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Financial Contagion, Vulnerability and Information Flow: Empirical Identification[1]

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Abstract

This paper proposes a new approach to modelling financial transmission effects. In simultaneous systems of stock returns, fundamental shocks are identified through heteroscedasticity. The size of contemporaneous spillovers is determined in the fashion of smooth transition regression by the innovations' variances and (negative) signs, both representing typical crisis-related magnitudes. Thereby, contagion describes higher inward transmission in times of foreign crisis, whereas vulnerability is defined as increased susceptibility to foreign shocks in times of domestic turmoil. The application to major American stock indices confirms US dominance and demonstrates that volatility and sign of the equity returns significantly govern spillover size.

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1 Introduction

This paper presents a new approach to financial contagion. It deals with major shortcomings that have plagued the relevant literature (e.g., see Rigobon 2003a) in a unified econometric framework. Additionally, it offers conceptional advancements like endogenising transmission strength by smooth transition techniques and complementing the notion of contagion by a feature named vulnerability. The methodology is applied to stock exchanges based in the Americas.

It is common sense that in stable periods, trade, policy coordination, common shocks and other channels lead to international stock market comovement. The main strand of research on contagion focuses on definitions that imply some form of rising strength of spillovers between markets in times of economic or financial turmoil (Forbes and Rigobon 2001).[2] An obvious problem in testing for such change in transmission mechanism, so-called shift contagion, lies in simultaneous interdependence: Since exogeneity assumptions can hardly be maintained, often reduced-form approaches, e.g. correlation analyses, were pursued to avoid endogeneity bias. In general, this comes at the cost of losing exact information about directions and channels of contagion. A further problem is given by heteroscedasticity (Forbes and Rigobon 2002): During crisis periods stock market volatility increases, introducing upward bias in standard estimates of cross-market correlations. At last, a certain degree of arbitrariness arises by reason of deciding to consider a particular sample period as "the crisis".

As the major methodological contribution, I propose an econometric framework that copes with this mixture of difficulties by virtue of the following customised modelling. The heteroscedasticity is taken into account by ARCH-type processes specified for the structural disturbances in a simultaneous system. Since the implied time variation in volatility ensures full identification (Sentana and Fiorentini 2001), endogeneity can be made explicit in the model set-up; see as well Caporale et al. (2005) and Dungey et al. (2008) in a contagion context. The key issue is to elaborate on the details of a contagion mechanism: Instead of assuming distinct periods of turmoil, changes in transmission are determined in an inherently data-driven way. In detail, high volatility and unexpected negative returns, major determinants picking up episodes of crisis and high market activity, flexibly govern spillover size in the style of smooth transition regression (STR, e.g. Luukkonen et al. 1988). This overcomes the drawback of ex post crisis definitions, which are not helpful for

[2] For extensive surveys of the relevant literature, see for example the volume edited by Claessens and Forbes (2001).

example in creating early warning systems for use in economic policy or risk management. While heteroscedasticity has traditionally been a handicap when analysing contagion, I take double advantage of it, firstly in identifying the simultaneous structure and secondly in endogenously determining transmission strength.

Following the established concept, the employed notion of contagion comprises extraordinarily high transmission from crisis to other (non-crisis) countries. This highlights the role of *foreign* returns and variance in dynamically describing the size of spillovers from foreign to home market. For cases, however, where domestic turmoil triggers higher inward spillovers, I introduce the term (temporary) *vulnerability* of the home market. Dungey et al. (2008) provide some discussion in this direction, too, but still define crises ex post as exogenously specified time periods. The current approach can deal with this phenomenon by adding *domestic* negative returns and variance to the set of transition variables.

Apart from uncovering evidence on contagion and vulnerability, my model specification allows an alternative perspective on the topic: While existing investigations use one-sided hypotheses (even if not always explicit) for detecting an *in*crease in market dependence, the direction of the effect of the two components volatility and negative returns is determined in a potentially more complex way: For example, on the one hand, volatile domestic shocks may imply that the home market is dominated by domestic information, leaving no room for relevant spillovers from abroad; on the other hand though, in case high volatility is triggered by financial turmoil and insecurity, the influence of a foreign market appreciated as reliable anchor may even increase. Reversely, higher foreign volatility may lead to contagious spillovers, but if domestic agents do not ascribe valuable information content to the excessive fluctuations, spillover intensity may even shrink.

Within the new econometric setting, I analyse transmission effects between the major equity indices of the United States, Mexico, Brazil and Argentina. In a multi-step analysis of bivariate models, first exogeneity of the US and second of Mexico (conditional on the US) is established. Throughout, significant time variation in spillover size is detected, a finding that represents the main empirical contribution of this study. Thereby, negative returns tend to dominate markets, in line with the contagion hypothesis. US spillovers are the more important the less volatile US market fluctuations are compared to other stock markets. Interestingly, this constellation is exactly reversed for Mexico, which seems more to be a source of contagious effects.

The reader can expect the following: The next section presents the model, identification issues and the estimation procedure. Section 3 applies the methodology to the American stock indices. The last section concludes.

2 Econometric Methodology

2.1 Simultaneous Model and Identification

The data generating process of the n-dimensional vector y_t (here containing different American stock returns) is approximated by the structural VAR with lag length q

$$Ay_t = \mu_0 + \mu_1 d_t + \sum_{j=1}^{q} B_j y_{t-j} + \varepsilon_t \ , \tag{1}$$

where the B_j represent $n \times n$ coefficient matrices of lagged effects and ε_t is a n-dimensional vector of uncorrelated structural residuals. The contemporaneous impacts are included in the matrix A with diagonal elements normalised to one. Importantly, it is these effects, which model the correlation of returns in the current setting. Notwithstanding, common shocks are a natural feature of stock market interaction. Therefore, the empirical procedure (see section 3.1) will show how for example the US returns act as a common factor for Latin America. The deterministics comprise a constant and day-of-the-week dummies d_t.

Model (1) as it stands is not identified and therefore cannot be consistently estimated by standard means. A first step thus derives the reduced-form VAR

$$y_t = \mu_0^r + \mu_1^r d_t + \sum_{j=1}^{q} B_j^r y_{t-j} + u_t \tag{2}$$

with all coefficients obtained by premultiplying A^{-1} in (1), therefore marked by the superscript r for "reduced". Accordingly, the new residuals are given by $u_t = A^{-1}\varepsilon_t$.

Naturally, it proves impossible to recover the structural parameters from the reduced form without further constraints: In the matrix A with normalised diagonal, $n(n-1)$ simultaneous impacts have to be estimated, whereas in (2), this contemporaneous interaction is reflected by cross-correlation of the reduced-form residuals. However, the information contained in the according covariance-matrix is not sufficient for identification, because due to its symmetry, it delivers only $n(n-1)/2$ determining equations.

Going back as far as Wright (1928)[3], the recent literature of identification through heteroscedasticity (e.g. Sentana and Fiorentini 2001, Rigobon 2003b) addresses this problem

[3]Thanks to Roberto Rigobon for providing the text.

by assuming some type of separate time regimes with differing variances of the structural residuals ε_t. The volatility shift between two such regimes would deliver two distinct reduced-form covariance-matrices, so that $n(n-1)/2$ additional covariance and n additional variance equations could be obtained from the second matrix. Since the number of free parameters only rises by n, the number of structural variances, full identification can be achieved.

Dealing with typical financial data, instead of assuming separate volatility regimes, I model the variances in a conditionally heteroscedastic fashion (compare Sentana and Fiorentini 2001). In particular, the approach of Weber (2007a) specifies multivariate EGARCH processes for the structural residuals, thereby basically keeping up the intuition of identification through volatility regimes: An ARCH-type model practically defines a distinct variance state for every single observation, leading to a quasi continuum of regimes. For a concrete discussion on identification issues in this context, see as well Weber (2007b).

Formalising the model setup, first denote the conditional variances of the elements in $\varepsilon_t = Au_t$ by

$$\mathrm{Var}(\varepsilon_{jt}|\Omega_{t-1}) = h_{jt} \qquad j = 1, \dots, n \; , \tag{3}$$

where Ω_{t-1} stands for the whole set of available information at time $t-1$. The assumption of uncorrelated structural shocks supersedes considering any *co*variances.

Furthermore, denote the standardised innovations by

$$\tilde{\varepsilon}_{jt} = \varepsilon_{jt}/\sqrt{h_{jt}} \qquad j = 1, \dots, n \; . \tag{4}$$

A simplified version of the EGARCH(1,1)-process, as suggested by Weber (2007a), is given by

$$\log h_{jt} = c_j + g_j \log h_{jt-1} + d_j(|\tilde{\varepsilon}_{jt-1}| - \sqrt{2/\pi}) + f_j \tilde{\varepsilon}_{jt-1} \qquad j = 1, \dots, n \; , \tag{5}$$

where c_j, g_j, d_j and f_j represent the coefficients. $\sqrt{2/\pi}$ serves to demean the absolute shock. In addition, going beyond the pure magnitude of shocks, the signed $\tilde{\varepsilon}_t$ introduce asymmetric volatility effects. The logarithmic formulation ensures positive variances without relying on parametric restrictions.

2.2 Contagion and Vulnerability

The matrix A in (1) implies spillovers between the endogenous variables that are proportional to the size of shocks, with proportionality factors constant over time. While this represents the standard in structural VARs, the current research questions require a more ambitious specification:

- The term *contagion* is used in the sense that foreign market stress triggers a higher proportion of shocks to spill over to home markets.
- The concept of *vulnerability*, as perceived in this paper, implies that the home market is subject to higher than proportional foreign transmission in times of domestic market stress.

It follows that the spillover parameters have to feature time variation sufficiently general to allow for both types of hypotheses. In this respect, I go beyond the existing literature, including Weber (2007a). Formally, A is substituted by A_t in (1); A_{ijt}, $i \neq j$, then denote the coefficients of transmission from variable j to i at time t. Evidently, the crucial question is how to grasp such time variation econometrically. The heterogeneity of the literature of contagion and its definitions provide little guidance in this respect. However, it should be common sense that financial "market stress" is linked to falling stock prices and high volatility. Consequently, the size of the A_{ijt} would be governed by measures of return variation and downside market state, which endogenously pick up market turbulence. These measures belonging to the respective foreign market are intended to capture possible contagion effects. Those representing home-made turmoil shall provide the opportunity to assess vulnerability. To fix ideas, consider the following setup:

$$A_{ijt} = A_{ijt}(h_{it}, D_{it}, h_{jt}, D_{jt}) \ , \tag{6}$$

where D_{it} is a dummy that takes the value one if $u_{it} < 0$ and zero else ("bear dummies" henceforth). The dummy coefficients have the straightforward interpretation of additional spillover impacts in presence of unexpected negative market development. Therefore, I consider it natural to linearly include the bear dummies. The situation is different with the variance: While a linear specification would be most convenient for estimation, no case can be made that it would be in some sense natural. In order to allow for flexible effects of the volatility on the size of transmission, I adopt the concept of smooth transition regression (e.g. Luukkonen et al. 1988). Specifically, (6) takes the form

$$A_{ijt} = \alpha_{0i} + \alpha_{1i}/(1 + e^{-\gamma_{1i}(\tilde{h}_{it} - \beta_{1i})}) + \alpha_{2i}/(1 + e^{-\gamma_{2i}(\tilde{h}_{jt} - \beta_{2i})}) + \alpha_{3i} D_{it} + \alpha_{4i} D_{jt} \ . \tag{7}$$

Here, $\tilde{h}_{it}$ denotes the conditional variance of ε_{it}, relative to its unconditional variance. Thus, deviations from one measure *unusually* high (or low) volatility. The exact form of the transition is determined by the logistic function $(1 + e^{-\gamma(\tilde{h} - \beta)})^{-1}$, which is monotonically increasing[4] in $\tilde{h}$ and bounded between zero and one. Thus, the notion of contagion corresponds to $\alpha_{2i} < 0$ and $\alpha_{4i} < 0$ (foreign variance and unexpected negative returns increase spillover size), while vulnerability would be given by $\alpha_{1i} < 0$ and $\alpha_{3i} < 0$ (domestic variance and unexpected negative returns increase spillover size).[5] The slope parameter γ indicates the speed or smoothness of transition: As $\gamma \to \infty$, the logistic function approaches the indicator function $I(\tilde{h}_{it} > c)$, i.e. a single threshold. In contrast, $\gamma = 0$ simply gives the linear case. The parameter β represents the location of the transition; note however, since the present transition variable cannot become negative, β will not be exactly the midpoint.

The aim of the STR-based specification is letting the data decide about the shape of the volatility effect on spillover size. To give an example, linear specification would imply that every variance unit must have the same effect on spillover size, regardless of the prevailing level of volatility. However, one may intuitively expect that the impact of variance changes is rather unremarkable when volatility is not an issue due to its low size or when it is high enough so that marginal changes count no longer. In between these states, there lies a more or less clear-cut frontier dividing normality from inactivity and turmoil, where a more or less steep transition would take place. This is exactly what a smooth transition function can achieve.

It is understood that besides volatility, returns could have been included in the smooth transition instead of the bear dummies. Nevertheless, as mentioned above, the bear dummies are intended to capture the pure sign effect of unexpected returns. In contrast, the size (i.e., expected quadratic deviation) is instead reflected in the variances, playing the role of smooth transition variables. It is in this sense that the use of bear dummies allows both clear-cut interpretation and manageable estimation.

2.3 Inference

Conducting Quasi Maximum Likelihood estimation, I apply the BHHH algorithm (Berndt et al. 1974) to numerically maximise the log-likelihood function for a sample of T observations (complemented by an adequate number of pre-sample observations)

$$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(n \log 2\pi + \log|\Sigma_t| + u_t'\Sigma_t^{-1}u_t) \; . \tag{8}$$

[4]I think of the volatility effect being monotonous, even if not necessarily linear. More involved STR functions should thus not be required.

[5]Since A_t stands left hand side, it is negative impacts that increase spillover intensity.

The vector θ stacks all free parameters from (1), (5) and (7). Σ_t denotes the conditional covariance-matrix of the reduced-form residuals $A_t^{-1}\varepsilon_t$

$$\Sigma_t = A_t^{-1} \begin{pmatrix} h_{1t} & & 0 \\ & \ddots & \\ 0 & & h_{nt} \end{pmatrix} (A_t^{-1})' \,, \tag{9}$$

which is assured to be positive definite due to the quadratic form and the positivity of the EGARCH variances (see Weber 2007a).

A last comment is devoted to testing significance of the influence of the transition variables. In the current model setup, the importance of this test comes from the fact that the null hypothesis defines the case of no contagion or vulnerability, respectively. Luukkonen et al. (1988) show that straightforward hypotheses like $\alpha_{1i} = 0$ or $\alpha_{2i} = 0$ (respectively $\gamma_{1i} = 0$ or $\gamma_{2i} = 0$) are inappropriate because of the presence of unidentified nuisance parameters under the null. Instead, for testing purposes the functions are approximated by third-order polynomials, so that standard likelihood ratio (LR) principles apply to the test that all three coefficients are jointly zero. Of course, linearisation may adversely affect the power of the test. However, as Skalin (1998) points out, simulation-based techniques would be extremely computationally demanding and bootstrapping does not provide superior size and power properties. Therefore, I will rely on the LR test in the linearised transition model.

3 Application to American Equity Markets

3.1 Data and Empirical Procedure

In this section, I present the application to a set of American stock indices. As will be seen, this illustrates the usefulness of the developed methodology and contributes to the empirical literature by providing interesting economic implications. In detail, daily closing prices of the US Dow Jones Industrial Average, the Mexican IPC, the Brazilian Ibovespa and the Argentine Merval index for the sample 06/03/1991 (from whereon the last index was available) until 09/30/2008 have been collected from Reuters. Weekends and holidays are uniformly excluded. Since the locations of the involved stock exchanges differ in longitude but little in latitude, the trading times have a large to perfect overlap.[6]

[6]Trading hours in New York are 9.30 am until 4 pm local time (UTC-5 / UTC-4 during daylight saving time). Mexico City is located in a different time zone (UTC-6 / UTC-5), but trades nonetheless

Hence, data are observed nearly contemporaneously on a daily basis, clarifying the need for appropriate simultaneous modelling and identification.[7] Figure 1 shows continuously compounded daily returns.

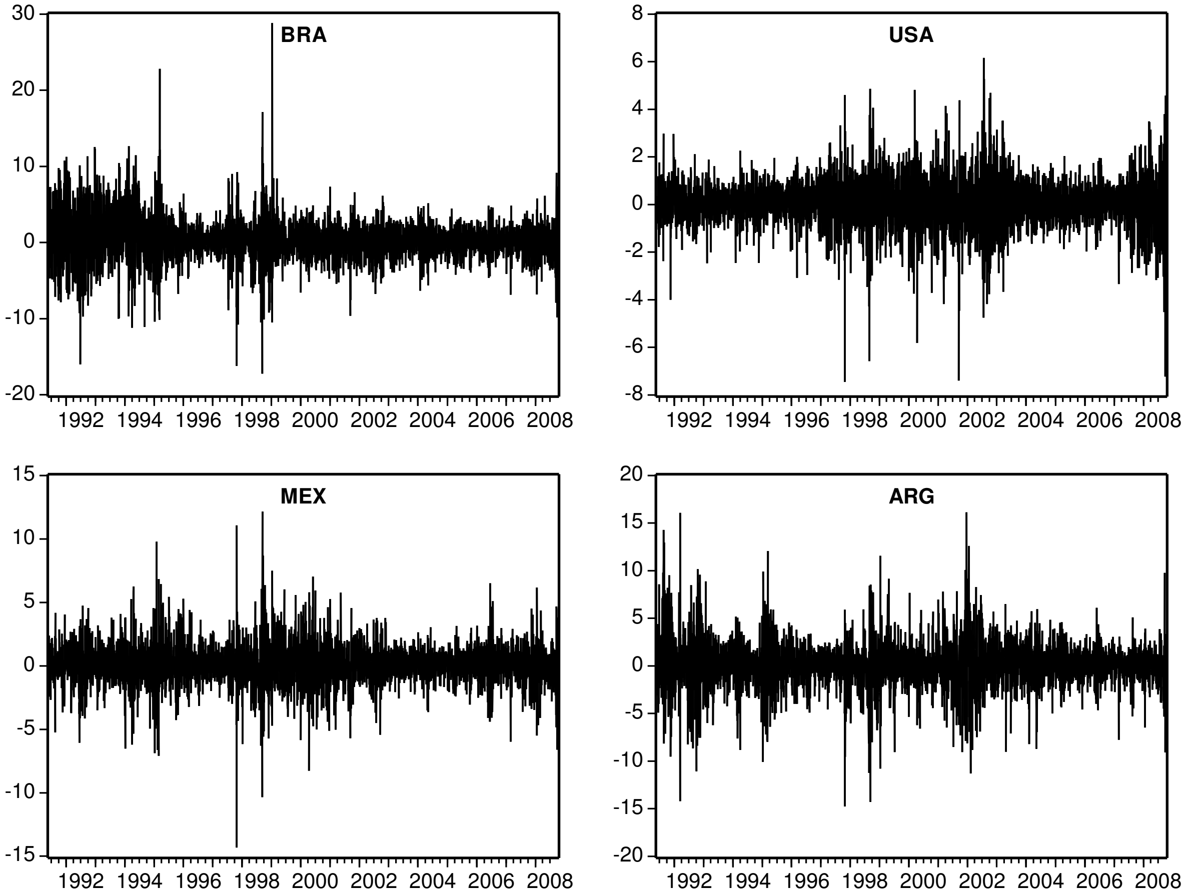


Figure 1: Major stock index returns

Several major crisis periods might have left their mark in the returns: the 1994 peso crisis ("Tequila effect"), the 1997/8 Asian financial crisis ("Asian flu"), the 1998 Russian bond default ("Russian cold"), the 1999 Brazilian currency crisis ("Brazilian fever"), the 2000/1 Argentine crisis, the 2001 US recession and 9/11 as well as the 2007/8 subprime and mortgage crisis. Evidently, the sample should contain sufficient information for detecting empirical regularities. Importantly, note that no assumption is made that all crises in the sample are alike in any strict sense. Rather, the flexible transition setup allows for diverse transmission characteristics according to the development of idiosyncratic volatility and

perfectly aligned to Wall Street. São Paulo and Buenos Aires, opening at 10 am and closing at 5 (6) pm local time (UTC-3 / UTC-2), have slightly different trading hours.

[7]Applying the current methodology to further countries around the globe would lead to employing intradaily measured data.

the occurrence of downside market states.

Econometrically, I will proceed as follows: Due to the highly interdependent model structure and the large number of parameters, bivariate systems are preferred. I begin with estimating models including Mexico, Brazil or Argentina on the one side and the US on the other side in section 3.2. Since, as it could be expected, the US emerges as largely exogenous, the following subsections 3.3 and 3.4 concentrate on the relations within Latin America, conditional on the influences found before.

Two further simplifications make the estimation procedure reasonably manageable: Firstly, means, day-of-the-week effects (if any) and serial correlation are filtered out of the returns by estimating the reduced-form VAR models (2), so that the analysis can continue with the residuals u_t. Lag lengths were determined by the Akaike criterion. Since no significant off-diagonal elements in any of the B_j^r were found, the VAR models reduced to single AR processes. Secondly, the simultaneous systems are estimated at first with constant A matrix, before the nonlinear effects of volatility and unexpected negative returns are introduced. Thereby, in case variable i emerges as exogenous, I abstain from including time variation in A_{ij}, the spillover affecting this variable. While in principle, some of the transition variables in (7) could still exert relevant influence, there are considerable gains from simplification. Moreover, if A_{ijt} is zero on average[8], any time variation needs to produce offsetting positive and negative values, quite an unlikely result for stock market spillovers.

3.2 Latin America vs. United States

For the Latin American countries, the US stock market is likely to play the role of a common factor. In order to verify this presumption, bivariate structural heteroscedastic systems for Mexico, Brazil and Argentina combined with the US are estimated in the first step. Table 1 shows the off-diagonal spillover coefficients from A, with standard errors in parentheses. For interpreting all following estimates, recall that A stands on the left hand side of (1), so that actually positive spillovers carry a negative sign.

Large effects run from the Dow Jones returns to those of the Latin American countries. Precisely, 0.864, 0.596 and 0.685 of a unit shock in the Dow spill over to Brazil, Mexico and Argentina, respectively. In terms of standard variance decompositions, this amounts

[8]Note that estimating constant coefficients A_{ij} should yield about the mean value of time-varying coefficients A_{ijt}.

Effect on:	BRA	US	MEX	US	ARG	US
Estimates	-0.864 (0.044)	-0.009 (0.006)	-0.596 (0.036)	-0.064 (0.017)	-0.685 (0.046)	-0.004 (0.008)

Table 1: Bivariate simultaneous spillovers between Latin America and the US

to US contributions of 11.2%, 14.5% and 8.7% (reconsider Figure 1 to verify that US volatility is rather low in comparison to Latin America). The only statistically significant feedback originates from Mexico, but stays economically small. Therefore, as discussed above, I adopt the time-varying specification (7) for the US transmission impacts. Note that this specification is extended by a transition function with time as its argument, which controls for secular effects but will not be in the centre of interest. At first, as formal statistical tests for the presence of contagion or vulnerability, I check the significance of the domestic and foreign variances and bear dummies for the nonlinearities.[9] P-values of LR tests (t-tests for the dummy variables) of no impact on nonlinearity (see section 2.2) can be taken from Table 2.

	BRA	US	MEX	US	ARG	US
$\tilde{h}_{it}$	0.002	0.002	0	0.184	0	0
D_{it}	0.012	0	0.037	0.003	0.430	0.396

Table 2: p-values of tests of no influence on nonlinearity in US spillovers

In most cases, the variables have significant influence on the susceptibility of Latin American stock markets to US equity shocks. Only the US variance in the case of Mexico and the bear dummies in the case of Argentina fail to reach statistical significance. For economic interpretation however, information on size, sign and form of the effects is necessary. In this, the relatively simpler issue is evaluating the dummy coefficients, which are shown in Table 3.

	BRA	US	MEX	US	ARG	US
α_{31}, α_{41}	0.245 (0.096)	-0.465 (0.095)	0.149 (0.064)	-0.224 (0.069)	0 (−)	0 (−)

Table 3: Effects of bear dummies on US spillover size

In the Argentine model, both coefficients were set to zero due to the insignificance result from Table 2. In the remaining cases of Brazil and Mexico, US unexpected negative returns raise spillover size (again, remember that A_t stands left hand side) while domestic unexpected negative returns have a dampening impact. Thereby, the additional effect of a

[9] Likewise, the time variable is tested and excluded when insignificant.

US shock nearly doubles the one of a domestic shock of the same size. Concretely, negative US returns spill over by additional 0.456 to Brazil, compared to positive ones. For Mexico, the coefficient amounts to 0.245. Taken the overall unconditional spillovers of 0.864 and 0.596 from Table 1 into regard, the bear market impacts are considerable. Consequently, following the concept from section 2.2, one may see this as clear evidence for the contagion hypothesis. Further evidence in this line can be obtained from (unconditional) variance decompositions. For that purpose, let us define the non-time-varying estimates from Table 1 as the baseline scenario.[10] Then, the presence of a negative US return raises its variance contribution by additional 11.8% for Brazil and 9.8% for Mexico.

The positive coefficients of the domestic bear dummies are less straightforward. Obviously, US returns are transmitted by 0.245 (Brazil) and 0.149 (Mexico) *less* when the home market is in a bear state. At least, Latin American stock exchanges reveal no signs of heightened vulnerability in times of downside market movements. Far more, results show that *negative* domestic information outweighs influences from abroad to a certain extent. It may be that domestic investors experience such negative information as particularly intense, so that it dominates the market in the relevant periods.

Now, the idiosyncratic variances shall be addressed as drivers of cross-country transmission. Table 4 shows the estimates for α_{j1} (the multiplier coefficients of the transition functions, which indicate contagion or vulnerability), γ_{j1} (the slope parameters) and β_{j1} (the location parameters) from (7), $j = 1, 2$. Even though standard errors are given in parentheses, recall that usual t-ratios of the αs or γs do not have their customary asymptotic distribution due to the presence of nuisance parameters under the null.

	BRA	US	MEX	US	ARG	US
α_{11}, α_{21}	-3.269 (1.573)	0.565 (0.237)	-4.000 (6.608)	0 (–)	-2.102 (1.172)	0.437 (0.190)
γ_{11}, γ_{21}	0.689 (0.494)	2.484 (1.371)	0.395 (0.696)	0 (–)	0.324 (0.199)	1.456 (1.193)
β_{11}, β_{21}	3.056 (1.806)	1.121 (0.387)	1.874 (3.426)	0 (–)	0.795 (0.860)	1.601 (0.695)

Table 4: Coefficients of smooth transition functions $\alpha_{j1}/(1 + e^{-\gamma_{j1}(\tilde{h}_{it}-\beta_{j1})})$

The slope parameters γ_{j1} are clearly larger for US (except the restricted case) than for domestic volatility. The location parameters β_{j1} range from 0.795 to 3.056. Most importantly, following the α_{j1} coefficients, high domestic volatility increases spillover size

[10] Since variance decompositions provide non-linear measures, the starting points matter when varying the spillover coefficients. Therefore, I use values that may be taken as representative. As usual, the decompositions are calculated from the variances of the reduced-form disturbances $u_t = A_t^{-1}\varepsilon_t$.

(negative left-hand-side effect), whereas US volatility decreases it (positive left-hand-side effect). Above, the bear dummies supported the contagion hypothesis, but were in conflict with the effect that might have been expected on vulnerability. With the variances, it is just the opposite: Evidently, in times of foreign financial turmoil, the according volatile fluctuations are not incorporated as readily as otherwise by the respective home market. That is, domestic investors might ascribe a lower information content to such foreign news, in line with the interpretation developed above. Contagion, defined as the spreading of crisis-alike effects, does not occur in this respect. From this point of view, there is no contradiction in having one positive (bear dummies) and one negative (variance) result for contagion: Negative news are dominant and contagious, while volatile news do not receive but a rather limited weight as market signals. Following this analysis, high domestic volatility should make the market more prone to impacts from abroad, since domestic investors would be willing to put more weight on the more solid foreign information. Indeed, the estimations confirm this view of vulnerability. In summary, the US market might play the role of a "reliable anchor", which is the more effective, the less volatile its returns are compared to the Latin American countries.

To gain a better feeling for size and shape of the variance effects, the logistic smooth transition functions from (7) shall be illustrated graphically. Figure 2 plots the impact on the size of US spillovers to Latin America against the smooth transition variables (domestic and foreign conditional variance relative to the according unconditional variance).

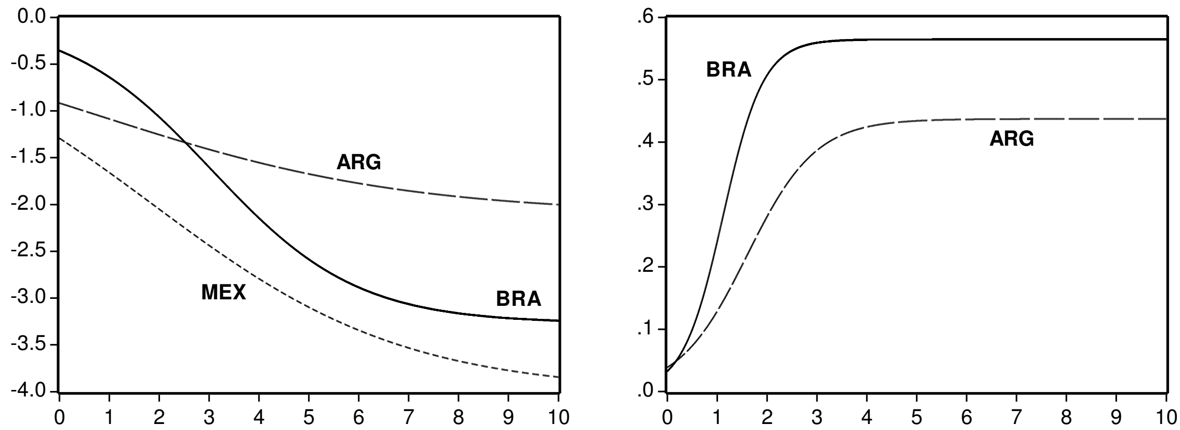


Figure 2: Smooth transition effects of multiples of own (left) and foreign (right) unconditional variances on US spillover size

The graphs mirror the numerical results from Table 4: Domestic variance raises spillover size, foreign variance lowers it. The first effects are large with slow transition, the latter relatively small with fast transition. In a word, domestic variance is much more influential, especially in highly volatile states. However, with regard to variance decompositions, two effects have to be taken into account, which are counteracting in the present case: First, the change in spillover coefficients triggered by the conditional variances as shown in Figure 2, and second of course the direct effect of changing one of the idiosyncratic variances. Table 5 provides the additional variance contributions of US shocks in presence of domestic and foreign conditional variances twice, three and five times their unconditional values (i.e., $\tilde{h}_{it} = 2, 3, 5$). Again, the baseline scenario is given by the non-time-varying estimates from above.

$\tilde{h}_{it}$	BRA	US	MEX	US	ARG	US
$\times 2$	-1.7%	-3.0%	+4.3%	–	-1.8%	+1.7%
$\times 3$	+1.1%	-1.1%	+8.5%	–	-2.2%	+1.3%
$\times 5$	+5.4%	+4.3%	+13.7%	–	-2.5%	+4.1%

Table 5: Additional US variance contributions due to higher domestic and foreign variance

In standard linear models, only the direct variance effect would be present, so that higher home variance (the respective first columns) would decrease the US contribution, and higher foreign variance (the respective second columns) would increase it. However, here the home variance even increases the US proportion (or decreases it only very slightly), and the foreign variance decreases the US proportion (or increases it only slightly). It follows that even though the percentage numbers do not seem to be impressive, exactly this fact demonstrates the importance of the nonlinear mechanisms.

To assess variation and range of the transition variables $\tilde{h}_{jt}$, Figure 3 displays these conditional variances relative to the unconditional variances for the Mexican case as an illustrative example.

For the Dow Jones, high volatility states prevailed from 1998 until 2002 (new economy bubble, 9/11, 2001 recession) and 2007/08 (subprime crisis). Apart from the former period, Mexico witnessed financial turmoil in the early 1990s (e.g., peso crisis). In general, these connections clarify that the transition variables (as well as the bear dummies) provide adequate measures that endogenously pick up market stress. To complement Figure 3, I present the EGARCH equations for the Mexican case in (10) and (11).

$$\log h_{1t} = \underset{(0.006)}{0.018} + \underset{(0.008)}{0.978} \log h_{1t-1} + \underset{(0.032)}{0.163}(|\tilde{\varepsilon}_{1t-1}| - \sqrt{2/\pi}) - \underset{(0.015)}{0.073}\tilde{\varepsilon}_{1t-1} \quad (10)$$

$$\log h_{2t} = \underset{(0.002)}{0.001} + \underset{(0.004)}{0.985} \log h_{2t-1} + \underset{(0.015)}{0.107}(|\tilde{\varepsilon}_{2t-1}| - \sqrt{2/\pi}) - \underset{(0.013)}{0.080}\tilde{\varepsilon}_{2t-1} \quad (11)$$

One clearly observes the typical features of GARCH-type models, in detail high persistence, pronounced impact of lagged shocks on the conditional variance and the leverage

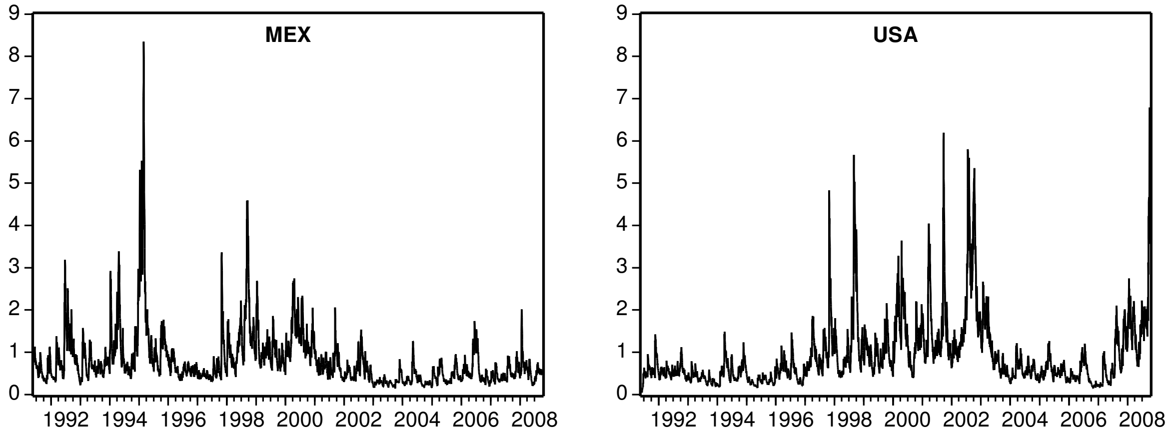


Figure 3: Idiosyncratic conditional variance relative to the unconditional variance ($\tilde{h}_t$)

effect as negative asymmetry.

3.3 Latin America conditional on the United States

Since the US was found largely exogenous in the previous analysis, I consider the relations within Latin America conditionally on the US. In detail, the new endogenous variables $\tilde{u}_{it}$ are given by $u_{1t} + A_{12t}u_{2t}$, the residuals from the respective US models.[11] Note that this implies that the following models for Latin America are conditioned on *time-varying* US impacts, going beyond the usual inclusion of US returns as exogenous regressors in linear regressions. That is, any cross-market linkage, notably including its time variation, simply due to common factor effects is filtered out in advance. With the $\tilde{u}_{it}$ at hand, again bivariate models, now among the Latin American countries, are estimated. Consistently, I begin with constant parameter specifications, which provide at the same time a certain measure for the "average" transmission size. Table 6 shows the off-diagonal spillover coefficients from A.

Effect on:	BRA	MEX	BRA	ARG	ARG	MEX
Estimates	-0.354 (0.028)	-0.030 (0.010)	-0.162 (0.030)	-0.169 (0.023)	-0.278 (0.026)	-0.027 (0.010)

Table 6: Bivariate simultaneous spillovers within Latin America conditional on the US

Evidently, Mexico takes on the leading role behind the US: Its spillover coefficients to Brazil and Argentina are statistically and economically significant (4% and 3% in terms of variance contributions), but inward effects are close to economically negligible. Impacts

[11]Recall that u_{1t} denoted the respective domestic return disturbance and u_{2t} the one from the US.

between Brazil and Argentina are balanced. However, this issue cannot be conclusively addressed but conditional on the common influences from Mexico. These are now investigated, where the time-varying specification is adopted for the Mexican transmission impacts. Before presenting the outcome, significance of the domestic and foreign variances and bear dummies for the nonlinearities is checked in Table 7.

	BRA	MEX	ARG	MEX
$\tilde{h}_{it}$	0.003	0.002	0.524	0
D_{it}	0.010	0	0.587	0.068

Table 7: p-values of tests of no influence on nonlinearity in Mexican spillovers

Apart from the Argentine variance and bear dummy, all variables have significant influence on the spillover size (at least on the 10% level). I proceed with showing the estimates for the dummy coefficients in Table 8.

	BRA	MEX	ARG	MEX
α_{31}, α_{41}	0.171 (0.060)	−0.338 (0.062)	0 (−)	−0.094 (0.038)

Table 8: Effects of bear dummies on Mexican spillover size

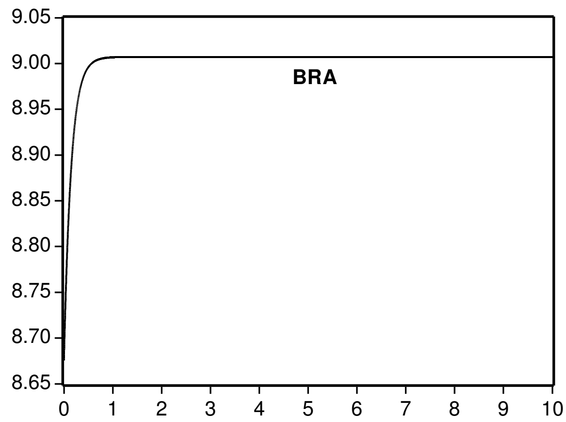
One sees the same pattern as in the previous section, leading to the same interpretation: Domestic unexpected negative returns reduce spillover size, foreign ones increase it. The foreign bear dummies again exert the higher influence, representing contagion. An unexpected negative return raises the Mexican variance contributions by additional 9.5% for Brazil and 2.3% for Argentina.

Concerning the transition effects of the variances, it has been shown that the US might bear a certain anchor function. Intuitively, such a constellation is not to be expected for Mexico, which possesses a far smaller and less developed stock market. This assertion is verified in the following, first depicting the parameter estimates of the smooth transition for the idiosyncratic variances in Table 9.

	BRA	MEX	ARG	MEX
α_{11}, α_{21}	9.007 (39.698)	−0.629 (0.380)	0 (−)	−0.647 (0.236)
γ_{11}, γ_{21}	6.905 (5.248)	1.296 (1.355)	0 (−)	0.599 (0.310)
β_{11}, β_{21}	−0.473 (0.834)	2.165 (0.709)	0 (−)	1.492 (1.367)

Table 9: Coefficients of smooth transition functions $\alpha_{j1}/(1 + e^{-\gamma_{j1}(\tilde{h}_{it}-\beta_{j1})})$

Indeed, one discovers a substantial deviation from the results related to the US: Higher foreign (Mexican) variance now *in*creases spillover strength, while the opposite holds for domestic variance (at least for Brazil, but as well for Argentina, even if the effect had been eliminated due to statistical insignificance). Consequently, the volatility effects within Latin America seem to be in line with the bear dummies: Firstly, turbulences in the home market decrease susceptibility to foreign impacts; logically (and plausibly), Mexico does not play the same role as a reliable anchor as the US had taken. Secondly, foreign turmoil spills over with particular strength; this describes what is called contagion, which does occur within Latin America, but not in its relations towards the US (at least as to the transition effects of the variances). To sum up, while US signals counted most in firm states of the world, Latin American stock market information tends to gain special weight in volatile times, when fear of crisis might dominate the price formation. For quantitative assessment, Figure 4 visualises the smooth transition in the domestic and foreign conditional variance (relative to the unconditional variance).



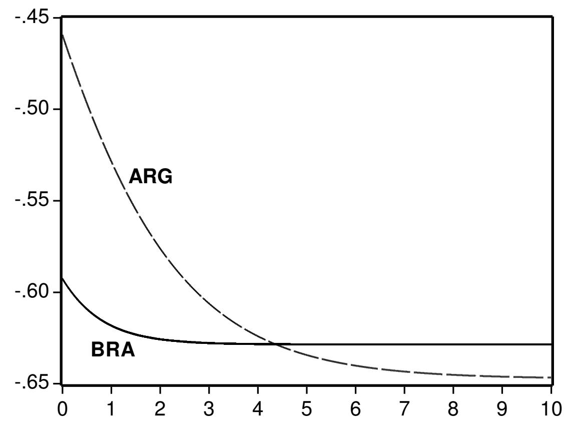


Figure 4: Smooth transition effects of multiples of own (left) and foreign (right) unconditional variances on Mexican spillover size

To begin with, the maximum effects are much smaller than in the US models. This is rather unsurprising, as a good part of the nonlinearities is already covered by the conditioning. The transition slope is in general quite steep; particularly the left Brazilian curve has almost reached the maximum impact at a value of one (that is, the unconditional variance). In this case, it is not extraordinarily high domestic variance that decreases spillover size, but far more extraordinarily low volatility that increases it. Consequently, foreign market signals seem to penetrate the price discovery process predominantly in a state of low intensity of domestic information flow. Contagion of an economically relevant extent is revealed only for Argentina. Here, the presence of a Mexican conditional variance of twice, three or five times its unconditional value raises the Mexican variance contribution by additional 4.7%, 10.0% and 19.4% compared to the baseline scenario. Of course, different from the US case, here the increasing foreign variance and the increasing spillover size work in the same direction. However, as the direct effect of higher variance alone accounts only for 2.8%, 5.4% and 10.2%, there is still a significant portion left to be explained by the nonlinear contagion impacts.

3.4 Brazil vs. Argentina conditional on the US and Mexico

In the last step of the empirical examination, I look at the Brazilian-Argentine relations, which were rather balanced in terms of spillover interaction. This analysis is conducted conditionally on the US and Mexico, so that I resume with the endogenous variables $\tilde{\tilde{u}}_{it}$, obtained as $\tilde{u}_{1t} + A_{12t}\tilde{u}_{2t}$. For $i = 1$, this model is to be read as that of Brazil, and for $i = 2$ as that of Argentina from the previous section.

The constant spillover coefficients (and standard errors) are estimated as -0.119 (0.025) and -0.110 (0.019). The variance contributions amount to 1.2% from Argentina to Brazil and 1.3% in the reverse direction. As has been seen before, there is bi-directional transmission in this case. For that reason, time variation is allowed for both A_{ijt}. When testing the nonlinear effects, only the bear dummies were convincingly significant. The variances failed to reach significance at least at the 5% level. Furthermore, the total transition effects stayed rather small and the slope coefficients were poorly determined. This evidence gave reason to exclude all variances from the spillover functions (7).

The estimates for the bear dummies turn out as shown in Table 10. In line with the pattern from the estimations including the US and Mexico, one discovers that own bear market state decreases (inward) spillover size, while the opposite holds true for foreign downside movements. In presence of unexpected negative returns abroad, the small variance contributions from above increase by additional 18.0% and 8.9%, once again demonstrating important contagion effects.

Effect on:	BRA		ARG	
Dummy of:	BRA	ARG	BRA	ARG
Estimates	0.270 (0.081)	-0.405 (0.062)	-0.204 (0.060)	0.218 (0.054)

Table 10: Effects of bear dummies on Brazilian and Argentine spillover size

3.5 Robustness Checks

The whole inference procedure was subjected to the following robustness checks. Despite the considerable complexity of the models, it seems that a fair degree of confidence in the empirical results is justified.

- Regarding lag length and deterministics, the choice among fairly reasonable mean models (2) proved uncritical.
- Converting all series into US dollars, though not totally nonrelevant, left the quality and overall strength of the results unchanged.
- Due to the complexity of the model, numerical optimisation is rather intricate. Therefore, various reasonably sensible starting values were chosen in order to strengthen confidence in having found global maximums.
- The same applies to the use of different numerical algorithms.

4 Discussion and Summary

Contagious spreading of market stress has become an important issue on the policy agenda during the 1990s, and was recently resurrected due to the subprime crisis. However, measuring such effects has proven to be a complicated task. The underlying study is motivated by several notorious shortcomings of the contagion literature and provides at the same time an innovative view on bilateral interaction of financial markets and the information flow between them. This is achieved by constructing a unified econometric framework, which serves to identify endogenous changes in the strength of financial transmission, known as shift contagion.

Methodologically, smooth transition regression techniques are adapted for determining the endogenous time variation in spillover intensity. Volatility and downside market states are employed as transition variables governing the extent of cross-market interaction. The endogeneity problem is solved by identifying fully simultaneous systems by heteroscedasticity, modelled in structural EGARCH equations.

When applied to major American stock markets, the method largely confirms exogeneity of the US. Conditional on the US influence, Mexico, too, turned out as nearly exogenous for Brazil and Argentina. The two latter countries still reveal mutual interaction, given the aforementioned influences. Concerning the nonlinear impacts on transmission size, results can be summarised as follows:

- Unexpected negative foreign returns generally spill over to the home country with increased intensity, but in presence of negative domestic shocks, the influence of foreign developments is markedly reduced.
- The strength of Latin American inbound effects from the US rises with domestic and falls with foreign (US) variance.
- In contrast, spillover size from Mexico to Latin America shrinks with domestic and increases with foreign (Mexican) variance.

The first point implies that negative news tend to dominate markets, regardless of their origin. Evidently, the contagion phenomenon can be explained in this context. The second point suggests that the anchor function, which surely distinguishes US-sourced financial information, gains the more weight the more stable the US market develops compared to other stock markets. The last point clarifies that for the transmission from a country like Mexico, of course far from taking an anchor function, time-varying volatility has consequences in line with the logic of contagion. Further empirical and theoretical research in these three directions seems to be highly promising.

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