NBER WORKING PAPER SERIES

CONTAGION: HOW TO MEASURE IT?

Roberto Rigobon

Working Paper 8118
http://www.nber.org/papers/w8118

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2001

I thank Giancarlo Corsetti, Sebastian Edwards, Jeffrey Frankel, and Enrique Mendoza for helpful comments. This paper was prepared for the NBER conference on Currency Crisis Prevention held in January 2001 in Florida, organized by Sebastian Edwards and Jeffrey Frankel. I thank the participants for all their suggestions. Financial support from the NBER is gratefully acknowledged. All remain errors are mine. Comments are welcomed to 50 Memorial Drive, Room E52 447, Cambridge, MA 02142. email: rigobon@mit.edu. home page: http://web.mit.edu/rigobon/www/. The views expressed herein are those of the author and not necessarily those of the National Bureau of Economic Research.

Contagion: How to Measure It?
Roberto Rigobon
NBER Working Paper No. 8118
February 2001
JEL No. C30, F32, F40, G15

ABSTRACT

The empirical literature on contagion has mainly measured the propagation of shocks across countries using daily stock markets, interest rates, and exchange rates. Several methodologies have been used for this purpose, however, the properties of the data introduces important limitations on the implementation of these procedures, as well as on the interpretation of the results.

This paper, has three objectives: First, it evaluates some of the techniques that have been used frequently to measure contagion. The paper argues that if the data suffers from heteroskedasticity (conditional or not), omitted variables and simultaneous equation problems, the conclusions drawn from most of the procedures could be biased. Second, the paper summarizes two new procedures that have been developed to cope with these problems. One methodology is aimed to test for the stability of parameters, while the other one estimates consistently the contemporaneous relationship across countries. Finally, the paper estimates (consistently) the contemporaneous transmission mechanism between emerging stock markets, and bond markets. Furthermore, it is found that regional variables, as well as trade linkages, constitute a sizeable explanation of the strength of the propagation of shocks across bond markets, but not as important in stock markets.

Roberto Rigobon
Class of 1943 Assistant Professor of Economics
Sloan School of Management, MIT
E52-447
Cambridge, MA 02142-1347
and NBER
rigobon@mit.edu
http://web.mit.edu/rigobon/www/

Contents

List of Tables

List of Figures

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 that exists among economists on which events have constituted instances of contagion: the Debt crises in 1982 , the Mexican *Tequila* effect in December of 1994, the Asian *Flu* in the last half of 1997, the Russian *Cold* in August 1998 (including the LTCM crisis), the Brazilian *Sneeze* in January of 1999, and the NASDAQ *Rash* in April of 2000. Paradoxically, on the other hand, there is no accordance 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 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, macro similarities, common lender, learning, or market phycology, what determines the degree of contagion. And second, does the transmission mechanism is stable through time? or more specifically does it change during the crises?

Providing the answer to any of the previous two questions encounters important 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 them. This data is plagued with simultaneous equations, omitted variables, conditional and unconditional heteroskedasticity, serial correlation, non-linearity and non-normality problems. Unfortunately, there is no procedure that can handle all these problems at the same time. And therefore, the literature has been forced to take short cuts.

In this paper, the performance of some of those techniques is evaluated. 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 in the three main problems exhibited by the data: simultaneous equations, omitted variables, and heteroskedasticity. Issues related to serial correlation, non-normality and non-linearity are left out of the analysis.

The paper briefly examines two new procedures that are robust to the problems here studied. One designed to test for the stability of parameters, and the second one aimed 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 2 introduces the statistical models that are used in the discussions. Section 3 investigates the problems surrounding the second question in contagion: 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. The section studies alternative corrections for the standard tests and the conditions where they can be used. Finally, a new procedure to test for parameter stability under simultaneous equations, omitted variables and heteroskedasticity is summarized. The assumptions required for its use are also pointed out.

Section 4 considers the more complicated question: 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, OLS or Principal Components. At the end of the section, a new procedure to estimate the contemporaneous interrelationship across countries is reviewed. This procedure is robust to the data problems here emphasized.

Section 5 applies the two new techniques to measure contagion in Latin American and South East Asian countries. First, the test on stability of parameters across time is implemented. And second, the transmission mechanism is estimated. Section 6 explores avenues

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

for future research. And, section 7 concludes.

2 The models

In order to discuss the problems involved in the measurement of contagion several simple models are used. Even though, the true description of the world is probably the union of these particular pieces, the main reason to use minimal statistical frameworks is because it is easier to highlight the problems there.

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 them. Without loss of generality, assume that x_t and y_t have being 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 also independent from the common shocks. The models concentrate on the bivariate case, although most of the results can be easily extended to larger setups.

When the paper focus on the problems of simultaneous equations, the following model to describe the interrelationship between the countries is used:

$$\begin{aligned} y_t &= \beta x_t + \varepsilon_t, \\ x_t &= \alpha y_t + \eta_t, \end{aligned} \qquad \text{(Model 1)}$$

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, the model used is

$$\begin{aligned} y_t &= \beta x_t + \gamma z_t + \varepsilon_t, \\ x_t &= z_t + \eta_t. \end{aligned} \qquad \text{(Model 2)}$$

where, additionally 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 or not 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 where it could be claimed otherwise. For example, it is possible to assume that OECD countries are unaffected by emerging markets based of large economy arguments. 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 US 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 measure 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 has to 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 country's $x_{i,t}$ return would be described by a latent factor model as follows:

$$
\begin{aligned}
x_{i,t} &= \alpha_1 X_{\char`~i,t} + \alpha_2 Trade_{i,\char`~i} X_{\char`~i,t} + \alpha_3 Macro_{i,\char`~i} X_{\char`~i,t} + \alpha_4 Region_{i,\char`~i} X_{\char`~i,t} + ... \\
&\quad + \beta_{1,i} Liquidity_t + \beta_{2,i} Risk_t + ... + \varepsilon_{i,t}
\end{aligned}
$$

where $x_{i,t}$ is the i'th country return. $\varepsilon_{i,t}$ is the idiosyncratic shock to country i's fundamentals. $X_{\char`~i,t}$ are the returns of the rest of the countries. $Trade_{i,\char`~i}$ is the vector that measures trade between country i and other countries, $Macro_{i,\char`~i}$ is the degree of macro similarities across the countries, while $Region_{i,\char`~i}$ 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:

$$A_1 X_t + A_2 [Trade] X_t + A_3 [Macro] X_t + A_4 [Region] X_t + ... = B_1 Liquidity_t + B_2 Risk_t + ... + \varepsilon_t.$$

which can be rewritten as

$$
\begin{aligned}
AX_t &= BZ_t + \varepsilon_t \qquad (2) \\
A &= A_1 + A_2 [Trade] + A_3 [Macro] + A_4 [Region] + ... \\
B &= \{B_1, B_2, ...\} \\
Z_t &= \{Liquidity_t, Risk_t, ...\}'
\end{aligned}
$$

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 different from zero and non-triangular. In particular, the model with three countries is:

$$\begin{aligned} y_t &= \beta x_{1,t} + z_t + \varepsilon_t, \\ x_{1,t} &= \gamma_1 z_t + \eta_{1,t}, \\ x_{2,t} &= \gamma_2 z_t + \eta_{2,t}, \end{aligned} \tag{Model 3}$$

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:

$$A \begin{pmatrix} y_t \\ x_{1,t} \\ x_{2,t} \end{pmatrix} = \begin{pmatrix} \varepsilon_t \\ \eta_{1,t} \\ \eta_{2,t} \end{pmatrix}, \tag{Model 3a}$$

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 researched fits the following equation:

$$y_t = \beta_1 x_{1,t} + \beta_2 x_{2,t} + \nu_t. \tag{3}$$

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:

$$y_t^* = 1\left[c + \beta_1 x_{1,t} + \beta_2 x_{2,t} > \tilde{y}\right] \tag{4}$$

Again, 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.

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 GLS and FGLS), Principal Components, and correlation coefficients. The objective of the tests is to determine if there is a change in the coefficients across two different samples; usually crisis and tranquil periods.

As will become clear below, if the data suffers from heteroskedasticity and any 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 highlight that the standard techniques are only inappropriate if all problems are present. For example, if the data is 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 has to be explained by parameter instability. The test does not provide an answer to 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 there exists procedures 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 why this is the case is simple: both the endogenous and the omitted variable biases depend on the relative variances. If the data exhibits 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 formally show these results. 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 some particular cases there exist exact corrections. However, these adjustments are not general and often only approximations can be used. Finally, it reviews a new test that is robust to the presence of all three problems. The section indicates the situations where the test can be used and what are the assumptions needed.

3.1 Testing using OLS

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

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

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

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

Assume that the question of interest is whether or not the parameters are stable along the sample. In general, the structural change test takes two forms: either it estimates a β in the two sub-samples and performs a comparison, or it introduces a dummy in one of the sub-samples and test for its significance. Independently of the setup, though, 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 sub-samples. Formally, the difference in the estimates is

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

in Model 1 and

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

in Model 2, where $s1$ and $s2$ stand for each sub-sample.

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 has heteroskedasticity and 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) shifted. To exemplify this point, assume there is heteroskedasticity and that the parameters are constant. The difference in the estimates is:

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

in Model 1 and

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

in Model 2.

The biases across the samples cancel each other if there is homoskedasticity or the heteroskedasticity implies a proportional increase in the variance of all shocks ($\frac{\sigma_\eta}{\sigma_\varepsilon}$ or $\frac{\sigma_\eta}{\sigma_z}$ 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 is characterized by large shifts in second moments. Thus, making inference about the stability of parameters in the linear regression context complicated; the test does not provide the reason for the rejection.

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 Kamisky and Reinhart [2000] "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 non 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 best as possible. Thus, it minimizes the discrepancies of

$$X - a'p$$

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

[3] See Theil [1971] for a formal derivation.

where p is the Principal Components, and a' is a matrix of scalars. p is only identified up to a constant, and therefore some normalization is imposed (usually $p'p = 1$ or the diagonal of the p matrix is equated to one). 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 has simultaneous equations and omitted variables problems.[4] This aspect of the measurement is perhaps the biggest 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 too. 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

$$\begin{aligned} \Theta_1 &= 1 + \alpha^2 + \left(1+\beta^2\right)\theta, \\ \Theta_2 &= \left(1+\beta^2\right)^2\theta^2 - 2\left[\left(1-\beta^2\right)\left(1-\alpha^2\right) - 4\alpha\beta\right]\theta + \left(1+\alpha^2\right)^2, \\ \theta &= \frac{\sigma_\eta}{\sigma_\varepsilon}. \end{aligned}$$

[4] See Calvo and Reinhart [1995], Kamisnky 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 qualitative the same under omitted variables.

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

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

where

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

Note that the eigenvalues and eigenvectors only depend 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). These property of the Principal Components is what grants its use to test for parameter stability. However, similarly as before, this result only holds 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 are 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]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.

3.3 Testing using the Correlation

The first paper (to my knowledge) testing for changes in the propagation mechanism using correlation measures was the influential contribution by King and Wadhwani [1990]. The intuition of the 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 where a change in correlations imply 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 the problem of endogenous variables does not exist (make $\alpha = 0$ in Model 1). The correlation between x_t and y_t is

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

which is a function of θ.

Shocks to the variance of x_t imply an increase in θ, which causes the absolute value of the correlation to rise too. 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 one. On the other hand, when the variance of η_t goes to zero the correlation is zero. Note that the correlation moves from zero to one and the parameter β remains the same.[8]

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

The result is stated on *unadjusted* correlation because there are some cases where the bias can be corrected. This adjustment was first proposed by Ronn [1998] in the bivariate

[7] See Boyer, Gibson and Loretan [1999], Forbes and Rigobon [1998], and Loretan and English [2000] for generalizations of Ronn's result.

[8] See Rigobon [1999], Forbes and Rigobon [2000] for a simple example higlighting the biases induced by using correlation coefficients.

setting.[9] The main assumption required is 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 provides 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 the unconditional correlation 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 sub-sample is given by

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

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

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

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:

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

The ρ_u's can be compared across samples. And under the assumptions stated in this derivation, if they change then it is the case that the β's have shifted too. The two main advantages of this procedure are: First, δ can be estimated directly 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 only be used if there are no

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

simultaneous equations and omitted variables issues.[10] In fact, in this situation, there is no problem using OLS; thus no need to estimate the correlation coefficient in the first place. This is the main weakness of using correlation coefficients as an indication of 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.

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 that were 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) that 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 there are several events where this information is not available. For example, during the EMS crises, who is the country to be blamed for the increase in volatility? The second

[10] However, as is claimed in Forbes and Rigobon [1998], if the adjustment is practiced only using 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 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 by equation (5) the biases tend to zero in both the simultaneous equations and the omitted variable cases. The estimates get closer to the one when $\alpha = 0$ or $\gamma = 0$. The periods of crises follow closely this description. For example, during the Mexican crisis in 1994 the variance of their stock market increased by 15 times following the devaluation in December. One limitation of this approach is that the adjustment can only be preformed in pair-wise comparisons where the variable x_t always corresponds to the country under crisis. Hence, the stability of parameters among two countries that are not the "originators" of the crisis cannot be tested. The procedure proposed by Boyer, et al. [1999] has the same characteristics as the one indicated in Forbes and Rigobon and therefore it can be applied in the same conditions.

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.

Assume the variables are described by Model 1.[11] Additionally, assume that it is known that in a sub-sample the variances of x_t and y_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 volatile period, and one for the high volatile period:

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

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 *(DCC Test) The determinant of the change in the covariance 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 common shocks together with simultaneous equations and still this result holds.[12]

[11] The omitted variables case produces identical results.

[12] Conversations with Giancarlo Corsetti help me generalize the test can be applied to models as compli-

Two remarks about the test are worth highlighting: (1) 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. This second rejection is uninteresting for the purposes of contagion. (2) the test requires the knowledge of the country generating the increase in volatility, as well as its timing. 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, so far, there is no procedure to disentangle between the two alternative hypothesis. However, an advantage of the test is that if there is no rejection then the assumption of stability, and the assumption 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 [2000] studies the power against two possible alternative hypothesis: (1) a change in β, and (2) shifts in the two variances. The main conclusions of that exercise is that with samples sizes around 60 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 5 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 10 times are common in stock markets,

---

cated as the following

$$A\binom{x_t}{y_t} = \Gamma z_t + B\binom{\varepsilon_t^1}{\eta_t^1} + \binom{\varepsilon_t^2}{\eta_t^2}$$

where A, Γ and B are non diagonal matrices. Where the vector of idiosyncratic shocks ε_t^1 and η_t^1 are transmitted across countries with higher intensity than other vector of idiosyncratic shocks; ε_t^2 and η_t^2. In this model, still it is the case that if the heteroskedasticity in a sub-sample 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 him for all his comments.

domestic interest rates, exchange rates and Brady Bond returns. Second, estimates larger than 0.8 imply extremely high interrelationships not even found 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 upward 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 beginning of the crises are relatively clear, but not their end. On the other hand, the cost of the misspecification is that the test losses 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]

When to use the test? The traditional techniques testing for structural change, in general, are not appropriate to test for contagion because the data has simultaneous equations, omitted variables, and heteroskedasticity problems. There are some adjustments that might reduce the biases, but in fact, there is no guarantee that those corrections are improving the

[13] See Rigobon [1999] for an application to testing the stability of the international propagation of shocks across stock markets.

test. More importantly, the conditions under which Principal Components and correlations estimates can be adjusted are those when OLS could be estimated, and should.

The test summarized in this section deals with some of the problems that the data has. Obviously, it depends on a different important assumption: mainly, that the heteroskedasticity has to be explained by a subset of the idiosyncratic shocks. This is the major assumption (and therefore weakness) of the procedure and should be taken 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 December 19, 1994 devaluation) is explained by shocks to those particular countries and not a direct consequence of Mexican problems. In fact, as it 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 the Korean crises is more difficult. Which country should be blamed by 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 the 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 exists a period of 10 consecutive days without a crisis in another SEA country. By the characteristics of these two crises, it should be expected a rejection. However, claiming that it is due to parameter instability is impossible. Again, this is a case where the rejections are non interesting.

In the implementation of this methodology the two main questions should be: First, whether or not the data is heteroskedastic, and that it is large enough. This is the precondition for the second question: can it be described by shifts in the variances of a subset of the idiosyncratic shocks? If so, then the procedure here described is a valid test for parameter stability. Most of the contagion events, however, can answer affirmatively both questions.

4 Measuring the channels of contagion.

The second question that most empirical applications of contagion tackle 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 exists essentially three approaches used to measure them: Probit, OLS, and Principal Components.

4.1 Measuring using Probit-Logit.

One of the first empirical papers in the contagion literature was Eichengreen, Rose, and Wyplosz [1996]. They asked the question, what is the probability that country y faces 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 the crisis as large movements in such indexes, and third they compute the interrelationship across countries using Probit.[15] In order to test for the importance of the different channels of contagion they interacted the right hand side crises indexes with measures of trade, country similarities, etc. The interpretation of their results are undoubtedly engaging. However, this model encounters 2 problems: (1) when the residuals are heteroskedastic, (2) 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 dependant variable regressions is the consistency of the estimates when the residuals of the selection equation are heteroskedastic. Several procedures have been developed to deal

[14] These channels are based on a large theoretical literature and they usually include trade, country similarities, common lender, learning, liquidity, distance, etc. 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.[2000] in the context of measuring the probability of issuing foreign debt. See also Bae, Karolyi and Stulz [2000] for an application using multinomial regressions.

with this issue: For example, Maximum Score (see Manski [1985] , Horowitz [1992, 1993]) and Symmetric Trimming (see Powell [1986], and also Honore [1992] and Honore, Kyriazidou and Udry). These methodologies are able to handle the estimation biases. Nevertheless, they have not being used in contagion applications yet. On the other hand, the lack of control for heteroskedasticity affects significantly 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, where the matrix A is given by

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

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

The Monte Carlo simulation consists of 500 random-independent draws of the three shocks, with sample length of 1000 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 are studied: increases by 2, 5, and 10 times. Three different values of α are also studied (0.1, 0.2, and 0.3).

The variables y_t, $x_{1,t}$, and $x_{2,t}$ are computed for each realization using Model 3a, and the variable $y_t^* = 1\left[y_t > 0\right]$ is calculated afterwards. Finally, the Probit regression (equation (4)) is estimated: $y_t^* = 1\left[c + \beta_1 x_{1,t} + \beta_2 x_{2,t}\right]$.

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 Tables 1 and 2.

In Table 1 the results for the first coefficient ($\hat{\beta}_1$) are summarized. The first four rows are the estimates when $\alpha = 0.1$, the next four rows are the estimates when $\alpha = 0.2$, while the last four are the results for $\alpha = 0.3$. For each value of α there are four rows: The first one are the results under homoskedasticity, which is the benchmark for comparison. The next three rows are the three heteroskedasticities studied.

	First Coefficient: $\hat{\beta}_1$			
	Estimate	Difference	Stdev of Difference	T-stat
True α=0.1				
Homoskedasticity	0.1897			
Increase in variance: 2	0.1927	-0.0030	0.0071	0.42
Increase in variance: 5	0.1965	-0.0067	0.0124	0.55
Increase in variance: 10	0.1977	-0.0080	0.0160	0.50
True α=0.2				
Homoskedasticity	0.3465			
Increase in variance: 2	0.3624	-0.0159	0.0123	1.28
Increase in variance: 5	0.3762	-0.0297	0.0205	1.45
Increase in variance: 10	0.3825	-0.0360	0.0252	1.43
True α=0.3				
Homoskedasticity	0.4728			
Increase in variance: 2	0.5037	-0.0310	0.0225	1.38
Increase in variance: 5	0.5320	-0.0592	0.0351	1.69
Increase in variance: 10	0.5429	-0.0702	0.0408	1.72

Table 1: Probit estimates of the $x_{1,t}$ coefficient, for different values of α, and different degrees of heteroskedasticity. For each simulation 500 draws are computed. The tranquil sample and the high volatile sample are 500 observations long each.

The first column are the point estimates. 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 them were statistically different from zero. The second column is the difference between the estimates with heteroskedasticity and the respective one under homoskedasticity. The third column shows the computed standard deviation of the difference. It was obtained by bootstrapping. The fourth column calculates the t-statistic.

Three remarks can be extracted from the table: First, an increase in the heteroskedasticity of $x_{2,t}$ biases the estimates of $x_{1,t}$ upward. Second, the larger the heteroskedasticity is, the larger its bias is. Thirdly, the larger the true coefficient is (α bigger) 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.

Table 2 shows the results for the $x_{2,t}$ coefficient. In this case the hypotheses of equality across degrees of heteroskedasticity are rejected.

	Second Coefficient: $\hat{\beta}_2$			
	Estimate	Difference	Stdev of Difference	T-stat
True α=0.1				
Homoskedasticity	0.1887			
Increase in variance: 2	0.1567	0.0319	0.0145	2.20
Increase in variance: 5	0.1241	0.0646	0.0259	2.50
Increase in variance: 10	0.1093	0.0794	0.0311	2.55
True α=0.2				
Homoskedasticity	0.3493			
Increase in variance: 2	0.2875	0.0617	0.0199	3.11
Increase in variance: 5	0.2292	0.1200	0.0323	3.72
Increase in variance: 10	0.2042	0.1450	0.0374	3.88
True α=0.3				
Homoskedasticity	0.4711			
Increase in variance: 2	0.3918	0.0793	0.0329	2.41
Increase in variance: 5	0.3188	0.1523	0.0444	3.43
Increase in variance: 10	0.2956	0.1755	0.0511	3.43

Table 2: Probit estimates of the $x_{2,t}$ coefficient, for different values of α, and different degrees of heteroskedasticity. For each simulation 500 draws are computed. The tranquil sample and the high volatile sample are 500 observations long each.

First, note that the bias is downward, as oppose to upward. Second, the patterns about the effects of the heteroskedasticity and the size of α on the bias are the same as before. Thirdly, changes in volatility of the order of 10 times imply coefficients that are almost half the size from those under homoskedasticity.

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, under these parameters, when one of the variables suffers from heteroskedasticity, its estimate goes down, while the estimate of the other one goes up. Moreover, their differences are statistically significant.

This later property is perhaps 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 particular, assume that stock market in dollars are more heteroskedastic during flexible regimes than during fixed regimes. A Probit regression, in this case, might conclude that countries that share the same regime have stronger interrelationships, and thus more likely to suffer from contagion.

Identification of parameters: A second difficulty in the estimation of equation (4) arises when the data has simultaneous equations or omitted variables problems alone. In order to illustrate this issue, a Monte Carlo simulation is run, estimating Model 4 where the underlying returns are given by Model 3.[16]

The same procedure as before is implemented: (i) 500 independent realizations of the shocks are drawn; (ii) $x_{i,t}$ and y_t are constructed using Model 3; (iii) $y_t^* = 1\,[y_t > 0]$ is computed; and (iv) the Probit is run, where $y_t^* = 1\,[c + \beta_1 x_{1,t} + \beta_2 x_{2,t}]$.

The parameters chosen were: $\beta = 0.2$, $\gamma_1 = 0.1$, γ_2 was varied from 0.1 to 0.5, the variance of ε_t, $\eta_{1,t}$, and $\eta_{2,t}$ are equal to one, and the variance of z_t was changed as follows $\{0.1, 1, 5, 10\}$. Just as a clarification point, there is no heteroskedasticity in this exercise. The different volatilities of z_t are studied to understand the implications on the estimates when the (relative) importance of the omitted variable changes.

The objective of these simulation, indeed, is to show how the biases in the estimates change for the different volatilities and coefficients of the omitted variable shock.

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 3, confirm this intuition.

The first set of three columns show the point estimate, standard deviation, and t-stat of the $x_{1,t}$ coefficient. The second set of three columns are 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.

Four remarks can be extracted from the table. First, when the variance of z_t is 0.1 the estimates are close to the true ones; All the $\hat{\beta}_1$ estimates are near by 0.20 while the

[16] The omitted variables problem is simpler to analyze, but similar conclusions are found in simultaneous equations setups.

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

Table 3: Probit estimates of both coefficients. Standard Deviations computed using bootstrap. Simulations for different variances of z_t (Relative Variance). Variances of the other shocks have been normalized to one. For each simulation 500 draws are computed. The sample is 1000 observations long.

estimates of $\hat{\beta}_2$ are statistically insignificant. Second, when the variance of the common shock increases both estimates are biased upward. This is the case because the γ_i's are positive in both structural equations. Third, as should be expected, the larger γ_2 is, the higher the bias on $\hat{\beta}_2$ is. Fourth, it is possible that $\hat{\beta}_2 > \hat{\beta}_1$ and statistically significant.

In the theoretical literature of contagion, unobservable shocks have constituted an integral part of the propagation mechanisms. There is a large literature arguing in favor of liquidity shocks and shifts in risk preferences as major contributors to the excess comovement of stock markets, interest rates, and exchange rates in emerging markets.[17] If all coefficients are positive, then the existence of these common shocks upward biases the degree of interrelationship across countries.

4.2 Measuring using OLS

A second strand of the literature measures the propagation mechanism using OLS regressions.[18] The problems are similar to the ones described in the previous sub-section.

Assume the data is produced by Model 3. The OLS estimates are given by (after some algebra):

$$\begin{aligned}
\hat{\beta}_1 &= \beta_1 + \frac{\sigma_z}{\phi}\gamma_1\sigma_{\eta,2} \\
\hat{\beta}_2 &= \beta_2 + \frac{\sigma_z}{\phi}\gamma_2\sigma_{\eta,1} \\
\phi &= \sigma_z\left[\gamma_2^2\sigma_{\eta,1} + \gamma_1^2\sigma_{\eta,2}\right] + \sigma_{\eta,1}\sigma_{\eta,2}
\end{aligned}$$

Note that the true values are $\beta_2 = 0$ and $\beta_1 = \beta$. However, the biases can make $\hat{\beta}_2$ larger than zero, and even significant. Moreover, depending on the signs of the $\gamma' s$ and the relative variances, it is also possible that $\hat{\beta}_1$ is insignificant. In this model, any conclusion about the

[17] See Calvo [1999], Calvo and Mendoza [2000], and Kodres and Pritsker [1999] for theoretical models of contagion based on common unobservable shocks. The first one looks at liquidity shocks, the second one at market sentiment shocks, and the third one at all these shocks plus another transmission mechanisms.

[18] See Baig and Goldfjan [1998, 2000], De Gregorio and Valdes [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.

relationship between y_t and the $x_{i,t}$'s can be obtained. Similar conclusions could be drawn if Model 3a is used. See appendix A for an example.

A Monte Carlo simulation is run, using the same coefficients as in the previous subsection, to compare the size of the biases. In Table 4 the results are shown. As can be seen, the patterns in the estimates are similar to those from Table 3.

	$\hat{\beta}_1$: $x_{1,t}$ Coefficient			$\hat{\beta}_2$: $x_{2,t}$ Coefficient		
	Estimate	Std. Dev.	T-Stat	Estimate	Std. Dev.	T-Stat
True γ_2=0.1						
Relative Variance: 0.1	0.2114	0.0330	6.41	0.0110	0.0338	0.32
Relative Variance: 1	0.2987	0.0443	6.75	0.0977	0.0456	2.14
Relative Variance: 5	0.6534	0.0736	8.88	0.4520	0.0753	6.00
Relative Variance: 10	1.0309	0.0940	10.96	0.8297	0.0954	8.69
True γ_2=0.2						
Relative Variance: 0.1	0.2076	0.0333	6.23	0.0186	0.0320	0.58
Relative Variance: 1	0.2934	0.0431	6.81	0.1888	0.0420	4.49
Relative Variance: 5	0.5986	0.0654	9.15	0.7993	0.0630	12.70
Relative Variance: 10	0.8652	0.0788	10.97	1.3339	0.0739	18.06
True γ_2=0.3						
Relative Variance: 0.1	0.2098	0.0345	6.09	0.0304	0.0331	0.92
Relative Variance: 1	0.2912	0.0459	6.34	0.2736	0.0410	6.67
Relative Variance: 5	0.5340	0.0680	7.85	1.0011	0.0530	18.90
Relative Variance: 10	0.7009	0.0786	8.92	1.5010	0.0554	27.08
True γ_2=0.4						
Relative Variance: 0.1	0.2086	0.0320	6.53	0.0395	0.0337	1.17
Relative Variance: 1	0.2837	0.0429	6.61	0.3422	0.0431	7.95
Relative Variance: 5	0.4671	0.0616	7.58	1.0810	0.0483	22.37
Relative Variance: 10	0.5665	0.0693	8.17	1.4814	0.0446	33.19
True γ_2=0.5						
Relative Variance: 0.1	0.2104	0.0341	6.17	0.0492	0.0314	1.57
Relative Variance: 1	0.2801	0.0419	6.69	0.3976	0.0355	11.20
Relative Variance: 5	0.4182	0.0540	7.75	1.0870	0.0360	30.22
Relative Variance: 10	0.4787	0.0586	8.17	1.3886	0.0327	42.40

Table 4: OLS estimates of both coefficients. Standard Deviations computed using bootstrap. Simulations for different variances of z_t (Relative Variance). Variances of the other shocks have been normalized to one. For each simulation 500 draws are computed. The sample is 1000 observations long.

One advantage of OLS over Probit is that it is robust to heteroskedasticity, while 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.

4.3 Measuring using Principal Components

As was indicated in the section 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: the estimates, by itself, are inconsistent too.

Using the same example as in section 3.2, equation (7) is the first Principal Component, reproduced here for convenience:

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

Note that it 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). Then, those countries in which its idiosyncratic variance changes more (larger volatility in θ_t) have higher loadings (all 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 brevity the results are not presented, only the conclusions from that exercise. First, the heteroskedasticity in the second shock implies that the loading of the first country in the first component is downward biased. 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 explaining their common component. Moreover, the larger the heteroskedasticity is, the higher the downward bias is. Second, when the loadings are compared across different degrees of heteroskedasticity, their estimates were statistically different. Finally, it is easy to show that if the structural errors are properly normalized, then the bias disappears. However, this normalization is only possible if the data does not suffer from simultaneous equations nor omitted variable problems. In these cases, it is worth asking why 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 where it can be corrected are those in which OLS should be used.

4.4 New procedure

In the contagion literature, the issues of heteroskedasticity, simultaneous equations and omitted variables are unavoidable. Specially, because there are no good instruments to solve them.[19] Moreover, the fact that most papers use "indexes" instead of exchange rates, or interest rates, directly exacerbates the problems even more.

In general, the index is constructed as a linear combination of the high frequency macro variables. The advantage is, for example, that speculative attacks 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. On the other hand, the disadvantage is that using prices and exchange rates jointly in an index aggravates the endogeneity problems. Making the inference about the transmission mechanism more complicated. Using 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 complications.

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

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

relationship across variables even if the data suffers 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 KxK non-triangular matrix, X_t is the matrix of country variables, and ε_t is the vector of idiosyncratic shocks. The diagonal of A is usually set to one: which is the normalization assumption. Additionally, it is commonly assumed, in macro applications, that the idiosyncratic shocks are uncorrelated: $E\left[\varepsilon_{i,t}\varepsilon_{j,t}\right] = 0$ for all $i \neq j$. This is the covariance restriction used in most macro-applications. Still 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

$$\Omega_t = A'^{-1}\Omega_t^{\varepsilon}A^{-1}.$$

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

Ω_t is estimated from the sample and it provides $\frac{K(K+1)}{2}$ 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 knows. This is the standard identification problem raised by simultaneous equations.

The key feature of the Rigobon's identification is the realization that under the exact same restrictions the existence of heteroskedasticity adds additional constraints.

The simplest case is when 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 implemented and the parameter stability can be examined.

The key assumptions are that there is heteroskedasticity, that the parameters are stable, and that the structural shocks are uncorrelated. This is exactly the case of most macro applications where VAR models have been used, and financial applications where ARCH or GARCH models have been computed. In the derivation here developed, only unconditional heteroskedasticity has been studied. Similar arguments can be extended to include the case where 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. Afterwards, A can be explained as a function of the different channels of contagion. This is the objective of the next section.

5 An application to Emerging Markets.

This section examines the questions of stability of the propagation of shocks across Latin American and South East Asian countries around the recent crises; how important those linkages are; and what determines them. The first question is implemented as the test for parameter stability introduced in Section 3.4. While the other two questions are answered by using the methodology described in Section 4.4.

Two data sets are used: sovereign bonds and stock markets. The data for stock markets was collected from Datastream, and it consists of daily stock market returns (in dollars) for 14 countries, covering the period from January 1993 to December 1998. The countries studied are: Argentina, Brazil, Chile, Hong Kong, Malaysia, Mexico, Peru, Philippines, Singapore, Korea, Taiwan, Thailand, US, and Venezuela.

The sovereign bond data contains 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 also other foreign denominated bonds are taken into consideration. The indexes are computed by simulating holding 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 South East Asian countries in the JPMorgan data are Korea and Philippines, but the length of their data is small in comparison to the other countries. Thus, they were dropped from the analysis.

Information on US interest rates is obtained from Datastream. For all the results presented in this paper the 10 year US 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 (1 year and 3 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 shock in both.

5.1 Test for stability

The stability of parameters for both the stock and bond markets is studied by performing the DCC test described in section 3.4. This test is based on the assumption that in a sub-sample the heteroskedasticity is explained by the heteroskedasticity in only a sub-set of the shocks. Moreover, it has to be either a sub-set of the idiosyncratic shocks, or a sub-set of 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 a consequence of the country producing the crisis is a reasonable one.

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

5.1.1 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, Γ are the parameters of how common shocks affect country returns (or vulnerabilities). 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 one, and the coefficient on the US 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 has to be conducted.

The reduced form of this model is the following:

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

Where the reduced form residuals satisfy,

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

Note that the procedures developed in section 3.4 deals with the stability and identification of parameters is equation (9). Because the reduced form residuals share the same contemporaneous properties as the returns, in the estimation first, a VAR is 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. An immediate question that arises concerning this procedure is what are the parameters tested for. Indeed, it is testing for the stability of A, Γ, and $\phi(L)$. At a first glance, the inclusion of $\phi(L)$ in this list this might be surprising, but see the appendix for a formal derivation.

For brevity, the results from the VAR's are not presented.

5.1.2 Definition of the windows.

In order to implement the DCC test a high and low volatile regime has to be defined. Moreover, for the alternative hypothesis to be informative, the periods have to 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 3 major crisis. Those are used to define the regimes. In Table 5 the low and high volatile dates are shown.

For the Mexican crisis, the low volatile regime is defined as the period from June to December of 1994 right before the devaluation. The high volatile regime starts with the devaluation in December, 19th of 1994. The end of this period, however, is unclear. After the Mexican devaluation several other shocks occurred; the discussion of the rescue package in January, for instance. These shocks maintained the high volatility for several months.

	Tranquil Window		High Volatility Window	
	Starts	Ends	Stars	Ends
Mexican Crisis				
Currency Devaluation	6-1-1994	12-16-1994	12-19-1994	1-8-1995
No Rollover	6-1-1994	12-19-1994	1-9-1995	3-31-1995
Curr. Dev. + No Rollover	6-1-1994	12-16-1994	12-19-1994	3-31-1995
Asian Crises				
Hong Kong	1-2-1997	6-2-1997	10-27-1997	11-14-1997
Korea	1-2-1997	6-2-1997	12-1-1997	1-9-1998
Hong Kong + Korea	1-2-1997	6-2-1997	10-27-1997	1-10-1997
Thailand	1-2-1997	6-2-1997	6-10-1997	8-29-1997
All	1-2-1997	6-2-1997	6-10-1997	1-10-1997
Russian Crisis				
Russia	3-2-1998	6-1-1998	8-3-1998	8-21-1998
LTCM	3-2-1998	6-1-1998	8-21-1998	9-30-1998
Russia+LTCM	3-2-1998	6-1-1998	8-3-1998	9-30-1998
Brazilean speculative attack	3-2-1998	6-1-1998	10-1-1998	10-30-1998
All	3-2-1998	6-1-1998	8-3-1998	10-30-1998

Table 5: Windows for the DCC Test..

Therefore, two possible crisis regimes are studied: one ending in January 8th, and the other one lasting until March 31st. The choice of January 8th is based on the fact that in January 9th the non-rollover of the short term debt was announced. This produced 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 therefore, in the model here estimated as a common shock. The DCC would reject if there is heteroskedasticity in both a idiosyncratic and a common shock. Therefore, these samples should be considered separately. Indeed, three cases are studied, one staring with the devaluation and ending before January 9, another one starting in January 9th and lasting until the end of March, and the last one that includes both periods.

Looking at this 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, is a test of how powerful the test is in this data. However, if indeed there is a shift in the parameters after January 9, but not before, then the test is rejected also when that period is under consideration. In other words, if the rejection only occurs when the two high volatile samples are put together, then it is possible to argue that it is due to not satisfying the heteroskedasticity assumption. On the other hand, if there is a rejection in one of the sub-samples, it must be the case that together they 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 started in June of 1996 with Thailand's devaluation and lasted further into 1998 until 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 volatile periods are defined. The Thailand crisis started at the beginning of June 1997. The Hong Kong crisis started in October 27th, 1997. The Korean crisis started around December 15th, 1997. The Hong Kong crisis is the only one that has a clear initial date which is obtained by the day in which short term interest rates increased dramatically. For the other two crises, however, the initial day is unclear because there is important action on the bond and stock market 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 crisis, they should not become a violation of the heteroskedasticity assumption. In the bond market data, all South East Asian countries are excluded from the regression, thus, these crises are summarized by the common unobservable shock. Therefore, it is a sub-set 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, and therefore the South East Asian crises can be modelled as changes in the volatility of a sub-set of the idiosyncratic shocks. Again, the DCC should not be rejected because of ill-specified heteroskedasticity.

Finally, the third crisis studied is the Russian and LTCM collapses. The tranquil period goes from March to July of 1998, and several high volatile 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, there is another shocks which is a speculative attack to the Brazilian currency. Hence, as in the Mexican case, the LTCM collapse has been associated with an aggregate liquidity shock.

Several sensitivity analysis 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 no robustness should be expected to a random definition of regimes. It is crucial, and I hope this discussion has make it clear, that in order to implement the test a comprehensive view of the changes in second moments have to be imposed before running the test. Otherwise, rejections are meaningless.

5.1.3 Stock markets

Given the regimes/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, 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 8 times was observed. Similarly, during the Hong Kong speculative attack the increase in stock markets was almost 12. These increases in volatility represent a significant rise in volatility in emerging markets. Remember that the data include countries such as US, Singapore, Chile, etc. where the increases in volatility during this sample were smaller than 2.

After the covariance matrices are estimated, the determinant on their change is computed. The results for the Stock market test are shown in Table 7. The first column indicates the point estimate, the second column is the computed standard deviation, the third one is the mass below zero, and the fourth one is and indicator, where 1 means that the test of stability was rejected. The standard deviation and the mass below zero are computed using

	Average increase in variances	Increase in maximum singular value
Mexican Crisis		
Currency Devaluation	3.36	9.23
No Rollover	3.61	7.93
Curr. Dev. + 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
Brazilean speculative attack	3.44	3.07
All	4.04	3.17

Table 6: Changes in variances measured as several matrix norms.

a bootstrap. The procedure uses the changes in conditional variance across the windows to produce several covariance matrices. Then it computes the determinant on the change and estimates both the standard deviation as well as 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 one if the proportion of the simulations with determinant smaller that zero (mass below zero) is either 10 or 90 percent.

Observe that in Table 7, there is no single case in which the test is rejected. The immediate question is whether or not the test has power. Two remarks 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, using bond data there are some rejections. Therefore, the lack of rejection could not be entirely blamed on the power of the test. Hence, this evidence suggests that the propagation of shocks across stock markets is (relatively) stable during the recent crises.

	DCC in Stock Market			
	Point Estimate	Standard Deviation	Mass Below Zero	Rejection
Mexican Crisis				
Currency Devaluation	-1.4632877	49.559015	0.357	0
No Rollover	34.918946	182.90394	0.762	0
Curr. Dev. + No Rollover	16.135432	63.385381	0.778	0
Asian Crises				
Hong Kong	-8131.1469	5140.3177	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	5145.213	0.668	0
LTCM	2926.3835	73705.659	0.418	0
Russia+LTCM	3171.8639	16813.048	0.358	0
Brazilean speculative attack	7.6768399	27581.466	0.676	0
All	-2091.3015	19540.064	0.615	0

Table 7: DCC Test for Stock Markets.

5.1.4 Bond markets

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

In Table 8, 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 shift in the variances are larger than the ones found in stock markets.

Specially, 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 that was already experienced by the Russian crash. Take into consideration that this pattern was absent in the stock market data (see Table 6). This confirms the common wisdom in market participants that the aftermath of the Mexican crisis and the LTCM shocks were mainly shocks to the bond markets.

On the other hand, an interesting aspect in 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. Remember that if the heteroskedasticity is small

	Average increase in variances	Increase in maximum singular value
Mexican Crisis		
Currency Devaluation	12.71	10.14
No Rollover	19.96	22.92
Curr. Dev. + 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
Brazilean speculative attack	13.31	11.88
All	38.79	37.53

Table 8: DCC Test for Bond Markets. Changes in variances measured as several matrix norms.

the DCC test has little power. So, a lack of rejection should be expected during the South East Asian crisis for the bond data.

The results for the Bond market DCC test are shown in Table 9. The interpretation of the table is the same as in the stock market. In this case, there are two instances in which the parameters are unstable. The January 9th 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 a shift in the parameters during those times, and not because there is the alternative hypothesis is misspecified.

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

In summary, the events in which the test is rejected reflect instances where important

	Point Estimate	Standard Deviation	DCC in Bond Market Mass Below Zero	Rejection
Mexican Crisis				
Currency Devaluation	1.3062012	2.1833245	0.76	0
No Rollover	14.264603	18.034845	0.94	1
Curr. Dev. + 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	2.006E-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
Brazilean speculative attack	0.0029295	0.0009354	0.264	0
All	8.307991	3.1489852	0.993	1

Table 9: DCC Test for Bond Markets.

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

5.2 Estimation of the propagation mechanism

In this sub-section, 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 trade and regional variables explain A? And what is the relative importance of the common shocks (z_t) across crises and regimes?

5.2.1 Model and identification

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

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

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

Identification: The procedure described in Section 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 righ enough.

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

$$\begin{aligned} \frac{K(K+1)}{2} &> K + C \\ K(K-1) &> 2C \end{aligned} \tag{12}$$

This is the "catch up" constraint.

After condition (12) is satisfied, then there has to exist a minimum number of regimes that imply that there exists at least the same number of equations than unknowns. The number of knows is provided by the covariance matrix in each regime and it is equal to:

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

Therefore, imposing that equation (13) is larger or equal than 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 the following:

1. In the bond markets there are 8 countries (endogenous variables). The "catch up" constraint (12) is easily satisfied and the minimum number of regimes is $S \geq 14/6$.
2. For the stock market case there are 14 countries. Thus, inequality (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

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

Where the left hand side are the estimate of the covariance matrix in regime $t \in \{1,\ldots,S\}$, and the right hand side are the coefficients of interest. This is a non-linear system of equations that is estimated by GMM, where equation (15) is the set of moment restrictions.[20]

[20] Actually, instead of computing inverses of A the moment restriction estimated is

$$A\Omega_t^{\nu}A' - \Gamma\Omega_t^{z}\Gamma' - \Omega_t^{\varepsilon} = 0$$

After the VAR is estimated and the residuals have been recovered (which in fact are the same residuals as those used in the previous section), the regimes are defined, the covariance matrices 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. Therefore, the definition of the windows is by looking at the periods of medium and high volatility derived from the conditional volatility. Furthermore, the identification is obtained if the changes in variance are conditional or not, thus, the use of the sample covariance matrices to determine the regimes is easily justified.[21]

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 April 1st 1995 until July 31st 1998. The assumption of parameter stability is crucial for the identification, and the previous sub-section have already shown that bond markets had unstable parameters during the first quarter of 1995 and after August 21st of 1998.

Again, the results from the VAR are not shown.

5.2.2 Stock markets

Definition of the regimes: Taking the residuals from the VAR, first, a 20 days 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 volatile regime are those days in which the matrix norm is smaller than the average; the high volatile regime are the dates in which the norm is larger than two standard deviations of the mean; and the medium regime is the rest of the sample.

which is simpler and more stable. However, always the invertibility of A has to be checked.

[21] 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 MLE can be used directly. The intuition of the identification, though, is exactly the same as the one derived here. The paper will be available in my web page at the end of January 2001 (when proper reference will be provided).

In Figure 1 the three regimes are shown, where 1 corresponds to the low, 2 is the medium and 3 is the high volatile period. There are 848 observations in the low volatile regime, 329 in the medium volatile regime, and 95 in the high volatile regime. It is important to highlight that the regimes coincide with most of the crises and events in which "contagion" had been 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).

Distributions and standard deviations were computed by bootstrap. The idea is to draw several covariance matrices and solve the system of equations for each realization. However, assuming 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 this process is 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 10. The diagonal is omitted because it is known that it is equal to one, and the sign of the coefficients have been changed so they can be understood as the elasticities in the right hand side (its natural interpretation).

The row represents the equation of that 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 90 percent confidence are in bold type, where the confidence interval is computed using the bootstrapped distribution.

Several remarks from Table 10 are worth highlighting. First, the coefficients in the US

Point Estimate														
	Arg	Bra	Chi	HK	Mal	Mex	Per	Phi	Sin	Kor	Tai	Tha	USA	Ven
Arg		**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
Bra	**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
Chi	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
HK	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
Mal	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
Mex	**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
Per	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
Phi	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
Sin	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
Kor	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
Tai	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
Tha	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
USA	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
Ven	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 10: Point estimates of A.

equation are all non statistically significant. Note that this was not imposed in the estimation procedure, even though our prior would have suggested so. On the other hand, US affects importantly 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 there are 32 out of 182 coefficients that are statistically different from zero. Among the Latin American countries, there are 13 significant estimates out of 30 possible coefficients. Similarly, among the South East Asian countries 12 out of 42 are significantly different from zero. Interestingly, there are only 3 (out of 84) coefficients across regions (excluding those from the US) that 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.

In Table 11, the standard deviation of the coefficients is shown, which are obtained from the bootstrap. One appealing fact from Table 11 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

	Standard Deviation													
	Arg	Bra	Chi	HK	Mal	Mex	Per	Phi	Sin	Kor	Tai	Tha	USA	Ven
Arg		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
Bra	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
Chi	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
HK	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
Mal	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
Mex	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
Per	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
Phi	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
Sin	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
Kor	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
Tai	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
Tha	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
USA	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
Ven	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	

Table 11: Standard Deviation of A estimates.

either the originators of the crises or the main affected countries. The standard deviations for these estimates is 0.063. On the other hand, US estimates are less precisely estimated. The average standard deviation is 0.1366. The reason behind this outcome is how the identification problem is solved; the heteroskedasticity is the identifying device. The quality of the estimation, and therefore 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 or magnitude larger than those from US (or Singapore) and that is why those standard deviations are smaller.

Finally, in Table 12, 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 between the average of the bootstrapped distribution and 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 using the z-statistic than by looking at the bootstrapped distribution. In Table 10, there are 32 out of 182 significant coefficients, while using the z-statistic 47 would have been significant. It is important to

	Z statistic													
	Arg	Bra	Chi	HK	Mal	Mex	Per	Phi	Sin	Kor	Tai	Tha	USA	Ven
Arg		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
Bra	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
Chi	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
HK	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
Mal	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
Mex	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
Per	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
Phi	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
Sin	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
Kor	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
Tai	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
Tha	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
USA	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
Ven	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 12: z-stats of A estimates.

mention that all the coefficients that are significant using the bootstrapped distribution are also significant using the z-statistic. On the other hand, if a 95 percent confidence interval is used as the criteria on the z-statistics, then 31 coefficients pass the test. The coefficient that looses significance is the transmission between US and Peru.

At a first glance, notice that Chile has as many significant coefficients as USA. Does this means that Chile is more important than USA in this data? Certainly not. What this means is simply that those coefficients are estimated with more efficieny. In order to answer the question of importance of countries, though, a different exercise has to be performed. The interpretation of the coefficients require a variance decomposition. This is performed below. This is the right measure to evaluate the relative impact 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 is then, what are the possible explanations behind them. Later in this section, a partial structural model is provided by analyzing 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 US elasticity was chosen to be equal to 0.1. In Table 13 the results are shown. The first column corresponds to the point estimate. The second column shows the standard deviation computed from the bootstrapped distribution. And the third column is the z-statistic calculated as before.

	Point Estimate	Standard Deviation	Z stat.
Arg	0.39	0.26	0.84
Bra	0.41	0.35	1.05
Chi	0.34	0.14	0.97
HK	0.09	0.10	0.60
Mal	0.27	0.22	0.87
Mex	0.44	0.28	0.88
Per	0.52	0.25	1.01
Phi	0.35	0.14	1.02
Sin	0.38	0.34	0.90
Kor	0.68	0.32	1.02
Tai	0.30	0.22	0.71
Tha	0.64	0.19	0.94
USA	0.10		
Ven	0.55	0.28	1.06

Table 13: Vulnerabilities (estimates of γ)

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 US. For example, Argentina, Brazil, and Mexico are close to be 4 times more vulnerable to the US to the same common liquidity shock. Even though this pattern is quite informative, it was impossible to reject the hypothesis that the estimates were all equal to zero. Because of this, instead of studying their aspects, the next subsection turns its attention to the variance decomposition between idiosyncratic and common shocks.

As before, the coefficients estimated are difficult to interpret and in the next subsection a variance decomposition is analyzed. 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 is further explored.

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 vulnerability 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 compare 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 Ω_t^z is set to zero. This is the unconditional covariance only with idiosyncratic shocks (or in other words, without common shocks). In Table 14, the ratio between the variance of each country explained by idiosyncratic shocks only is divided by the its variance when common shocks are included. This procedure is repeated for each regime.

	Variance Decomposition		
	Low	Medium	High
Arg	89.4%	78.8%	75.0%
Bra	94.0%	88.6%	85.5%
Chi	92.0%	83.7%	80.8%
HK	73.4%	65.4%	57.6%
Mal	71.5%	72.4%	64.4%
Mex	86.8%	77.5%	75.1%
Per	92.6%	83.9%	81.2%
Phi	77.4%	67.1%	49.4%
Sin	72.6%	56.8%	51.1%
Kor	89.2%	84.1%	89.6%
Tai	98.1%	95.3%	87.3%
Tha	72.1%	60.8%	53.2%
USA	95.8%	92.7%	89.0%
Ven	97.8%	93.3%	97.1%

Table 14: Variance Decomposition. Percentage explained by the idiosyncratic shocks.

Three remarks can be extracted from the table. First, notice that USA 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 US stock returns is explained by idiosyncratic shocks. This does not mean that liquidity shocks or risk preferences are unimportant in the US. What this is saying is that the common component of these shocks can be described mainly as idiosyncratic shocks to the US. Therefore, in this exercise, the common liquidity shock not affecting US is the one that is being evaluated.

Second, the high volatile 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 explaining during the low variance regime. This pattern is suggestive that during the recent crises there was a common component to emerging markets that 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 volatile regimes the countries that had the largest component of common shock where the Asian countries. Surprisingly, for the Latin American countries the change in the common component is small between the low through the high regimes.

Variance Decomposition: Country idiosyncratic shocks contribution. The interpretation of the matrix A coefficients is easier understood in a variance decomposition exercise. In table 15, we computed the proportion of the idiosyncratic variance of each row country explained by the column country shock. 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 15 presents the ratio between the diagonals of these two matrices, for each country.

The Table does not include standard errors on the variance decomposition, thus, its interpretation has to be taken cautiosly. 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

	Arg	Bra	Chi	HK	Mal	Mex	Per	Phi	Sin	Kor	Tai	Tha	USA	Ven
Arg	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
Bra	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
Chi	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
HK	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
Mal	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
Mex	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
Per	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
Phi	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
Sin	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
Kor	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
Tai	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
Tha	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
USA	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
Ven	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 15: Variance Decomposition. Percentage explained by each country shock in the total idiosyncratic shock variance.

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 (USA and HK) the mayority of the variance is explained by their own shocks.

Second, most of the variation per regions is explained by regional idiosyncratic shocks. For example, 73.6 percent of the variantion of the Latin American countries is explained by their shocks, 23.0 is due to shocks to Asian countries, and 3.4 percent is the result of US shocks. On the other hand, 71.0 percent of the volatility in Asia is responsibility of Asian shocks, 18.1 percent is due to Latin American shocks, and 10.9 percent is explained by the US. In the particular case of US, 80.5 percent is accounted by US 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 perfomed in this section.

The additional data collected is the following: information on trade is obtained from Feenstra's World Data Flows. The trade share is computed as the average trade share of the countries in the 90's. Information on distance, sharing border, and belonging to Latin

America and South East Asia dummy is also included in the regression. The left hand side are the point estimates from matrix A and the regression run is the following:

$$\beta_{ij} = c_0 + c_1 LA + c_2 SEA + c_3 Trade_{ij} + c_4 Border + c_5 \log(Distance) + \varepsilon_t$$

It is likely that this regression has heteroskedasticity because the A coefficients were estimated with different degrees of precision. Therefore, a GLS was estimated where the covariance matrix of the coefficients obtained in the bootstrapping was used to weight the regression. In Table 16, the results are shown.

Variable	Coefficient	Std. 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	0.036155	0.057056	0.633	0.527122
SEA	-0.020357	0.056898	-0.357	0.720934
R-squared	0.06632			
Prob(F-statistic)	0.03241			

Table 16: Explaining A coefficients.

Note that trade is almost significant and with the correct sign: higher 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 me) is the fact that the regional dummies are not statistically significant. The R-squared is quite low even though the F-test shows that the regression is significant as a whole. Therefore, trade, even though has some explanatory power on the coefficients, it only has a limitted 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. This results, however, contrast with the findings from the bond market; this is the topic that follows.

5.2.3 Bond markets

The data on bond markets is restricted to the period between April 1995 until July 1998. However, the estimation methodology is the same as in stock markets. In Figure 2, the volatile regimes are shown (determined with the procedure highlighted above). In this case, there are 526 observations in the low-medium volatile regime, 268 in the medium volatile regime, and 41 in the high volatile regime. Notice, that the high volatilities occur during the Hong Kong crisis and in June of 1995.[22]

Contemporaneous transmission mechanism: In Table 17, 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 directly interpreted 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 90 percent confidence are in bold type. As before, the distributions and the mass below zero are obtained by bootstrapping using the same procedure as the one described above.

	Estimate							
	Arg	Bra	Ecu	Mex	Pan	Per	Ven	USA
Arg		**0.33**	**0.18**	**0.37**	0.04	0.02	0.19	0.11
Bra	**0.20**		0.14	**0.51**	0.06	0.12	0.18	**0.47**
Ecu	**0.36**	0.28		0.20	0.12	**0.35**	**0.44**	**0.62**
Mex	**0.21**	0.22	0.10		0.07	0.11	**0.29**	0.19
Pan	**0.26**	0.25	0.02	**0.46**		0.29	**0.44**	**0.73**
Per	0.38	0.13	0.23	**0.43**	0.15		0.09	**0.61**
Ven	0.40	0.07	0.06	**0.35**	**0.26**	0.10		0.32
USA	0.03	0.07	0.01	0.04	0.04	0.01	0.02	

Table 17: A estimates.

Several lessons can be extracted from the table. First, again, notice that USA is not affected by any Latin American country. Observe that not only the coefficients are not

[22] In June of 1995, the rescue package was under way, and good news about Mexico were released; its access to international financial markets was renewed. Thus, laugh is also contagious.

significant, but also the point estimates are very small. This was not impose 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 17 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 excluding Peru and Venezuela.

Third, the US has an important impact on Latin American countries. This data was constructed to reflect the country risk premium (in the first stage the indexes were regressed on US 10 year bond rates). Hence, the fact that the US coefficients are positive and significant indicates that the country risk premium in these countries increases with US interest rates. In other words, the pass through on international interest rates is larger than one.[23]

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 in a couple of countries:

1. For example, the Mexican coefficient in the Argentinean equation is 0.37 here and 0.23 before. Both statistically different from zero, but not between them. Brazilian coefficient in the same equation is 0.33 here and 0.26 before.

2. Before, Mexico affected significantly Argentina, Brazil and Peru, here the same three countries (and other two) are affected. The regularities across the two exercises is worth further exploring.

In Table 18, the standard deviation of the coefficients is shown. Note that even though the standard deviations of the US equation are quite small the estimates were not statistically significant from zero. Therefore, the reason for the lack of significance is not the need of

[23] See Frankel [2000] and Hausmann and [2000]

precision. As oppose to the stock market case, there is no further pattern about the precision of the estimates.

	Standard Deviation							
	Arg	Bra	Ecu	Mex	Pan	Per	Ven	USA
Arg		0.11	0.09	0.13	0.06	0.04	0.11	0.11
Bra	0.13		0.09	0.15	0.07	0.08	0.12	0.16
Ecu	0.18	0.15		0.15	0.14	0.13	0.21	0.25
Mex	0.12	0.13	0.10		0.08	0.09	0.13	0.16
Pan	0.17	0.19	0.05	0.21		0.18	0.19	0.20
Per	0.21	0.12	0.13	0.18	0.14		0.10	0.22
Ven	0.14	0.08	0.06	0.15	0.09	0.09		0.18
USA	0.04	0.08	0.03	0.06	0.05	0.03	0.03	

Table 18: Standard Deviation of A estimates.

In Table 19 the quasi-z statistic was computed. As before, the statistic tends to overestimate the significance of the estimates. For example, if a single side 90 percent confidence interval is used (as was the case with the bootstrapped distribution) then more coefficients are significant. In Table 17 there are 20 out of 56 significant coefficients, while using the z-statistic 26 would be significant. Again, all the estimates that are significant using the bootstrapped distribution, are also significant with the z-statistic. 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.

	z-statistics							
	Arg	Bra	Ecu	Mex	Pan	Per	Ven	USA
Arg		2.95	2.09	2.84	0.74	0.59	1.72	0.98
Bra	1.50		1.53	3.43	0.92	1.53	1.54	2.95
Ecu	1.98	1.88		1.32	0.84	2.74	2.14	2.51
Mex	1.78	1.66	1.03		0.86	1.17	2.27	1.17
Pan	1.54	1.33	0.41	2.23		1.67	2.36	3.63
Per	1.85	1.16	1.85	2.38	1.09		0.87	2.79
Ven	2.94	0.85	1.06	2.35	2.86	1.16		1.77
USA	0.59	0.83	0.50	0.68	0.87	0.32	0.65	

Table 19: z-stats of A estimates.

Before explaining the coefficients with trade and regional variables, the next subsections look at 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 US was equated to 0.1. In Table 20 the results are shown. The first column correspond to the point estimate, where the coefficients with mass above zero larger than 90 percent are highlighted in bold. The second column show the standard deviation computed from the bootstrapped distribution. And the third columns is the z-statistic calculated as the ratio between the point estimate and the standard deviation.

	Vulnerability		
	Point Estimate	Standard Deviation	zstat
Arg	0.15	0.11	1.32
Bra	0.29	0.17	1.72
Ecu	0.17	0.26	0.65
Mex	**0.36**	0.17	2.14
Pan	**0.60**	0.29	2.08
Per	**0.57**	0.26	2.17
Ven	0.31	0.17	1.86
USA	0.10		

Table 20: Vulnerabilities (estimates of γ)

Before discussing the coefficients is important to clarify what is, in this case, the interpretation of the shock z_t. In this 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 included in the sample. In particular, all the South East Asian countries. Therefore, the common shock aggregates all those disturbances, and the coefficient is the average response of the countries in the sample to those shocks. This implies that, unfortunately, this estimates cannot be directly compared with those obtained for the stock markets.

An interesting aspect in Table 20, however, is that the estimates of all countries are larger than the US coefficient. Again, it is impossible to reject the hypothesis that the coefficients are the same to the USA one[24], but they share a similar pattern as the ones obtained from

[24] Remember that the test performed in the table is whether or not the coefficient is different from zero, not to 0.10.

the Stock Market data.

Variance Decomposition: Common versus Idiosyncratic shocks. Instead of concentrating on the vulnerability coefficients, it is better to compute the contribution to the variance by the common shocks. The variance decomposition was 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. In Table 21 the results are reported.

	Variance Decomposition		
	Low	Medium	High
Arg	50.13%	43.48%	17.28%
Bra	67.18%	53.41%	30.36%
Ecu	57.34%	40.66%	24.30%
Mex	66.30%	52.42%	31.47%
Pan	78.94%	65.48%	46.27%
Per	79.07%	69.67%	41.49%
Ven	66.46%	51.65%	28.93%
USA	99.98%	99.94%	99.90%

Table 21: Variance Decomposition. Percentage explained by the idiosyncratic shocks..

The objective of this exercise is to evaluate the relative importance of common shocks across regimes. Given the span of the data (mainly covering the South East 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 volatile regimes more than in the stock market case. This intuition is confirmed by the results. In the low regime (excluding US) idiosyncratic shocks explain an average 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 volatile regime, the contribution of idiosyncratic shocks fall to 31.44 percent; less than half of their importance during the low volatile regime.

Additionally, observe that USA is almost unaffected by common shocks. In all three regimes more than 99 percent of the variation in US interest rates are 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 decomposition between bonds 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 taken cautiously.

Variance Decomposition: Country specific shocks contribution. We repeat the other variance decomposition performs for stock markets. Again, here 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 some missleading interpretation could be drawn. For example, in Table 17, the coefficient from US to Mexico is non statistically significant. Does this means that US interest rates have no explanatory power on Mexican interest rates? The answer is no.

In Table 22 the results from the variance decomposition are reproduced for the bond market.

	Arg	Bra	Ecu	Mex	Pan	Per	Ven	USA
Arg	24.2	10.4	11.0	10.2	7.5	10.4	4.8	21.4
Bra	3.9	8.8	6.8	0.1	2.5	29.6	23.2	25.1
Ecu	0.8	6.0	12.1	8.8	9.6	15.8	15.9	31.1
Mex	2.9	17.4	8.7	15.7	15.1	11.6	7.4	21.1
Pan	3.9	6.2	13.7	0.3	38.5	12.9	5.5	19.1
Per	2.4	4.4	19.4	9.0	2.9	12.8	17.8	31.3
Ven	1.6	7.2	11.9	13.3	8.7	15.0	7.0	35.4
USA	0.7	3.7	0.5	5.9	3.9	8.4	0.0	76.9

Table 22: Variance Decomposition. Percentage explained by each country shock in the total idiosyncratic shock variance.

Note that US interest rates explain a sizeable proportion of the idiosyncratic shocks in each of the Latin American countries in the sample. Indeed, US explains as much variance in Argentina as in Mexico, even though one of the coefficients is statistically significant and the other one is not.

From the table it can be extracted the conjecture that countries that have their exchange rate fixed to the dollar (Argentina and Panama) tend to have larger proportion 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 through. Another interpretation is that the pass through is the same across all countries but the volatility of the fixed exchange rate countries is larger.

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

Estimating the importance of trade: The last examination of the data is to consider the question of how much does trade explains the coefficients of matrix A. The procedure is to run a simple linear regression where the coefficients are explained by trade between the two countries, their distance, and a dummy representing whether or not they share a border. The information about trade is the same as before.

Again, the coefficients in the left hand side are estimated with different 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 23 the results from the estimation are reported.

Variable	Coefficient	Std. 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-squared	0.749			
Prob(F-statistic)	0.000246			

Table 23: Explaining A coefficients.

First, note that the coefficient on trade is significant and with the correct sign. Moreover,

[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.

notice that the coefficient is 0.449 which is close to the one reported in 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 16 is that here the border dummy is very significant. However, it seems to suggest that it goes in the wrong direction.

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

6 Future Research

The question of measuring 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, yet, 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. More has to 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 exist hope that some of the inconveniences of the price data can be overcome. Below is a list of what I think are the next set of questions that the contagion literature has to address (there are in my particular order of importance, and feasibility to be answered, but clearly this is almost a random order).

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

As far as I know, I have seen this fact 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 stock markets. Second, in an earlier paper with Eduardo Fernandez Arias we reported this finding by just 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 datas. The correlations among these countries, implied by the unconditional variance regime are documented in Table 24.

	Stock Market Correlations			Bond Market Correlations		
	Low	Medium	High	Low	Medium	High
Arg - Bra	0.61	0.71	0.73	0.78	0.70	0.91
Arg - Mex	0.52	0.63	0.64	0.72	0.64	0.85
Arg - Per	0.25	0.46	0.44	0.46	0.40	0.82
Arg - Ven	-0.01	0.17	0.08	0.76	0.71	0.92
Bra - Mex	0.51	0.59	0.58	0.36	0.60	0.68
Bra - Per	0.30	0.44	0.41	0.33	0.43	0.74
Bra - Ven	-0.04	0.08	0.07	0.52	0.62	0.81
Mex - Per	0.33	0.51	0.46	0.36	0.42	0.70
Mex - Ven	-0.07	0.05	-0.02	0.57	0.61	0.79
Per - Ven	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

Table 24: Unconditional correlation per regime.

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.

The previous discussion has indicated that common shocks is a sizeable proportion of the explanation of the changes in the pattern of correlations across time. It is possible that this is too the explanation for bond prices. That question could not be answered here because the two data are not comparable, and because it will be beyond the scope of the 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 (give the exact stylized fact) and explain it.

Measurement of Contagion: Revisited. Most of the discussion of contagion has concentrated on the simultaneous reaction across countries. Thus, it 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 section 3.4 is able to detect for changes in parameters of the lag variables. However, the measurement of the propagation mechanism was entirely estimated by the contemporaneous relationship (most papers look at weekly, 2-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 justify why the literature did that (and so this paper): First, the pattern of contemporaneous correlations is puzzling enough (and as I mentioned above, it continues to be the case). Second, without estimating the simultaneous coefficients, there is no way of estimating economically meaningful lag coefficients. With the methodologies highlighted above, now it is 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 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 not be considered contagion.

Prices versus Volumes: A third important topic is that most of the papers in the area look at prices rather than volumes. The main reason being the easily availability of high frequency data, of the former, and the almost complete unavailability of the later one.

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's positions. In fact, the implications on prices are derived from those volume decisions. Looking only at prices misses these rich set of implications. The main limitation is data availability, but it should be clear that if prices encountered important econometric problems, volumes will do too.

Is the propagation through the means or the variances? Fourth, the question whether the shocks are transmitted directly through prices, or the fall in prices reflects higher volatilities has not been raised with the emphasis it should. The only paper (to my knowledge) looking at these issues is Edwards and Susmel [2000]. Unfortunately, they have to makes the necessary assumption to avoid the identification problem. The models here studied 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 disentangled 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:

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

where

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

and where $\sigma_\varepsilon, \sigma_\eta$ follow a Bivariate ARCH

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

where $\nu_{\varepsilon,t}$ and $\nu_{\eta,t}$ are uncorrelated, and the matrices A and B are not diagonal.[26] A reflects

[26] I have already solved the problem of identification in GARCH models if B is a triangular matrix. This

the propagation through prices, while B explains the propagation through variances. Because in the reduced form only conditional covariance matrices are computed, in general, there is no procedure to separate A from B. Future research should develop techniques that could deal with this question.

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

A casual look to the data clearly indicates that either the distributions are not normal, or the models are non-linear (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 normal circumstances. See Bae, Karolyi and Stulz [2000], and Longuin and Slonik [1995] for some evidence. Further research in the area is clearly granted.

7 Conclusions

The empirical question of contagion is one of the most difficult tasks we have encountered in international macroeconomics in the recent years. The data suffers from the worst of (what I call) the macro problems: simultaneous equations and omitted variable biases. And, the data also exhibits the worst of finance: conditional and unconditional heteroskedasticity, non-linearity, non-normality, and serial correlation.

This paper has several objectives: First, it provides a critical view to the most frequently used techniques in applied papers of contagion. The first two sections discuss the biases and inconsistencies that arise in OLS, Probit, and specially Principal Components and correlation estimates. In those sections, I propose the use of two new techniques that can deal with some of the problems, but certainly further research should and will continue to improve the techniques.

is an extension of the Identification through Heteroskedasticity paper to the case in which only conditional heteroskedasticity exists. The paper will be available soon in my web page. I do not have it yet.

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 simulations). Section 5 tested for parameter stability and the importance of trade in bond and stock markets. Two surprising results in this section are; (1) The parameters are stable in stock market 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 non-linearity. 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 the stock market and bond return contemporaneous coefficients. In the stock market, these variables only explain 6 percent of the variation, but they explain almost 75 percent of the variation of the Bond coefficients.

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

References

Arias, E. F., Hausmann, R., and Rigobon, R. (1998). Contagion in bond markets. *IDB Working Paper.*

Bae, K.-H., Karolyi, G. A., and Stulz, R. M. (2000). A new approach to measuring financial contagion. *NBER Mimeo 7913.*

Baig, T. and Goldfajn, I. (1998). Financial markets contagion in the asian crises. *IMF Mimeo.*

Baig, T. and Goldfajn, I. (2000). The russian default and the contagion to brazil. *Universidade Catolica, Mimeo.*

Boyer, B. H., Gibson, M. S., and Loretan, M. (1999). Pitfalls in tests for changes in correlations. *Federal Reserve Boars, IFS Discussion Paper No. 597R.*

Calvo, G. (1999). Contagion in emerging markets: When wall street is a carrier. *University of Maryland*, Mimeo.

Calvo, G. and Mendoza, E. (2000). Rational contagion and the globalization of security markets. *Journal of International Economics*, 51:79–113.

Calvo, S. and Reinhart, C. (1995). Capital inflows to latin america: Is there evidence of contagion effects. *Mimeo. World Bank and International Monetary Fund.*

Cashin, P., Kumar, M., and McDermott, C. J. (1995). International integration of equity markets and contagion effects. *IMF Working Paper WP/95/110.*

Chen, S. and Khan, S. (1999). $\sqrt{n}$-consistent estimation of heteroskedastic sample selection models. *University of Rochester, Mimeo.*

Edwards, S. and Susmel, R. (2000). Interest rate volatility and contagion in emerging markets: Evidence from the 1990's. *UCLA, Mimeo.*

Eichengreen, B. and Mody, A. (2000). Contagion from the russian crisis: Who was infected and why? *UC Berkeley, Mimeo.*

Eichengreen, B., Rose, A., and Wyplosz, C. (1996). Contagious currency crises. *NBER Working Paper 5681.*

Favero, C. and Giavazzi, F. (2000). Looking for contagion: Evidence from the 1992 ERM crisis. *Bocconi University, Mimeo.*

Fisher, F. M. (1976). *The Identification Problem in Econometrics.* Robert E. Krieger Publishing Co., New York, second edition.

Forbes, K. (1999). How are shocks propagated internationally? firm-level evidence from the russian and asian crises. MIT Mimeo.

Forbes, K. and Rigobon, R. (1999). No contagion, only interdependence: Measuring stock market co-movements. *NBER Working Paper, 7267.*

Forbes, K. and Rigobon, R. (2000). Measuring contagion: Conceptual and empirical issues. *MIT mimeo.*

Froot, K., O'Connell, P., and Seasholes, M. (2000). The portfolio flows of international investors. *Harvard University, Mimeo.*

Gelos, G. and Sahay, R. (2000). Financial markets spillovers in transition economies. *IMF, Mimeo.*

Glick, R. and Rose, A. (1998). Contagion and trade: Why are currency crises regional? *Mimeo.*

Goldstein, M., Reinhart, C., and Kaminsky, G. (2000). *Assessing Financial Vulnerability : An Early Warning System for Emerging Markets.* Institute for International Economics.

Gregorio, J. D. and Valdés, R. (2000). Crisis transmission: Evidence from the debt, tequila and asian flu crises. *Universidad Catolica de Chile, Mimeo.*

Honore, B. E. (1992). Simple estimation of a duration model with unobserved heterogeneity. *Econometrica*, 58(2):453–73.

Honore, B. E., Kyriazidou, E., and Udry, C. (1997.). Estimation of type 3 tobit models using symmetric trimming and pairwise comparisons. *Journal of Econometrics*, 76(1-2):107–28.

Horowitz, J. (1992). A smoothed maximum score estimator for the binary response model. *Econometrica*, 60:505–531.

Horowitz, J. (1993). Semiparametric estimation of a work-trip mode choice model. *Journal of Econometrics*, 58:49–70.

Kaminsky, G. and Reinhart, C. (2000). The center and the periphery: Tales of financial turmoil. *GWU, Mimeo.*

Karolyi, G. A. and Stulz, R. M. (1996). Why do markets move together? an investigation of u.s. - japan stock return comovements. *The Journal of Finance*, 51(3):951:986.

King, M. and Wadhwani, S. (1990). Transmission of volatility between stock markets. *Review of Financial Studies*, 3(1):5–33.

Klein, R. and Vella, F. (2000). Identification and estimation of the binary treatment model under heteroskedasticity. *Rutgers mimeo.*

Kodres, L. and Pritsker, M. (1999). A rational expectations model of financial contagion. *Mimeo. Board of Governors of the Federal Reserve System.*

Longuin, F. and Slonik, B. (1995). Is the correlation in international equity returns constant: 1960-1990. *Journal of International Money and Finance*, 14(1):3–26.

Loretan, M. and English, W. B. (2000). Evaluation "correlation breakdowns" during periods of market volatility. *Federal Reserve Board, Mimeo.*

Manski, C. (1985). Semiparametric analysis of discrete response: Asymptotic properties of the maximum score estimator. *Journal of Econometrics*, 27:313–334.

Masson, P. (1997). Monsoonal effects, spillovers, and contagion. *IMF Mimeo.*

Powell, J. L. (1986). Symmetrically trimmed least squares estimation for tobit models. *Econometrica*, 54:1435–60.

Rigobon, R. (1999). Does contagion exists? *The Investment Strategy Pack, Banking Department of the BIS.*

Rigobon, R. (2000a). Identification through heteroskedasticity: The bivariate case. *MIT Mimeo. http://web.mit.edu/rigobon/www/.*

Rigobon, R. (2000b). On the measurement of the international propagation of shocks: Is the transmission stable? *MIT Mimeo: http://web.mit.edu/rigobon/www/.*

Rigobon, R. (2000c). A simple test for stability of linear models under heteroskedasticity, omitted variable, and endogneous variable problems. *MIT Mimeo: http://web.mit.edu/rigobon/www/.*

Rijckeghem, C. V. and Weder, B. (2000). Financial contagion: Spillover effects through banking centers. *University of Basel, Mimeo.*

Ronn, E. (1998). The impact of large changes in asset prices on intra-market correlations in the stock and bond markets. *Mimeo.*

Sentana, E. and Fiorentini, G. (1999). Identification, estimation and testing of conditional heteroskedastic factor models. *CEMFI mimeo.*

Stulz, R. (1999). International portfolio flows and security markets. *The Charles A. Dice Center for Reseach in Financial Economics*, WP 99-3.

A Measuring the channels under simultaneous equations using OLS .

Assume a simple set up where

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

where

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

Note that in this case the interrelationship between all variables is 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 lot of algebra):

$$\begin{aligned} \hat{\beta}_1 &= \alpha + \alpha\left(1+\alpha\right)\sigma_{\varepsilon}\frac{\alpha\sigma_{\eta 1} - \left(1-\alpha\right)\sigma_{\eta 2}}{\alpha^2\sigma_{\eta 1}\sigma_{\varepsilon} + \alpha^2\sigma_{\eta 2}\sigma_{\varepsilon} + \sigma_{\eta 1}\sigma_{\eta 2}} \\ \hat{\beta}_2 &= \alpha + \alpha\left(1+\alpha\right)\sigma_{\varepsilon}\frac{\alpha\sigma_{\eta 2} - \left(1-\alpha\right)\sigma_{\eta 1}}{\alpha^2\sigma_{\eta 1}\sigma_{\varepsilon} + \alpha^2\sigma_{\eta 2}\sigma_{\varepsilon} + \sigma_{\eta 1}\sigma_{\eta 2}} \end{aligned}$$

where the difference in the estimates is

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

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 smallest coefficient. In the limit, assume that the variance of $x_{2,t}$ goes to infinity then the estimates are

$$\begin{aligned}\hat{\beta}_1 &= \alpha + \alpha(1+\alpha)\sigma_{\varepsilon}\frac{\alpha}{\alpha^2\sigma_{\varepsilon} + \sigma_{\eta 2}} \\ \hat{\beta}_2 &= \alpha + \alpha(1+\alpha)\sigma_{\varepsilon}\frac{-(1-\alpha)}{\alpha^2\sigma_{\varepsilon} + \sigma_{\eta 2}}.\end{aligned}$$

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

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 from 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 if 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 if changes in $\phi()$ can be found too. Assume there is a shift in the structural coefficients:

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

which imply the following reduced forms

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

Because, in the VAR we are imposing that the lag coefficients have 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 from, then will be described by:

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

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

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

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 coefficients A and/or Γ change.

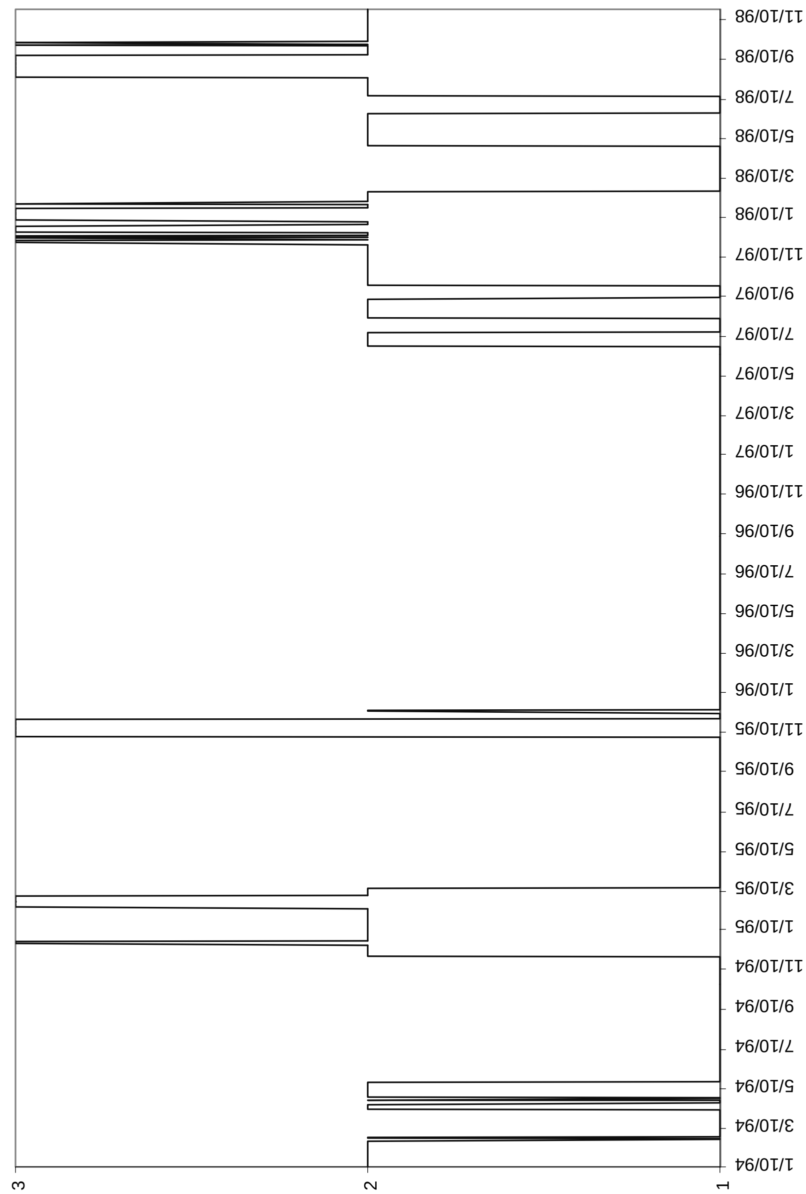

Figure 1: Regimes in the Stock Market data.

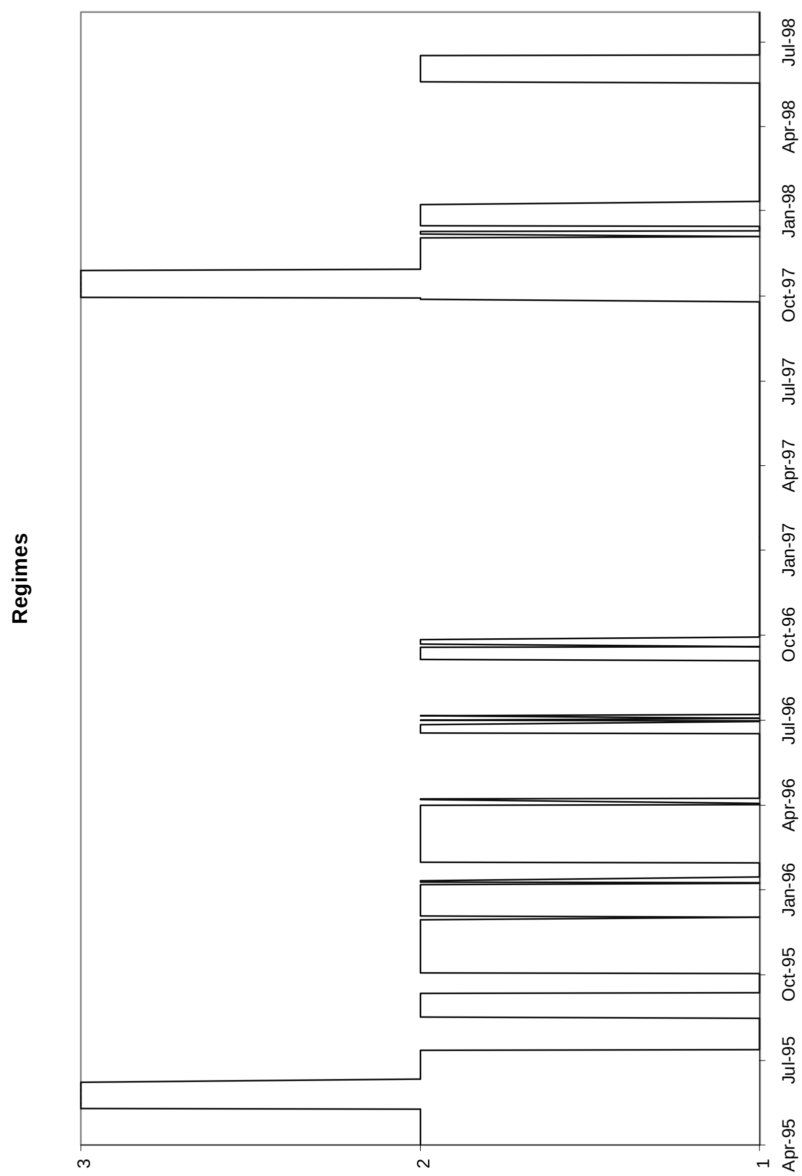

Figure 2: Regimes in the Bond Market.