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Detecting shift-contagion in currency and bond markets

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Abstract

This paper investigates why financial market crises often increase the interdependence between assets associated with different countries. Two sources of increased co-movement in asset returns are considered: (i) larger common shocks operating through standard cross-country linkages and (ii) changes in the structural transmission of shocks across countries, referred to as “shift-contagion”. To examine this issue, we develop a method for detecting shift-contagion with three notable features. First, parameters corresponding to the structural transmission of shocks across countries are identified in the presence of changing volatility regimes for the shocks. Second, the timing of changes in volatility is endogenously estimated instead of being exogenously assigned. Third, the countries in which crises originate need not be known or even included in the analysis. We apply the method to currency returns for developed countries and bond returns for emerging-market countries.

Keywords: Contagion; Financial market crises; Regime switching; Asset markets; Structural transmission

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1. Introduction

The spillover of crises from one financial market to another is loosely referred to as contagion, but precise definitions of contagion are many. One is that contagion occurs whenever

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asset returns associated with different countries co-vary in excess of what would be implied by the usual commercial, financial, and institutional links between countries. Another more narrow definition is that contagion occurs whenever shocks spread through herding behaviour in financial markets. A third broader definition refers to any increased co-movement between asset returns during crises as contagion. A fourth definition, referred to as "shift-contagion", suggests that to qualify as contagion, increased co-movement between asset returns during crises must be driven by change in the structural transmission of shocks across countries, rather than just a change in size of underlying shocks.

Given this multiplicity of definitions, it is not surprising to find widely varying opinions as to which crisis events cause or have caused contagion.[1] Early tests for a shift in the way shocks are transmitted across countries suggested the existence of contagion. For example, King and Wadhwani (1990) modeled contagion as a spillover of volatility from one financial market to another in the presence of imperfect information availability across markets. They considered a number of tests for volatility spillovers, including estimating time-varying correlations between equity returns in international markets. They found correlations increased significantly just after the October 1987 stock market crash. Other studies, including Bennett and Kelleher (1988) and Lee and Kim (1993) reached similar conclusions. However, Forbes and Rigobon (2002) argued that the conclusions from these and similar studies might be misleading due to the simultaneous nature of financial interactions and the presence of heteroskedasticity in equity returns.[2] For example, in the case of heteroskedasticity, they pointed out that when the variances of two assets increase (as they typically do during periods of crises), their correlation also increases regardless of whether or not the structural transmission of shocks between these assets changes. Taking such econometric concerns into account, a number of recent studies have concluded that there is, in fact, little or no evidence of contagion in financial markets. For example, Forbes and Rigobon (2002) and Rigobon (2001) found little incidence of shift-contagion in equity and bond markets during the Mexican, Asian, and Russian crises of the 1990s. Similarly, Rigobon (2003a) concluded that no shift-contagion occurred between 1994 and 1999 in the Brady bond markets of Argentina and Mexico.

In this paper we develop a method for detecting shift-contagion with three notable features that are designed to address concerns about the previous empirical literature. First, the parameters related to the structural transmission of common shocks across countries are identified in the presence of regime-switching volatility in the common shocks. In particular, structural identification occurs as long as the heteroskedasticity in idiosyncratic structural shocks is not perfectly synchronous with the heteroskedasticity in the common structural shocks. This is an example of "identification through heteroskedasticity" (see Sentana and Fiorentini, 2001; Rigobon, 2003a). In terms of testing for shift-contagion, if the change in structural impact coefficients is proportional given a change in volatility regime, it suggests a change in the size of

[1] The literature on contagion is vast and includes Baig and Goldfajn (1999, 2001), Bordo and Murshid (2001), Buiter, Corsetti, and Pesenti (1998), Calvo and Medoza (2000a,b), Claessens, Dornbusch, and Park (2001), Eichengreen, Rose, and Wyplosz (1996), Favero and Giavazzi (2002), and Kaminsky and Reinhart (2000), among others discussed in this paper. See Kaminsky, Reinhart, and Végh (2003) for a recent survey.

[2] A number of recent papers have pointed out the pitfalls in interpreting changes in estimated correlations as evidence of contagion, including Bekaert, Harvey, Ng (2005), Boyer, Gibson, and Loretan (1999), Caporale, Cipollini, and Spagnolo (2005), Corsetti, Pericoli, and Sbracia (2001, 2002), Forbes and Rigobon (2001, 2002), Karolyi (2003), and Rigobon (2001, 2003a,b).

shocks, but not in the structural transmission of shocks.[3] Importantly, this approach addresses the econometric concerns raised by Forbes and Rigobon (2002) about early studies of contagion. Second, the timing of changes in volatility is endogenously estimated, instead of being exogenously assigned. There is considerable evidence of Markov regime switching in asset markets.[4] Furthermore, the estimated regimes tend to match with events such as the Mexican, Asian and Russian crises of the 1990s. While endogenously estimating regimes obviously lowers the power of any test of contagion versus exogenously assigning the correct timing based on an ex post dating of crises, it is not always clear a priori what the correct timing should be. Meanwhile, results for tests of contagion can be quite sensitive to even small changes in the dating of crises (see Rigobon, 2003b).[5] Third, the countries in which crises originate need not be known or even included in the analysis. While crises often can be linked to specific countries, there are sometimes more general crises driven by large common shocks such as movements in U.S. macroeconomic variables, changes to international demand conditions, liquidity shocks, or changes in attitudes towards risk (see Calvo, 2002). Methods that assume crises are always caused by large idiosyncratic shocks in one country and look for spillovers to other countries will mistakenly find evidence of contagion whenever common shocks affect more than one country simultaneously. A related drawback of such methods is that the country generating the crisis may not always be known with certainty. For example, it is difficult to assign the instability in the European monetary system in the early 1990s to only one country, as many of them were experiencing a crisis at the same time. Our method detects common shocks, regardless of their source, and produces evidence of shift-contagion only if the structure of their simultaneous transmission to any pair of countries is fundamentally altered by crises.

We apply our method to investigate the presence of shift-contagion in currency markets for developed countries and bond markets for emerging-market countries. A priori, one might expect evidence of shift-contagion would be harder to detect in the currency markets for developed countries than bond markets for Latin American countries, in part because the currency markets are relatively less volatile. However, confirming the power of our test, we reject the null hypothesis of no shift-contagion for a number of currency returns, especially for European countries. Meanwhile, confirming the results in Rigobon (2003a), we find little evidence of shift-contagion in Latin American bond markets.

The paper proceeds as follows. Section 2 presents our model and explains the assumptions required for its identification. Section 3 describes the data and reports diagnostic tests that provide general support for our modeling assumptions. Section 4 reports model estimates and results for a number of diagnostic tests of the model. Section 5 reports results for our test of shift-contagion and provides some interpretation of the results. Section 6 concludes with a brief discussion of policy implications.

[3] Our test is similar to Sims and Zha (2004), who consider a change in the structural transmission of monetary shocks versus a change in their size by examining whether the impact coefficients in a given equation of an identified structural VAR remain proportionate across changes in regime. While our test is similar to theirs, our approach to structural identification is completely different.

[4] For exchange rates, see Engel and Hamilton (1990) and more recent studies including Beine, Laurent, and Lecourt (2003), Bollen, Gray, and Whaley (2000), and Wu and Chen (2001). For international interest rate data, see Ang and Bekaert (2002a,b), Edwards and Susmel (2003), and references therein. For international equities, see Bekaert and Harvey (1995), Edwards and Susmel (2001), and references therein.

[5] Also, modeling the regime-switching process allows us to make more general inferences about causality. In particular, we can examine whether high volatility common shocks cause contagion instead of whether a specific historical event caused contagion on a one-off basis. Considering this more general form of causality makes our results more useful for predictive rather than just descriptive purposes.

2. Model

In this section, we develop an empirical model of changing interdependence between two assets (e.g., two foreign currencies or two foreign bonds). Let r_{1t} and r_{2t} denote continuously compounded returns on the two assets. Conceptually, the returns can be decomposed as follows:

$$r_{it} = \mu_i + u_{it}, \tag{1}$$

where μ_i is the expected return on asset i, with $i = 1, 2$ throughout the remainder of the paper, and u_{it} is a forecast error reflecting unexpected news about the asset. Corresponding to an assumption of serially uncorrelated returns, the expected return is constant and the forecast error has mean zero and is uncorrelated across time (i.e., $E_t[u_{it+k}] = 0$ for all $k > 0$).[6] Meanwhile, for two assets in the same general market (e.g., the foreign exchange market or the bond market), the forecast errors are contemporaneously correlated ($E[u_{1t}u_{2t}] \neq 0$).

Contemporaneous correlation between forecast errors implies the existence of common structural shocks to the asset returns. In particular, we can decompose each forecast errors into common and idiosyncratic structural shocks:

$$u_{it} = \sigma_{cit} z_{ct} + \sigma_{it} z_{it}, \tag{2}$$

where z_{ct} is the common shock, the z_{it} is an idiosyncratic shock, and σ_{cit} and σ_{it} determine the impact of the structural shocks on the asset returns. In particular, the variance of the z shocks are normalized to unity, giving the σ impact coefficients the interpretation of standard deviations of the structural shocks. As such, we normalize the impact coefficients to be positive, except for σ_{c2t}, which can be positive or negative in order to allow for a positive or negative correlation between u_{1t} and u_{2t}. The shocks have mean zero and are uncorrelated both across time and with each other ($E_t[z_{jt+k}] = 0$ for all $k > 0$ and $E[z_{jt} z_{j't}] = 0$ for $j \neq j'$, where $j = c, 1, 2$ throughout the remainder of the paper).

We use the impact coefficients on the common shocks to investigate why the interdependence between two assets changes over time. For example, suppose that an increased co-movement between asset returns during financial market crises reflects larger common shocks operating through standard market linkages. Then, both σ_{c1t} and σ_{c2t} will be larger during crises. However, they will both increase in proportion to the larger size of the common shocks. That is, the ratio $\sigma_{c1t}/\sigma_{c2t}$ will remain unchanged before and after the onset of a crisis. By contrast, suppose that crises produce a change in the structural transmission of common shocks to the two countries under consideration, as would be the case under shift-contagion. Then, the ratio $\sigma_{c1t}/\sigma_{c2t}$ will be different during crises than in normal times. Thus, we can test for shift-contagion by estimating the impact coefficients for the common shocks and determining whether or not their ratio changes during crises.

Given the setup in (1)–(2), the main challenge is how to estimate the impact coefficients for the common shocks. Note that the variance–covariance matrix for the forecast errors can be represented in terms of the σ coefficients:

$$\Sigma_t = \begin{bmatrix} \sigma_{c1t}^2 + \sigma_{1t}^2 & \sigma_{c1t} * \sigma_{c2t} \\ \sigma_{c1t} * \sigma_{c2t} & \sigma_{c2t}^2 + \sigma_{2t}^2 \end{bmatrix}. \tag{3}$$

[6] As discussed in the next section, the assumption of serially uncorrelated returns is more tenable for the currency returns than for the bond market returns. Thus, for the bond market returns, we consider a specification of time-varying expected returns, which, for simplicity of presentation, we describe in the next section.

Therefore, we can use estimates of the variance–covariance matrix $\boldsymbol{\Sigma}_t$ to make inferences about σ_{c1t} and σ_{c2t} and to test for shift-contagion.

It is not immediately obvious that σ_{c1t} and σ_{c2t} will be identified given $\boldsymbol{\Sigma}_t$. Indeed, if the variances of the structural shocks remain constant, the impact coefficients will not be identified. In particular, there are only three moments corresponding to the forecast error variances and covariance, while there are four structural parameters:

$$\mathrm{var}(u_{1t}) = \sigma_{c1}^2 + \sigma_1^2, \tag{4}$$

$$\mathrm{var}(u_{2t}) = \sigma_{c2}^2 + \sigma_2^2, \tag{5}$$

$$\mathrm{cov}(u_{1t}, u_{2t}) = \sigma_{c1}\sigma_{c2}. \tag{6}$$

Of course, with constant variances, there would be no change in the interdependence between the two assets over time. Therefore, there would be no shift-contagion, by definition. On the other hand, in the presence of regime switching in the volatility of the structural shocks, there can be changes in the interdependence between assets. In this case, the structural impact coefficients may be identified.

For our model, we assume that each type of structural shock switches between low volatility and high volatility regimes, although only regime switching in the common shocks is necessary for identification of σ_{c1t} and σ_{c2t}.[7] In terms of the structural impact coefficients in (2), the regime switching can be represented as follows:

$$\sigma_{cit} = \sigma_{ci}(1 - S_{ct}) + \sigma_{ci}^* S_{ct}, \tag{7}$$

$$\sigma_{it} = \sigma_i(1 - S_{it}) + \sigma_i^* S_{it}, \tag{8}$$

where the state variables $S_{jt} = \{0, 1\}$. We normalize the regimes such that an asterisk corresponds to higher volatility (i.e., $|\sigma^*| > |\sigma|$). Then, to see identification, consider the following moments related to a high volatility regime for each structural shock:

$$\mathrm{var}(u_{1t}|S_{ct} = 1) = \sigma_{c1}^{*2} + \sigma_1^2, \tag{9}$$

$$\mathrm{var}(u_{2t}|S_{ct} = 1) = \sigma_{c2}^{*2} + \sigma_2^2, \tag{10}$$

$$\mathrm{cov}(u_{1t}, u_{2t}|S_{ct} = 1) = \sigma_{c1}{}^*\sigma_{c2}{}^*, \tag{11}$$

$$\mathrm{var}(u_{1t}|S_{1t} = 1) = \sigma_{c1}^2 + \sigma_1^{*2}, \tag{12}$$

$$var(u_{2t}|S_{2t} = 1) = \sigma_{c2}^2 + \sigma_2^{*2}. \tag{13}$$

[7] More precisely, the requirement for identification is some heterogeneity in the heteroskedasticity of the different structural shocks. Given regime-switching common shocks, homoskedastic idiosyncratic shocks would satisfy this requirement, but so would regime-switching idiosyncratic shocks, as long as the changes in regimes are not perfectly correlated across different types of shocks.

Combined with the three moments in (4)–(6) corresponding to low variance regimes, these five moments are sufficient to identify the eight structural parameters in (7)–(8).[8] This approach is an example of "identification through heteroskedasticity".

We complete the model by specifying how the volatility regimes evolve over time. In order to allow for sudden jumps between high and low volatility, we assume that the volatility regimes are Markov switching:

$$Pr\left[S_{jt} = 0 | S_{jt-1} = 0\right] = q_j, \tag{14}$$

$$Pr\left[S_{jt} = 1 | S_{jt-1} = 1\right] = p_j. \tag{15}$$

Under this specification, the timing of changes in volatility is endogenously estimated instead of being exogenously assigned ex post. This approach stands in contrast to a number of papers looking at shift-contagion, including Rigobon (2001, 2003a,b), Forbes and Rigobon (2001), and Favero and Giavazzi (2002), in which crises are identified ex post based on "conventional wisdom" or as occurring whenever a shock is two or three standard deviations greater than average.[9]

The complete model is given by (1)–(2) (7)–(8) and (14)–(15). Then, given data on asset returns and an assumption of Normality for the underlying structural shocks, we can estimate the parameters via maximum likelihood using the techniques for Markov-switching models presented in Hamilton (1989).

3. Data

In principle, the model presented in the previous section can be applied to any pair of assets. In this paper we examine two categories of assets: currencies for Australia, Germany, Japan, Norway, Sweden and Switzerland, and Brady bonds for Mexico, Brazil, Venezuela and Argentina. Exchange rates for the currencies are quoted relative to the US dollar at weekly frequency and extend from the week of January 2, 1985 to the week of June 6, 2001. We did not use a systematic method in choosing these currencies except that we sought to use the Deutsche Mark as a proxy for the Euro. Thus, we excluded other countries that are part of the Euro-zone from the set of foreign exchange data. The bond data are weekly spread-yields on the EMBI index constructed by JP Morgan and are US-dollar-denominated. The bond yields extend from the week of January 2, 1991 to the week of September 19, 2001 for all cases except Argentina where they start the week of May 5, 1993. For both currencies and bonds, we calculate continuously compounded returns by taking natural logs, differencing, and multiplying by 100 to get percentages.

Table 1 reports results for a number of diagnostic tests for the asset return data. In particular, we test for serial correlation, Normality, autoregressive conditional heteroskedasticity (ARCH),

[8] There are additional moments corresponding to the simultaneous occurrence of high volatility regimes for more than one type of structural shock. Thus, the structural parameters are potentially overidentified by sample moments, although these additional moments may not be particularly relevant if the high volatility regimes for different structural shocks do not coincide very often in the sample.

[9] Caporale, Cipollin, and Spagnolo (2005) endogenously estimate regimes in a test of shift-contagion in East Asian stock markets during the period of June 1997–June 1998. However, instead of using Markov switching, they determine the timing of crisis as corresponding to the dates that would maximize the value of their test statistic for shift-contagion. The computational burden of their approach (including determining the bootstrap distribution of their test statistic) constrains their analysis to consider only one possible crisis during a relatively short period of time. By contrast, endogenous estimation via the assumption of Markov-switching volatilities allows us to consider much longer sample periods that potentially include multiple crises.

Table 1
Diagnostic tests for asset returns

	Q(1)	LM(1)	Q(4)	LM(4)	Jarque–Bera	ARCH(1)	ARCH(4)	LR
Currency returns, developed countries								
Australia	2.04	2.03	17.72***	15.27***	707.17***	59.05***	66.09***	133.37***
Germany	0.15	0.15	4.19	3.95	99.90***	0.93	26.88***	55.02***
Japan	0.38	0.38	10.14**	9.41**	480.30***	8.88***	11.18**	83.97***
Norway	0.16	0.16	2.80	2.72	145.84***	3.53*	24.91***	83.59***
Sweden	0.35	0.35	2.92	2.98	600.97***	0.01	19.74***	75.39***
Switzerland	0.04	0.04	5.29	5.23	50.25***	0.24	13.70***	32.63***
Bond returns, emerging-market countries								
Argentina	5.16**	5.15**	27.37***	25.69***	1640.01***	4.45**	17.20***	169.50***
Brazil	12.86***	12.84***	43.25***	36.56***	7107.59***	2.40	23.14***	282.16***
Mexico	1.79	1.80	14.40***	14.18***	394.84***	39.72***	73.90***	173.68***
Venezuela	1.22	1.22	16.37***	17.27***	1838.93***	1.05	41.17***	142.71***

$Q(k)$ refers to the Ljung–Box test for no serial correlation up to lag k, LM(k) is the Breusch–Godfrey Lagrange Multiplier test for no serial correlation up to lag k, J–B is the Jarque–Bera test for the null of Normality, ARCH(k) is the Lagrange Multiplier test for no ARCH effects of order k, and LR is the likelihood ratio statistic for the null of no Markov switching in the variance. *** denotes significance at 1% level, ** denotes significance at 5% level, and * denotes significance at 10% level. All test statistics have a $\chi^2(k)$ distribution under the null hypothesis, except for the LR test. The significance for the likelihood ratio test of Markov-switching is based on Garcia (1998).

and Markov-switching volatility. The tests for serial correlation suggest some predictability for all of the bond returns, but generally not for the currency returns. Reflecting skewness and excess kurtosis, the hypothesis of Normality can be strongly rejected in all cases. There also appears to be some form of conditional heteroskedasticity in all cases. Meanwhile, a constant variance assumption can be strongly rejected in favour of Markov-switching volatility in all cases. We note that the strength of this finding is unambiguous despite the nonstandard distribution of the likelihood ratio statistic due to the presence of nuisance parameters. Based on the critical values provided in Garcia (1998), we can reject the null hypothesis at the 1% level in every case. Thus, there is strong support for the regime-switching heteroskedasticity that serves as a prerequisite for our shift-contagion identification methodology.

In terms of the apparent serial correlation in bond returns, we speculate that the short-horizon predictability could reflect a risk premium that varies with the level of volatility in the bond market. Specifically, for our model of bond returns only, we replace the assumption of a constant expected return in (1) with an assumption that the expected return is time-varying and depends on the state of the common shock:

$$\mu_{it} = \mu_i(1 - S_{ct}) + \mu_i^* S_{ct}, \tag{16}$$

Note that we do not relate the expected return to the idiosyncratic shocks, which are uncorrelated with the common shocks and, therefore, provide diversifiable risk that should not be priced according to basic financial theory (e.g., the CAPM). In the next section, we present diagnostic tests to support this assumption for the bond returns.

4. Estimates

Table 2 reports estimates of model parameters related to common structural shocks. While the impact coefficients in the low volatility regime, σ_{c1} and σ_{c2}, vary greatly across countries, they

Table 2
Estimates of impact coefficients for common shocks

	σ_{c1}	σ_{c2}	σ_{c1}*	σ_{c2}*	γ
Currency returns, developed countries					
Australia/Germany	0.106 (0.054)	1.249 (0.225)	1.393 (0.211)	2.082 (0.254)	7.88
Australia/Japan	0.362 (0.215)	−0.327 (0.188)	1.096 (0.115)	0.992 (0.147)	1.00
Australia/Norway	0.248 (0.113)	0.690 (0.243)	1.415 (0.177)	1.708 (0.211)	2.30
Australia/Sweden	0.232 (0.062)	0.832 (0.042)	1.424 (0.162)	1.598 (0.174)	3.20
Australia/Switzerland	0.103 (0.084)	0.963 (0.086)	1.426 (0.188)	1.893 (0.150)	7.04
Germany/Japan	0.743 (0.046)	0.901 (0.054)	1.555 (0.141)	2.096 (0.159)	1.11
Germany/Norway	1.290 (0.047)	1.109 (0.038)	1.931 (0.110)	1.851 (0.102)	1.12
Germany/Sweden	1.264 (0.054)	1.217 (0.054)	1.728 (0.065)	1.274 (0.048)	1.31
Germany/Switzerland	1.383 (0.044)	1.510 (0.051)	2.212 (0.174)	2.003 (0.159)	1.21
Japan/Norway	0.841 (0.053)	0.665 (0.055)	2.113 (0.150)	1.178 (0.097)	1.42
Japan/Sweden	0.823 (0.056)	0.663 (0.084)	2.044 (0.155)	1.094 (0.096)	1.51
Japan/Switzerland	0.834 (0.049)	0.949 (0.090)	2.116 (0.189)	1.692 (0.207)	1.42
Norway/Sweden	1.023 (0.037)	1.020 (0.033)	1.894 (0.113)	1.814 (0.110)	1.04
Norway/Switzerland	1.087 (0.040)	1.375 (0.056)	1.851 (0.104)	1.835 (0.114)	1.28
Sweden/Switzerland	1.037 (0.037)	1.490 (0.052)	1.969 (0.163)	1.915 (0.161)	1.48
Bond returns, emerging-market countries					
Argentina/Brazil	4.598 (0.473)	4.592 (0.556)	17.455 (3.779)	17.431 (3.697)	1.00
Argentina/Mexico	3.483 (0.321)	5.456 (0.309)	8.824 (1.098)	14.590 (1.283)	1.06
Argentina/Venezuela	5.096 (0.259)	3.732 (0.286)	21.945 (3.713)	17.535 (3.060)	1.09
Brazil/Mexico	3.249 (0.226)	4.007 (0.239)	14.194 (1.516)	12.695 (1.319)	1.38
Brazil/Venezuela	4.084 (0.596)	3.301 (0.527)	18.825 (2.900)	15.049 (2.381)	1.01
Mexico/Venezuela	5.098 (0.214)	2.998 (0.261)	6.837 (2.281)	13.875 (4.542)	3.45

Standard errors are reported in parentheses.

are of similar magnitude for a given country. For example, the standard deviation of common shocks in the low volatility regime is small for Australia, ranging between 0.103 and 0.362. By contrast, it is large for Mexico, ranging from 4.007 and 5.456. Meanwhile, the impact coefficients in the high volatility regime, σ_{c1}^*, and σ_{c2}^*, are more similar across countries, at least within the currency and bond markets. For currency returns, the standard deviations range between 0.992 and 2.212. For bond returns, they range between 6.837 and 21.945. Consistent with the idea of shift-contagion, the implication of these results is that common shocks have disparate effects on different countries in normal times, but even very different countries get lumped together during crises.

In order to consider the implications of the estimates for shift-contagion, we also report a ratio of the estimated impact coefficients in Table 2. The ratio reveals whether impact coefficients in the high volatility regime are proportional to the impact coefficients in the low volatility regime. Again, the coefficients would be proportional if crises correspond to a change in the size of shocks, but not a change in the structural transmission of the shocks across countries. Our statistic, denoted γ, is constructed as follows:

$$\gamma \equiv \max\left\{ \left| \frac{\sigma_{c1}^* \sigma_{c2}}{\sigma_{c1} \sigma_{c2}^*} \right|, \left| \frac{\sigma_{c1} \sigma_{c2}^*}{\sigma_{c1}^* \sigma_{c2}} \right| \right\}. \tag{17}$$

In particular, γ is the ratio of the impact coefficients in the high volatility regime to the ratio of the impact coefficients in the low volatility regime. For straightforward comparison across country pairs, we consider the absolute value of the ratios and we normalize the order of the

Table 3
Diagnostic tests for standardized residuals and model specification

	Q(1)	LM(1)	Q(4)	LM(4)	Jarque–Bera	ARCH(1)	ARCH(4)	LR
Currency returns, developed countries								
Australia	0.19	0.19	8.03*	7.54	10.44***	0.47	3.04	266.28***
Germany	0.06	0.06	4.97	4.69	10.11***	0.45	13.27***	235.46***
Japan	1.55	1.54	11.30**	9.92**	17.77***	5.96**	6.52	235.90***
Norway	0.66	0.66	4.32	4.11	3.35	0.07	6.32	267.39***
Sweden	0.30	0.30	3.52	3.39	32.52***	0.65	11.96**	428.83***
Switzerland	0.01	0.01	5.21	4.99	6.56**	0.30	4.78	179.24***
Bond returns, emerging-market countries								
Argentina	0.30	0.30	5.50	5.72	5.28*	0.45	7.68*	299.39***
Brazil	0.16	0.16	8.05*	8.36*	2.69	0.87	4.43	303.33***
Mexico	0.23	0.23	3.21	3.32	6.12**	1.36	6.49	299.39***
Venezuela	5.03**	10.42**	5.01**	4.38**	1.04	0.28	11.39**	291.41***

The table reports median test statistics for the different country pairs. $Q(k)$ refers to the Ljung–Box test for no serial correlation up to lag k, LM(k) is the Breusch–Godfrey Lagrange Multiplier test for no serial correlation up to lag k, J–B is the Jarque–Bera test for the null of Normality, ARCH(k) is the Lagrange Multiplier test for no ARCH effects of order k, and LR is the likelihood ratio statistic for the null of no Markov switching in the variances of model shocks. *** denotes significance at 1% level, ** denotes significance at 5% level, and * denotes significance at 10% level. All test statistics have a $\chi^2(k)$ distribution under the null hypothesis, except for the LR test. The significance for the likelihood ratio test of Markov-switching is based on Monte Carlo analysis using the bootstrap procedure discussed in Hansen (1996).

countries such that γ is greater than or equal to 1. In some cases in Table 2, the estimated ratio is essentially equal to 1, which corresponds to a change in the size of shocks only. However, in other cases, the change in the impact coefficients is extremely disproportionate, with the estimated γ as high as 7 for Australia/Germany and Australia/Switzerland. While these cases are suggestive of shift-contagion, the large standard errors for the underlying parameter estimates cast some doubt on the significance of the evidence for shift contagion. In the next section, we consider a formal likelihood ratio test of shift-contagion.

Before conducting the formal test of shift-contagion, we check the appropriateness of our model specification, including the key assumption of regime switching in the volatility of common shocks. Table 3 reports the results for a number of diagnostic tests. First, we examine whether the standardized model residuals display the same degree of serial correlation, non-Normality, and heteroskedasticity displayed by the underlying data in Table 1. Because there are multiple sets of standardized residuals for each country, we report median test statistics for different country pairs, although we note that the results are similar across country pairs. In general, the standardized residuals display much less serial correlation than the asset returns, supporting our assumptions for expected returns. Normality can still be rejected in most cases. However, the violations of Normality are clearly much less severe than before. Also, having accounted for Markov-switching volatility, we find much less evidence for ARCH effects in the standardized residuals.[10] Second, we consider a likelihood ratio test for Markov switching as specified in (7)–(8) and (14)–(15) against the null hypothesis of no regime changes in the variances of the common and idiosyncratic shocks. The likelihood ratio statistic has a

[10] Furthermore, even though there are still rejections of the specification assumptions in some cases, there is no correspondence between the cases where we reject and particular findings in terms of shift-contagion.

nonstandard distribution due to the presence of nuisance parameters. Therefore, we employ the bootstrap procedure discussed in Hansen (1996) to construct the test statistic distribution under the null and find relevant critical values.[11] Given the simulated distributions, we find p-values of 0.01 for the actual likelihood ratio statistics in every case. Therefore, we can reject the null hypothesis of no regime switching for every country pair.

5. Test

The point estimates in the previous section suggest the possibility of shift-contagion in a number of cases. We formally test for its presence using a likelihood ratio statistic for the following hypotheses:

$$H_0 : \frac{\sigma_{c1}^*}{\sigma_{c2}^*} = \frac{\sigma_{c1}}{\sigma_{c2}} \text{ vs. } H_1 : \frac{\sigma_{c1}^*}{\sigma_{c2}^*} \neq \frac{\sigma_{c1}}{\sigma_{c2}}, \tag{18}$$

where the null hypothesis corresponds to no shift-contagion and the alternative hypothesis corresponds to shift-contagion. Given general support for our model specification, including the Markov-switching assumption, the likelihood ratio statistic has a $\chi^2(1)$ distribution under the null hypothesis of no shift-contagion.[12]

Table 4 reports the likelihood ratio test results. In terms of the currency returns, we can strongly reject the null hypothesis of no shift-contagion for all of the European country pairs, except when Norway and Sweden are considered together. The likelihood ratio statistics range from 16.551 for Germany/Norway to 46.932 for Sweden/Switzerland. Also, for Japan, we can reject in most cases. The likelihood ratio statistics range from 0.470 for Germany/Japan to 6.433 for Japan/Sweden. However, for Australia, we are unable to reject at conventional levels. The likelihood ratio statistics range from 0.481 for Australia/Sweden to 2.643 for Australia/Japan.[13] In terms of the bond returns, we can only reject the null hypothesis of no contagion when Mexico is included in the country pair. For the other country pairs, the likelihood ratio statistics range from 0.000 for Argentina/Brazil and Brazil/Venezuela to 0.900 for Argentina/Venezuela.

[11] Specifically, imposing the parameter estimates of the null, we generate data (one draw) from the restricted model. With this generated data, we estimate the null and alternative models and obtain a simulated likelihood ratio statistic. We make 100 such draws to capture a simulated distribution of the likelihood ratio statistic under the null hypothesis.

[12] In addition to the Markov-switching assumption, the likelihood ratio test is predicated on the assumption that the impact coefficients in (18) are nonzero or, equivalently, that the asset returns are correlated for each country pair. An examination of the contemporaneous correlations between the asset returns supports this assumption. Correlations are generally above 0.5 and they are statistically significant at the 1% level in every case.

[13] In comparing these results to those in Table 2, it is apparent that the significance levels for the currency returns are sometimes influenced more by precision of the impact coefficient estimates than by the point estimates. This sensitivity to the precision of estimates suggests that the failure to reject may be due to lack of power of the test in some circumstances. In particular, for the country pairs that include Australia, the estimated effect of the high volatility regime tends to be highly disproportionate, but analysis of the timing of regime changes reveals that there were relatively few of the common high volatility shocks necessary to identify the structural impact coefficients. The exception is the case of Australia/Japan, for which the evidence in Table 4 for shift-contagion is strongest. In this case, there were a larger number of common high volatility shocks and the point estimates, despite being proportional, still suggest shift-contagion because the sign of the impact of common shocks changes. That is, currency returns for Australia and Japan go from having a negative correlation in the low volatility regime to a positive correlation in the high volatility regime, which is certainly indicative of a change in the structural transmission of common shocks.

Table 4
Likelihood ratio test for shift-contagion

Currency returns, developed countries

	Australia	Germany	Japan	Norway	Sweden
Germany	2.221 (0.126)				
Japan	2.643 (0.104)	0.470 (0.493)			
Norway	0.077 (0.781)	16.551 (0.000)	6.275 (0.012)		
Sweden	0.481 (0.488)	41.807 (0.000)	6.433 (0.011)	0.524 (0.469)	
Switzerland	0.605 (0.437)	26.133 (0.000)	6.173 (0.013)	25.948 (0.000)	46.932 (0.000)

Bond returns, emerging-market countries

	Argentina	Brazil	Mexico
Brazil	0.000 (1.000)		
Mexico	2.012 (0.156)	8.780 (0.003)	
Venezuela	0.900 (0.343)	0.000 (1.000)	7.731 (0.005)

Likelihood ratio statistic is for the null of no contagion against the alternative of contagion for the indicated country pairs. The test statistic has a $\chi^2(1)$ distribution under the null hypothesis. p-values are reported in parentheses.

For the country pairs that include Mexico, the likelihood ratio statistics range from 2.012 for Argentina/Mexico to 8.780 for Brazil/Mexico.[14]

In order to interpret the findings from the likelihood ratio tests, it is useful to examine the probabilities of high volatility regimes for some of the country pairs. Fig. 1 displays probabilities of high volatility regimes for common shocks to European currency returns. The high volatility in 1991, 1992, and 1993 is present in every case and is likely related to difficulties over the Exchange Rate Mechanism (ERM) requiring foreign exchange intervention for countries seeking to join the common Euro currency. The crisis clearly affected all of the countries, including those outside of the ERM. However, while the structural links appear to change in most cases, the high volatility common shocks have the same proportionate effect as the low volatility common shocks for Norway/Sweden, suggesting no change in the structural links between these two countries. Meanwhile, Fig. 2 displays probabilities of high volatility regimes for common shocks to Latin American bond returns. There are common high volatility regimes in early 1994, early 1995, late 1997, the second-half of 1998, and early 1999. The 1994 regime likely corresponds to the Venezuelan banking and currency crisis at the time, the 1995 regime likely corresponds to the Mexican crisis, the 1997 regime likely corresponds to the Asian crisis, the 1998 regime likely corresponds to the Russian crisis, and the 1999 regime likely corresponds to the Brazilian devaluation. It is notable that all of these common high volatility regimes are present even when the country that is the source of a given crisis is not included in a given country pair. Also, it is perhaps surprising that the Argentinean crisis in late 2000 and 2001 does not generally show up as a common high volatility regime, meaning that any ex post dating procedure that includes this crisis in the common regime would distort inferences about shift-contagion. What is most notable for the bond returns is the lack of shift-contagion for Argentina/Brazil, Argentina/Mexico, Argentina/Venezuela, and Brazil/Venezuela. The only

[14] For the bond returns, there is a direct correspondence between the point estimates in Table 2 and the likelihood ratio test results in Table 4, suggesting that the test has high power.

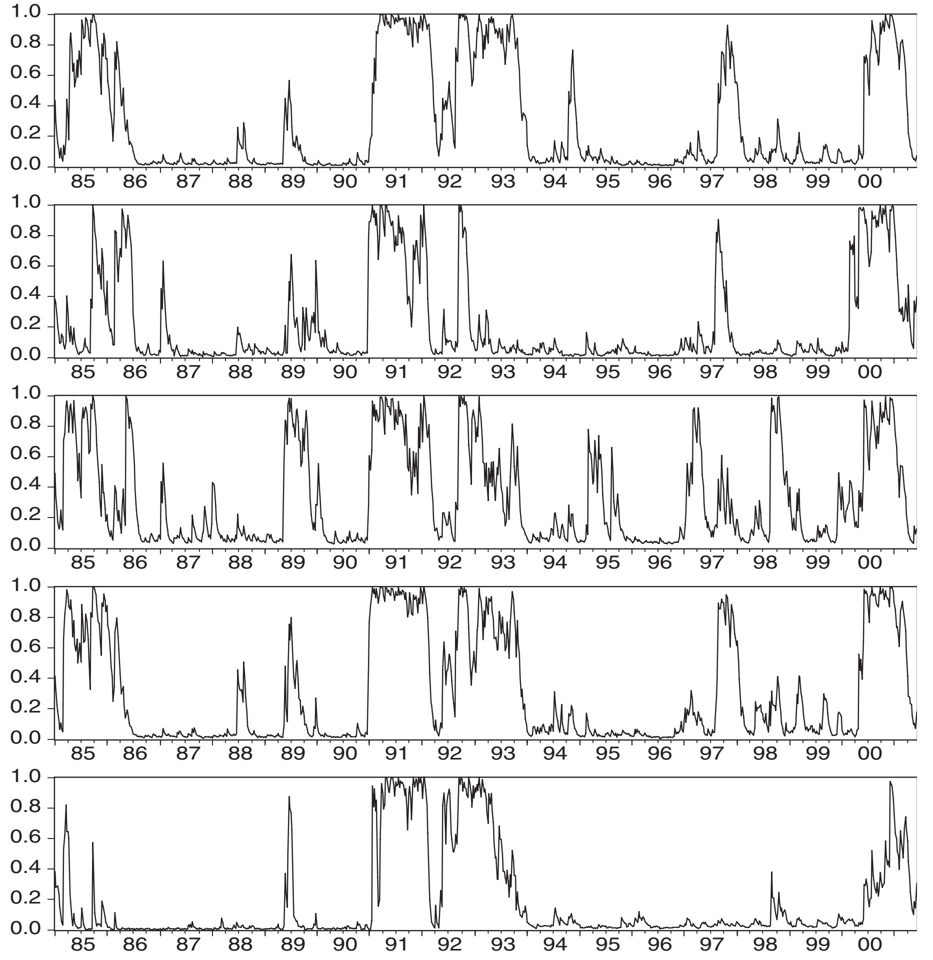

Fig. 1. The timing of high volatility regimes for common shocks to European currency returns. The five rows display the filtered probabilities of high volatility common shocks for Germany/Norway, Germany/Switzerland, Norway/Sweden, Norway/Switzerland, and Sweden/Switzerland, respectively.

evidence for shift-contagion occurs when Mexico is included in the country pair, suggesting that episodes such as the Mexican crisis in early 1995 altered the structural links between Mexico and the other countries, but not between the other countries.

6. Conclusions

One motivation of the contagion literature is to address how countries can reduce their vulnerability to external shocks during periods of heightened volatility. In this vein, it is important to understand whether a shock is transmitted across markets via channels that only appear during turbulent periods (crisis-contingent channels) or whether they are transmitted via links that exist in all states of the world. For Latin American countries, the empirical results presented in this paper suggest that shocks are generally transmitted via long-term linkages

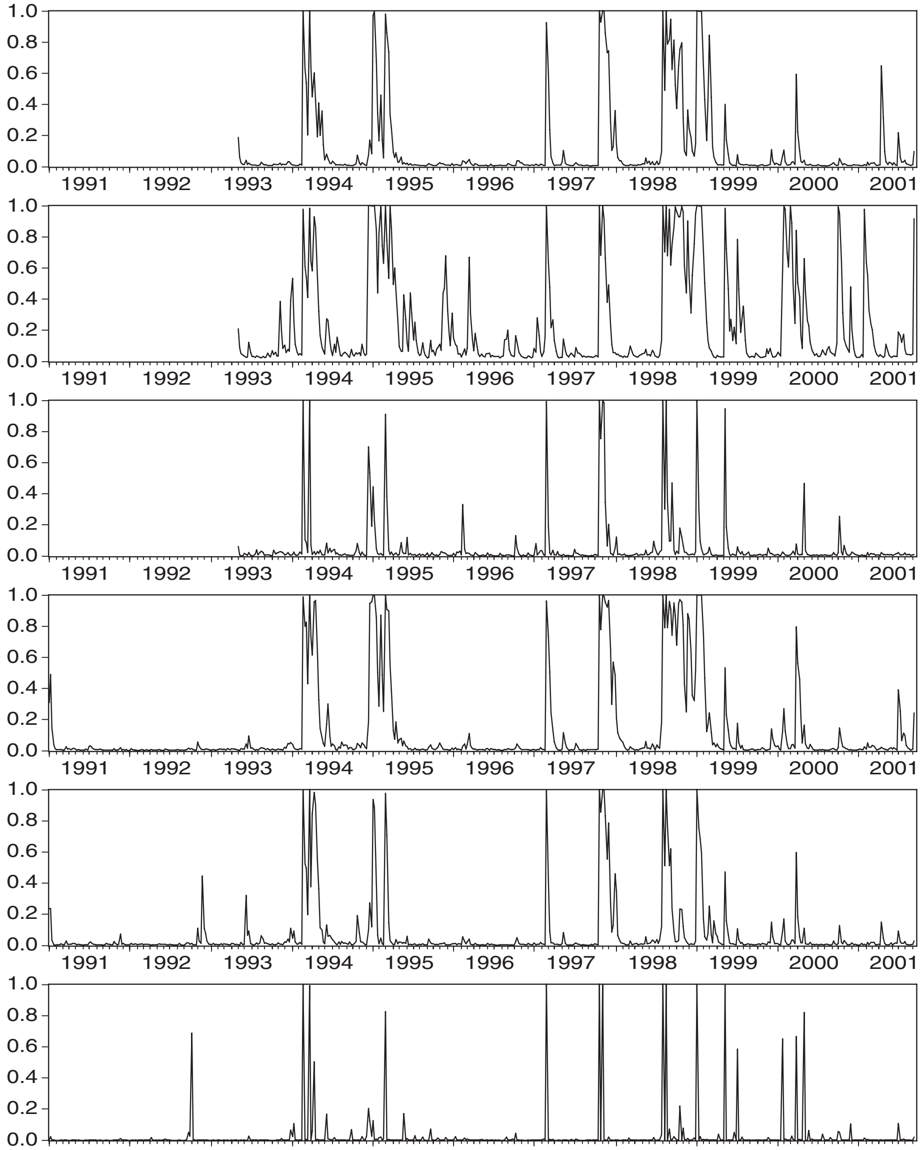

Fig. 2. The timing of high volatility regimes for common shocks to Latin American bond returns. The six rows display the filtered probabilities of high volatility common shocks for Argentina/Brazil, Argentina/Mexico, Argentina/Venezuela, Brazil/Mexico, Brazil/Venezuela, and Mexico/Venezuela, respectively.

between these countries, so that attempts at reducing their vulnerability to contagion via short-term or temporary strategies may be ineffective. On the other hand, for many of the developed countries, there is evidence to suggest that some shocks get transmitted only during turbulent periods. This would imply that certain short-term stabilizing policies, such as foreign exchange intervention or tighter monetary policy, could be warranted during periods of heightened volatility and crisis.

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