However, (in this simulation) when one of the variables suffers from heteroskedasticity, its estimate goes down, while the estimate of the other goes up, and their differences are statistically significant.

This latter property is conceivably the most important regarding the interpretation of the results from the contagion literature: If the heteroskedasticity is correlated with some channel, then we could be finding spurious relationships. For example, assume all contemporaneous coefficients are the same and the heteroskedasticity is correlated with the exchange rate regime; in this case the estimates might erroneously indicate that countries sharing the same regime have stronger interrelationships, and thus are more likely to suffer from contagion.

Identification of Parameters

A second difficulty in the estimation of equation (4) arises when the data have either simultaneous equations or omitted variables problems alone. To illustrate this issue, a Monte Carlo simulation, estimating model 4 where the

16. Their standard deviations are not shown because the objective of the simulation is to concentrate on the difference between the estimates. However, it is important to highlight that all of the estimates were statistically different from zero.

underlying returns are given by model 3, is run.[17] The bootstrap performed follows the same procedure as the one described before.

In the simulations, the parameters chosen were as follows: $\beta = 0.2$; $\gamma_1 = 0.1$; γ_2 was varied from 0.1 to 0.5; the variances of ε_t, $\eta_{1,t}$; and $\eta_{2,t}$ are each equal to 1; and the variance of z_t was changed as follows $\{0.1, 1, 5, 10\}$. For the sake of clarity, there is no heteroskedasticity in this exercise. For each choice of parameters, the variance of the shocks is constant across time. The different volatilities of z_t are studied to understand the implications on the estimates when the (relative) importance of the omitted variable changes.

By construction, if the estimates are consistent, $\hat{\beta}_1$ should be equal to β, and $\hat{\beta}_2$ should be equal to zero. In the omitted variable case, when the variance of z_t is small relative to the other shocks, it is expected that the bias is small. The converse should occur when the variance of z_t is large. The results shown in table 6.2 confirm this intuition.

The first set of three columns shows the point estimate, standard deviation, and t-statistic of the $x_{1,t}$ coefficient. The second set of three columns shows the results for the coefficient on $x_{2,t}$. The simulation is run for all five values of γ_2 and four possible variances of z_t. The results from each of the parameters are reported in their respective rows.

As can be seen in table 6.2, it is possible (depending on the variances) to obtain almost any relationship between $\hat{\beta}_1$ and $\hat{\beta}_2$. This result should cast some doubt on contagion tests that have not controlled for simultaneous equations and omitted variables. Indeed, in the theoretical literature of contagion, unobservable shocks, such as liquidity shocks and shifts in risk preferences, have constituted an integral part of the propagation mechanisms.[18] As this section has shown, the existence of these shocks could change the assessment of the size and importance of contagion.

6.4.2 Measuring Using OLS

A second strand of the literature measures the propagation mechanism using OLS regressions.[19] The problems are similar to the ones described in the previous subsection. Thus, the paper does not present the results of the simulations but concentrates mainly on the conclusions.

17. The omitted variables problem is simpler to analyze, but similar conclusions are found in simultaneous equation setups.

18. See Calvo (1999), Calvo and Mendoza (2000), and Kodres and Pritsker (1999) for theoretical models of contagion based on common unobservable shocks. The first model examines liquidity shocks; the second, market sentiment shocks; and the third, all these shocks plus other transmission mechanisms.

19. See Baig and Goldfjan (1998, 2000), De Gregorio and Valdés (2000), Favero and Giavazzi (2000), Forbes (1999), Gelos and Sahay (2000), Glick and Rose (1998), and Van Rijckeghem and Weder (2000), to name a few.

Table 6.2 **Probit Estimates of Both Coefficients**

	$\hat{\beta}_1$: $x_{1,t}$ Coefficient			$\hat{\beta}_2$: $x_{2,t}$ Coefficient		
Relative Variance	Point Estimate	Standard Deviation	t-statistic	Point Estimate	Standard Deviation	t-statistic
			True γ_2 = 0.1			
0.1	0.2008	0.0411	4.89	–0.0006	0.0400	0.01
1	0.2112	0.0407	5.18	0.0672	0.0404	1.66
5	0.4469	0.0417	10.71	0.3969	0.0414	9.59
10	0.6079	0.0459	13.25	0.5731	0.0478	11.99
			True γ_2 = 0.2			
0.1	0.2013	0.0425	4.74	0.0036	0.0403	0.09
1	0.2148	0.0411	5.23	0.1357	0.0373	3.63
5	0.3808	0.0451	8.44	0.6422	0.0423	15.16
10	0.4487	0.0584	7.68	0.8011	0.0546	14.68
			True γ_2 = 0.3			
0.1	0.1999	0.0424	4.72	0.0038	0.0428	0.09
1	0.2109	0.0420	5.02	0.1971	0.0426	4.62
5	0.3230	0.0533	6.06	0.7527	0.0481	15.65
10	0.3544	0.0687	5.16	0.8649	0.0635	13.62
			True γ_2 = 0.4			
0.1	0.2000	0.0393	5.09	0.0036	0.0415	0.09
1	0.2081	0.0404	5.15	0.2507	0.0398	6.29
5	0.2801	0.0556	5.03	0.8009	0.0503	15.94
10	0.2946	0.0775	3.80	0.8804	0.0658	13.39
			True γ_2 = 0.5			
0.1	0.1991	0.0401	4.96	0.0033	0.0415	0.08
1	0.2059	0.0406	5.07	0.2970	0.0394	7.54
5	0.2574	0.0619	4.16	0.8058	0.0508	15.85
10	0.2672	0.0877	3.05	0.8686	0.0734	11.83

Notes: Standard deviations computed using bootstrap method. Simulations for different variances of z_t (relative variance). Variances of the other shocks have been normalized to 1. For each simulation, 500 draws are computed. The sample contains 1,000 observations.

Assume the data are described by model 3. The OLS estimates are given (after some algebra) by

$$\hat{\beta}_1 = \beta_1 + \frac{\sigma_z}{\phi}\gamma_1\sigma_{\eta,2}$$

$$\hat{\beta}_2 = \beta_2 + \frac{\sigma_z}{\phi}\gamma_2\sigma_{\eta,1}$$

$$\phi = \sigma_z(\gamma_2^2\sigma_{\eta,1} + \gamma_1^2\sigma_{\eta,2}) + \sigma_{\eta,1}\sigma_{\eta,2}$$

Note that if the true values are $\beta_2 = 0$ and $\beta_1 = \beta$, still the biases can produce any outcome on the estimates. Similar conclusions can be drawn if model 3a is used; see appendix A for the derivation. One advantage of OLS over probit is that OLS is robust to heteroskedasticity, whereas probit is not. In the OLS case, the larger inconvenience that introduces the existence of heteroskedasticity is to underestimate the standard deviations, but there are several procedures that can handle this concern.

6.4.3 Measuring Using Principal Components

As was indicated in section 6.3.2, tests for changes in parameters based on principal components are biased in the presence of heteroskedasticity. In this section, a stronger claim is made: that the estimates, by themselves, are also inconsistent.

Using the same example as in section 6.3.2, equation (7) is the first principal component (reproduced here for convenience):

$$\begin{bmatrix} \frac{1}{2}\frac{\alpha_\varepsilon}{\alpha + \beta\theta}\left(\Theta_3 + \sqrt{\Theta_2}\right) \\ 1 \end{bmatrix}$$

Note that the first component is not a linear function of θ. Therefore, the heteroskedasticity (volatility in θ) biases the loadings. For example, assume the countries are positively correlated (which is almost always the case in contagion: α and β are positive). Those countries in which idiosyncratic variance changes more (larger volatility in θ_t) have higher loadings (all other things equal). It is possible, therefore, that strong linkages are found because the heteroskedasticity is high for those countries.

A Monte Carlo simulation was run in this case, but for the sake of brevity the results are not presented; only the conclusions from that exercise are discussed here. First, the heteroskedasticity in the second shock implies that the loading of the first country in the first component is biased downward. This should be expected because when α and β are positive, equation (7) is a convex function of θ. An increase in the heteroskedasticity implies that the second country becomes relatively more important in explaining their common component. Second, when the loadings are compared across different degrees of heteroskedasticity, their estimates are statistically different. Finally, it is easy to show that if the structural errors are properly normalized, the bias disappears. However, this normalization is possible only if the data do not suffer from simultaneous equations or omitted variable problems. In these cases, it is worth asking why one would use principal components when OLS (or FGLS) is consistent. This is conceivably the highest weakness of principal components as a procedure to test and measure contagion. If the heteroskedasticity is not taken into consideration, then the estimates and conclusions might be biased. On the other hand, the only circumstances in which heteroskedasticity can be corrected are those in which OLS should be used.

6.4.4 New Procedure

In the contagion literature, the issues of heteroskedasticity, simultaneous equations, and omitted variables are unavoidable, especially because there are no good instruments to correct for them.[20] Moreover, the fact that most papers use "indexes" instead of exchange rates or interest rates directly exacerbates the problem even more.

In general, the index is constructed as a linear combination of the high-frequency macrovariables. The advantage is, for example, that a speculative attack might have different implications, depending on how central banks decide to cope with it. The index captures the aggregate strength of the response by looking at all its possible consequences. The disadvantage, on the other hand, is that using prices and exchange rates jointly in an index aggravates the endogeneity problems, making the inference about the transmission mechanism more complicated. The use of an index to measure the propagation of shocks has strong theoretical justification, and intuitive appeal, but it is important to remember that it encounters equally strong econometric problems.

In this section, a review of a new procedure developed by Rigobon (2000a) is presented. The objective of the methodology is to provide a consistent estimate of the contemporaneous relationship across variables even if the data suffer from heteroskedasticity, simultaneous equations, and omitted variables. Here, only the case of simultaneous equations is illustrated; for the general treatment see the original reference.

Assume there are K variables jointly determined satisfying the following relationship:

$$AX_t = \varepsilon_t$$

where A is a $K \times K$ nontriangular matrix, X_t is the matrix of country variables, and ε_t is the vector of idiosyncratic shocks. The diagonal of A is set to 1, which is the normalization assumption. Additionally, it is commonly as-

20. For example, the use of lag returns is not a valid instrument for simultaneous equations. It is instrumenting for other problems, such as errors in variables, but not for endogeneity.

Arguing that lag-dependent variables are instruments is making the implicit assumption that home stock market returns depend on own past returns and current foreign returns but not on lag foreign returns, and that, conversely, foreign current returns depend on own lag and current home returns, but not on lag home returns. The theoretical foundations for this assumption are extremely weak. If foreign returns are informative about domestic returns at any time and past home returns are informative about current home returns, then why are past foreign returns not informative about current home returns? In fact, I have not (yet) seen a theoretical model that has the three implications. Either all lag values explain contemporaneous returns or not. In practice, the lag-dependent variables are instrumenting for other issues such as errors in variables and the like, but they are not instrumenting for endogeneity. Moreover, causality tests in this environment are biased. It is well known that simultaneous equations with lag endogenous variables can have any implication on the Granger-causality tests.

sumed in macro-applications that the idiosyncratic shocks are uncorrelated: $E(\varepsilon_{i,t}\varepsilon_{j,t}) = 0$ for all $i \neq j$. This is the covariance restriction used in most macro-applications. Even with all these assumptions, however, A cannot be estimated. The reason is that from the reduced form, only the covariance matrix from X_t can be obtained, which constitutes an underidentified system of equations.

Formally, the reduced form is

$$X_t = A^{-1}\varepsilon_t = \eta_t,$$

which implies a covariance matrix

$$\Omega = A'^{-1}\Omega^{\varepsilon}A^{-1},$$

where Ω^{ε} is diagonal due to the covariance restriction.

The value of Ω is estimated from the sample and provides $K(K + 1)/2$ independent equations. The unknowns are K from the variances of the idiosyncratic shocks, and $K(K - 1)$ from matrix A. Note that for any $K > 1$ the number of unknowns is strictly larger than the number of knowns. This is the standard identification problem raised by simultaneous equations.

The key feature of Rigobon's identification is the realization that under the exact same restrictions the existence of heteroskedasticity adds additional constraints. The simplest case is one in which the heteroskedasticity can be described by two regimes, high and low variance. In this instance, there are two covariance matrices providing $K(K + 1)$ equations, whereas the number of unknowns is $2K$ from the variances of the idiosyncratic shocks (K for each regime), but *the same* $K(K - 1)$ from matrix A. Thus, the system is just identified: $K(K + 1) = 2K + K(K - 1)$. Moreover, it should be clear that it is overidentified when there are more than two regimes. Therefore, for richer descriptions of the heteroskedasticity, an overidentification test can be used and the parameter stability examined.

The assumptions needed to achieve identification are the following: first, heteroskedasticity of the structural shocks; second, stability of the parameters; and third, uncorrelation of the structural shocks. This is exactly the case in most macro-applications in which vector autoregression (VAR) models have been used, and financial applications in which ARCH (autoregressive conditional heteroskedasticity) or GARCH (generalized ARCH) models have been computed. In the derivation developed here, only unconditional heteroskedasticity has been studied. Similar arguments can be extended to include the case in which only conditional changes in the volatility occur.

Using this methodology, a consistent estimate of A can be obtained regardless of the problem of endogenous and omitted variable biases. Afterward, A can be explained as a function of the different channels of contagion. This is the objective of the next section.

6.5 An Application to Emerging Markets

This section examines the questions of stability in the propagation of shocks across Latin American and Southeast Asian countries around the recent crises, the importance of those linkages, and what determines them. The first question is implemented as the test for parameter stability introduced in section 6.3.4, while the other two questions are answered using the methodology described in section 6.4.4.

Two data sets are used: sovereign bonds and stock markets. The data for stock markets were collected from Datastream and consist of daily stock market returns (in U.S. dollars) for fourteen countries, covering the period from January 1993 to December 1998. The countries studied are Argentina, Brazil, Chile, Hong Kong, Malaysia, Mexico, Peru, the Philippines, Singapore, Korea, Taiwan, Thailand, the United States, and Venezuela.

The sovereign bond data contain the daily country bond returns from January 1994 to December 1998, obtained from the Emerging Markets Bond Index Plus (EMBI+) constructed by JPMorgan. The EMBI+ country indexes track total returns for traded external debt instruments in emerging markets. Most of the bonds covered are Brady bonds, but other foreign-denominated bonds are also taken into consideration. The indexes are computed by simulating a portfolio with the weights determined by risk, market capitalization, liquidity, and collateral considerations. The countries included in the bond data are Argentina, Brazil, Ecuador, Mexico, Panama, Peru, and Venezuela. The only two Southeast Asian countries in the JPMorgan data are Korea and the Philippines, but the number of their observations is small in comparison to the other countries. Thus, they were dropped from the analysis.

Information on U.S. interest rates is obtained from Datastream. For all the results presented in this paper, the ten-year U.S. government bond was used. This bond has the closest maturity to the average sovereign bond in the data. However, robustness checks were performed by using shorter horizons (one-year and three-month), and the results were qualitatively the same.

The objectives of looking at these two markets are to compare the transmission mechanisms, to determine how much trade explains about the propagation mechanism in each of them, and to compute the importance of liquidity shocks in both.

6.5.1 Test for Stability

The stability of parameters for both the stock and the bond markets is studied by performing the determinant of the change in covariance (DCC) test described in section 6.3.4. This test is based on the assumption that, in a subsample, the heteroskedasticity is explained by the heteroskedasticity in only a subset of the shocks. Moreover, it must be a subset of either the idiosyncratic shocks or the common shocks. The easiest way to satisfy this condition is to concentrate the analysis around the crises. During these periods, the assumption that the increase in the variance of all emerging markets is caused by the country producing the crisis is a reasonable one.

As will become clear, a considerable amount of time is devoted to the definition of these windows. The main reason is that, if a rejection is found in a poorly designed test, its interpretation becomes cumbersome.

The Model

It is assumed that returns in stock and bond markets are described by a latent factor model

$$AX_t = \phi(L)X_t + \Gamma z_t + \varepsilon_t,$$

where X_t represent the country returns, A is the contemporaneous linkages (the coefficients of interest), $\phi(L)$ is a matrix of lags, z_t is a one-dimensional unobservable shock, all Γ are the parameters of how common shocks affect country returns (or vulnerabilities), and all ε_t are the idiosyncratic shocks assumed to be uncorrelated among themselves and with respect to the common shock.

For normalization purposes, the diagonal of A is assumed to be equal to 1, and the coefficient on the United States in Γ is set to 0.1. The imposition of this normalization means that studying the relative importance of common shocks versus idiosyncratic shocks cannot be performed by looking at the standard deviation of the shocks. Rather, a variance decomposition exercise must be conducted.

The reduced form of this model is the following:

$$\begin{aligned} X_t &= A^{-1}\,\phi(L)X_t + A^{-1}(\Gamma z_t + \varepsilon_t) \\ &= \Phi(L)X_t + \nu_t \end{aligned} \tag{8}$$

where the reduced-form residuals satisfy

$$A\nu_t = \Gamma z_t + \varepsilon_t. \tag{9}$$

Note that the procedure developed in section 6.3.4 deals with the stability and identification of parameters in equation (9). Because the reduced-form residuals share the same contemporaneous properties as the returns, in the estimation, a VAR is first run in the whole sample to eliminate the serial correlation (equation [8]). After the residuals, ν_t, are recovered from the estimation, the regimes are defined, and the test for stability is performed on the residuals. This procedure is testing for the stability of A, Γ, and $\phi(L)$. At first glance, the inclusion of $\phi(L)$ in this list this might be surprising, but see appendix B for a formal derivation.

For the sake of brevity, the results from the VARs are not presented.

Definition of the Windows

To implement the DCC test, one must define a high- and a low-volatility regime. Moreover, for the alternative hypothesis to be informative, the periods must be determined in such a way that the assumption about the heteroskedasticity is likely to be satisfied. In practice, concentrating around the crises should increase the likelihood of satisfying such assumptions.

From 1994 to 1998, international markets faced three major crises; these are used to define the regimes. In table 6.3 the low- and high-volatility dates are shown.

For the Mexican crisis, the low-volatility regime is defined as the period from June to December of 1994 right before the devaluation. The high-volatility regime begins with the devaluation on 19 December 1994; the end of this period, however, is unclear. After the Mexican devaluation several other shocks occurred (e.g., the discussion of the rescue package in January). These shocks maintained the high volatility for several months. Therefore, two possible crisis regimes are studied: one ending on 8 January, and the other lasting until 31 March. The choice of 8 January is based on the fact that on 9 January the nonrollover of the short-term debt was announced, producing a large shock in bond markets around the world. Indeed, the EMBI+ dropped by almost 6 percent that day. This shock could be interpreted as a liquidity shock, and thus, in the model estimated here, as a common shock. The DCC would reject if there is heteroskedasticity in both an idiosyncratic and a common shock. Therefore, these samples should be considered separately. In fact, three cases are studied, one beginning with

Table 6.3 Windows for the DCC Test

	Tranquil Window		High-Volatility Window	
	Begins	Ends	Begins	Ends
Mexican crisis				
Currency devaluation	06/01/1994	12/16/1994	12/19/1994	01/08/1995
No rollover	06/01/1994	12/19/1994	01/09/1995	03/31/1995
Currency devaluation + no rollover	06/01/1994	12/16/1994	12/19/1994	03/31/1995
Asian crises				
Hong Kong	01/02/1997	06/02/1997	10/27/1997	11/14/1997
Korea	01/02/1997	06/02/1997	12/01/1997	01/09/1997
Hong Kong + Korea	01/02/1997	06/02/1997	10/27/1997	01/10/1997
Thailand	01/02/1997	06/02/1997	06/10/1997	08/29/1997
All	01/02/1997	06/02/1997	06/10/1997	01/10/1997
Russian crisis				
Russia	03/02/1998	06/01/1998	08/03/1998	08/21/1998
LTCM	03/02/1998	06/01/1998	08/21/1998	09/30/1998
Russia + LTCM	03/02/1998	06/01/1998	08/03/1998	09/30/1998
Brazilian speculative attack	03/02/1998	06/01/1998	10/01/1998	10/30/1998
All	03/02/1998	06/01/1998	08/03/1998	10/30/1998

the devaluation and ending before 9 January, another one beginning on 9 January and lasting until the end of March, and another that includes both periods.

Looking at these two samples together has the following advantages. It should be expected that the DCC test will produce a rejection in the bond market data for the two periods together; this implicitly indicates how powerful the test is with these data. However, if indeed there is a shift in the parameters after 9 January but not before, then the test is rejected when that period is under consideration, as well. In other words, if the rejection occurs only when the two high-volatility samples are put together, one may argue that the rejection is due to the failure to satisfy the heteroskedasticity assumption. On the other hand, if there is a rejection in one of the subsamples, it must be the case that together the two subsamples are also rejected. This will allow us to identify the period in which the parameters have shifted. Similar exercises are implemented in the next two crises.

The Asian crises began in June 1996 with Thailand's devaluation, and lasted into 1998 until the end of the Korean crisis. For the particular case of the Asian crises, the tranquil period is always defined as the six months prior to Thailand's devaluation. Several high-volatility periods are defined. The Thailand crisis began at the start of June 1997; the Hong Kong crisis began on 27 October 1997; and the Korean crisis began around 15 December 1997. The Hong Kong crisis is the only one that has a clear initial date, which is the day on which short-term interest rates increased dramatically. For the other two crises, however, the initial day is unclear because important action took place on the bond and stock markets prior to the exchange rate devaluation.

During the Asian crises several combination of windows are studied. However, it is important to highlight that even though some of these windows include several crises, they should not become a violation of the heteroskedasticity assumption. In the bond market data, all Southeast Asian countries are excluded from the regression; thus, these crises are summarized by the common unobservable shock. Therefore, the common shock is a subset of the shocks and no rejection should be obtained because the heteroskedasticity assumption was not satisfied. On the other hand, for the stock market data, all the countries are included in the regression. Therefore, the Southeast Asian crises can be modeled as changes in the volatility of a subset of the idiosyncratic shocks. Again, the DCC should not be rejected because of ill-specified heteroskedasticity.

Finally, the third crisis studied is the combination of the Russian and LTCM collapses. The tranquil period extends from March to July of 1998, and several high-volatility periods are studied. First, the pure Russian collapse started at the beginning of August. Second, the LTCM problems appeared at the end of August and lasted until the end of September. Finally, in October, another shocks (a speculative attack on the Brazilian currency) occurred. Hence, as in the Mexican case, the LTCM collapse has been associated with an aggregate liquidity shock.

Several sensitivity analyses were performed to evaluate the robustness of the results to (minor) changes in the definition of the windows. The results are robust to those, but robustness to a random definition of regimes should not be expected. It is crucial, and I hope this discussion has made it clear, that in order to implement the test one must first impose a comprehensive view of the changes in second moments. Otherwise, rejections are meaningless.

Stock Markets

Given the regimes and windows, the next step is to estimate the covariance matrix of the residuals from the reduced form and perform the DCC test.

In table 6.4, the change in covariance matrices is shown for all the choices of windows. This table shows how large the heteroskedasticity (on average) is. In order to compute the change in the covariance matrix, two different norms were used. The first column represents the average change in the variances. The relative change for all countries is computed from the covariance matrices and the average is reported. The second column shows the increase in the maximum singular value, which is perhaps the most informative measure.

As can be seen, the volatile regimes represent important changes in variance. For example, during the Mexican crisis an average increase in variance of eight times was observed. Similarly, during the Hong Kong specu-

Table 6.4 Changes in Variances Measured as Several Matrix Norms

	Average Increase in Variances	Increase in Maximum Singular Value
Mexican crisis		
Currency devaluation	3.36	9.23
No rollover	3.61	7.93
Currency devaluation + no rollover	3.59	7.90
Asian crises		
Hong Kong	6.96	12.80
Korea	5.99	20.08
Hong Kong + Korea	1.84	2.05
Thailand	2.15	3.41
All	0.99	0.97
Russian crisis		
Russia	2.70	2.77
LTCM	5.29	4.78
Russia + LTCM	4.34	3.62
Brazilian speculative attack	3.44	3.07
All	4.04	3.17

Table 6.5 **DCC Test for Stock Markets**

	DCC in Stock Market			
	Point Estimate	Standard Deviation	Mass Zero	Rejection
Mexican crisis				
Currency devaluation	–1.4632877	49.559015	0.357	0
No rollover	34.918946	182.90394	0.762	0
Currency devaluation + no rollover	16.135432	63.385381	0.778	0
Asian crises				
Hong Kong	–8,131.1469	5,140.3177	0.381	0
Korea	8.022301	192.47444	0.675	0
Hong Kong + Korea	2.808E-06	0.00078	0.566	0
Thailand	–0.0023061	0.3208153	0.465	0
All	–7.162E-21	2.011E-07	0.408	0
Russian crisis				
Russia	–28.163079	5,145.213	0.668	0
LTCM	2,926.3835	73,705.659	0.418	0
Russia + LTCM	3,171.8639	16,813.048	0.358	0
Brazilian speculative attack	7.6768399	27,581.466	0.676	0
All	–2,091.3015	19,540.064	0.615	0

lative attack the increase in stock markets was almost twelve times. These increases in volatility represent a significant rise in volatility in emerging markets. Remember that the data include countries such as the United States, Singapore, Chile, etc., where the increases in volatility during this sample were smaller than two times.

After the covariance matrices are estimated, the determinant on their change is computed. The results for the stock market test are shown in table 6.5. The first column indicates the point estimate, the second column is the computed standard deviation, the third is the mass below zero, and the fourth is an indicator for which a value of 1 means that the test of stability was rejected. The standard deviation and the mass below zero are computed using a bootstrap. The procedure uses the changes in conditional variance across the windows to produce several covariance matrices, then computes the determinant on the change and estimates both the standard deviation and the mass below zero. Standard deviations are large because the small sample distribution of the determinant is not normal; thus, to give the test some chance of rejection, the mass below zero is used. The dummy is set to 1 if the proportion of the simulations with determinants smaller than 0 (mass below zero) is either 10 or 90 percent.

Observe that in table 6.5, there is no single case in which the test is rejected. The immediate question is whether the test has power. Two remarks should be made in this respect. In Rigobon (2000b) it is shown that for the size of these windows and the observed changes in variance, the test is quite powerful (type II errors were smaller than 10 percent for a test with size 5 percent). Second, as will be seen below, there are some rejections when bond data are used. Therefore, the lack of rejection could not be blamed entirely on the power of the test. This evidence suggests that the propagation of shocks across stock markets is (relatively) stable during the recent crises.

Bond Markets

This section turns its attention to the bond market. The same windows used before were used to test for the stability of parameters among EMBI+ indexes.

In table 6.6, the change in covariance matrices is shown again to highlight the changes in variances experienced in the sample. The interpretation of the columns is the same as before. Note that in this case, however, the shifts in the variances are larger than the ones found in stock markets.

In particular, observe that during the Mexican crisis after the non-rollover announcement the variances doubled. Likewise, the LTCM collapse implied an increase in volatility above the one already experienced by the Russian crash. Take into consideration that this pattern was absent in the stock market data (see table 6.4); this confirms the common wisdom among market participants that the aftermath of the Mexican crisis and the LTCM shocks consisted mainly of shocks to the bond markets.

On the other hand, an interesting aspect of this table is that, excluding the Hong Kong speculative attack, the Asian crises had almost no impact on the variance of Latin American bond markets, at least in their volatilities.

Table 6.6 **DCC Test for Bond Markets**

	Average Increase in Variances	Increase in Maximum Singular Value
Mexican crisis		
Currency devaluation	12.71	10.14
No rollover	19.96	22.92
Currency devaluation + no rollover	18.56	20.21
Asian crises		
Hong Kong	13.69	15.73
Korea	2.39	3.11
Hong Kong + Korea	1.14	1.28
Thailand	0.82	1.04
All	1.00	1.01
Russian crisis		
Russia	49.15	47.72
LTCM	58.89	56.75
Russia + LTCM	51.54	50.69
Brazilian speculative attack	13.31	11.88
All	38.79	37.53

Notes: Changes in variances measured as several matrix norms.

Table 6.7 **DCC Test for Bond Markets**

	DCC in Bond Market			
	Point Estimate	Standard Deviation	Mass below Zero	Rejection
Mexican crisis				
Currency devaluation	1.3062012	2.1833245	0.76	0
No rollover	14.264603	18.034845	0.94	1
Currency devaluation + no rollover	16.541713	15.496773	0.981	1
Asian crises				
Hong Kong	–0.0002571	0.0008754	0.24	0
Korea	6.841E-10	5.164E-08	0.345	0
Hong Kong + Korea	–1.306E-12	7.95E-11	0.549	0
Thailand	–2.812E-10	5.66E-09	0.325	0
All	1.028E-19	2.00E-11	0.616	0
Russian crisis				
Russia	–0.0005737	0.0011142	0.549	0
LTCM	–6.8381042	5.7270025	0.04	1
Russia + LTCM	–6.3514527	4.5857572	0.021	1
Brazilian speculative attack	0.0029295	0.0009354	0.264	0
All	8.307991	3.1489852	0.993	1

Remember that if the heteroskedasticity is small the DCC test has little power. Thus, a lack of rejection should be expected during the Southeast Asian crisis for the bond data.

The results for the bond market DCC test are shown in table 6.7. The interpretation of the table is the same as for the stock market. In this case, there are two instances in which the parameters are unstable: the 9 January shock and the LTCM collapse. Note that the DCC test is rejected when these crises are analyzed separately or jointly with other events, suggesting that the test is rejected because of a shift in the parameters during those times, and not because of misspecification of the alternative hypothesis.

In the Mexican case the test is rejected if the sample covers the period from January to March, or from 19 December to March. Similarly, the test is rejected for the LTCM crisis alone (end of August plus September) or if it is included with the Russian crisis, or with the Russian and Brazilian attacks. However, no instability was found after October 1998, indicating that the changes in the transmission mechanism across bond markets occurred shortly after the LTCM collapse.

In summary, the events for which the test is rejected reflect incidents of important common shocks occurring in the bond market. Market participants have identified these two particular events with liquidity shocks. In the setup estimated here, there is more to these shocks than a pure liquidity shock. In equation (9) the presence of a liquidity shock has already been taken into consideration by the inclusion of z_t. The fact that the DCC is rejected implies, then, that either the relationship is nonlinear or there is a change in the intensity with which the liquidity shocks are propagated. With the techniques available, unfortunately, there is no procedure that can disentangle these two explanations.

6.5.2 Estimation of the Propagation Mechanism

In this subsection, the contemporaneous relationship between stock markets and bond returns is estimated. The questions of interest are threefold: What is the estimate of A? How much do trade and regional variables explain A? Finally, what is the relative importance of the common shocks (z_t) across crises and regimes?

Model and Identification

As before, it is assumed that returns are described by the same latent-factor model

$$AX_t = \phi(L)X_t + \Gamma z_t + \varepsilon_t. \tag{10}$$

Assume that there are C common shocks and K endogenous variable. Again, a VAR is estimated first and the tests are performed on the reduced-form residuals equation (9).

Identification. The procedure described in section 6.4.4 shows that under orthogonality of the structural shocks and the existence of heteroskedasticity, it is possible to identify an equation such as equation (10) if the heteroskedasticity is high enough.

Given the number of endogenous and omitted variables, the unknowns in the system of equations are as follows: $K(K-1)$ unknowns are the parameters from matrix A; $C(K-1)$ unknowns are the parameters from Γ after normalization; K times S variances are from the idiosyncratic shocks (there are K variances of idiosyncratic shocks for each regime in heteroskedasticity [S]); and C times S variances are from the common shocks (there are C variances of common shocks for each regime). Therefore, the total number of unknowns is

$$\underbrace{K(K-1)}_{\text{from A}} + \underbrace{C(K-1)}_{\text{from }\Gamma} + \underbrace{KS}_{\text{idiosyncratic shocks}} + \underbrace{CS}_{\text{common shocks}}. \tag{11}$$

The first condition for identification is that each regime in the heteroskedasticity should add more equations than unknowns. This is required for the order condition to be satisfied. Each new covariance matrix adds $K(K+1)/2$ equations (which is the covariance matrix estimated on the residuals), while it adds K new idiosyncratic variances and C new common shock variances. Therefore, each regime adds more equations than unknowns if and only if

$$\frac{K(K+1)}{2} > K + C \tag{12}$$

$$K(K-1) > 2C$$

This is the "catch-up" constraint.

After the condition of equation (12) is satisfied, there must be a minimum number of regimes that imply that there are at least as many equations as unknowns. The number of knowns is provided by the covariance matrix in each regime and is equal to

$$\frac{K(K+1)}{2}S. \tag{13}$$

Therefore, imposing that equation (13) is larger than or equal to equation (11), and solving for S, the minimum number of regimes required for identification is

$$S \geq 2\frac{(K+C)(K-1)}{K^2 - K - 2C}. \tag{14}$$

In the two examples studied here, one common shock is allowed. Therefore, the number of regimes required for identification in each case is as follows:

1. There are eight countries (endogenous variables) in the bond markets. The catch-up constraint (equation [12]) is easily satisfied and the minimum number of regimes is $S \geq 14/6$.
2. There are fourteen countries in the stock markets. Thus, the inequality in equation (12) is satisfied and the number of regimes required is $S \geq 13/6$.

In summary, three regimes are enough to achieve identification in both examples.

Estimation. From the reduced form, equation (9), the covariance matrix of residuals is given by

$$\Omega_t^\nu = A^{-1}\Gamma\Omega_t^z\Gamma' A'^{-1} + A^{-1}\Omega_t^z A'^{-1}, \tag{15}$$

where the left-hand side is the estimate of the covariance matrix in regime $t \in (1, \ldots, S)$, and the right-hand side expresses the coefficients of interest. This is a nonlinear system of equations that is estimated by generalized method of moments (GMM), in which equation (15) is the set of moment restrictions.[21]

21. Actually, instead of computing inverses of A, the moment restriction estimated is $A\Omega_t^\nu A' - \Gamma\Omega_t^z\Gamma' - \Omega_t^\varepsilon = 0$, which is simpler and more stable. However, the invertibility of A must always be checked.

After the VAR has been estimated and the residuals (which in fact are the same residuals as those used in the previous section); have been recovered, the regimes are defined, the covariance matrices are calculated, and the system of equations is estimated. An important aspect of the identification through heteroskedasticity is that the estimates are consistent even if the regimes are misspecified. Thus, the windows are defined by the periods of medium and high volatility derived from the conditional volatility. Furthermore, the identification is obtained regardless of whether the changes in variance are conditional; thus, the use of the sample covariance matrices to determine the regimes is easily justified.[22]

For stock markets the sample studied runs from July 1994 to the end of 1998. For bond markets, we exclude the Mexican and Russian crises; thus the sample runs from 1 April 1995 until 31 July 1998. The assumption of parameter stability is crucial for the identification, and the previous subsections have already shown that bond markets had unstable parameters during the first quarter of 1995 and after 21 August 1998.

Again, the results from the VAR are not shown.

Stock Markets

Definition of the Regimes. First, taking the residuals from the VAR, a twenty-day rolling window covariance matrix was computed. A norm on the covariance matrix was defined (in this paper, the maximum singular value was used; however, other measures produced very similar splits in the regimes). Second, using the conditional covariance matrices, the regimes were defined as follows: the low-volatility regimes are those dates on which the matrix norm is smaller than the average; the high-volatility regimes are the dates on which the norm is larger than 2 standard deviations of the mean; and the medium-volatility regime is the rest of the sample.

In figure 6.1 the three regimes are shown, with 1 corresponding to the low-volatility, 2 to the medium-volatility, and 3 to the high-volatility periods. There are 848 observations in the low, 329 in the medium, and 95 in the high-volatility regimes. It is important to note that the regimes coincide with most of the crises and events in which contagion is suspected to have existed.

Finally, after the windows are defined, the covariance matrix in each regime is computed and the GMM is implemented to estimate equation (15).

22. In a separate paper, I have already solved the problem of identification when only conditional heteroskedasticity exists. The proof is very similar to the one shown here. Deriving the reduced form from a structural model where the residuals have GARCH effects and the structural shocks are uncorrelated produces a restricted GARCH equation that fully identifies the simultaneous coefficients in the level equation. The estimation in this case is simpler because the maximum likelihood estimator (MLE) can be used directly. The intuition of the identification, however, is exactly the same as the one derived here (see Rigobon 2001).

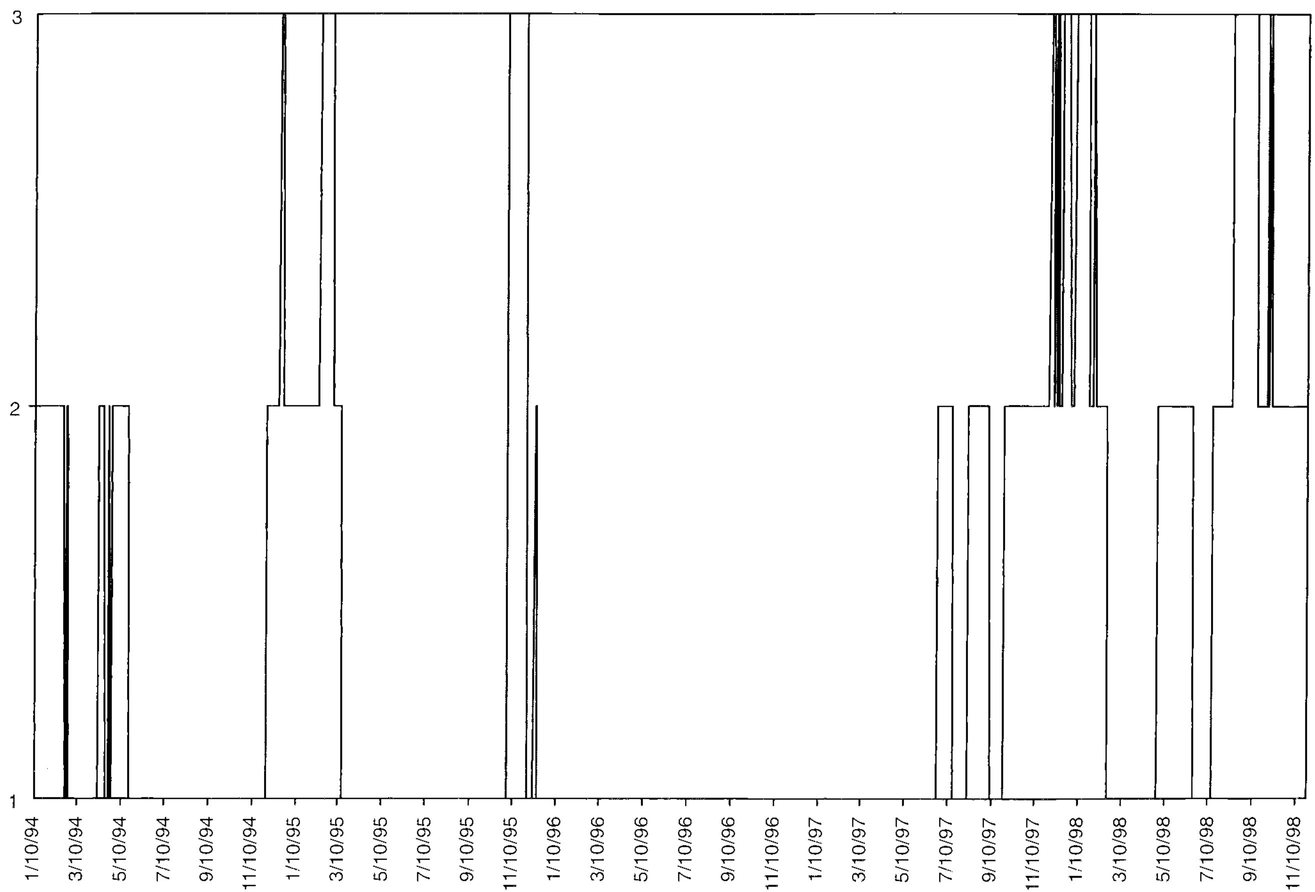

Fig. 6.1 **Regimes in the stock market data**

Distributions and standard deviations were computed by bootstrap in order to draw several covariance matrices and solve the system of equations for each realization. However, the assumption that the covariance matrices across regimes are independent is unsatisfactory; thus, in order to take into consideration the serial correlation in the covariance matrices, it was assumed that only the change in the covariances was independent across regimes. Therefore, conditional on the point estimates of the covariance matrices of the reduced form, random draws of covariance matrices were obtained consistent with the sample size in each regime and its covariance structure. For each set of covariance matrices the system of equations is solved (using GMM) and the process repeated 100 times. The distribution of the coefficients is the solution to each of the realizations of the system of equations.

Contemporaneous Transmission Mechanism. The results of estimating A are shown in table 6.8. The diagonal is omitted because it is known that it is equal to 1, and the signs of the coefficients have been changed so they can be understood as the elasticities in the right-hand side (its natural interpretation).

The rows represent the equations of each country, and the columns are the regressors. Therefore, the reading of the coefficients is as follows: The row country (Argentina) is contemporaneously affected by the column country (Mexico) by a coefficient of 0.234. The coefficients that are statistically significant different from zero at the 90 percent confidence interval are in boldface type, where the confidence interval is computed using the bootstrapped distribution.

Several remarks on table 6.8 are worth making. First, the coefficients in the U.S. equation are all nonstatistically significant. Note that this was not imposed on the estimation procedure, even though our prior would have suggested so. On the other hand, the United States importantly affects some of the emerging markets.

Second, the coefficients are relatively large, explaining the high comovement that exists among international stock markets. In fact, these coefficients explain correlations of an average of 22 percent among all countries.

Third, in the table, 32 of 182 coefficients are statistically different from zero. Among the Latin American countries, there are 13 significant estimates out of 30 possible coefficients. Similarly, among the Southeast Asian countries, 12 of 42 are significantly different from zero. Interestingly, only 3 (of 84) coefficients across regions (excluding those from the United States) are statistically different from zero; these are the propagations from Chile to Korea, from Chile to Thailand, and from Korea to Mexico. This confirms, quite strongly, the common wisdom that the propagation of shocks across countries was concentrated within geographical regions.

Table 6.9 shows the standard deviations of the coefficients, which are ob-

Table 6.8 **Point Estimates of A**

Country	Regressor													
	Argentina	Brazil	Chile	Hong Kong	Malaysia	Mexico	Peru	The Philippines	Singapore	Korea	Taiwan	Thailand	United States	Venezuela
Argentina		0.26	0.51	0.09	0.17	0.23	0.55	0.35	0.24	0.04	0.20	0.22	0.76	0.00
Brazil	0.51		0.60	0.33	0.00	0.29	0.69	0.09	0.44	0.08	0.00	0.12	0.61	0.04
Chile	0.24	0.08		0.26	0.13	0.01	0.28	0.23	0.00	0.05	0.36	0.20	0.64	0.00
Hong Kong	0.13	0.00	0.00		0.00	0.00	0.37	0.04	0.63	0.10	0.00	0.21	0.00	0.06
Malaysia	0.22	0.09	0.23	0.72		0.05	0.32	0.27	0.13	0.23	0.37	0.35	0.06	0.05
Mexico	0.35	0.17	0.72	0.31	0.23		0.14	0.22	0.53	0.16	0.08	0.24	0.55	0.00
Peru	0.06	0.00	0.58	0.33	0.27	0.47		0.34	0.02	0.16	0.03	0.23	0.44	0.12
The Philippines	0.00	0.06	0.17	0.02	0.03	0.17	0.02		0.41	0.14	0.47	0.32	0.31	0.00
Singapore	0.14	0.00	0.69	0.38	0.20	0.01	0.25	0.37		0.04	0.17	0.41	0.39	0.01
Korea	0.25	0.14	0.57	0.07	0.16	0.10	0.11	0.39	0.32		0.09	0.39	0.53	0.04
Taiwan	0.23	0.00	0.01	0.43	0.22	0.16	0.48	0.43	0.34	0.18		0.37	0.21	0.04
Thailand	0.06	0.09	0.70	0.15	0.26	0.00	0.49	0.35	0.51	0.31	0.15		0.36	0.00
United States	0.19	0.09	0.09	0.37	0.18	0.24	0.22	0.47	0.30	0.17	0.12	0.30		0.07
Venezuela	0.21	0.00	0.71	0.00	0.11	0.10	0.25	0.59	0.56	0.19	0.39	0.31	0.06	

Table 6.9 **Standard Deviation of A Estimates**

Country	Argentina	Brazil	Chile	Hong Kong	Malaysia	Mexico	Peru	The Philippines	Singapore	Korea	Taiwan	Thailand	United States	Venezuela
Argentina		0.082	0.153	0.080	0.046	0.079	0.115	0.121	0.124	0.025	0.071	0.069	0.170	0.019
Brazil	0.138		0.178	0.106	0.014	0.122	0.169	0.073	0.160	0.069	0.084	0.093	0.182	0.057
Chile	0.060	0.041		0.056	0.024	0.032	0.060	0.062	0.069	0.028	0.071	0.042	0.141	0.014
Hong Kong	0.053	0.031	0.065		0.009	0.041	0.082	0.071	0.119	0.043	0.077	0.068	0.050	0.025
Malaysia	0.076	0.037	0.119	0.111		0.079	0.090	0.082	0.130	0.062	0.091	0.098	0.041	0.031
Mexico	0.106	0.073	0.203	0.118	0.042		0.120	0.109	0.150	0.081	0.079	0.074	0.149	0.026
Peru	0.032	0.032	0.167	0.110	0.041	0.095		0.102	0.052	0.052	0.064	0.078	0.172	0.045
The Philippines	0.074	0.068	0.126	0.071	0.050	0.086	0.049		0.108	0.069	0.087	0.074	0.144	0.011
Singapore	0.047	0.036	0.117	0.085	0.047	0.040	0.053	0.084		0.016	0.048	0.065	0.122	0.018
Korea	0.080	0.078	0.181	0.090	0.062	0.092	0.106	0.143	0.145		0.101	0.111	0.173	0.068
Taiwan	0.040	0.047	0.089	0.140	0.042	0.056	0.123	0.119	0.110	0.064		0.074	0.146	0.025
Thailand	0.044	0.039	0.188	0.124	0.066	0.031	0.108	0.116	0.146	0.072	0.060		0.148	0.035
United States	0.060	0.045	0.105	0.070	0.022	0.049	0.080	0.087	0.085	0.036	0.065	0.045		0.023
Venezuela	0.085	0.039	0.170	0.033	0.020	0.054	0.140	0.164	0.168	0.064	0.157	0.081	0.139	

tained from the bootstrap. One appealing fact from table 6.9 is that the precision of the estimates depends on how severe the country was affected by the crises.

For example, Argentina, Brazil, Hong Kong, Malaysia, Mexico, Korea, and Thailand were either the originators of the crises or the main countries affected. The standard deviations for these estimates is 0.063. On the other hand, U.S. estimates are less precisely estimated; the average standard deviation is 0.1366. The reason for this outcome is the way the identification problem is solved: the heteroskedasticity is the identifying device. The quality of the estimation, and thus its precision, depends on how large the heteroskedasticity is. The larger the shift in the variance of that country, the better-estimated the coefficients of the propagations from that country are. The increases in volatility in emerging markets are almost an order of magnitude larger than those from the United States (or Singapore), which is why those standard deviations are smaller.

Finally, in table 6.10, the quasi–z-statistic was computed. Even though the test of significance was implemented by looking at the distribution, it is informative to calculate the ratio of the average bootstrapped distribution to the standard deviation because the conclusions of both procedures are similar, and this one is much easier to implement. The inconvenience is that the z-statistic tends to overestimate the significance of the coefficients.

For example, if a 90 percent confidence interval is used (as was the case with the bootstrapped distribution) then more coefficients are significant under use of the z-statistic than use of the bootstrapped distribution. In table 6.8, there are 32 out of 182 significant coefficients; using the z-statistic, 47 would have been significant. It is important to mention that all the coefficients that are significant under the bootstrapped distribution are also significant using the z-statistic. On the other hand, if a 95 percent confidence interval is used as the criterion on the z-statistics, then 31 coefficients pass the test. The coefficient that loses significance is the transmission between the United States and Peru.

At first glance, Chile has as many significant coefficients as the United States. Does this mean that Chile is more important than the United States in these data? Certainly not. What this does mean is simply that those coefficients are estimated with more efficiency. To answer the question of importance of countries, however, a different exercise must be performed. The interpretation of the coefficients requires a variance decomposition (performed below). This is the correct measure to evaluate the relative impacts of countries and shocks in this model.

Finally, the patterns shown by the coefficients estimated in matrix A imply unconditional correlations that are relatively large. What are the explanations underlying them? In this interpretation, it is important to remember that these coefficients are the combination of several possible channels of contagion. The question, then, is what are the possible explanations

Table 6.10 **z-statistics of *A* Estimates**

Country	Argentina	Brazil	Chile	Hong Kong	Malaysia	Mexico	Peru	The Philippines	Singapore	Korea	Taiwan	Thailand	United States	Venezuela
Argentina		2.98	3.91	0.85	1.47	2.79	1.20	1.38	1.75	0.56	0.71	1.37	3.91	0.47
Brazil	3.42		3.59	1.11	0.25	2.06	2.46	0.67	1.67	0.88	0.87	1.15	2.78	1.35
Chile	1.78	1.94		1.38	0.99	0.64	0.97	1.39	1.46	0.59	1.01	1.18	3.32	0.70
Hong Kong	1.06	0.43	0.71		0.33	1.05	2.18	1.62	4.52	1.95	1.29	1.61	0.57	0.90
Malaysia	0.94	0.52	0.78	3.65		1.29	1.74	0.94	1.58	2.16	0.91	1.73	0.32	1.20
Mexico	2.67	1.83	2.85	1.33	0.63		2.06	1.14	1.93	2.11	1.02	0.88	2.89	0.52
Peru	0.61	0.72	2.50	0.99	0.89	2.05		1.16	0.45	1.00	0.80	0.84	1.93	1.17
The Philippines	1.32	0.94	1.04	1.39	0.94	1.47	0.75		3.53	2.66	1.38	2.40	1.23	0.48
Singapore	0.87	0.95	4.47	2.89	2.72	0.83	0.84	1.82		0.26	0.82	1.89	1.71	0.99
Korea	0.87	1.03	2.49	0.98	0.83	1.04	1.50	1.13	1.53		1.63	2.29	2.68	1.15
Taiwan	0.46	0.64	0.75	1.15	1.09	0.82	1.27	1.09	0.97	0.98		0.84	1.31	0.90
Thailand	0.49	0.67	2.66	1.08	1.54	0.55	1.81	1.90	2.53	1.65	0.84		1.19	0.74
United States	1.40	1.49	1.70	1.14	0.33	1.46	1.32	1.47	1.35	1.50	1.27	0.57		1.47
Venezuela	0.95	0.53	4.04	0.46	0.35	0.62	1.59	1.44	1.73	0.92	1.57	0.86	1.40	

Table 6.11 **Vulnerabilities (estimates of γ)**

Country	Point Estimate	Standard Deviation	z-statistic
Argentina	0.39	0.26	0.84
Brazil	0.41	0.35	1.05
Chile	0.34	0.14	0.97
Hong Kong	0.09	0.10	0.60
Mayalsia	0.27	0.22	0.87
Mexico	0.44	0.28	0.88
Peru	0.52	0.25	1.01
The Philippines	0.35	0.14	1.02
Singapore	0.38	0.34	0.90
Korea	0.68	0.32	1.02
Taiwan	0.30	0.22	0.71
Thailand	0.64	0.19	0.94
United States	0.10		
Venezuela	0.55	0.28	1.06

behind them? Later in this section, a partial structural model is provided using the analysis of the importance of trade and regional variables.

Vulnerabilities. The GMM procedure also provides an estimate of the sensitivity of countries' stock markets to common shocks. These coefficients are identified only up to a normalization, and in this particular case, the U.S. elasticity was chosen to be equal to 0.1. The results are shown in table 6.11. The first column corresponds to the point estimate. The second column shows the standard deviation computed from the bootstrapped distribution. The third column is the z-statistic, calculated as before.

As was claimed in the introduction, the common shocks represent changes in risk preferences, liquidity shocks, etc. Note that all coefficients (except the one from Hong Kong) are larger than 0.1, suggesting that emerging economies are more vulnerable to common shocks than the United States. For example, Argentina, Brazil, and Mexico are close to four times more vulnerable than the United States to the same common liquidity shock. Even though this pattern is quite informative, it is impossible to reject the hypothesis that the estimates are all equal to zero.

Because the coefficients estimated are difficult to interpret, the next subsection—rather than studying their aspects—analyzes a variance decomposition. First, the proportion of the variance explained by the common shocks versus idiosyncratic shocks is analyzed, and later, the proportion of the variance explained by each country within the idiosyncratic shocks.

Variance Decomposition: Common versus Country-Specific Shocks. The variance decomposition indicates the relative importance of the common shock in each of the regimes and countries. Thus, the analysis of vulnera-

Table 6.12 Variance Decomposition (percentage explained by idiosyncratic shocks)

	Variance Decomposition		
Country	Low	Medium	High
Argentina	89.4	78.8	75.0
Brazil	94.0	88.6	85.5
Chile	92.0	83.7	80.8
Hong Kong	73.4	65.4	57.6
Malaysia	71.5	72.4	64.4
Mexico	86.8	77.5	75.1
Peru	92.6	83.9	81.2
The Philippines	77.4	67.1	49.4
Singapore	72.6	56.8	51.1
Korea	89.2	84.1	89.6
Taiwan	98.1	95.3	87.3
Thailand	72.1	60.8	53.2
United States	95.8	92.7	89.0
Venezuela	97.8	93.3	97.1

bility can also be studied in this context. Moreover, given the interpretation of the common shock as liquidity or risk preferences, this disaggregation can be useful to understand the relevance of those shocks in the explanation of the recent crises.

The variance decomposition was estimated by calculating the total unconditional variance per regime and comparing it with the implied unconditional variance, assuming that the common shocks do not exist. The procedure is as follows: Using the estimated coefficients and variances in each regime, the unconditional covariance matrix is estimated using equation (15). Then the same equation is estimated, but $\Omega z \backslash t$ is set to zero. This is the unconditional covariance with only idiosyncratic shocks (in other words, without common shocks). In table 6.12, the ratio between the variance of each country explained by idiosyncratic shocks alone to the variance when common shocks are included. This procedure is repeated for each regime.

Three remarks can be extracted from the table. First, notice that the United States is almost unaffected by common shocks (surprisingly, Venezuela is also equally unaffected by common shocks). In all three regimes, close to 90 percent of the variation in U.S. stock returns is explained by idiosyncratic shocks. This does not mean that liquidity shocks or risk preferences are unimportant in the United States. What it does mean is that the common component of these shocks can be described mainly as idiosyncratic shocks to the United States. Therefore, in this exercise, the common liquidity shock not affecting the United States is the one that is being evaluated.

Second, the high-volatility regime includes a larger proportion of common shocks: the average decomposition during the high-volatility regime implies that 74 percent of the variation is explained by idiosyncratic shocks.

This should be compared with 86 percent, which is the average of the idiosyncratic-shock explanation during the low-volatility regime. This pattern suggests that during the recent crises a component common to emerging markets contributed to the comovement across stock markets. As will be seen below, this stylized fact is even stronger in bond markets.

Third, during the high-volatility regimes, the countries having the largest component of common shock were the Asian countries. Surprisingly, for the Latin American countries the change in the common component is small from the low- to high-volatility regimes.

Variance Decomposition: Country Idiosyncratic-Shock Contribution. The interpretation of the matrix A coefficients is more easily understood in a variance decomposition exercise. Table 6.13 computes the proportion of the idiosyncratic variance of each row country explained by the country shock column. The total idiosyncratic variance is calculated as $A^{-1}\Omega^{\varepsilon}A'^{-1}$. To compute the contribution of country j shocks on the other countries, all elements of Ω^{ε} (except $\omega_{\varepsilon,jj}$) are set equal to zero. Table 6.13 presents the ratio between the diagonals of these two matrices for each country.

The table does not include standard errors on the variance decomposition, and its interpretation must be taken cautiously. However, it has interesting patterns. The reading of the table is as follows: The row country is the variance to be explained, while the columns indicate the shock that is analyzed. For example, Argentinean shocks explain 68 percent of the idiosyncratic variance of Argentina, 18 percent of the Brazilean variance, and 19 percent of the Mexican variance.

Two remarks are worth mentioning. First, note that in more developed markets (the United States and Hong Kong) the majority of the variance is explained by each country's own shocks.

Second, most of the variation per regions is explained by regional idiosyncratic shocks. For example, 73.6 percent of the variation of the Latin American countries is explained by their own regional shocks, 23.0 percent is due to shocks to Asian countries, and 3.4 percent is due to U.S. shocks. On the other hand, 71.0 percent of the volatility in Asia is due to Asian shocks, 18.1 percent is due to Latin American shocks, and 10.9 percent is due to U.S. shocks. In the particular case of the United States, 80.5 percent is accounted for by U.S. idiosyncratic shocks, while 12.5 percent and 7.0 percent are explained by Latin American and Asian shocks, respectively.

Estimating the Importance of Trade. The final exercise is to explain the coefficients from the A matrix by trade and regional variables. Thus, an evaluation of the strength of these channels of contagion is performed in this section.

The additional data collected are the following: Information on trade is obtained from Feenstra's World Data Flows. The trade share is computed as the

Table 6.13 **Variance Decomposition (percentage explained by each country shock in the total idiosyncratic shock variance)**

Country	Argentina	Brazil	Chile	Hong Kong	Malaysia	Mexico	Peru	The Philippines	Singapore	Korea	Taiwan	Thailand	United States	Venezuela
Argentina	68.1	0.8	2.8	13.1	0.4	0.2	0.1	1.8	8.8	0.7	0.9	1.6	0.1	0.6
Brazil	18.1	24.6	8.3	2.8	0.2	2.4	3.0	0.3	22.1	5.0	0.7	3.3	8.1	1.1
Chile	9.1	0.1	54.0	0.1	1.0	0.9	12.2	1.3	0.1	2.6	0.1	1.9	12.3	4.4
Hong Kong	4.7	0.8	1.8	78.0	0.4	3.2	0.3	0.6	0.8	0.4	0.3	0.5	7.7	0.6
Malaysia	18.9	2.7	7.0	1.6	24.6	1.8	0.1	2.8	0.0	0.0	8.3	1.7	24.5	5.9
Mexico	7.7	0.0	8.2	0.1	0.2	62.4	0.4	0.0	6.7	0.8	1.3	4.2	0.1	8.0
Peru	9.0	1.5	0.0	19.3	0.4	0.1	54.5	3.0	3.1	0.0	2.8	0.1	4.3	1.8
The Philippines	7.0	1.1	0.5	10.4	0.0	9.0	1.8	39.6	4.3	3.6	0.7	2.1	19.0	0.9
Singapore	1.2	0.3	6.5	0.8	0.5	10.1	4.3	0.1	62.5	0.1	0.0	0.0	11.5	2.0
Korea	3.3	0.2	2.1	24.3	0.3	0.0	0.1	5.0	0.0	43.0	9.9	3.8	6.0	2.1
Taiwan	0.0	0.0	11.1	22.4	0.7	19.6	8.6	1.4	0.4	0.1	28.4	0.1	6.4	0.7
Thailand	3.3	1.4	2.5	14.0	0.4	0.1	1.8	2.4	2.3	0.1	5.7	58.5	6.9	0.7
United States	5.3	1.4	1.3	0.6	0.1	0.4	0.3	0.0	0.9	0.0	3.8	1.6	80.5	3.9
Venezuela	1.4	0.0	0.2	5.4	0.2	0.2	10.5	0.1	5.6	2.3	0.3	1.7	0.1	72.0

Table 6.14 **Explaining *A*-coefficients**

Variable	Coefficient	Standard Error	*t*-statistic	Prob.
C	0.504718	0.162908	3.098	0.002267
TRADE	0.333628	0.169129	1.972	0.050104
log (DISTANCE)	–0.032304	0.01664	–1.941	0.05382
BORDER	–0.018185	0.058949	–0.308	0.758069
LA	0.36155	0.057056	0.633	0.527122
SEA	–0.020357	0.056898	–0.357	0.720934
R^2	0.06632			
Prob (*F*-statistic)	0.03241			

Notes: See text for explanation of variables.

average trade share of the countries in the 1990s. Information on distance, border sharing, and belonging to the Latin America (LA) or Southeast Asia (SEA) dummy is also included in the regression. The left-hand side represents the point estimates from matrix *A*, and the regression run is the following:

$$\beta_{i,j} = c_0 + c_1\text{LA} + c_2\text{SEA} + c_3\text{TRADE}_{i,j} + c_4\text{BORDER} + c_5\log(\text{DISTANCE}) + \varepsilon_t$$

It is likely that this regression has heteroskedasticity because the *A* coefficients were estimated with different degrees of precision. Therefore, a GLS was estimated in which the covariance matrix of the coefficients obtained in the bootstrapping was used to weight the regression. In table 6.14, the results are shown.

Note that TRADE is almost significant and with the correct sign: high trade share tends to imply a larger contemporaneous coefficient. The point estimate is 0.33 with a standard deviation of 0.17. This estimated will be compared with the one obtained in the bond regression.

The estimates on distance are also (almost) significant and with the correct sign. Surprisingly (at least to the author) is the fact that the regional dummies are not statistically significant. The R^2 is quite low even though the *F*-test shows that the regression is significant as a whole. Therefore, trade, although it has some explanatory power on the coefficients, has only a limited role in explaining most of the contemporaneous relationship across countries. Future studies should extend the present analysis to provide a better understanding about the transmission mechanism across stock markets. These results, however, contrast with the findings from the bond market; this is the topic that follows.

Bond Markets

The data on bond markets are restricted to the period between April 1995 and July 1998. However, the estimation methodology is the same as in stock markets. In figure 6.2, the volatile regimes are shown (determined with the

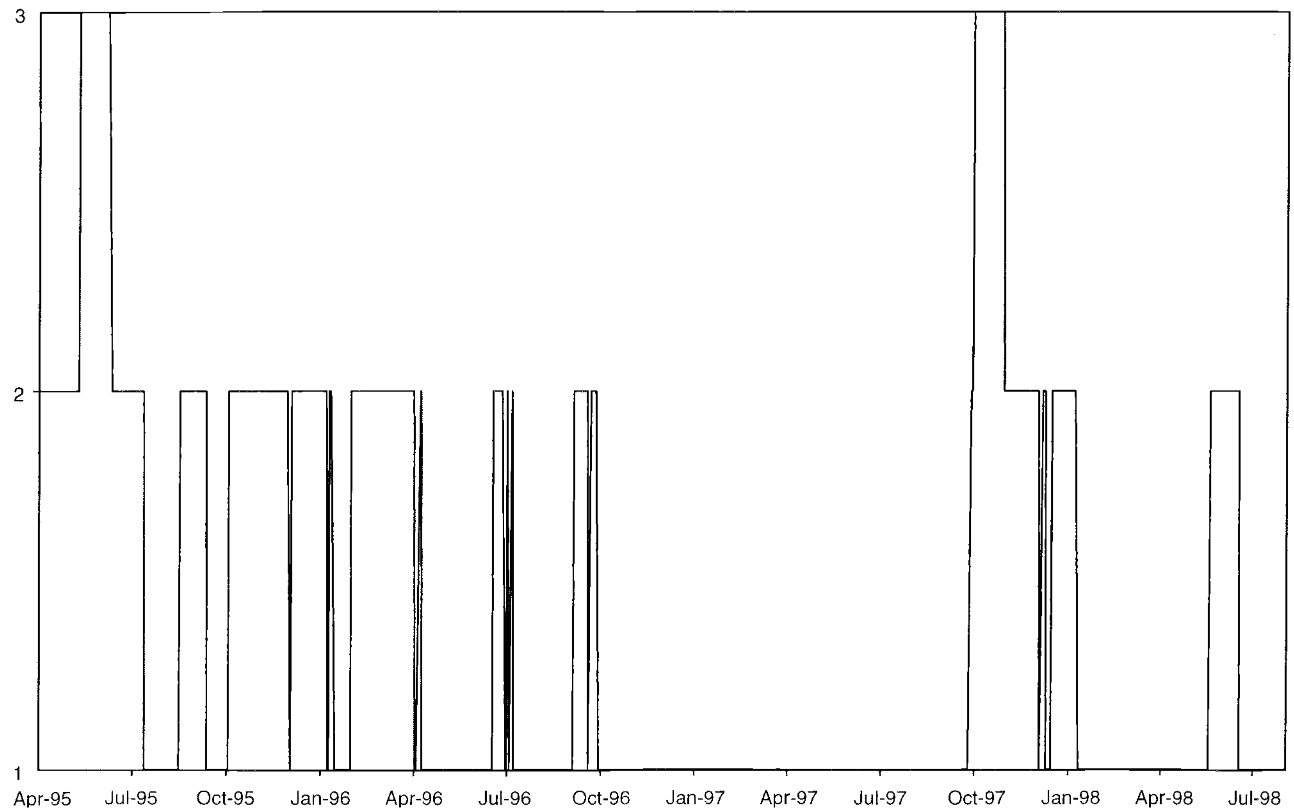

Fig. 6.2 Regimes in the bond market

Table 6.15 *A* **Estimates**

Country	Argentina	Brazil	Ecuador	Mexico	Panama	Peru	Venezuela	United States
Argentina		**0.33**	**0.18**	**0.37**	0.04	0.02	0.19	0.11
Brazil	**0.20**		0.14	**0.51**	0.06	0.12	0.18	**0.47**
Ecuador	**0.36**	0.28		0.20	0.12	**0.35**	**0.44**	**0.62**
Mexico	**0.21**	0.22	0.10		0.07	0.11	**0.29**	0.19
Panama	**0.26**	0.25	0.02	**0.46**		0.29	**0.44**	**0.73**
Peru	0.38	0.13	0.23	**0.43**	0.15		0.09	**0.61**
Venezuela	0.40	0.07	0.06	**0.35**	**0.26**	0.10		0.32
United States	0.03	0.07	0.01	0.04	0.04	0.01	0.02	

procedure highlighted earlier). In this case, there are 526 observations in the low- to medium-volatility regime, 268 in the medium-volatility regime, and 41 in the high-volatility regime. (Notice that the high volatilities occur during the Hong Kong crisis and in June 1995.[23])

Contemporaneous Transmission Mechanism. In table 6.15, the results from estimating matrix *A* are shown. The diagonal is omitted and the sign of the coefficients have been changed so they can be interpreted directly as the right-hand-side elasticities. The table should be read as before: the row country (Argentina) is contemporaneously affected by the column country (Mexico) by the coefficient 0.37.

Those coefficients that are statistically significant at the 90 percent confidence interval are in boldface type. As before, the distributions and the mass below zero are obtained by bootstrapping, using the same procedure as the one described above.

Several lessons can be extracted from the table. First, notice again that the United States is unaffected by any Latin American country. Observe that not only are the coefficients not significant, but the point estimates are very small. This was not imposed in the estimation procedure, but our priors would have indicated that indeed this should be the case.

Second, bond market participants agree that the two most important countries in the sovereign bond market are Argentina and Mexico. The bonds from these two countries are generally used as benchmarks to define prices for other countries. The results from table 6.15 confirm this common wisdom. Mexico affects all Latin American countries in the sample except for Ecuador, while Argentina significantly influences all countries in the region except for Peru and Venezuela.

Third, the United States has an important impact on Latin American

23. In June 1995, the rescue package was under way, and good news about Mexico was released; its access to international financial markets was renewed. Thus, laughter is also contagious.

countries. These data were constructed to reflect the country risk premium (in the first stage, the indexes were regressed on U.S. ten-year bond rates). Hence, the fact that the U.S. coefficients are positive and significant indicates that the country risk premium in these countries increases with U.S. interest rates. In other words, the pass-through on international interest rates is greater than 1 (see Frankel 2000).

Finally, notice that the coefficients are similar to those obtained from the stock markets. Even though a direct comparison cannot be made because the samples are very different, it is informative to concentrate on a couple of countries:

1. The Mexican coefficient in the Argentinean equation, for example, is 0.37 here and 0.23 before. Both estimates are statistically different from zero, but their difference is not. The Brazilian coefficient in the same equation is 0.33 here and 0.26 before.
2. Before, Mexico significantly affected Argentina, Brazil, and Peru; here, the same three countries (and two others) are affected. The regularities across the two exercises is worth further exploration.

In table 6.16, the standard deviation of the coefficients is shown. Note that even though the standard deviations of the U.S. equation are quite small, the estimates are not statistically significant from zero. Therefore, the reason for the lack of significance is not the need for precision. As opposed to the stock market case, there is no further pattern among the precision of the estimates.

In table 6.17 the quasi–z-statistic was computed. As before, the statistic tends to overestimate the significance of the estimates. For example, if a single-sided 90 percent confidence interval is used (as was the case with the bootstrapped distribution), then more coefficients are significant. In table 6.15, twenty out of fifty-six coefficients are significant; using the z-statistic, twenty-six would be significant. Again, all the estimates that are significant using the bootstrapped distribution are also significant with the z-statistic.

Table 6.16 **Standard Deviations of *A* Estimates**

Country	Argentina	Brazil	Ecuador	Mexico	Panama	Peru	Venezuela	United States
Argentina		0.11	0.09	0.13	0.06	0.04	0.11	0.11
Brazil	0.13		0.09	0.15	0.07	0.08	0.12	0.16
Ecuador	0.18	0.15		0.15	0.14	0.13	0.21	0.25
Mexico	0.12	0.13	0.10		0.08	0.09	0.13	0.16
Panama	0.17	0.19	0.05	0.21		0.18	0.19	0.20
Peru	0.21	0.12	0.13	0.18	0.14		0.10	0.22
Venezuela	0.14	0.08	0.06	0.15	0.09	0.09		0.18
United States	0.04	0.08	0.03	0.06	0.05	0.03	0.03	

Table 6.17 ***Z*-statistics of *A* Estimates**

Country	Argentina	Brazil	Ecuador	Mexico	Panama	Peru	Venezuela	United States
Argentina		2.95	2.09	2.84	0.74	0.59	1.72	0.98
Brazil	1.50		1.53	3.43	0.92	1.53	1.54	2.95
Ecuador	1.98	1.88		1.32	0.84	2.74	2.14	2.51
Mexico	1.78	1.66	1.03		0.86	1.17	2.27	1.17
Panama	1.54	1.33	0.41	2.23		1.67	2.36	3.63
Peru	1.85	1.16	1.85	2.38	1.09		0.87	2.79
Venezuela	2.94	0.85	1.06	2.35	2.86	1.16		1.77
United States	0.59	0.83	0.50	0.68	0.87	0.32	0.65	

Table 6.18 **Vulnerabilities (estimates of γ)**

	Vulnerability		
Country	Point Estimate	Standard Deviation	z-statistic
Argentina	0.15	0.11	1.32
Brazil	0.29	0.17	1.72
Ecuador	0.17	0.26	0.65
Mexico	0.36	0.17	2.14
Panama	0.60	0.29	2.08
Peru	0.57	0.26	2.17
Venezuela	0.31	0.17	1.86
United States	0.10		

The size of the test is incorrect, but if a coefficient is not significant assuming normality then it will not be so using the small sample distribution.

Before explaining the coefficients with trade and regional variables, the next subsections examine the vulnerability coefficients and the variance decomposition.

Vulnerabilities. The second set of coefficients estimated from the structural equation (10) are the elasticities to aggregate shocks. The coefficients are identified only up to a normalization; thus the United States was equated to 0.1. In table 6.18 the results are shown. The first column corresponds to the point estimate, in which the coefficients with mass above zero larger than 90 percent are highlighted in bold. The second column shows the standard deviation computed from the bootstrapped distribution. The third column is the z-statistic, calculated as the ratio between the point estimate and the standard deviation.

Before discussing the coefficients is important to clarify what is, in this case, the interpretation of the shock z_t. In these data, the unobservable common shocks are (as before) changes in risk preferences, liquidity shocks, etc. However, these shocks also include shocks to other countries that are not

Table 6.19 **Variance Decomposition (percentage explained by the idiosyncratic shocks)**

Country	Variance Decomposition		
	Low	Medium	High
Argentina	50.13	43.48	17.28
Brazil	67.18	53.41	30.36
Ecuador	57.34	40.66	24.30
Mexico	66.30	52.42	31.47
Panama	78.94	65.48	46.27
Peru	79.07	69.67	41.49
Venezuela	66.46	51.65	28.93
United States	99.98	99.94	99.90

included in the sample, in particular, all the Southeast Asian countries. Therefore, the common shock aggregates all these disturbances, and the coefficient is the average response of the countries in the sample to those shocks. This implies that, unfortunately, these estimates cannot be directly compared with those obtained for the stock markets.

An interesting aspect of table 6.18, however, is that the estimates of all countries are larger than the U.S. coefficient. Again, it is impossible to reject the hypothesis that the coefficients are the same as the U.S. one,[24] but they share a pattern similar to the ones obtained from the stock market data.

Variance Decomposition: Common versus Idiosyncratic Shocks. Instead of concentrating on the vulnerability coefficients, it is better to compute the common-shock contribution to the variance. The variance decomposition is estimated as before: The predicted unconditional variance in each regime is computed by using the estimated coefficients and variances; then the predicted variance assuming only idiosyncratic shocks is calculated; and finally, the ratio between these two variances is calculated for each country. The results are reported in table 6.19.

The objective of this exercise is to evaluate the relative importance of common shocks across regimes. Given the range of the data (mainly covering the Southeast Asian crises) and the interpretation of the common shocks in the bond market (mainly SEA as well as liquidity and risk-preference shocks), it should be expected that the contribution of these shocks increases during the high-volatility regimes more than in the stock market case. This intuition is confirmed by the results: In the low-volatility regime (excluding the United States), idiosyncratic shocks explain an aver-

24. Remember that the test performed in the table is to determine whether the coefficient is different from 0, not from 0.10.

age of 66.49 percent of that variation. During the medium-volatility regime, they explain 53.82 percent, which reflects a small drop in the importance of idiosyncratic shocks. In the high-volatility regime, the contribution of idiosyncratic shocks falls to 31.44 percent—less than half of their importance during the low-volatility regime.

Additionally, observe that the United States is almost unaffected by common shocks. In all three regimes, more than 99 percent of the variation in U.S. interest rates is explained by idiosyncratic shocks. This is in sharp contrast with the emerging-market countries, where the common shocks always explain at least 20 percent of the variation.

An interesting comparison between the variance decompositions of bond and stock markets is that the relative importance of the common shocks in this data is significantly larger than in stock markets. However, this comparison should be made with caution.

Variance Decomposition: Country-Idiosyncratic Shock Contribution. We repeat the other variance decomposition for stock markets. Again, we are interested in improving the interpretation of the coefficients in matrix A by looking at the contribution of each shock to the total idiosyncratic shock volatility. This is important, because by looking at the coefficients directly one could draw some misleading conclusions. For example, in table 6.15, the coefficient from the United States to Mexico is nonstatistically significant. Does this means that U.S. interest rates have no explanatory power on Mexican interest rates? The answer is no.

In table 6.20, the results from the variance decomposition are reproduced for the bond market. Note that U.S. interest rates explain a sizeable proportion of the idiosyncratic shocks in each of the Latin American countries in the sample. Indeed, the United States explains as much variance in Argentina as in Mexico, even though one of the coefficients is statistically significant and the other is not.

From the table can be extracted the conjecture that countries whose ex-

Table 6.20 **Variance Decomposition (percentage explained by each country shock in the total idiosyncratic shock variance)**

Country	Argentina	Brazil	Ecuador	Mexico	Panama	Peru	Venezuela	United States
Argentina	24.2	10.4	11.0	10.2	7.5	10.4	4.8	21.4
Brazil	3.9	8.8	6.8	0.1	2.5	29.6	23.2	25.1
Ecuador	0.8	6.0	12.1	8.8	9.6	15.8	15.9	31.1
Mexico	2.9	17.4	8.7	15.7	15.1	11.6	7.4	21.1
Panama	3.9	6.2	13.7	0.3	38.5	12.9	5.5	19.1
Peru	2.4	4.4	19.4	9.0	2.9	12.8	17.8	31.3
Venezuela	1.6	7.2	11.9	13.3	8.7	15.0	7.0	35.4
United States	0.7	3.7	0.5	5.9	3.9	8.4	0.0	76.9¡

Table 6.21 Explaining A-coefficients

Variable	Coefficient	Standard Error	t-statistic	Prob.
C	1.098510242	0.24084432	4.561	5.99E-05
TRADE	0.448457005	0.19432761	2.307	0.027045
log (DISTANCE)	–0.091464254	0.02850499	–3.208	0.002852
BORDER	–0.262485462	0.06064281	–4.328	–0.00012
R^2	0.749			
Prob (F-statistic)	0.000246			

Note: See text for explanation of variables.

change rates are fixed to the dollar (Argentina and Panama) tend to have larger proportions of their own variance explained by their own idiosyncratic shocks. This does not seem to be the case for the other countries in the sample. Additionally, if the variance decomposition is used as a measure of the pass-through of interest rates, these results suggest that countries with strong fixed regimes have a smaller pass-throughs. Another interpretation is that the pass-through is the same across all countries but that the volatility of the fixed exchange rate countries is greater.

Further research should look at the patterns arising from this estimation and should offer not only theoretical explanations, but more conclusive evidence.

Estimating the Importance of Trade. The last examination of the data is a consideration of how much trade can explain the coefficients of matrix A. The procedure is to run a simple linear regression in which the coefficients are explained by trade between the two countries, their distance from one another, and a dummy representing whether they share a border. The information about trade is the same as before.

Again, the coefficients on the left-hand side are estimated with varying degrees of efficiency; in this regression there exists heteroskedasticity that could produce the wrong standard deviations. Therefore, from the first step, the covariance matrix of the estimates is used to estimate a GLS.[25]

In table 6.21 the results from the estimation are reported. First, note that the coefficient on TRADE is significant and with the correct sign. Moreover, notice that the coefficient is 0.449, which is close to the one reported for the stock markets (0.333). The coefficient on the distance is equally significant and with the correct sign. One difference between this regression and table 6.14 is that here the border dummy is very significant. However, the coefficient seems to suggest that it goes in the wrong direction.

25. If the covariance matrix is not used and a straight OLS is estimated, the point estimates are close to the ones reported, but the standard deviations are larger. In that regression, only the constant is statistically significant.

More important is the fact that these three variables explain almost 75 percent of the variation of the coefficients. This is in sharp contrast to the results obtained from the stock market exercise.

6.6 Future Research

The question of how to measure contagion is far from answered. Nevertheless, there has been plenty of research in exchange rates, interest rates, and stock markets. The results are not conclusive, but suggestive: propagations are relatively stable trough time, and trade and regional variables produce a sizeable explanation of the observed comovement. The results in this paper confirm these two views, but more must be done.

There are, however, other aspects of contagion that have not been explored with the same intensity. Indeed, these are areas in which there is hope that some of the inconveniences of the price data can be overcome. The following is a set of questions that, in my opinion, the contagion literature must address; (they are arranged according to my own opinion of their importance and are of uncertain feasibility, but clearly this is almost a random order).

6.6.1 Pattern of Correlations

One unstudied aspect of contagion is the pattern of correlations across different instruments. In particular, the correlation among bond markets returns is twice as large (on average) as the one on stock markets, which is double the one that exists among exchange rates.

As far as I know, this fact has been reported in only two papers: First, Kaminsky and Reinhart (2000) compute the principal components and show that the proportion explained by the first component is larger in bonds than in stock markets. Second, in an earlier paper with Eduardo Fernandez Arias (Arias, Haussman, and Rigobon 1998) we reported this finding by simply looking at the correlations. As was mentioned in the previous sections, if the variances of bond and stock market returns are different, then both the correlation and the principal components estimates are biased. However, the results in this paper confirm this finding. It is the case that the coefficients and unconditional correlations across bond markets is larger than in stock markets. In order to provide some evidence I concentrate on Argentina, Brazil, Mexico, Peru, and Venezuela, which are in both data sets. The correlations among these countries, implied by the unconditional variance regime, are documented in table 6.22.

First, note that the correlations increase with the regimes, as should be expected by the increase in variance implied by the crises. Nevertheless, the correlations obtained in bond markets are an order of magnitude larger than those from stock markets. Remember, this is the predicted correlation given the A and Γ coefficients.

Table 6.22 Unconditional Correlation per Regime

	Stock Market Correlations			Bond Market Correlations		
	Low	Medium	High	Low	Medium	High
Argentina-Brazil	0.61	0.71	0.73	0.78	0.70	0.91
Argentina-Mexico	0.52	0.63	0.64	0.72	0.64	0.85
Argentina-Peru	0.25	0.46	0.44	0.46	0.40	0.82
Argentina-Venezuela	–0.01	0.17	0.08	0.76	0.71	0.92
Brazil-Mexico	0.51	0.59	0.58	0.36	0.60	0.68
Brazil-Peru	0.30	0.44	0.41	0.33	0.43	0.74
Brazil-Venezuela	–0.04	0.08	0.07	0.52	0.62	0.81
Mexico-Peru	0.33	0.51	0.46	0.36	0.42	0.70
Mexico-Venezuela	–0.07	0.05	–0.02	0.57	0.61	0.79
Peru-Venezuela	0.02	0.13	0.15	0.31	0.30	0.76
Average	0.24	0.38	0.35	0.52	0.54	0.80

The previous discussion indicated that common shocks explain a sizeable proportion of the changes in the pattern of correlations across time. It is possible that this is also the explanation for bond prices. That question could not be answered here because the two data sets are not comparable, and the question is beyond the scope of this paper. However, with the techniques illustrated here it is possible that an answered could be provided.

Future research should concentrate on developing the theories and empirical tests to report and explain the stylized facts.

6.6.2 Measurement of Contagion, Revisited

Most of the discussion of contagion has concentrated on the simultaneous reaction across countries; thus, this has been the emphasis in this paper. However, the propagation mechanism could take important lags not fully captured in the A matrix, but in the $\phi(L)$ coefficients.

Regarding the question of stability, the test highlighted in subsection 6.3.4 can detect changes in parameters of the lag variables. However, the measurement of the propagation mechanism was estimated entirely by the contemporaneous relationship (most papers look at weekly, two-day, or daily effects).

In the model estimated in the previous section, all the dynamics from $\phi(L)$ have been disregarded. There are at least two reasons that the previous literature (and this paper) did so: First, the pattern of contemporaneous correlations is puzzling enough. Second, without estimating the simultaneous coefficients, there is no way of estimating economically meaningful lag coefficients. With the methodologies highlighted above it is now possible to estimate the contemporaneous relationship properly, and a closer look at the dynamics of the propagation of shocks could be fruitful.

In this process, reporting the facts and understanding the dynamics become aspects of the discussion of the propagation of shocks. Not only does the estimation of impulse responses play a crucial role, but the definition of sensible statistics over those responses will represent an important part of the discussion of what should (or should not) be considered contagion.

6.6.3 Prices versus Volumes

A third important point is that most of the papers in the area examine prices rather than volumes, mainly due to the easy availability of high-frequency data on the former, and the almost complete unavailability of the latter.

There have been some papers, however, that have studied the behavior of quantities around the recent crises. The three most influential papers in this are Eichengreen and Mody (2000); Froot, O'Connell, and Seasholes (2000); Karolyi and Stulz (1996); and Stulz (1999).

Further research in this area is promising. Most of the theories of contagion have strong implications about trading volumes and investor positions. In fact, the implications on prices are derived from those volume decisions. Looking only at prices misses this rich set of implications. The main limitation is data availability, but it should be clear that if prices encounter important econometric problems, volumes will, as well.

6.6.4 Is the Propagation through the Means or the Variances?

Fourth, the question of whether the shocks are transmitted directly through prices or the fall in prices reflects higher volatilities has not been raised with the emphasis it deserves. The only paper (to my knowledge) looking at these issues is Edwards and Susmel (2000). Unfortunately, they have to make the necessary assumption to avoid the identification problem. The models studied here have highlighted the direct propagation of prices, but they could perfectly represent a reduced form of a volatility transmission model. So far, the procedures emphasized are unable to disentangle the exact channel.

From the theoretical point of view, this is an important question. How the propagation occurs has portfolio (as well as policy) implications. Formally, an extension of model 1, including lags and ARCH effects, is as follows:

$$A\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \Phi(L)\begin{bmatrix} y_t \\ x_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix},$$

where

$$A = \begin{bmatrix} 1 & -\beta \\ -\alpha & 1 \end{bmatrix},$$

and where σ_ε, σ_η follow a bivariate ARCH:

$$B\begin{bmatrix}\sigma_\varepsilon\\ \sigma_\eta\end{bmatrix}_t = \phi_\sigma(L)\begin{bmatrix}\sigma_\varepsilon\\ \sigma_\eta\end{bmatrix}_t + \phi_\varepsilon(L)\begin{bmatrix}\varepsilon_t\\ \eta_t\end{bmatrix} + \begin{bmatrix}\nu_{\varepsilon,t}\\ \nu_{\eta,t}\end{bmatrix},$$

where $\nu_{\varepsilon,t}$ and $\nu_{\eta,t}$ are uncorrelated, and the matrices A and B are not diagonal.[26] A reflects the propagation through prices, whereas B explains the propagation through variances. Because in the reduced form only conditional covariance matrices are computed, there is in general no procedure to separate A from B. Future research should develop techniques that could deal with this question.

6.6.5 Nonlinearity and Distribution-Free Techniques

Finally, even though some of the procedures highlighted here are not dependent on a particular distribution of the residuals, most of the papers assume linear models and normal distributions.

A casual look at the data clearly indicates that either the distributions are not normal, or the models are nonlinear (or both). There have been some attempts to look at extreme realizations as a way to compare the behavior of the statistical model in this situation with the model under normal circumstances; see Bae, Karolyi, and Stulz (2000) and Longuin and Slonik (1995) for evidence. Further research in the area is clearly warranted.

6.7 Conclusions

The empirical question of contagion is one of the most difficult to arise in international macroeconomics in recent years. The data suffer from the worst of (what I call) macroproblems: simultaneous equations and omitted variable biases. Moreover, the data also exhibit the worst problems of finance: conditional and unconditional heteroskedasticity, nonlinearity, nonnormality, and serial correlation.

This paper has several objectives. First, it provides a critical view of the techniques used most frequently in applied papers of contagion. The first two sections discuss the biases and inconsistencies that arise in OLS, probit, and (especially) principal components and correlation estimates. In those sections, I propose the use of two new techniques to deal with some of the problems, but certainly further research should continue to improve the procedures.

The second objective of the paper is to use these new techniques in a broad application of contagion (the original papers concentrated on very special cases, or only on simulations). Section 6.5 tested for parameter stability and the importance of trade in bond and stock markets. Two surprising results in this section are as follows: (1) The parameters are stable in

26. I have already solved the problem of identification in GARCH models if B is a triangular matrix. This extends Rigobon (2000a) to the case in which only conditional heteroskedasticity exists (see Rigobon 2001).

stock markets across very different crises and periods of time. However, the propagation of shocks across bond markets was not stable during the first quarter of 1995 and during the LTCM crisis. Both instances represented important liquidity shocks to bond markets. The parameter instability could be either a change in the coefficient or a nonlinearity. With the current techniques, unfortunately, no answer can be provided. (2) Regarding the importance of trade in explaining the contemporaneous coefficients, it was found that trade and regional variables are (almost) significant and with the correct sign in explaining contemporaneous coefficients on the bond and stock market returns. In the stock market, these variables explain only 6 percent of the variation, but for bond coefficients they explain almost 75 percent.

Finally, this paper has discussed extensively a list of further areas of research in which new stylized facts, new data, and probably new techniques will have to be developed to gain a better understanding of how shocks are propagated internationally.

Appendix A

Measuring the Channels under Simultaneous Equations using OLS

Assume a simple setup in which

$$A\begin{bmatrix} y_t \\ x_{1,t} \\ x_{2,t} \end{bmatrix} = \begin{bmatrix} \varepsilon_t \\ \eta_{1,t} \\ \eta_{2,t} \end{bmatrix}$$

where

$$A = \begin{bmatrix} 1 & -\alpha & -\alpha \\ -\alpha & 1 & -\alpha \\ -\alpha & -\alpha & 1 \end{bmatrix}.$$

Note that in this case the interrelationships among all variables are the same. Assume we estimate $y_t = \beta_1 x_{1,t} + \beta_2 x_{2,t}$. The OLS estimates of each of the coefficients are (after a great deal of algebra):

$$\hat{\beta}_1 = \alpha + \alpha(1+\alpha)\sigma_\varepsilon \frac{\alpha\sigma_{\eta 1} - (1-\alpha)\sigma_{\eta 2}}{\alpha^2\sigma_{\eta 1}\sigma_\varepsilon + \alpha^2\sigma_{\eta 2}\sigma_\varepsilon + \sigma_{\eta 1}\sigma_{\eta\varepsilon}}$$

$$\hat{\beta}_2 = \alpha + \alpha(1+\alpha)\sigma_\varepsilon \frac{\alpha\sigma_{\eta 2} - (1-\alpha)\sigma_{\eta 1}}{\alpha^2\sigma_{\eta 1}\sigma_\varepsilon + \alpha^2\sigma_{\eta 2}\sigma_\varepsilon + \sigma_{\eta 1}\sigma_{\eta\varepsilon}}$$

where the difference in the estimates is

$$\hat{\beta}_1 - \hat{\beta}_2 = (\alpha_{\eta 1} - \sigma_{\eta\varepsilon})\frac{\alpha\,(1+\alpha)\sigma_\varepsilon}{\alpha^2\sigma_{\eta 1}\sigma_\varepsilon + \alpha^2\sigma_{\eta 2}\sigma_\varepsilon + \sigma_{\eta 1}\sigma_{\eta\varepsilon}}.$$

Note that if the variances of countries $x_{1,t}$ and $x_{2,t}$ are different, then the estimates are also different. Moreover, the country with the higher variance has the larger coefficient. In the limit, assume that the variance of $x_{1,t}$ goes to infinity; then the estimates are

$$\hat{\beta}_1 = \alpha + \alpha(1+\alpha)\sigma_\varepsilon\frac{\alpha}{\alpha^2\sigma_\varepsilon + \sigma_{\eta 2}}$$

$$\hat{\beta}_2 = \alpha + \alpha(1+\alpha)\sigma_\varepsilon\frac{-(1-\alpha)}{\alpha^2\sigma_\varepsilon + \sigma_{\eta 2}}.$$

As can be seen, one of the coefficients is biased downward while the other one is biased upward.

Appendix B

Stability Test on the Reduced Form

The structural model is

$$AX_t = \phi(L)X_t + \Gamma z_t + \varepsilon_t,$$

but the stability test is performed on the reduced-form residuals:

$$\begin{aligned} X_t &= A^{-1}\phi(L)X_t + A^{-1}[\Gamma z_t + \varepsilon_t] \\ &= \Phi(L)X_t + \nu_t \\ A\nu_t &= \Gamma z_t + \varepsilon_t. \end{aligned}$$

The question is whether testing on the reduced form also is testing for the parameter stability of the structural equation.

It should be obvious that if there is a change in A or Γ the test on the reduced form is detecting them. The question is whether changes in $\phi(\,)$ can be found, as well. Assume there is a shift in the structural coefficients

$$\begin{aligned} A_1X_t &= \phi_1(L)X_t + \Gamma_1 z_t + \varepsilon_t \quad \text{for } t < T \\ A_2X_t &= \phi_2(L)X_t + \Gamma_2 z_t + \varepsilon_t \quad \text{for } t > T, \end{aligned}$$

which implies the following reduced forms:

$$\begin{aligned} X_t &= A_1^{-1}\phi_1(L)X_t + A_1^{-1}\Gamma_1 z_t + A_1^{-1}\varepsilon_t \quad \text{for } t < T \\ X_t &= A_2^{-1}\phi_2(L)X_t + A_2^{-1}\Gamma_2 z_t + A_2^{-1}\varepsilon_t \quad \text{for } t > T \end{aligned}$$

Because in the VAR we are requiring the lag coefficients to be the same in both samples, the actual estimate is an average of $A_1^{-1}\phi_1$ and $A_2^{-1}\phi_2$. Denote this estimate as $\hat{\Phi}$. The residuals from the reduced form, then, will be described by

$$\nu_t = \begin{array}{ll} [A_1^{-1}\phi_1(L) - \hat{\Phi}(L)]\, X_t + A_1^{-1}\Gamma_1 z_t + A_1^{-1}\varepsilon_t & \text{for } t < T \\ [A_2^{-1}\phi_2(L) - \hat{\Phi}(L)]\, X_t + A_2^{-1}\Gamma_2 z_t + A_2^{-1}\varepsilon_t & \text{for } t > T. \end{array}$$

As can be seen, the residuals of the reduced form are a function of ϕ_i. For simplicity, assume that $A_1 = A_2$, and $\Gamma_1 = \Gamma_2$. Then the covariance matrix of the reduced form in each regime would be

$$\Omega_1 = \Psi_1 X_t X_t' \Psi_1' + A^{-1}\Gamma\Omega_1^z\Gamma' A'^{-1} + A^{-1}\Omega_1^\varepsilon A'^{-1}$$
$$\Omega_2 = \Psi_2 X_t X_t' \Psi_2' + A^{-1}\Gamma\Omega_2^z\Gamma' A'^{-1} + A^{-1}\Omega_2^\varepsilon A'^{-1}$$
$$\Psi_1 \triangleq A_1^{-1}\phi_1(L) - \hat{\Phi}(L)$$
$$\Psi_2 \triangleq A_2^{-1}\phi_2(L) - \hat{\Phi}(L).$$

Note that if the change in the covariance matrix is explained by the shift in ϕ (for example), then the change in the covariance matrix is

$$\Delta\Omega = \Psi_2 X_t X_t' \Psi_2' - \Psi_1 X_t X_t' \Psi_1'.$$

It is unlikely that this transformation of coefficients would be less than full rank, in the same way that the determinant is not necessarily less than full rank when the coefficient A or Γ changes.

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Comment Enrique G. Mendoza

One of the most widely discussed issues in the context of the research and policy debates that emerged from the emerging-market crises of the 1990s is that of contagion. Yet, as the opening paragraphs of Roberto Rigobon's paper note, there is no consensus on the definition of contagion and even less consensus on how to model it or how to think of its policy implications. This analytical vacuum has not deterred empiricists from torturing financial markets data until results in support of or against one form of contagion or another can be obtained. In this context, Rigobon's article is one of the most thoughtful that the recent empirical literature on the subject has produced.

Rigobon begins with a true scientist's approach and sets aside the ideological controversy on the definition of contagion so as to focus on two key measurement questions at the core of empirical tests of contagion: First, what are the international propagation channels by which shocks from asset markets in one country spill over into those of other countries? Second, is the international transmission mechanism of shocks unstable during periods of crisis? These two questions are critical because the existing literature tends to evaluate whether there is contagion depending on whether the propagation channels feature a certain set of fundamental variables, and on whether during periods of crisis there is a sudden increase in the tendency of markets to move together.

Rigobon's paper evaluates whether the three econometric methods most commonly used in the literature to address the above questions (linear regression, logit-probit regressions, and tests of principal components and correlation coefficients) are useful tools, given the serious statistical problems posed by the data used to conduct the tests. In particular, he explores whether they are well-suited to handle the problems of simultaneous-equation bias, omitted variables, and heteroskedasticity (conditional and unconditional) that are pervasive in the data with which the methods need to work. The paper shows clearly that none of the three methods can handle these problems simultaneously, thus casting serious doubt on the results reported in many existing empirical studies on contagion. Rigobon moves on to propose his own robust estimation method and to develop its statistical foundation.

The objective of my comments is not to take issue with the method, but to highlight the message of its results and to raise some issues that seem very critical and yet are still unresolved by the development of a more accurate method to test for something that remains undefined (i.e., contagion). My interest in focusing on these controversial issues, however, does not under-

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mine either the significance of the flaws that Rigobon's work has identified in existing tests of contagion or the merits of the method he developed.

The paper uses daily returns data from equity and sovereign bond markets for several countries in Asia and Latin America and for the United States, and produces four key results:

1. Volatility in equity and bond markets increases sharply during periods of crisis.
2. Propagation parameters are stable during crises in equity markets but not during those in bond markets (in the cases of the Mexican crisis and the Russia/long-term capital markets [LTCM] crisis).
3. Unconditional correlations of returns across emerging markets are generally high.
4. Trade and regional variables are important for explaining contemporaneous comovements in the returns of equity and bond markets, although much more for the latter than for the former.

The flaws in the application of the three widely-used econometric methods that Rigobon identified in the empirical literature on contagion are not disputable, and the robustness of the method proposed in the paper to deal with the statistical problems posed by the data is also not subject to debate. What is more controversial is the author's interpretation of the scope of the method and the message of the results. Rigobon's paper stated as one of its goals to try to measure contagion without defining it, but it is unclear that he succeeded. The definition of contagion is difficult, if not impossible, to separate from assessments of the econometric methods used to study it and their ability to cope with the problems present in the data. Still, for the definitions and measures of contagion that have been adopted in several existing studies of the subject, this paper, and Rigobon's previous work with Kristin Forbes, raise serious issues with the validity of econometric tests and propose effective ways to address them.

If the author's position that one can proceed without defining contagion is taken at full value, the interpretation one can give to the results is that they shed light on important properties of the variance-covariance structure of asset returns across emerging markets, on the variables that determine it, and on its stability during crisis periods. Yet it is difficult to argue that they help us understand or test contagion, unless a definition of contagion is, after all, adopted. For instance, if contagion is defined as the crisis instability of propagation parameters, then one can say that Rigobon's method is a statistically correct approach that measures, tests, and largely rejects the existence of contagion.

The complex issues raised by the aim to study contagion without defining it explicitly emerge again when one tries to draw lessons from the results on the significance of trade and regional variables in driving comovements of returns. Does this mean that contagion is irrelevant? Or that contagion "unrelated to fundamentals" is irrelevant? Clearly, the answers to these questions depend on how we define contagion. If it is understood to be comovement in returns driven by "nonfundamental" variables, and the only fundamentals considered of relevance are trade and regional variables, then once again the results reject contagion. However, this requires a very model-specific notion of contagion.

The above issues also plague the rest of the empirical literature on contagion, and Rigobon is right in that the definition itself varies widely from one paper to the next. Some authors confuse contagion with correlation. For example, the notion that, in the presence of nominal rigidities, a large devaluation in one country could spark crises in neighboring countries that happen to be competitors in export markets provides a reasonable channel of comovement, but it is one that it is very well understood and hardly worth being surprised about. The surprise, rather, was how little of this we observed. Korea experienced several weeks of declining export volumes in the aftermath of the crises in Southeast Asia (despite its very competitive exchange rate), mainly on account of a total loss of access to international credit markets, including the market of trade credits. Observations such as this favor other commonly used notion of contagion as comovements driven by some form of speculation driven by "animal spirits" or market psychology.

This notion of contagion originated in Keynes's view of speculation as resulting from assessing asset values, and economic prospects in general, through "the activity of forecasting the psychology of the market," rather than through attempts to forecast "the prospective yield of assets over their whole life" (Keynes 1936, 158–59). The problem with this Keynesian notion is that, to make it operational, one needs an explicit economic model to identify precisely what is speculation or contagion, and what is enterprise. Once this separation is made, contagion can be measured with familiar concepts such as the excess volatility of asset returns or macroeconomic flows across countries that is not explained by the fundamentals listed under "enterprise." Under this definition of contagion, it follows that contagion need not be correlation. High correlation of returns does not necessarily indicate contagion and contagion does not necessarily imply high correlation. Contagion is model-specific. For instance, a theory of asset prices determines which variables are fundamental variables and how they enter into the determination of equilibrium asset prices; and if the theory features contagion vehicles, it can also determine what is to be measured as excess volatility. Economic models with features like these do exist and typically require different forms of asymmetric information and frictions in financial markets.

One example of a macroeconomic model of contagion was proposed recently by Paasche (2001). He proposes a two-country extension of the Fisherian-deflation model developed by Kiyotaki and Moore (1997). In his setting, a small productivity shock in one country translates into an adverse terms-of-trade shock for a neighboring export-competing country. The neighboring country suffers a sharp adjustment in the current account and output, not as a result of the competition for the export market, but as a result of financial frictions in the form of tightening collateral constraints. For an analyst looking casually at the data, trade and terms-of-trade changes will be associated with these adverse developments, but the channel of transmission is one of "excess volatility" inasmuch as it results from effects of the terms-of-trade shock that are largely magnified by financial frictions.

An example more related to equity markets follows from the work of Mendoza and Smith (2001). They examine an open economy variation of the model of margin requirements and asset-trading costs proposed by Aiyagari and Gertler (1999). Here, households in a small open economy trade equity with specialized foreign securities firms. Due to credit market frictions, households face a margin requirement that limits their ability to leverage their foreign debt on the value of their current equity holdings. Foreign traders face portfolio adjustment costs, intended to capture the notion that foreigners are at a disadvantage relative to domestic agents when trading emerging-markets equity. This disadvantage may result from informational frictions or from explicit institutional arrangements. In this setting, an adverse shock such as a productivity slowdown or a sudden increase in the world's real interest rate may switch the economy into a state in which the margin constraint becomes binding. Households must then fire-sell equity to meet their margin calls, but when they fire-sell equity they meet in world markets with foreign traders that adjusts their portfolios slowly. As a result, there is a sudden reversal in the current account and a collapse in equity prices below fundamental levels in the small open economy. The model dictates exactly how much of the change in net foreign assets, equity holdings, and equity prices is driven by these excess-volatility features, relative to the amount accounted for by fluctuations in the "fundamentals" (which is also pinned down exactly within the model).

The point of these examples is not to argue that they provide the models of contagion we need to focus on. Instead, the idea is simply to show how the Keynesian notion of contagion can be put to work in practice in particular economic models, and to note that the measure of contagion, the list of variables that are included in the fundamentals, and the magnitude of observed asset return comovements that fundamentals account for are all model-dependent concepts. It seems, therefore, that studying the statistical properties of the data with the adequate econometric techniques that Rigobon proposes—but in the light of the predictions of a specific analytical framework that sets a definition of contagion and its appropriate measure—would be a very interesting project for further research.

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Discussion Summary

Sebastian Edwards raised a few questions on the estimates in matrix A, namely, how the stock market (or bond market) returns in one country are affected by returns in all other countries in the sample. In particular, he pointed out two counterintuitive findings: First, the bond market returns in Mexico were unaffected by the returns in the United States; and second, the stock market returns in Chile did have a big effect on returns in most other Latin American countries. This is surprising because, in practice, Chile had capital controls during the sample period and a relatively small capital market.

Linda S. Goldberg commented that the estimation of the importance of trade in explaining the coefficients of matrix A through a simple gravity equation–like regression is not as aggressive as other parts of the paper. She suggested putting more structure in the regressions.

Aaron Tornell suggested using H-infinite robust estimation to get around problems caused by nonlinearity of the specification or by nonnormal distribution. *Nouriel Roubini* suggested that the author investigate the relative importance of trade and region in explaining the propagation mechanism. *Amartya Lahiri* raised questions on geographical explanation for unstable propagation parameters. *Giancarlo Corsetti* asked why the paper does not use factor model directly.

Roberto Rigobon recognizes that the two empirical findings pointed out by Edwards (namely, the nil effect of the U.S. bond market returns on the Mexican stock market returns and the large effect of the Chilean stock market on other countries) are different from our prior, and he promises to investigate it. In response to Tornell's question, Rigobon said that linear tests reject nonlinear specification.

Regarding Corsetti's question, Rigobon said that the factor model is a better specification in the case of heteroskedasticity, but not when the disturbance is nonnormal.