Bank of Canada Banque du Canada

Working Paper 2003-5 / Document de travail 2003-5

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ISSN 1192-5434

Printed in Canada on recycled paper

Bank of Canada Working Paper 2003-5

February 2003

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Abstract

The authors develop a new methodology to investigate how crises cause the relationship between financial variables to change. Two possible sources of increased co-movement between markets during high-variance episodes are considered: larger common shocks operating through standard market linkages, and a structural change in the propagation of shocks between markets, called "shift contagion." The methodology has three key features: (i) high- and low-variance episodes are model-determined, rather than exogenously assigned; (ii) the markets where crises originate need not be known; and (iii) the approach provides an unambiguous test of shift contagion. Applications to bivariate returns in currency markets of developed countries and bond markets of emerging-market countries suggest that shift contagion occurs among the former but not the latter.

JEL classification: F42, G15, C32
Bank classification: Financial markets; Econometric and statistical methods

Résumé

Les auteurs proposent une nouvelle méthodologie en vue d'étudier la façon dont les crises modifient les relations entre variables financières. Ils examinent deux sources possibles de hausse de la covariation entre les marchés durant les périodes de forte variance : la transmission des grands chocs communs par l'entremise des liens normaux entre marchés et la modification structurelle du mécanisme de propagation des chocs entre marchés (phénomène appelé en anglais *shift contagion*). La méthode utilisée présente trois caractéristiques importantes : i) les périodes de forte et de faible variance sont déterminées par le modèle plutôt que de façon exogène; ii) il n'est pas nécessaire de connaître les marchés où la crise prennent naissance; iii) la méthode fournit un test sans équivoque de la contagion liée à une modification structurelle. L'analyse bivariée de la corrélation des rendements incite à penser que ce type de contagion s'observe sur les marchés des changes des économies développées mais non sur les marchés obligataires des économies émergentes.

Classification JEL : F42, G15, C32
Classification de la Banque : Marchés financiers; Méthodes économétriques et statistiques

1. Introduction

It is well-known that equity, currency, or banking crises generate substantial real costs for the country in which they occur.[1] In addition, they can sometimes spill over to other countries. The recent Mexican, Asian, and Russian/Long-Term Capital Management (LTCM) crises are examples of shocks originating in one country that are believed to have spread to other nations and to have cost the international community significantly.

The transmission of crises from one country to another (or from one market to another) is loosely termed contagion, but precise definitions of contagion are many. One is that contagion occurs when the propagation of shocks is in excess of fundamentals; that is, when shocks have an impact beyond the amount channelled through the usual commercial, financial, and institutional ties between markets. Another, more narrow, definition is that contagion occurs when shocks spread through herding or irrational behaviour. A third definition refers to the transmission of shocks through any channels that cause markets to co-vary as contagion. A fourth, called shift contagion, suggests that contagion occurs when the propagation of shocks across markets increases systematically during crises.

Given these differing definitions, it is not surprising to find widely varying opinions as to which crisis events cause or have caused contagion. Even when there is agreement on the definition, conclusions often differ, depending on how empirical studies choose to quantify fundamentals.[2]

In this paper, we focus on shift contagion and develop a methodology to detect it statistically. In particular, we examine whether existing linkages between assets of different countries remain stable during crises, or whether they grow stronger. Our approach relies on testing for a recurring structural change in the relationship between assets of two markets.

Earlier tests for a shift in the way shocks are transmitted across countries have suggested the existence of contagion. For example, King and Wadhwani (1990) find that the correlation between international equities increases significantly after the October 1987 crash, and Lee and Kim (1993) arrive at a similar conclusion. But Forbes and Rigobon (1999) and others argue that the conclusions from such studies could be misleading, because the simultaneous nature of financial interactions and data heteroscedasticity are not taken into account. For example, in the case of heteroscedasticity, they point out that when the variances of two assets increase (as they typically do during periods of crises), their correlation coefficient will increase regardless of whether the transmission of shocks between these variables increases.

[1] For example, Thailand's 1997 crisis is estimated to have cost around 30 per cent of its GDP in bank recapitalization (World Bank 2000).

[2] For additional details, see, for example, Hernandez and Valdes (2001), Rigobon (2001), Forbes and Rigobon (2000), Goldstein, Kaminsky, and Reinhart (2000), Bordo and Murshid (2000), Chesnay and Jondeau (2000), and Eichengreen, Rose, and Wyplosz (1996).

Taking such econometric concerns into account, these authors conclude that there is, in fact, little or no contagion. For example, Lomakin and Paiz (1999) find low probabilities of contagion between various country bond markets when they compute the likelihood that a crisis will occur in one country given that it has occurred in another. Forbes and Rigobon (1999) and Rigobon (2001) find little incidence of shift contagion during the Mexican, Asian, and Russian/LTCM crises in various emerging-country equity and bond markets. Similarly, Rigobon (2000) concludes that no shift contagion occurred between 1994 and 1999 in the Brady bond markets of Argentina and Mexico.

Despite some advantages, however, these techniques have drawbacks. One is that crisis periods are designated as such ex post. That is, the beginning and ending dates of crises are determined exogenously. Yet, while there is relative agreement in the literature on the starting date of crises, there is far less consensus with respect to ending dates. The associated low-variance periods are generally also determined by a rule of thumb. Because test conclusions depend on the choice of the normal and crisis periods, such practices may lead to spurious results. A second disadvantage with some of these techniques is the ambiguity of how to interpret a rejection of the null hypothesis. These methods make the assumption that increases in the variance of returns during crises are caused entirely by increases in the idiosyncratic shock of the country in which the crisis originated. Therefore, a rejection of the null implies that either the propagation mechanism was unstable (i.e., shift contagion occurred) or variances of several countries increased simultaneously at the onset of the crisis.[3] A related drawback is that the country generating the crisis is assumed to be known, which may not always be the case.[4]

Our proposed methodology for detecting shift contagion, in addition to being valid in the presence of variable simultaneity and data heteroscedasticity, is not subject to the above concerns. First, crisis and low-variance periods are entirely model-determined, rather than exogenously assigned. Second, the country in which the crisis originated needs neither to be known nor to be included in the system being analyzed. Third, a rejection of the null hypothesis provides unambiguous evidence for shift contagion within the markets examined. We conduct our analysis on the bond markets of four emerging countries and on the currency markets of seven developed countries. The emerging-market data are included to allow comparison with previous studies, such as those by Rigobon (2000, 2001). In addition, we examine currency markets of developed countries. A priori, it is more difficult to detect a change in the propagation mechanism of shocks in these less-volatile markets. Thus, our finding of shift contagion among these assets indicates that our methodology has good power.

[3] The latter event is quite likely, given that common factors, such as unexpected commodity price shocks or the announcement of policy changes in a large economy, tend to increase the structural uncertainty in many economies together.

[4] For example, it is difficult to assign the instability in the European monetary system to only one country, as many of them were experiencing a crisis at the same time.

Section 2 describes our bivariate independent-switching model and explains the identification assumptions required in our framework. Section 3 presents the data, stylized facts, and arguments in favour of this identification strategy. These include univariate analyses of various asset returns; in particular, tests are conducted for the presence of two regimes and the calculation of correlations between different asset returns. Section 4 details the estimated model and indicates some of our findings. Section 5 describes the use of Hansen's (1996) simulation-based procedure to test for regime-switching (given the presence of non-identified parameters under the null hypothesis), and the tests for shift contagion. The results reveal strong evidence of shift contagion in some currency markets, but none in the Latin-American bond markets. Section 6 concludes.

2. An Independent-Switching Model

Our purpose is to study whether the interdependence between assets changes during turbulent times. We postulate a bivariate model where asset returns are correlated. Let r_{1t} and r_{2t} be asset returns of countries 1 and 2, respectively. Collecting these in the vector r_t, and assuming that they follow a vector autoregression, we can write:

$$r_t = \mu + \Phi(L) r_t + u_t, \tag{1}$$

where μ is the vector containing the drift terms of the two returns, $\Phi(L)$ is a lag polynomial, and u_t is the vector of disturbances. The latter are assumed to have zero mean and to be correlated. Thus, $E(u_{it}) = 0, i = 1, 2$ and $E(u_{1t}u_{2t}) \neq 0$. The non-zero correlation suggests the existence of underlying common shocks, so that we can decompose the disturbance terms into common and idiosyncratic structural shocks. Thus, we can write:

$$\begin{aligned} u_{1t} &= \sigma_{c1} z_{ct} + \sigma_1 z_{1t} \\ u_{2t} &= \sigma_{c2} z_{ct} + \sigma_2 z_{2t}, \end{aligned} \tag{2}$$

where z_{ct} is the common shock and $z_{it}, i = 1, 2$ are idiosyncratic shocks. The structural shocks are assumed to have zero mean and to be uncorrelated with each other. Therefore, $E(z_{it}) = 0, i = 1, 2, c$ and $E(z_{it}z_{jt}) = 0, i \neq j$. In addition, their variances are normalized to one, giving their loading coefficients the interpretation of standard deviations. The variance-covariance matrix of the disturbance terms is thus given by:

$$\Sigma = \begin{bmatrix} \sigma_{c1}^2 + \sigma_1^2 & \sigma_{c1}\sigma_{c2} \\ \sigma_{c1}\sigma_{c2} & \sigma_{c2}^2 + \sigma_2^2 \end{bmatrix}. \tag{3}$$

At this stage, not much can be learned about the propagation of shocks (i.e., the presence or absence of shift contagion), since the estimation of Σ yields only three reduced-form parameters. Indeed, compared with the four structural parameters in the model, only the ratio $(\sigma_{c1}/\sigma_{c2})$ can be identified. Nevertheless, we can determine whether shift contagion has occurred if common shocks do in fact come from two distinct regimes.[5] Let us denote these as "normal" and "turbulent" regimes, with the latter having a statistically higher variance than the former. Recalling that a common shock affects both equations of the model, its relative impact can then be compared across regimes, providing a basis for statistical testing of the hypothesis of shift contagion. That is, if a common shock changes not only the variance of specific assets but also their interdependence, we can say that there has been shift contagion. Thus, we can distinguish whether it is merely the size of the shocks (i.e., their impulses) that increases during crises periods, or whether impulses as well as the propagation mechanism change.

Crises can also originate in one country and not affect markets in other countries. Therefore, it is important to adequately separate large idiosyncratic shocks in the data from large common shocks. Accordingly, we allow for two possible variance regimes for each idiosyncratic shock in the model.

Let S_{it} be a state variable subject to two regimes (low and high variance) and associated with structural shock i. That is, $S_{it} = (0,1), i = c, 1, 2$. Defining δ as a "crisis multiplier" parameter that increases the impact of a structural shock on an asset return during a crisis, we can rewrite the model as:

$$\begin{aligned} u_{1t} &= \delta_{c1}(S_{ct}).\sigma_{c1}.z_{ct} + \delta_1(S_{1t}).\sigma_1.z_{1t} \\ u_{2t} &= \delta_{c2}(S_{ct}).\sigma_{c2}.z_{ct} + \delta_2(S_{2t}).\sigma_2.z_{2t}. \end{aligned} \tag{4}$$

In this notation, the different δs are functions of the state variables. In normal times, state variables take a value of zero and the $\delta_j(0), j = 1, 2, c1, c2$ are normalized to one. That is, the crisis multipliers are equal across countries during low-volatility periods and the variance-covariance matrix of $u_{jt}, j = 1, 2$ is given by the matrix Σ above. Conversely, during turbulent periods, state variables equal one and the crisis multipliers are given by $\delta_j(1) = \delta_j, \delta_j \geq 1, j = 1, 2, c1, c2$. Thus, another five reduced-form parameters associated with turbulent periods can be estimated. These are given by:

$$var(u_{1t}|S_{1t} = 1) = \sigma_{c1}^2 + \delta_1^2.\sigma_1^2, \tag{5}$$
$$var(u_{2t}|S_{2t} = 1) = \sigma_{c2}^2 + \delta_2^2.\sigma_2^2, \tag{6}$$
$$var(u_{1t}|S_{ct} = 1) = \sigma_1^2 + \delta_{c1}^2.\sigma_{c1}^2, \tag{7}$$
$$var(u_{2t}|S_{ct} = 1) = \sigma_2^2 + \delta_{c2}^2.\sigma_{c2}^2, \tag{8}$$
$$cov(u_{1t}, u_{2t}|S_{ct} = 1) = \sigma_{c1}.\delta_{c1}.\sigma_{c2}.\delta_{c2}. \tag{9}$$

The model is now identified, since only four new structural parameters were added. That is, there are a total of eight structural and eight reduced-form parameters.

[5] This approach is motivated by Rigobon's (2000) identification-through-heteroscedasticity technique.

We have yet to specify how the state variables themselves evolve. Rigobon (1999), Favero and Giavazzi (2000), and others use some type of ex post rule, such as designating the state as one of crisis when a shock is two or three standard deviations greater than average, or fixing the durations of crisis and tranquil periods subjectively.[6] A statistically more rigorous method is to estimate the state of the world endogenously, as in the regime-switching literature. We make the assumption that state variables are mutually independent and that they switch according to the transition probabilities given by:

$$P_i = Pr[S_{it} = 1], \quad i = 1, 2, c. \tag{10}$$

These probabilities are unconditional, to capture the idea that high-variance shocks are generally highly unpredictable. This completes the description of our model.[7]

To detect shift contagion, we examine the common-shock crisis multipliers. In the absence of shift contagion, a large unobserved news event that affects both asset returns should not change their interdependence. Thus, all of the increase in the variance and the correlation of returns will be due to the increase in the impulse of the common shock. Consequently, crisis multipliers for the two countries should remain equal. In other words, the null hypothesis of no shift contagion implies that:

$$H_0 : \delta_{c1}(1) = \delta_{c2}(1). \tag{11}$$

By contrast, if the arrival of a large common shock also causes the propagation mechanism to change, then we should observe statistically different values for the crisis multipliers. That is, shift contagion implies that:

$$H_1 : \delta_{c1}(1) \neq \delta_{c2}(1). \tag{12}$$

3. Data and Stylized Facts

The model described in section 2 is fairly general and, in theory, can be applicable to any pair of assets. In this paper, we examine two categories of assets: returns on the currencies of Australia, Canada, Germany, Japan, Norway, Sweden, and Switzerland (hereafter referred to as currency returns), and returns on the Brady bonds of Mexico, Brazil, Venezuela, and Argentina (hereafter referred to as bond returns). Specifically, bond returns are weekly spread-yields on the Emerging Markets Bond Index (EMBI) constructed by JPMorgan and are U.S.-dollar-denominated. For the first three countries, the data

[6] See also Forbes and Rigobon (2000), and Rigobon (2000, 2001).

[7] We ignore the possible impact of crises on the means of asset returns; that is, higher risk premiums may result during periods of higher uncertainty. This generalization is straightforward but left for future work.

extend from 2 January 1991 to 19 September 2001; those for Argentina start 5 May 1993 and end 19 September 2001. The exchange rates are quoted relative to the U.S. dollar at weekly frequency and extend from the week of 2 January 1985 to the week of 6 June 2001. We did not use a systematic method in choosing these currencies, except to use the mark as a proxy for the euro. We thus excluded the other 11 countries that are part of the euro zone from the set of foreign exchange data. Each return is described as the log difference of the asset multiplied by 100. Figures 1 to 3 plot these returns for each country.

Table 1 lists some stylized facts with respect to our data. We report the mean μ, variance σ^2, skewness, excess kurtosis, and autocorrelations $\rho(L)$ of order L for each asset return in our sample. The Canadian dollar displays the lowest volatility, and the Argentinian bonds display the highest.

Table 1
Stylized Facts on Asset Returns

Country	μ	σ^2	$skew$	$kurt$	$\rho(1)$	$\rho(2)$	$\rho(4)$
Currency returns, developed countries							
Australia	0.069	1.903	0.787	7.064	-0.042	0.074	0.088
Canada	0.024	0.369	0.144	3.908	0.041	-0.003	-0.036
Germany	0.027	2.469	-0.191	1.449	0.007	0.050	0.056
Japan	-0.061	2.403	-0.646	3.037	0.034	0.107	0.034
Norway	0.058	1.841	0.166	1.997	0.012	0.026	0.025
Sweden	1.087	2.214	0.456	6.869	-0.003	0.023	0.057
Switzer.	0.011	2.821	-0.364	0.980	0.029	0.032	0.078
Bond returns, emerging-market countries							
Mexico	-0.186	61.525	0.705	3.997	-0.059	0.150	-0.013
Brazil	-0.014	54.644	2.417	17.077	-0.153	0.224	0.020
Venezuela	0.001	59.846	1.667	8.318	0.046	0.153	-0.047
Argentina	0.133	82.530	1.634	9.129	-0.111	0.211	-0.018

We also conduct a number of tests on these returns and summarize the results in Table 2. These include Ljung-Box and Lagrange Multiplier tests for the hypothesis of no serial correlation at lag L, a Jarque-Bera test for normality, as well as a Lagrange Multiplier test for no heteroscedasticity of order L. First, we find that the hypothesis of normality is strongly rejected in all cases. In addition, we find little inertia in the first but much more in the second moments of most currency returns. For bond returns, we find evidence of autocorrelation and autoregressive conditional heteroscedasticity (ARCH) in all cases.

Table 2
Univariate Test Results

Country	$Q(2)$	$LM(2)$	$Q(10)$	$LM(10)$	$J-B$	$CH(2)$	$CH(4)$	LR
				Currency returns, developed countries				
Australia	0.132	0.141	0.013	0.083	0.000	0.000	0.000	109.48
Canada	0.406	0.394	0.410	0.363	0.000	0.002	0.000	18.41
Germany	0.239	0.241	0.343	0.327	0.000	0.000	0.000	30.24
Japan	0.001	0.001	0.014	0.022	0.000	0.001	0.003	73.92
Norway	0.628	0.622	0.317	0.264	0.000	0.000	0.000	37.92
Sweden	0.866	0.868	0.200	0.229	0.000	0.379	0.581	75.15
Switzer.	0.387	0.396	0.043	0.052	0.000	0.001	0.007	17.80
				Bond returns, emerging-market countries				
Mexico	0.001	0.001	0.023	0.013	0.000	0.000	0.000	130.02
Brazil	0.001	0.001	0.028	0.022	0.000	0.000	0.000	128.68
Venezuela	0.000	0.000	0.000	0.000	0.000	0.001	0.002	133.70
Argentina	0.000	0.000	0.000	0.000	0.000	0.000	0.000	241.94

Reported values are p-values in all cases except for the LR statistic. $Q(L)$ refers to the Ljung-Box test for no serial correlation at lag L, $LM(L)$ is the Lagrange Multiplier test for no serial correlation at lag L, $J-B$ is the Jarque-Bera test for the null hypothesis of normality, $CH(L)$ is the Lagrange Multiplier test for no heteroscedasticity of order L, and LR is the likelihood-ratio statistic for the null hypothesis of no independent switching in the variance.

We address the heteroscedasticity in the data by examining whether there are two distinct regimes in the variances of asset returns. For each case, we estimate a univariate model of returns that allows for a drift and for independent switching between two regimes in its variance. A likelihood-ratio test is then conducted for the null hypothesis of no independent switching in this variance and the obtained statistic is reported in Table 2. Under this null, the probability of switching does not exist and the distribution of the likelihood-ratio test statistic is thus non-standard. We therefore use the critical values provided by Garcia (1998), who derived this distribution analytically. We find that, for all of the assets examined, the null hypothesis is rejected at the 5 per cent level in favour of two regimes in the variance. This is a prerequisite for our shift contagion identification methodology.

Table 3 reports contemporaneous cross-correlations for the different pairs of asset returns. These somewhat reflect the extent to which countries have similar economies (such as the level of industrialization, amount of national debt, and productivity level), mutual trade, and financial and other fundamental linkages. Among the currency returns, we find that Australia and Canada generally exhibit low correlations with other countries, Germany and Switzerland have relatively high correlations, and the remaining countries have mixed outcomes. For bond returns, correlations are found to be fairly high in all of the considered cases. Therefore, it seems that there could well be common shocks affecting various country pairs.

Table 3
Contemporaneous Cross-Correlations

Currency returns, developed countries

	Australia	Canada	Germany	Japan	Norway	Sweden	Switzer.
Australia	1						
Canada	0.297	1					
Germany	0.211	0.169	1				
Japan	0.229	0.123	0.528	1			
Norway	0.253	0.200	0.884	0.465	1		
Sweden	0.217	0.191	0.750	0.392	0.785	1	
Switzer.	0.212	0.172	0.933	0.855	0.822	0.695	1

Bond returns, emerging-market countries

	Mexico	Brazil	Venezuela	Argentina
Mexico	1			
Brazil	0.695	1		
Venezuela	0.600	0.724	1	
Argentina	0.719	0.817	0.670	1

Figure 4 presents graphs of the Latin-American bond data in levels. The patterns show that, for the bond data, the relative yield premiums between countries have been fairly stable during the sample period, even though it is clear that individual country bond premiums increased substantially during the peso, Asian, and Russian crises. This observation suggests that the co-movements between these Latin-American bonds is high during both normal and crisis periods. Interestingly, Forbes and Rigobon (2000), using slightly different EMBI bond data, show that these premiums actually co-vary across very different emerging-market countries; for example, Morocco and Mexico or Brazil and Bulgaria. Since there are few fundamental or macroeconomic linkages (such as trade patterns) to explain these high correlations, Forbes and Rigobon suggest that this "excess interdependence" stems from market participant behaviour, where markets tend to extract signals from one country's ability to withstand shocks and apply this information to another country. Thus, market participants tend to trade the securities for these countries as a block.

Figures 5 and 6 show the log level of the foreign exchange data we have used. A pattern similar to that of the Latin-American bond data emerges for certain country pairs. Specifically, there is a high degree of correlation, in both normal and volatile periods, between Sweden and Norway, Germany and Switzerland, and, to a lesser extent, Australia and Canada. In sum, the results shown in Tables 1 to 3 and in Figures 4 to 6, collectively, indicate that the model described in section 2 is appropriate for examining shift contagion in these asset markets.

4. Model Estimation and Discussion

The assumption that common shocks exist is central to the model. Such shocks could be, for example, movements in U.S. macroeconomic variables, changes to international demand conditions, liquidity shocks, or changes in attitudes towards risk. We further divide these into normal-type and extraordinary or crisis-type common shocks, where the latter have a statistically higher variance. Examples of crisis-type common shocks are large unexpected changes in the U.S. federal funds rate or in world commodity prices, as well as major political announcements, wars, commercial bank failures, the possibility of country devaluations, and debt defaults.[8] As explained earlier, some will lead to shift contagion and some will not. For example, if a large and unexpected oil-price shock that originates from an OPEC decision to curb supply leads to a statistically significant increase in the variance of exchange rates in Canada and Australia, it will be considered to have been drawn from the "crisis" regime of common shocks. If the fundamental relationship between these two currency returns does not change, then this oil shock will not be classified as a contagion-generating type of shock. On the other hand, if a devaluation, such as that in Thailand in June of 1996, causes these same currency returns to exhibit a higher variance *and* alters the fundamental relationship between them during this period, then the devaluation will be considered to have generated shift contagion.

In the contagion literature, crisis-generating shocks are generally identified ex post. In other words, the origin and timing of such a shock is assumed to be known, in addition to when and where it might have spread, and when its effect finally dissipates.

[8] These shocks are similar to the ones seen, for example, in the 1994 Mexican peso crisis, the 1997 Asian crisis, and the 1998 Russian/LTCM crisis.

While such an approach might be economically informative, conclusions are nevertheless conditional on the considered path and timing of the shock.[9] We take a very different approach to detecting contagion. In particular, we are agnostic about a shock's location of origin, its cause and timing, and to which countries it may have spread.[10] We have the data statistically distinguish between common and idiosyncratic shocks, and classify these (again, statistically) into high- or low-variance regimes.[11] We conclude in favour of shift contagion only when large common news events lead to a statistical change in the relationship between assets. In other words, a rejection of the null hypothesis (described in equation (11)) indicates that common shocks in the data are sufficient to change the interrelationship between assets. In this respect, rejections of the null hypothesis provide strong evidence for the existence of shift contagion.

Having explained the methodology, we now describe its application. For now, we ignore any dynamics in the means of returns, as well as any increases in risk premiums during turbulent periods. These generalizations, although straightforward and pertinent, are left for future work. Instead, we obtain residuals simply by subtracting the mean from the returns.[12] For each bivariate case examined, the model features residuals of assets of the same market in two different countries. Estimation is carried out by maximum likelihood.

We show selected bond return results in Figures 7 to 9. These figures plot the estimated unconditional probabilities for a structural shock being in the high-variance regime, and are included for illustrative purposes. The closer the peaks are to 1.0, the higher the probability of being in the high-variance regime. These estimated probabilities are broadly consistent with the timing of known crisis events in these countries.[13]

Consider the case of Mexico and Argentina, in Figure 7. The top panel plots the unconditional probability of the idiosyncratic shock of Mexico being in the high-variance regime. The corresponding Argentinian idiosyncratic shock is plotted in the middle panel. The bottom panel plots the common shock probability. The latter show that there are high peak clusters in early 1994, from the end of 1994 to early 1995, at the end of 1997, around September-October 1998, and in early 1999. Three of these are compatible with

[9] The timing issue is particularly challenging. For instance, Rigobon (1999) fixes the duration of crises to 10 working days, and tranquil periods to 60 working days prior to a crisis. The conclusions of Rigobon's study thus depend on the accuracy of these approximations.

[10] Theoretically, our methodology allows for extraordinary common news events to originate from either or both countries included in the model, or from a country external to the system of equations. Given our weekly data frequency, a shock that originates in one country and that spreads within a week to the other will appear in the data as a large common shock.

[11] The existence of these regimes is key, especially for the common shocks in the data. Section 5 describes tests for the existence of these regimes.

[12] This assumption is actually quite suitable for the currency returns data.

[13] To conserve space, only selected results are described. The complete set of charts is available from the authors upon request.

the Mexican December 1994 crisis, the Asian 1996-97 crisis, and the 1998 Russian/LTCM crisis, respectively. In addition, the model does not classify the high-volatility shocks that affected Argentina around 2001 as being common to Mexico and Argentina.

Interestingly, the first peak in the common-shock panel seems to concur with the currency and banking crises that occurred in Venezuela in May 1994, whereas that of early 1999 seems to correspond to the Brazilian devaluation. These observations illustrate the usefulness of our method for capturing common shocks that occurred outside of the set of countries included in the empirical model.

An examination of the corresponding figures for the Mexico-Brazil and the Brazil-Argentina pairs reveals patterns of common shocks that are quite similar to the preceding case.[14]

Selected model results for currency returns are depicted in Figures 10 to 12. Again, we examine the plots of the estimated unconditional probabilities of shocks. Consider the case of Japan-Norway and Japan-Sweden, shown in Figures 10 and 11. For Sweden and Norway, there is a period of high-variance idiosyncratic shocks (middle panels) during the 1992 Exchange Rate Mechanism (ERM) crisis. This period of foreign exchange volatility, of course, did not affect Japan, and as such, does not appear in the bottom panel of these figures. In Figure 12, however, which plots the high-variance probabilities for the Sweden-Switzerland pair, the 1992 ERM crisis is a common shock to this pair (as it is for all of the European country pairs that we examine). Note also the similarities between Figures 10 and 11, which arise from the high correlation that exists between Sweden and Norway (Figure 6).

The bottom panel in Figure 13 shows the probability estimates of common large events affecting the Canadian and Australian currency returns. Some of the peaks that occur in the latter half of 1998 seem to correspond to the Russian/LTCM crisis. In addition, the Canadian idiosyncratic shocks in the middle panel exhibit a probability peak in 1995, which is compatible with a period of heightened concern regarding Quebec's desire for sovereignty.

In sum, our relatively simple framework appears to be able to distinguish own-country and common large news events that can be identified ex post as crisis-type. The question is whether the large, common shocks alter the propagation mechanism between asset pairs. This topic is addressed in section 5.

[14] During some of these high-variance common-shock periods, sometimes there are spillovers into our estimates of the idiosyncratic shocks. This is likely due to our use of independent switching for the probabilities, which puts greater emphasis on the simultaneous timing of shocks.

5. Testing and Results

We first statistically establish the existence of high- and low-variance regimes for the common shocks in our data. Although there is ample evidence for the existence of two regimes in the univariate cases (Table 2), it is important to ascertain the same for the model that contains common structural shocks, given that the validity of our outcomes depends strongly on this premise. We then test for the null hypothesis of no shift contagion within our bivariate model with the two variance regimes for the different structural shocks.

Testing for regime switching in the bivariate model cannot be carried out using standard asymptotic inference because, under the null hypothesis of no switching, the unconditional probability of switching, p_c, is not identified. Accordingly, we use Hansen's (1996) bootstrap technique to conduct this testing and to find relevant critical values. The statistic that we consider was suggested by Andrews (1993) and is the supremum likelihood ratio that results from a maximization over the space of the parameter p_c. Specifically, we proceed as follows:

(i) We estimate the null and alternative models by maximum likelihood and denote the obtained likelihoods as L_0 and L_1, respectively. The null model has no regime changes and is given by equation (2), while the alternative assumes two regimes in the variance of its common shock and a single regime for each idiosyncratic shock. That is,

$$\begin{aligned} u_{1t} &= \delta_{c1}(S_{ct}).\sigma_{c1}.z_{ct} + \sigma_1.z_{1t} \\ u_{2t} &= \delta_{c2}(S_{ct}).\sigma_{c2}.z_{ct} + \sigma_2.z_{2t}, \end{aligned} \tag{13}$$

along with equations (7), (8), and (9), where $S_{ct} = (0,1)$ with probability p_c. The likelihood-ratio statistic can then be calculated as $LR = 2\log(L_1/L_0)$.

(ii) With the parameter estimates obtained above, we generate data under the null. With this data we estimate the null model again and denote its likelihood value as $Lsim_0$. We also estimate the alternative model with this same data and for each fixed value of the p_c parameter. Since the probability has to fall in the range (0,1), our admissible space for this parameter is assumed to be $[0.1 - 0.9]$, and we consider values differing by increments of 0.1 within this set. The obtained likelihoods are denoted $Lsim_1(p_c)$ and the corresponding likelihood-ratio statistics are $LRsim(p_c) = 2\log(Lsim_1(p_c)/Lsim_0)$. We then determine the supremum among these likelihood ratios.

(iii) Step (ii) is repeated 100 times. Each time, new data are generated and the supremum likelihood ratio is obtained among the $LRsim(p_c)$ values. Thus, we obtain a

100-point distribution of generated-data supremum likelihood ratios. The test at the 5 per cent level then consists of referring the likelihood ratio LR obtained with the actual data to the 95th percentile of this distribution.

Applying the above bootstrap technique to our pairs of asset returns, we find that the null hypothesis is strongly rejected in favour of the alternative in all the considered cases.[15] Therefore, the evidence indicates the presence of high- and low-variance regimes of common shocks for these asset pairs.[16]

With the existence of the two regimes established, we can test the null hypothesis of no contagion. Thus, we estimate the system of equations (4) to (10) twice by maximum likelihood: once imposing the constraint in equation (11), and once without, as in equation (12). We then calculate the likelihood ratio given by $LR = 2\log(\hat{L}_1/\hat{L}_0)$, where $\hat{L}_1$ is the maximized value of the unconstrained likelihood function, and $\hat{L}_0$ is obtained by requiring that $\delta_{c1} = \delta_{c2}$. Under the null, this likelihood-ratio test statistic is asymptotically distributed as a χ^2 with one degree of freedom. We tabulate these LR statistics and their p-values in Table 4.

Test results suggest that there are indeed cases where shift contagion occurs. In particular, there is evidence, at the 5 per cent level, that the currency returns of Germany-Switzerland, as well as those of Sweden-Switzerland, have increased interdependence during turbulent times. Similarly, there is evidence at the 10 per cent level that currency pairs Australia-Norway, Germany-Sweden, Japan-Sweden, and Japan-Norway, behave differently at times of crises.

It is noteworthy that shift contagion is detected both for cases where the contemporaneous cross-correlations are less than 0.5 (Japan-Norway, Japan-Sweden, and Australia-Norway) and for cases where they are above (Germany-Switzerland, Germany-Sweden, and Switzerland-Sweden). Furthermore, among the cases where we do not detect shift contagion, some have high cross-correlations (for example, Norway-Switzerland) and some have low ones (Canada-Sweden). These observations imply that theories suggesting that contagion occurs strictly through fundamental links between countries (such as macroeconomic similarities in the two economies, and trade and financial dependencies) do not tell the whole story.

Indeed, an examination of the bond return results reinforces this point of view. The bottom half of Table 4 shows no evidence of shift contagion in any of the pairs of the Latin-American country returns examined. These results concur with the findings of Rigobon (2000) regarding returns on Brady bonds for Argentina and Mexico. That is, despite the high contemporaneous cross-correlations, and substantial increases in variances of returns

[15] For numerical tractability, we did not include regime-switching in the idiosyncratic shocks of the model.

[16] In particular, p-values are of the order of 0.01 for those cases where we later find evidence of shift contagion.

during turbulent periods, the propagation mechanism between assets seems to be stable for these Latin-American bond markets.

Table 4
Likelihood Ratio Statistics

	Australia	Canada	Germany	Japan	Norway	Sweden
Currency returns, developed countries						
Canada	0.387					
	(0.534)					
Germany	0.005	0.124				
	(0.941)	(0.724)				
Japan	0.000	0.000	1.509			
	(0.990)	(1.000)	(0.219)			
Norway	3.534	2.310	0.198	3.043		
	(**0.060**)	(0.129)	(0.656)	(**0.081**)		
Sweden	1.975	2.621	3.320	2.766	0.032	
	(0.160)	(0.105)	(**0.068**)	(**0.096**)	(0.859)	
Switzerland	0.961	0.234	8.357	1.146	0.374	12.695
	(0.327)	(0.629)	(**0.004**)	(0.284)	(0.541)	(**0.000**)

	Mexico	Brazil	Venezuela
Bond returns, emerging-market countries			
Brazil	1.560		
	(0.212)		
Venezuela	0.004	0.000	
	(1.000)	(1.000)	
Argentina	0.040	2.000	0.000
	(0.841)	(0.157)	(1.000)

Reported values are likelihood-ratio test statistics for the null hypothesis of no contagion for the indicated country pairs; p-values are in parentheses.

6. Conclusion

In this paper, we have developed a simple methodology to detect shift contagion in pairs of asset returns. We statistically separated idiosyncratic country shocks from common ones and distinguished between small and large shocks. Hansen's (1996) bootstrap procedure was used to test for the existence of high- and low-variance regimes in these common shocks. We then examined whether extraordinary news events alter the interrelationship between assets; that is, we tested for shift contagion.

Our technique offers a number of advantages over previous studies. Among them is the fact that high- and low-variance regimes of asset returns are model-determined rather than assigned ex post. Another is that our rejections of the null hypothesis of no contagion are unambiguous. In addition, our methodology does not require that the country where a crisis has generated be included in the system of equations examined. Applications to bond markets of emerging countries and to currency markets of developed countries reveal evidence of shift contagion in the latter but not the former.

One motivation of the contagion literature is to address how countries can reduce their vulnerability to external shocks during periods of heightened volatility. That is, the literature tries to determine whether short-term or temporary strategies aimed at this issue can be effective. In this vein, it is important to understand whether a shock is transmitted across markets via channels that appear only during turbulent periods (crisis-contingent channels) or whether they are transmitted via links that exist in all states of the world. The finding of shift contagion would imply that shocks are propagated via crisis-contingent channels.

For Latin-American countries, the empirical results described in this paper suggest that shocks are transmitted via long-term linkages 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 some of the developed currency markets, there is evidence to suggest that some shocks are transmitted only during turbulent periods. This would imply that certain short-term stabilizing policies, such as foreign exchange intervention or tighter monetary policy, may be warranted.

At this stage, the model has a number of simplifying assumptions. One is that it abstracts from having dynamics in the means of returns. Similarly, we do not consider any possible effects of changes in variances on these means. Another assumption is that regime changes occur according to unconditional probabilities. These issues are left for future research.

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Figure 1 - Foreign Exchange Returns

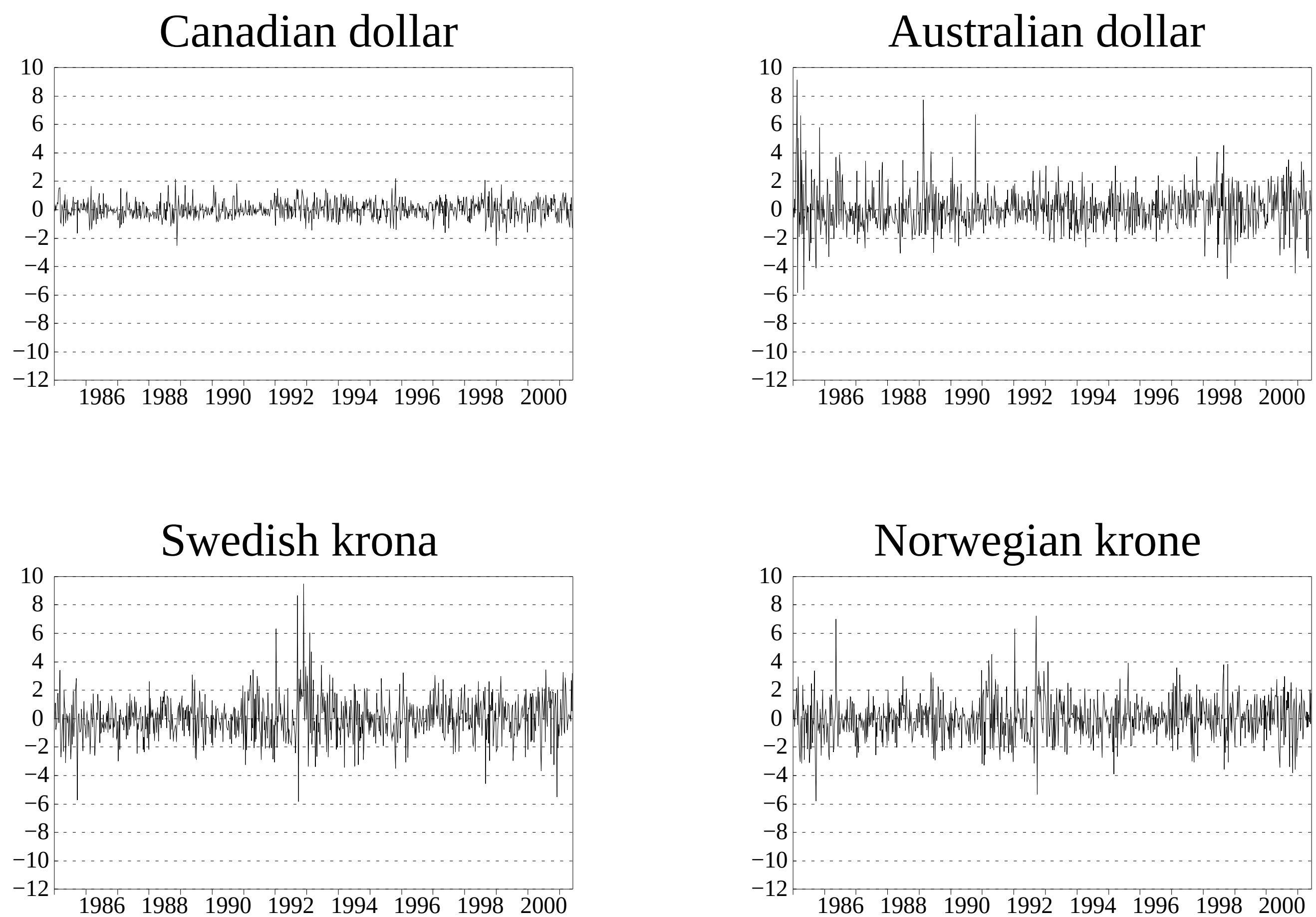


Figure 2 - Foreign Exchange Returns

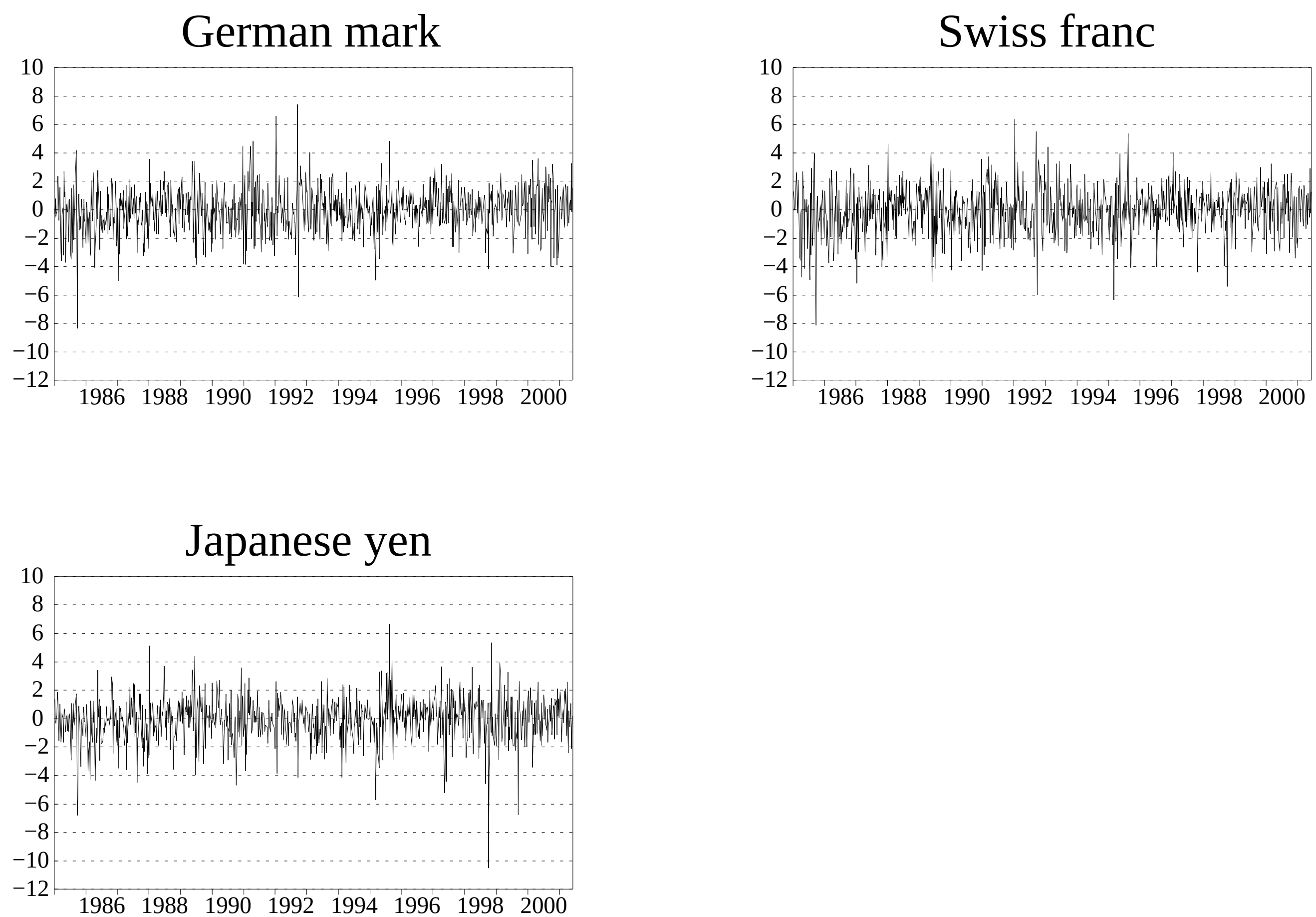


Figure 3 - Emerging-Country Bond Returns

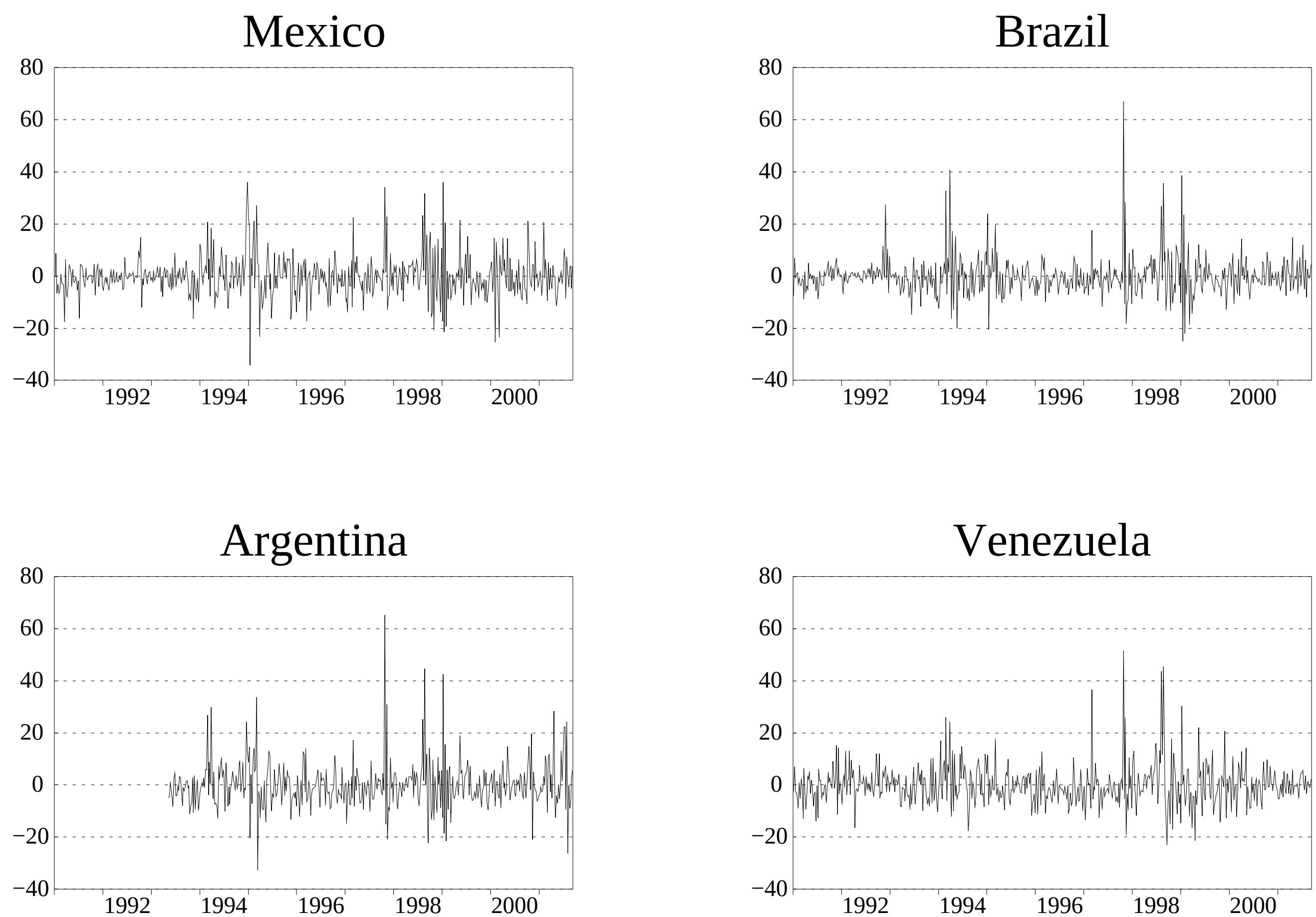
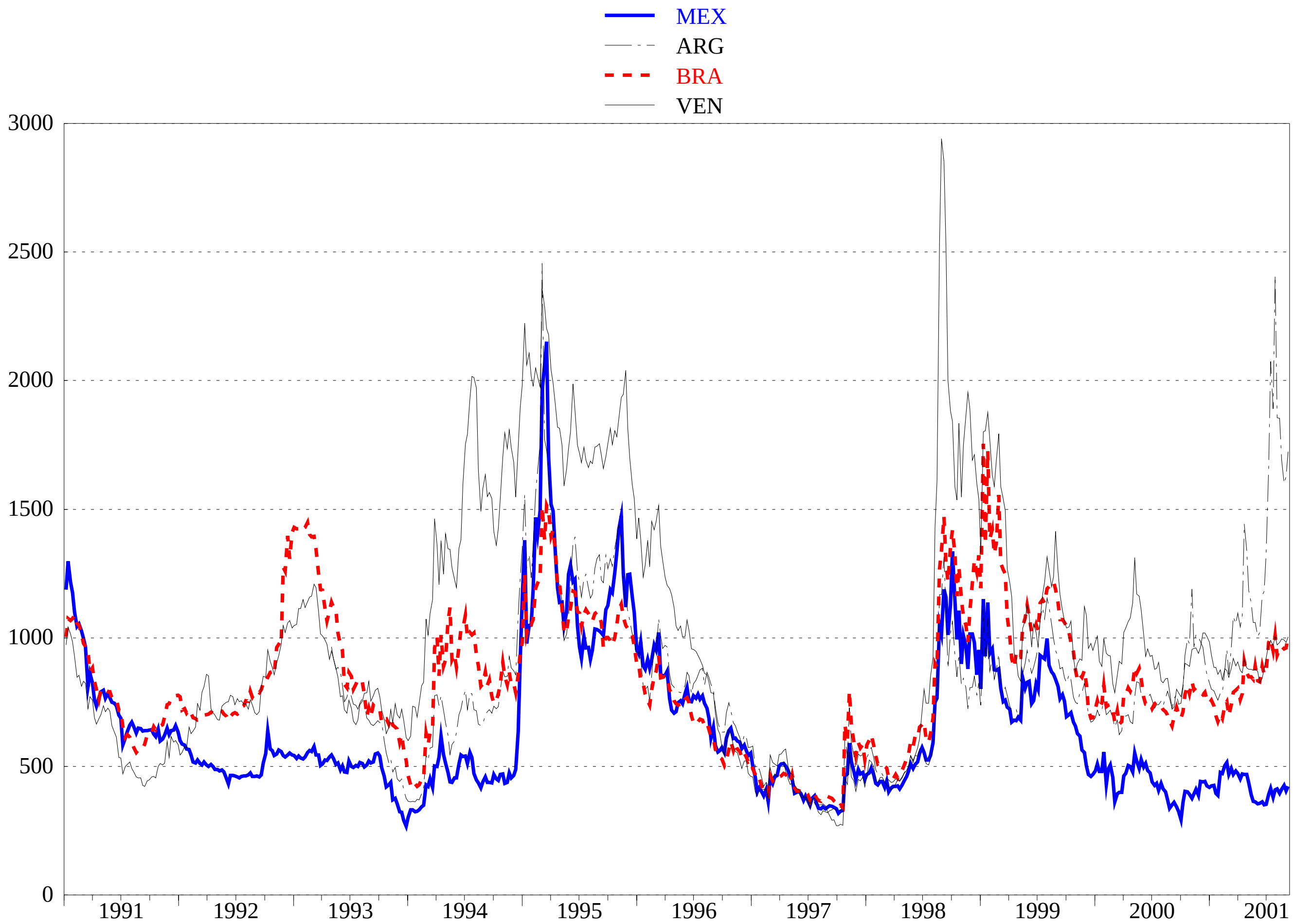


Figure 4 - Emerging-Country Bond Levels



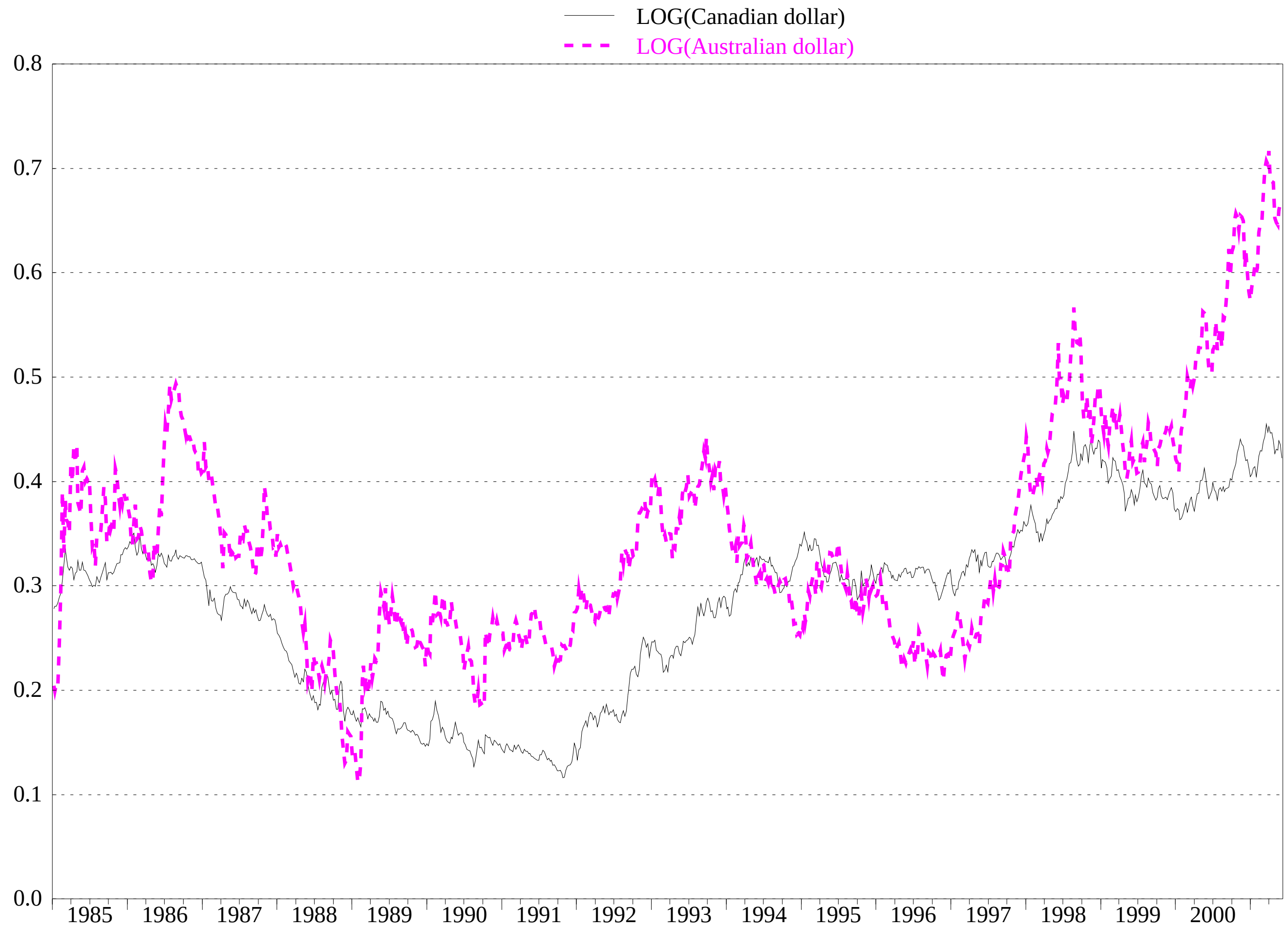


Figure 5 - Foreign Exchange Levels: Canadian dollar-Australian dollar

Figure 6 - Foreign Exchange (Log Levels)

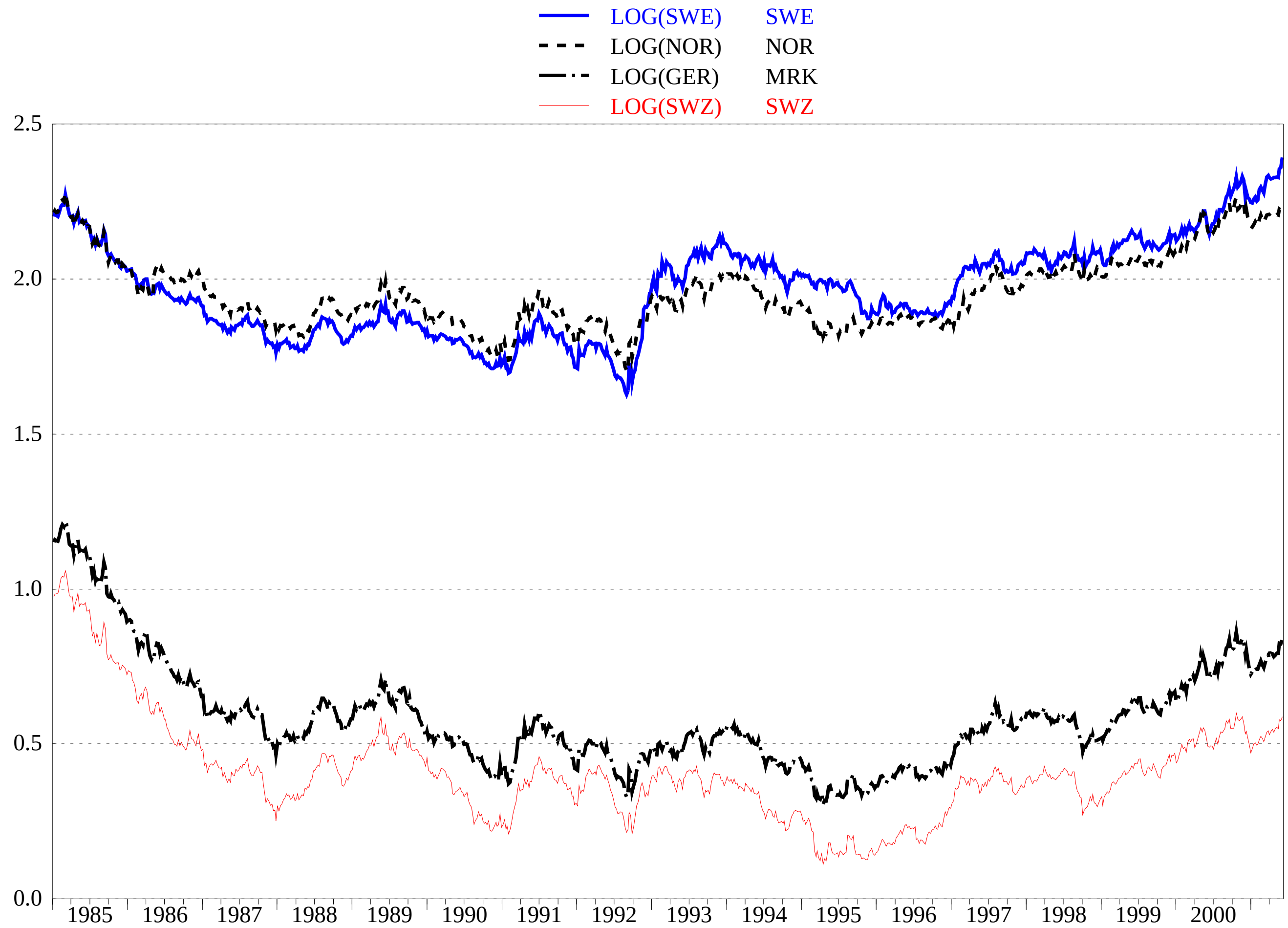


Figure 7 - Emerging-Country Bond Probabilities: Mexico−Argentina

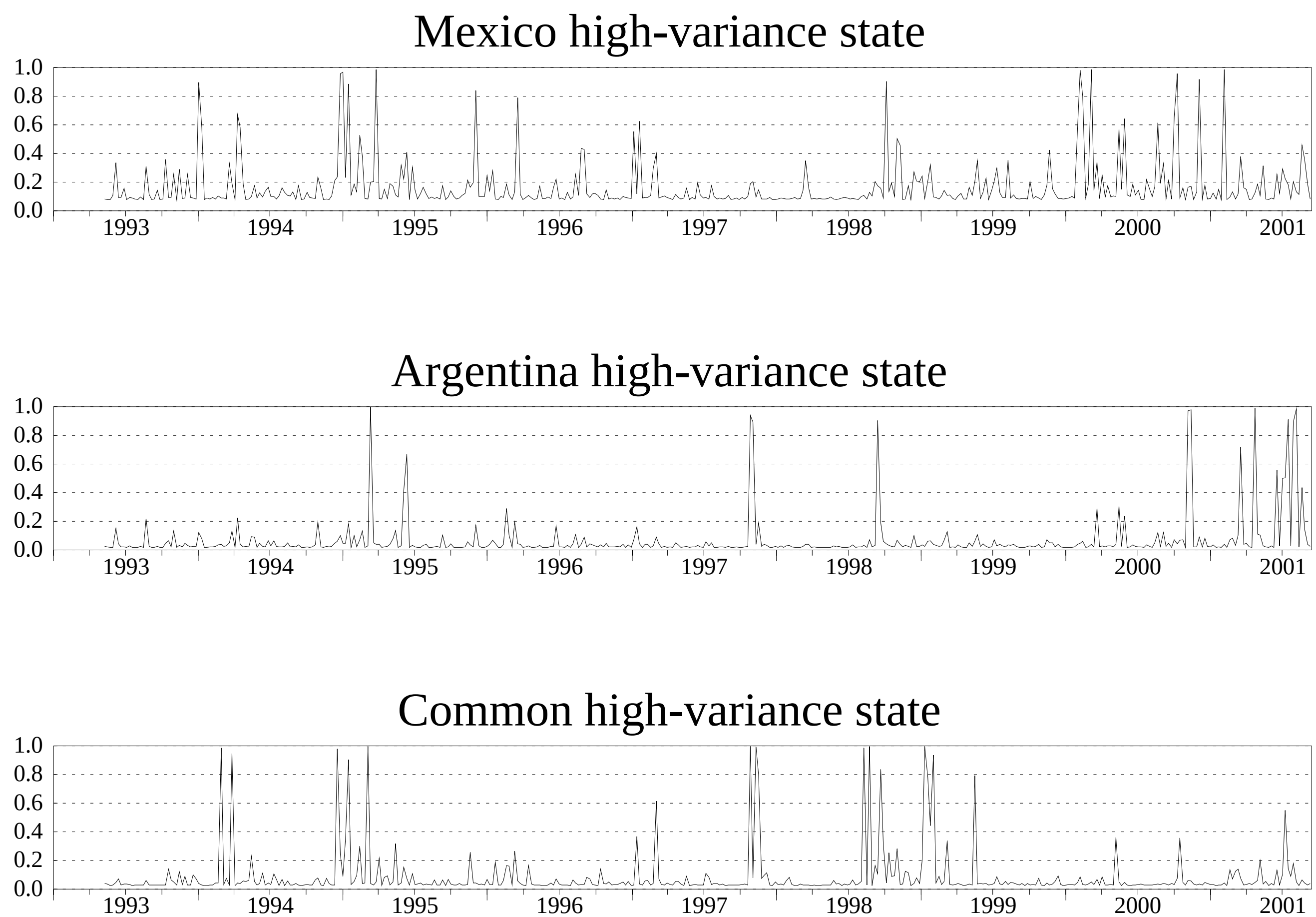


Figure 8 - Emerging-Country Bond Probabilities: Mexico−Brazil

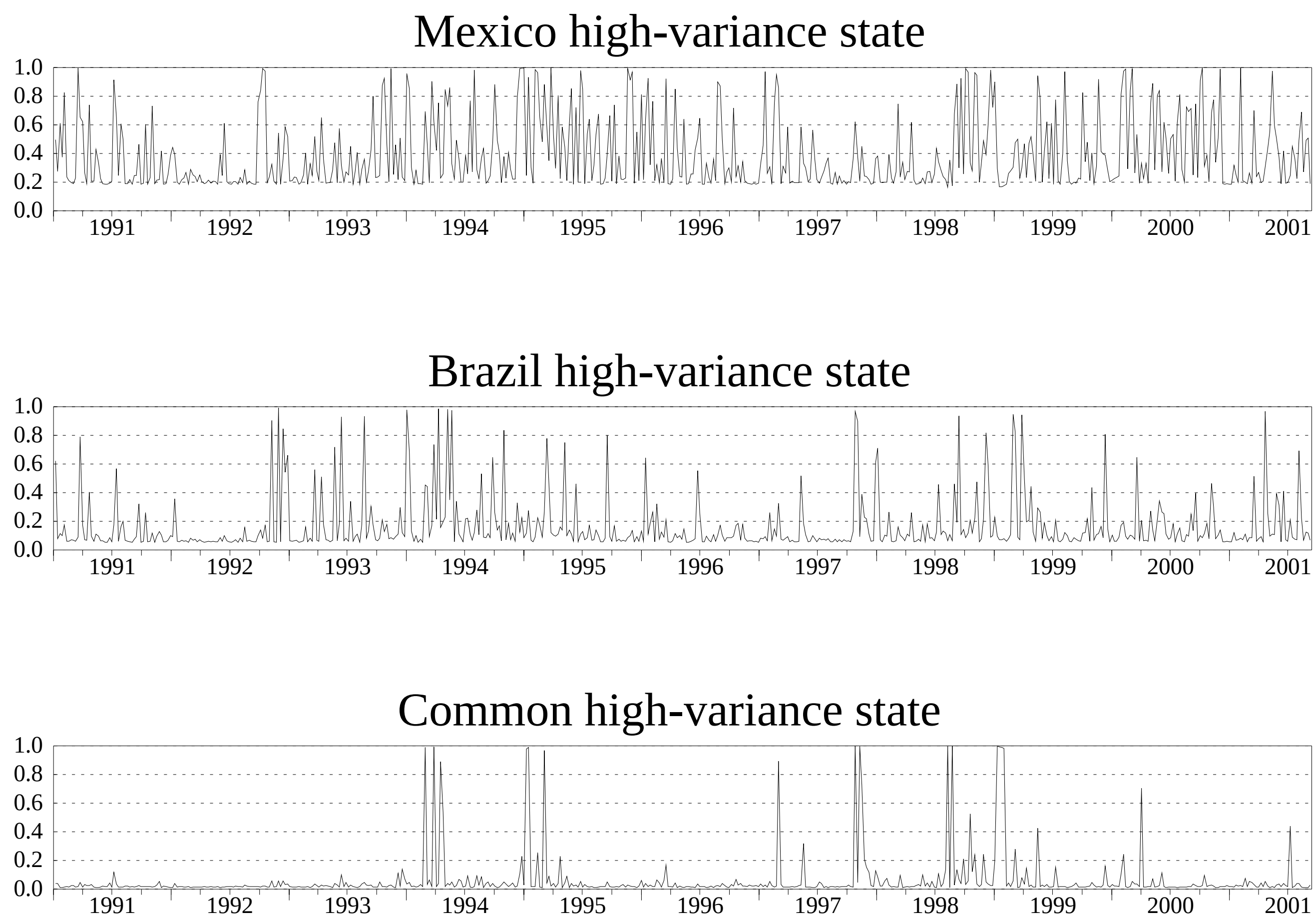


Figure 9 - Emerging-Country Bond Probabilities: Brazil−Argentina

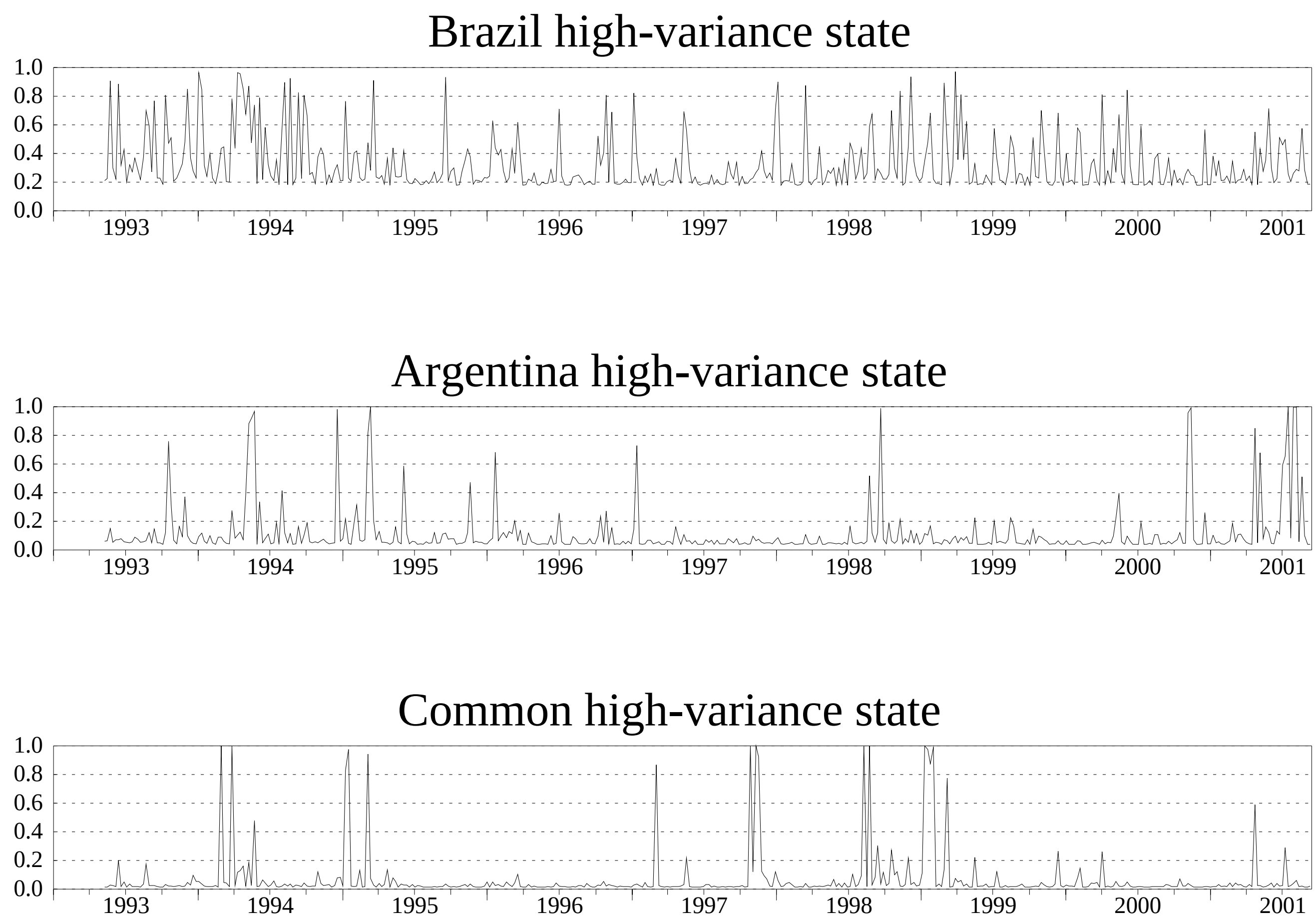


Figure 10 - Foreign Exchange Probabilities: Japan−Norway

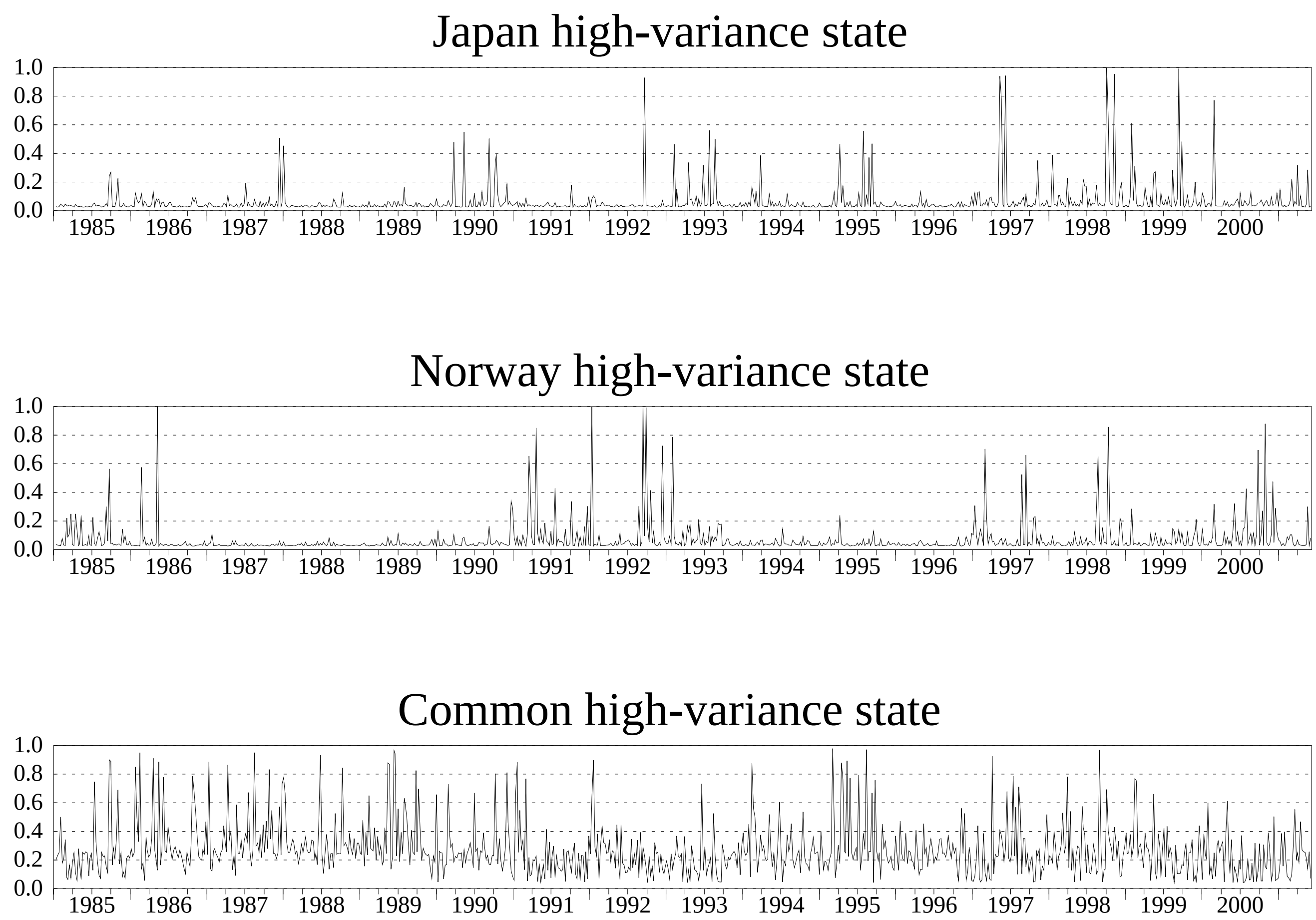


Figure 11 - Foreign Exchange Probabilities: Japan−Sweden

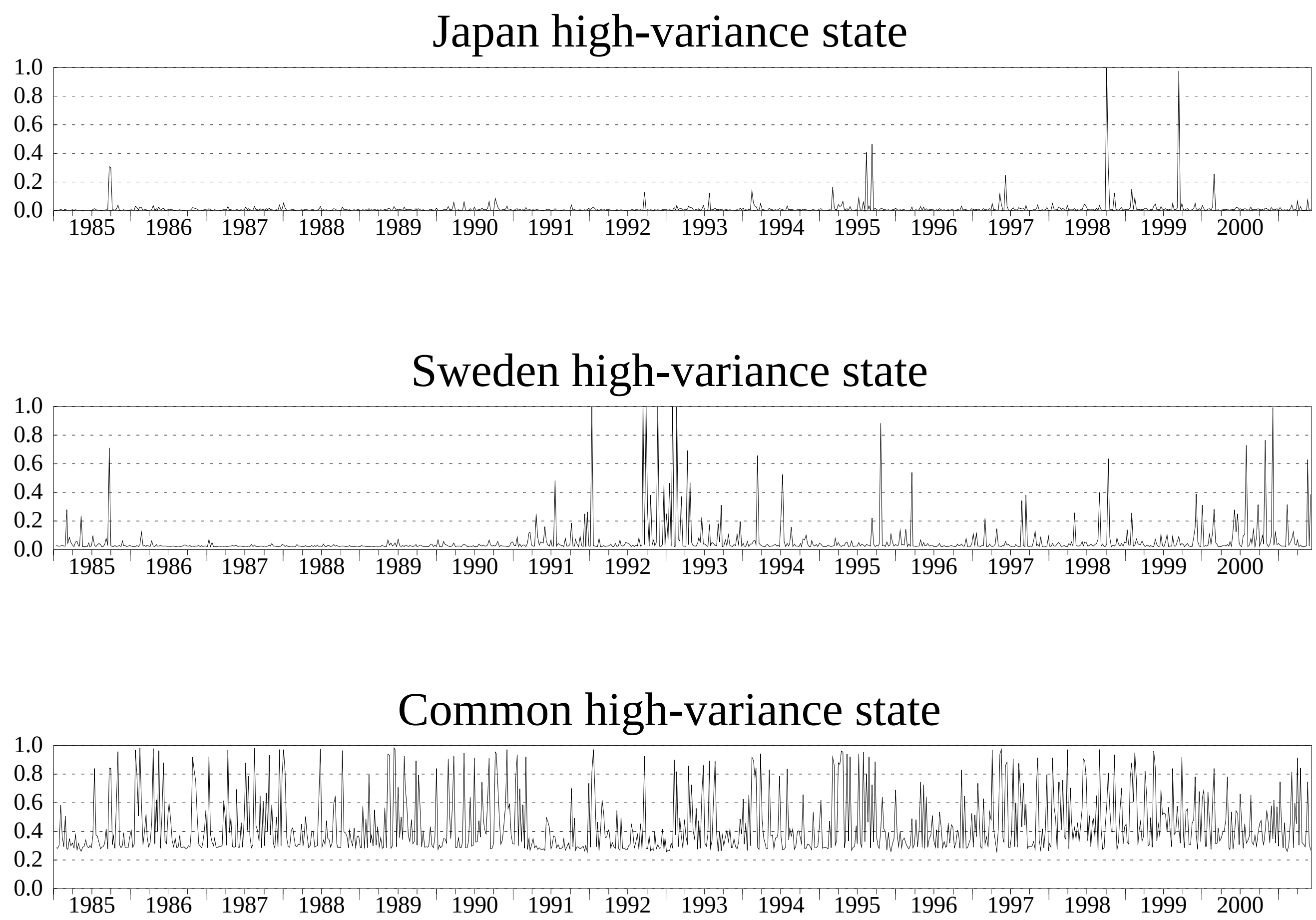
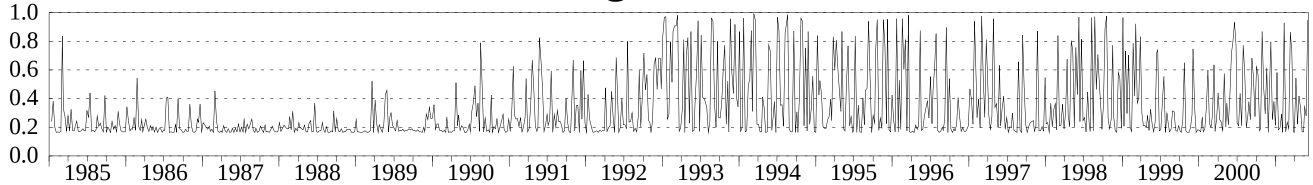
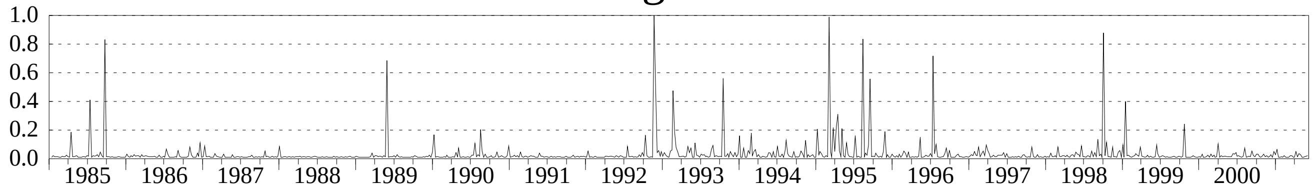


Figure 12 - Foreign Exchange Probabilities: Sweden−Switzerland

Sweden high-variance state



Switzerland high-variance state



Common high-variance state

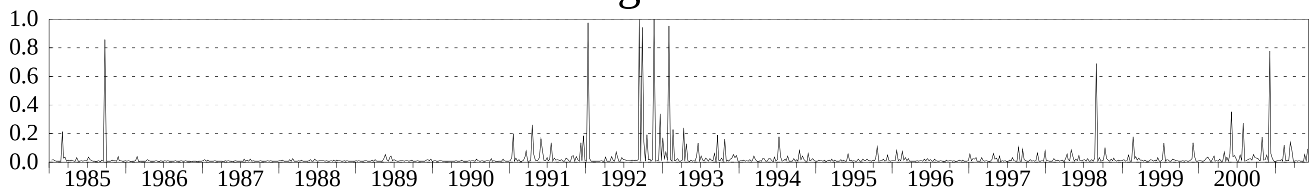
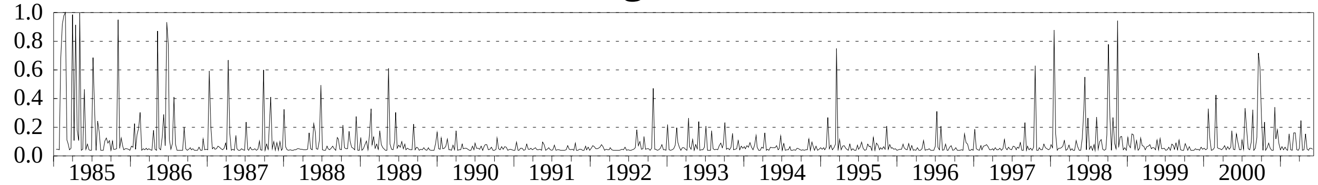
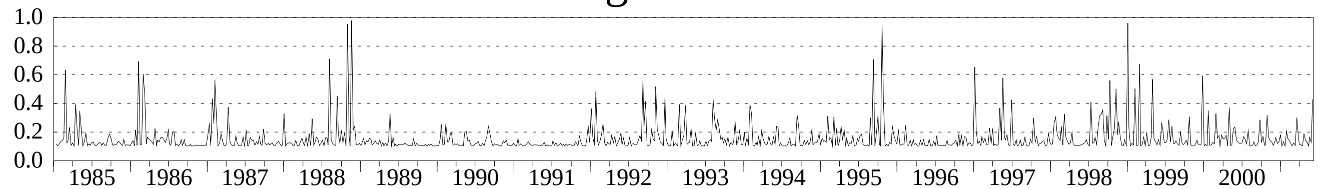


Figure 13 - Foreign Exchange Probabilities: Australia−Canada

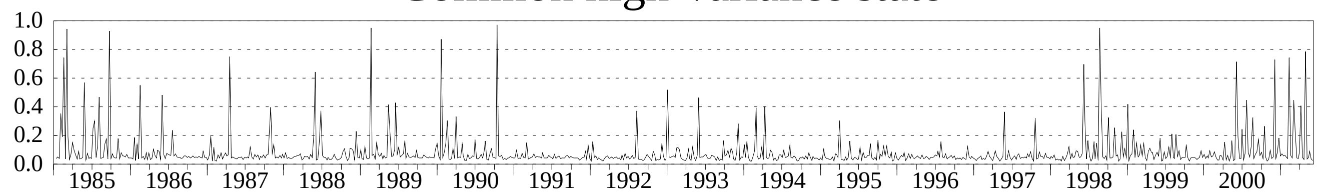
Australia high-variance state



Canada high-variance state



Common high-variance state



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