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ON THE STRUCTURE OF FINANCIAL CONTAGION: ECONOMETRIC TESTS AND MERCOSUR EVIDENCE

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We introduce a flexible copula-based semi-parametric test of financial contagion that is capable of capturing structural shifts in the transmission channel of shocks across a network of financial markets beyond the increase in the intensity of time-varying dependence. We illustrate the capabilities of the proposed test using returns of stock, money, sovereign debt, and foreign exchange markets of seven Latin-American countries, and test for the presence of pure contagion effects for each major financial crisis that affected the Mercosur region between 1994 and 2001. Besides strong evidence in favor of time-varying market interdependence, we cannot rule out the presence of pure contagion effects in the stock market transmission channel associated with the Mexican, Asian, and Russian financial crises.

JEL classification codes: C14, C32, C51, G15

Key words: financial contagion, copulae, directed acyclic graphs, Bayesian belief networks

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I. Introduction

In the aftermath of the financial crises that plagued the emerging markets in the 1990s and early 2000s, financial contagion has often been cited as the main cause of sharp co-movements in asset prices of countries and regions with no apparent economic fundamental linkage. Some researchers questioned this interpretation of the empirical evidence. After correcting for the heteroskedasticity bias present in the co-movement of asset prices, interdependence alone might explain the observed co-movement during bad economic times (Forbes and Rigobon 2001, 2002). A problem with this argument is that the magnitude of the cross-country specific shock e.g., using a multi-factor asset pricing model of asset returns, is too large to be fully explained by the interdependence hypothesis alone (Corsetti, Pericoli and Sbracia 2005; Bekaert, Harvey and Ng 2005; and Chiang, Jeon and Li 2007).[1]

The empirical evidence appears to be consistent with two hypotheses with very different theoretical and policy formulation implications. The only interdependence hypothesis suggests that excessive correlation and volatility spillovers during financial crises reflect the efficient market incorporation of all available information given a set of known common global time-varying economic fundamentals. Conversely, the financial contagion hypothesis contends that excessive correlation is the result of the transmission of unanticipated country-specific shocks to other markets, countries, and/or regions (Dungey, Fry, González-Hermosillo and Martin 2005). From the practitioner's point of view, the later hypothesis suggests that asset portfolio diversification across countries and/or geographical regions will be less effective during a major financial crisis. Moreover, after the recent financial crisis of 2008 and the recent events in the Euro zone, the identification of the

[1] Baig and Goldfajn (1998) show that during the Asian crisis of 1998 there was evidence of financial contagion between stock and foreign exchange markets. Baig and Goldfajn (2000) provide evidence of financial contagion in Brazil after the Russian sovereign default transmitted across the sovereign debt markets. Forbes and Rigobon (2001, 2002) contend that during the Wall Street crash of 1987, Mexican crisis of 1994, and Asian crisis of 1998, most of the evidence is in favor of market interdependence and against financial contagion. Corsetti, Pericoli, and Sbracia (2005) study the Asian crisis and show that in at least 5 out of the 17 countries in the region there was evidence of contagion (alongside with market interdependence). Chiang, Jeon, and Li (2007), using also the Asian crisis as empirical setup, show that there was evidence of financial contagion.

transmission channel through which financial contagion spreads is crucial from a policy perspective to decide whether to impose barriers to capital mobility, dollarize the economy, or implement government bailouts as an optimal response to external shocks.[2]

Admittedly, a major problem in developing a robust test of financial contagion is the lack of consensus in the specialized literature about what is financial contagion.[3] In its narrow version, financial contagion is defined as a volatility spillover across assets. Broadly defined, financial contagion is any spillover that cannot be explained alone in terms of economic fundamentals. We motivate our test of financial contagion via the large literature that stresses the role of multiple equilibria and self-fulfilling expectations in economic behavior. Under this view, financial contagion manifests as a jump to the bad economic regime triggered by a crisis elsewhere with no a priori fundamental link (Masson 1998, 1999, 2007; Chang and Majnoni 2002; Forbes and Rigobon 2002; and Corsetti, Pericoli and Sbracia 2005). As argued by Masson (1998, abstract), "… only models that admit multiple equilibria are capable of producing true contagion."[4]

Thus, consistent with this literature, we define the financial contagion event

[2] Important precedents to the financial contagion literature are King and Wadhwani (1990) and Lee and Kim (1993), who use comparative event studies of the cross-market correlation coefficients between a pre-crisis (stable) period and a subsequent crisis period. Other relevant precedents to the literature used ARCH and GARCH models to show the presence of significant volatility spillovers across countries during financial crises (e.g., see Hamao, Masulis, and Ng, 1990). Unfortunately, these studies are unable to capture potential asymmetries in the structure of dependence in asset returns. Consequently, multivariate GARCH or ARCH models capable of capturing the asymmetric effects were developed in Kroner and Ng (1998), and Engle and Sheppard (2001). The current framework to test for the presence of financial contagion is unified around the asset pricing theory (APT) of Ross (1976) with a latent factor structure representation of asset returns. For a review of the current methodologies used to test for the presence of financial contagion see Dungey, Fry, González-Hermosillo, and Martin (2005).

[3] Dornbusch, Park, and Claessens (2000) define contagion as: "…the dissemination of market disturbances, most of the time with negative consequences, from one emerging market to another." Pericoli and Sbracia (2003) list five definitions of contagion: 1) an increase in probability of a crisis in a country given the existence of a crisis in another country; 2) propagation of volatility as a proxy for uncertainty from the crisis in one country to the financial markets of another country; 3) a surge in co-movements across prices and quantities in several markets after the crisis triggers in one of the markets; 4) a change in the intensity of the transmission mechanism of contagion after the crisis; and 5) an increase in co-movements not explained by fundamentals. Kaminsky, Reinhart, and Vegh (2002) define the contagion event as the "unholy trinity" characterized by a: 1) a sudden stop in capital inflows; 2) comes by surprise; and 3) there is a large common provider of capital.

[4] Masson (1999) differentiates pure contagion effects from confounding effects like inter- and intra-market spillovers (horizontal shocks across markets transmitted through current and capital accounts in the balance of payments) and monsoonal effects (vertical shocks from industrial countries to the periphery due, for example, to a shift in U.S. Fed's monetary policy or a shock in the price of oil) driven by interdependence.

as a structural shift in the transmission mechanism linking a network of financial markets after some local negative shock. Under this definition, a robust test for financial contagion must rely on an unbiased theoretic measure of (time-varying) interdependence capable of capturing any shift in the causal direction of dependence aside from the increase in intensity conditional on the state of the market. This is not a trivial task due to the fact that the conditional correlation structure across financial markets is highly nonlinear on the volatility regime.

Methodologically, our paper is closely related to Bessler and Yang (2003). These authors use directed acyclic graphs (DAGs) to extend standard vector autoregression (VAR) analyses. A DAG representation facilitates the economic interpretation of the multi-factor model of asset returns represented in reduced form as a VAR providing the contemporaneous causal structure of the innovations when little is known a priori from theory.[5] However, our paper has salient differences with theirs. First, besides differences in the sample and the number of financial crises included in the empirical analysis, here we focus on the development of a formal test for the presence of pure financial contagion effects based on the DAG, including country-specific fundamentals like interest rates and exchange rates, which are missing in Bessler and Yang (2003).

Moreover, our paper also builds methodologically from an emerging financial econometric literature that uses novel statistical concepts such as copula functions and exceedance correlations to model the co-movement of financial assets (for a comprehensive review see Cherubini, Luciano and Vecchiato 2005). In particular, we model co-movement in asset returns using a mixed copula in the spirit of a finite mixture of models approach to represent multiple equilibria. This approach has enough flexibility to capture alternative patterns of dependence through a parsimonious set of parameters when little is known about the marginal distributions.

To illustrate the capabilities of the proposed test, we apply it to identify both the dynamic structure and intensity of dependence across the network of

[5] The motivation for using a DAG to factorize the VAR (or error correction model, ECM) is due to the shortages of previous standard methods. The standard Choleski factorization procedure in a VAR representation (or ECM) has the problem of imposing causality from the lower triangular ordering when the actual ordering may not be lower triangular. Moreover, the structural factorization of the VAR (or ECM) requires prior knowledge from theory, which might be missing or might be unknown outside the particular model used.

financial markets within the Mercosur region,[6] and test for the presence of pure contagion effects for each major financial crisis in the emerging world that affected the region since the inception of the treaty between 1994 and 2002. We limit the sample period to 2002, because since then Mercosur has been in the good economic regime. The financial crisis of 2008 clearly opens new threats to the region, but so far it has been limited to the developed world. This is done by means of nodes, influence connections (edges), and causal flows in an effort to represent graphically the Bayesian belief network (BBN)[7] held by investors about the multi-factor structure of asset returns. Thus, the "only interdependence" hypothesis can be re-stated in terms of an invariant property of the BBN after the outbreak of a major foreign financial crisis elsewhere: DAG–isomorphism or no structural change in the direction of causality.

Our paper is further motivated by the empirical literature that seeks to identify and test financial contagion across different classes of assets (Forbes and Rigobon 2002; Bekaert, Harvey and Ng 2005; Corsetti, Pericoli and Sbracia 2005; Dungey, Fry, González-Hermosillo and Martin 2005; and Chiang, Jeon and Li 2007). Consistent with this literature, our empirical results show that there is strong time-varying market interdependence between the major sovereign debt and equity markets of Mercosur. However, in some of these countries, the cross-market effects to some of the money and foreign exchange markets in the region suggest the existence of pure contagion effects.

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[6] We choose as the laboratory for our analysis Mercosur (Mercado Común del Sur), a regional cooperative organization comprised of seven Latin-American countries. On March 26, 1991 the Asunción Treaty was signed by Argentina, Brazil, Paraguay, and Uruguay, which was later ratified on November 29, 1991. The original plan was to align the members' external tariffs by January 1, 1995, but there was little progress toward this goal until the signing of the Protocol of Ouro Preto in December, 1994. In recent years, Bolivia and Chile joined the common market organization as associates. Venezuela joined as a regular member by political decision on December 2005. Note that these countries represent a diverse sample in terms of legal regulations and economic institutions.

[7] In principle a BBN is similar to an artificial neural network (ANN). The advantage of the BBN is that the individual nodes represent local propositions with well-defined semantics and probabilistic relations as precluded by Bayes, which are missing in the ANN. Given that the joint probability distribution defined by the BBN is factored by construction when constructing the DAG representation, statistical inference reduces to a top-down marginalization process discarding irrelevant variables across the graph. The drawback of BBNs is that exact inference from the graph can only be done in non-polynomial time constituting a NP-hard computational problem.

The rest of the paper is organized as follows. In section II we discuss the conceptual framework of market interdependence and financial contagion and introduce formally the econometric test of pure financial contagion. In section III we explain the empirical methodology adopted and discuss the test results for each major financial crisis that affected the Mercosur region between 1994 and 2001. Section IV concludes. In order to save space, technical details including a brief review of copula functions, BBN, DAGs, and the sequential EM algorithm, as well as secondary tables and figures have been relegated to an online appendix that can be used as reference material.

II. A robust econometric test of financial contagion

A. Multi-factor representation of financial asset returns

In this section, we introduce the proposed robust test of pure financial contagion in a network of financial markets. Conceptually, we frame the proposed test under the multi factor representation of returns with a common latent (world) risk factor. This setup has been used in the financial literature to test for the presence of financial contagion. Roughly speaking, financial contagion is defined as cross-effects that occur in a network of financial markets during a crisis period over and above the cross-market linkages at work during normal economic times.

Let $\{r_t^{1,1}, r_t^{2,1}, \cdots, r_t^{i,1}, r_t^{1,2}, r_t^{2,2}, \cdots, r_t^{i,2}, \cdots, r_t^{1,m}, r_t^{2,m}, \cdots, r_t^{i,m}\}$ be the vector of returns $n \leq N = I \times M$ of financial assets, where $i \leq I$ is the number of classes of financial assets e.g., equity, bonds, currencies, etc., and $m \leq M$ denotes the number of countries included in the financial network. Let $\mathcal{F} = (f_1, \cdots, f_k)'$ be the vector of $k \leq K$ asset pricing factors with nonsingular covariance matrix Σ_F According to the arbitrage pricing theory (APT) of Ross (1976) there exists an orthogonal projection on the span of f_k factors and a constant were for each asset $m = \{1,1\}, \{2,1\}, \cdots, \{I,1\}, \{1,2\}, \{2,2\}, \cdots, \{I,2\}, \cdots, \{1,M\}, \{2,M\}, \cdots, \{I,M\}$ it must be:

$$r_t^{i,m} = E[r^{i,m}] + cov(\mathcal{F}, r^{i,m})' \Sigma_F^{-1} (F - E[\mathcal{F}]) + \sigma^{i,m} u_t^{i,m}, \tag{1}$$

where $E[u^{i,m}] = 0$; $cov(f_k, u^{i,m}) = 0$; for each factor $k \leq K$; $cov(u^{i,m}, u^{j,l}) = 0$ for $i, j \leq I$, $m, l \leq M$, $i \neq j$ and $m \neq l$; $E[f_k] = 0$; $cov(f_k, f_q) = 0$ for $k, q \leq K$ and

$k \neq q$; $var(f_k) = 1$; $cov(\mathcal{F}, r^{i,m})'\Sigma_F^{-1}(\mathcal{F} - E[\mathcal{F}])$ is defined as systematic risk; and $\sigma^{i,m}u^{i,m}$ is called the asset's idiosyncratic risk with $u_t^{i,m} \sim i.i.d(0,1)$.

Moreover, if the APT admits a finite structure of priced sources of risk, it can be re-expressed with a new set of orthogonal factors that are linear combinations of the original risk factors, have unit variance, and all except one factor have a positive market price. That is, an economy with finite priced sources of risk where investors only observe asset prices and portfolio returns can also be described by an economy with a single source of risk (Connor 1984; Reisman 1992).

B. The standard approach to market interdependence and financial contagion

Using the APT as building block, the financial contagion literature models the joint behavior of returns assuming a generalized autoregressive and conditional heteroskedastic (GARCH) data generating process (DGP) for each asset $i, m = \{1,1\}, \{2,1\}, \cdots, \{I, 1\}, \{1,2\}, \{2,2\}, \cdots, \{I, 2\}, \cdots, \{1, M\}, \{2, M\}, \cdots, \{I, M\}$:

$$r_t^{i,m} - E[r^{i,m}] = \lambda^{i,m} w_t + \sigma_{normal}^{i,m} u_t^{i,m}, \tag{2}$$

where $w_t \sim i.i.d(0,1)$ represents the common source of risk that affects all returns in the financial network; $\sigma_{normal}^{i,m}$ is the coefficient during the status quo or good economic regime; and $u_t \sim N(0, h_t)$; $h_t = (1 - \alpha - \beta) + \alpha u_{t-1}^2 + \beta h_{t-1}$ is the GARCH structure of the variance return equation. Allowing for multiple equilibria and self-fulfilling expectations, financial contagion manifests as a jump to the crisis or bad economic regime triggered by a crisis somewhere else outside the financial network by surprise (Masson 1998, 1999, 2007; Chang and Majnoni 2002; Forbes and Rigobon 2002; Kaminski et al. 2002; and Corsetti et al. 2005). Thus, asset returns during the bad economic regime now have dynamics:

$$r_t^{i,m} - E[r^{i,m}] = \lambda^{i,m} w_t + \sigma_{crisis}^{i,m} u_t^{i,m} + \sum_{j=1, j\neq i}^{I-1} \sum_{l=1, l\neq m}^{M-1} \zeta^{j,l} u_t^{j,l}, \tag{3}$$

where $\sigma_{crisis}^{i,m} \neq \sigma_{normal}^{i,m}$. Thus, the conditional variance of each asset return is:

$$var(r_t^{i.m}) = (\lambda^{i,m})^2 + (\sigma_{crisis}^{i,m})^2 h_t^{i,m} + \zeta^2 h_t^{j,l}, \tag{4}$$

given previous assumptions of independence. The conditional covariance between each pair of asset returns $r^{i,m}$ and $r^{j.l}$ for $i,j \leq I, m,l \leq M, i \neq j$, and $m \neq l$ during the crisis period is:

$$cov(r_t^{i.m}, r_t^{j,l}) = \lambda^{i,m}\lambda^{j,l} + \zeta\sigma_{crisis}^{j,l} h_t^{j,l}, \tag{5}$$

Financial contagion between two financial markets is manifested ex-post as the opening of a causal relation $\{\zeta \neq 0, \sigma_{crisis}^{j,l} h_t^{j,l}\} \rightarrow \{r_t^{i,m} - E[r^{i,m}]\}$ over and above the relation expected a priori given equation (5) during the status-quo economic regime. In the existing literature, financial contagion has been tested using either some sort of covariance/correlation analysis or a Chow test for the presence of a structural break in equation (5) (for a survey see Dungey et al. 2005). The problem with these tests is that marginal distributions and correlation do not determine uniquely the joint distribution of asset returns. That is, given a correlation parameter and two marginal distributions, one can find an infinite number of alternative dependence structures.

C. Market interdependence and financial contagion revisited

We re-write the multi-factor model in state-space form where returns are assumed to follow a two-state $s_t = \{1,2\}$. Markov chain mimicking the dynamics of the (latent) state of the world factor driving returns in the financial network from the status quo regime to the crisis regime and vice-versa. The time-varying transition probability between regimes is defined as $\pi_t^{x,y} \equiv Pr\{s_t = y | s_{t-1} = x, \sum_{j=1,j\neq i}^{I-1} \sum_{l=1,l\neq m}^{M-1} \zeta^{j,l} u_t^{j,l}\} = \Psi(\zeta^{j,l} u_t^{j,l} - \psi)\ \forall x,y = 1.2;$ $,j \leq I, m,l \leq M, i \neq j$, and $m \neq l$ Notice that $\Psi(\cdot)$ is a continuous logistic function dependent on the vector of coefficients $\zeta^{j,l}$, the history of observations up to lag 1 on the innovations $u_t^{j,l}$, and the unknown threshold value ψ. The time-varying return equation for each asset $m = \{1,1\}, \{2,1\}, \cdots, \{I,1\}, \{1,2\}, \{2,2\}, \cdots, \{I,2\}, \cdots, \{1,M\}, \{2,M\}, \cdots, \{I,M\}$ follows:

$$\left(r_t^{i,m} - E[r^{i,m}]\right)|s_t = \lambda^{i,m}|s_t\, w_t + \sigma^{i,m}|s_t\, u_t^{i,m}\,, \tag{6}$$

where $\lambda^{i,m}|s_t$ and $\sigma^{i,m}|s_t = \left(\sigma_{normal}^{i,m} + \pi_t^{i,m}\Delta\sigma\right)$ and are now conditional on the state or regime s_t at time t with probability of jumping to the crisis regime $\pi_t^{i,m}$; $\Delta\sigma = \sigma_{crisis}^{i,m} - \sigma_{normal}^{i,m}$; $u_t \sim GED(0, h_t)$ with $ln(h_t) = (1 - \alpha - \beta)/(\sigma|s_t) + \alpha u_{t-1}^2/(\sigma|s_t) + E_t[h_{t-1}/(\sigma|s_t)]$; and *GED* denotes some general distribution. Financial contagion is represented as:

$$\left(\pi_t^{i,m}\middle|\zeta^{j,l} > \psi\right) > \left(\pi_t^{i,m}\middle\|\zeta^{j,l} \leq \psi\right), \tag{7}$$

where the variables are defined as before. Intuitively, after a crisis occurred in market 1, the probability of a crisis in market 2 is higher independently of fundamentals driving market 2.

The adopted specification allows for interdependence, spillover, and moonsonal effects. Market interdependence and moonsonal effects are transmitted through the single world factor proxying for systemic risk. Moonsonal effects can result from a shift in the stance of monetary policy in the center of the world financial network, a shock in the international price of oil, and/or a shock in the world demand. Spillover effects from one market to another are introduced in the model through the autoregressive structure of asset returns. These may arise from a change in terms of trade and/or portfolio reallocations if one country devalues/revalues while the other does nothing, if and only if their goods and capital markets are integrated.

Importantly, the model is also capable of explaining pure financial contagion that may be characterized by market overreaction and herding behavior. That is, if one introduces endogenous information acquisition in a strategic setting with short-sighted informed/noise traders and a risk neutral market maker, e.g., as in Brennan's (1990) model with latent assets and/or the Froot et al. (1992) three-period model.

Each generation of informed (institutional) traders learn about the probability of a common negative shock *w* in one of *N* financial markets with returns modeled for example as shown in equation (6). At any period *t*, one of the market prices is randomly drawn and publicly announced by the market maker with probability

1/N. In the next period *t+1*, new information arrives. For *N* sufficiently large, in the event that the announced price constitutes bad news, it might be optimal for the informed traders to ignore their private signals on *w* and follow the order flow of noise traders when rebalancing their portfolios acting as "carriers of bad news" in the financial network.

Intuitively, because *w* has a very low probability of occurrence and it might reveal "too late", the order flows of informed and noise traders' become strategic complements triggering overreaction and herding behavior in the financial markets (i.e., other traders' information is already priced in the markets with probability one). Furthermore, order flows might be correlated with some "sunspot variable" ζ not directly linked to fundamentals and consequently not present in equation (6). In this framework, pure contagion effects can arise even in the absence of correlation between markets during normal economic times.[8]

It is under this conceptual framework that we seek to recover investors' beliefs about the future joint behavior of returns in a network of financial markets using marginal distributions, a family of copula functions, and a directed acyclic graph (DAG). In a Bayesian belief network (BBN), each node of the network represents a different financial market equipped with a complete description of the joint behavior of expected returns. It defines a unique joint probability distribution shared with some underlying vector autoregression (VAR) representation of the multi factor model of returns.

The standard choice to model co-movement across asset returns in the financial literature that uses copulas has been the Gaussian copula (see e.g., Chen et al. 2003). There is increasing evidence that such a specification is not able to capture the complex behavior of financial assets either in the domestic or international markets (Richardson and Smith 1993; Ang and Chen 2002; and Ang and Bekaert 2002).[9] Hu (2006) shows that, in the spirit of a general mixture of models approach, when the focus of the analysis is on the structure of dependence rather than its

[8] What some authors have characterized as "bandwagon" effects, i.e., a sudden change in investors' expectations or sentiment unrelated to fundamentals triggering overreaction and herding behavior in the financial markets.

[9] In the empirical section we provide the results of a kernel-smoothing, nonparametric two-sided goodness of fit test introduced in Chen et al. (2003) to assess whether the benchmark Gaussian copula function constitutes a reasonable fit to our innovations.

intensity and little is known about the marginal distributions $(u_1,\dots,u_n)$ a more accurate representation of co-movement is:

$$MC(u_1,\cdots,u_n;\boldsymbol{\pi},\Theta) = \sum_{s=1}^{S} \pi_s\, C_s(u_1,\cdots,u_n;\theta_s), \tag{8}$$

where $\Theta = \{\theta_1,\cdots,\theta_S\}$ are the parameters in the copula functions C_s that control the degree of dependence between a given set of returns; $1 > \pi_s > 0$ are weights that control the structure of dependence between the returns such that $\sum_{s=1}^{S} \pi_s = 1$; and $s \leq S$ denotes the number of copula functions included in (8) that best model dependence across returns in some given region of the joint distribution, e.g., in the left and right tail of the distribution identified with bad and good economic times, respectively.

The DAG representation of the BBN includes the structure of dependence within the network conditional on the status quo and crisis regimes. The Markov property of the DAG specification allows for a compact factorization of the joint probability distribution resulting in computational tractability. For the technical details of the methodological approach adopted we refer the reader to the online technical appendix.

The multivariate test for the presence of pure financial contagion effects is defined in terms of a comparative analysis of the DAGs during the status-quo and crisis regimes.

Proposition 1: *Pure financial contagion manifests as a shift in the structure of dependence across asset returns in a network of financial markets after a local negative shock over and above the relation expected during the status-quo economic regime. As such, an econometric test of pure financial contagion consists in testing the null hypothesis of structural causal invariance or DAG-isomorphism (i.e., the only interdependence hypothesis) versus the alternative hypothesis of absence of DAG-isomorphism (i.e., the pure financial contagion hypothesis) in the BBN held by investors compatible with the multi factor model used to parameterize the structural dependence across asset returns in the financial network under analysis.*

Proof: It follows from the previous analysis and the online technical appendix.

III. Empirical application

A. Data

The sample used in the empirical analysis includes sovereign debt (EMBI), equity (STOCK), money (INTEREST), and foreign exchange (FOREX) returns of seven Mercosur countries: Argentina (ARG), Bolivia (BOL), Brazil (BRA), Chile (CHI), Paraguay (PAR), Uruguay (UR), and Venezuela (VZLA) from January 1994 to June 2002. Our sample period encompasses five major financial crises that affected the emerging markets between 1994 and 2001 – namely, the Mexican "Tequila" crisis of 1994, the Asian "Flu" crisis of 1997, the Russian and Brazilian crises of 1998/1999, and Argentina's crisis of 2001. Thus, we also include in the sample Mexico's (MEX), EASEA's (East Asia free markets except Japan) (ASIA), and Russia's (RUS) stock and sovereign debt markets as potential sources of contagion to the Mercosur region. We do not include the sovereign Brady debt and stock markets of Bolivia and Paraguay due to data constraints (this is not a serious limitation as these markets are marginal or non-existent). The Mercosur sample represents 100% of the region's market capitalization and more than 90% of its economic activity measured by real GDP during the sample period under analysis. These countries also represent a diverse sample in terms of legal regulations regarding financial capital mobility, pace of deregulation and privatization processes, globalization, foreign exchange rate regimes, and supervisory institutions.

All time-series are converted to monthly returns and bond equivalent yields (bey) measured in USD. The stock market index excess returns are obtained from Morgan Stanley Capital International (MSCI), except for Uruguay's INDIME index, which has been provided by República AFAP (http://www.rafap.com), a major pension fund from Uruguay. These are value-weighted indices from a broad list of companies representing about 60% of each country market capitalization and covering the most representative industries. The selection criteria to be included in the MSCI index takes into account size (i.e., market capitalization), long- and short-term trading volume, cross-ownership, and float of each stock. These are total returns, including dividend yields, except for Uruguay's INDIME for which only net returns are recorded.

We also include monthly time series of the closing official foreign exchange daily rates provided by the central banks of each Mercosur country. The short-term interest rate spreads are calculated as the log difference between the home country short-term interbank rate (obtained from the respective central banks when the time series is available, or the 7-day call deposit rate otherwise) and the equivalent USD-denominated LIBOR obtained from the Bank of England. Sovereign spreads are measured in basis points and calculated using JP Morgan Chase Emerging Market Bond (EMBI, EMBI+) value-weighted indices. In the case of Uruguay, we calculate the sovereign spread from the Uruguay Bond Index (UBI) provided by República AFAP. The EMBI+ index tracks returns for the whole sample of traded external debt instruments issued in each emerging market (i.e., Brady and Euro bonds, USD-denominated, and domestic currency denominated debt), while EMBI only includes Bradys. The selection criterion for countries and instruments to be part of the EMBI+ and EMBI takes into account the minimum balance of outstanding debt, ratings, remaining maturity, and international settlement.

B. Econometric estimation procedure

We identify econometrically the mixed copula function $MC\left[\hat{F}(u^i), \hat{F}(u^m); \alpha = \{\Theta, \boldsymbol{\pi}\}\right] = \sum_{s=1}^{S} \pi^s C^s\left[\hat{F}(u^i), \hat{F}(u^m); \theta_s\right]$ in three steps.

Arcidiacono and Jones (2003) show that, in those cases where a subset of the parameters have been estimated previously, using a two-step sequential version of the expectation-maximization (EM) algorithm of Dempster, Laird, and Rubin (1977) makes the estimation problem computationally feasible without a significant loss of efficiency relative to full information maximum likelihood (FIML). These authors also discuss the regular conditions under which the sequential estimator is asymptotically consistent and normally distributed, i.e., $\sqrt{n}(\hat{\alpha} - \alpha) \xrightarrow{n\to\infty} N(0, \sigma_\alpha^2)$

Step 1: Marginals and copula parameters

In the first step, we use a GARCH (1,1) filter to obtain the *i.i.d.* innovations. Then, we estimate their (unknown) marginals non-parametrically. One potential problem with the GARCH (1,1) filter is that it might introduce dynamic misspecification.[10] To avoid this problem, we adopt a second-order Gaussian kernel density function as prior for the unknown marginals and a flexible adaptive *k*th nearest neighbor non-parametric estimation procedure that has been shown to work well under heteroskedasticity of unknown form (see e.g., Robinson 1987). Furthermore, as robustness check we test the null hypothesis of serial independence in the marginals using the tests in Genest et al. (2002), and Hong (1999).

After obtaining the marginals, we estimate the vector of copula parameters $\widehat{\Theta}$ using quasi-maximum likelihood (QML). The copula functions included in $MC\left[\hat{F}(u^i),\hat{F}(u^m);\{\Theta,\boldsymbol{\pi}\}\right]$ are:

i) the Gumbel-Hougaard copula $C(\hat{u}_a,\hat{u}_b;\theta_1)=\exp\left\{-\left[(-\log\hat{u}_a)^{\theta_1}+(-\log\hat{u}_b)^{\theta_1}\right]^{1/\theta_1}\right\}$ with density function:

$$c\left(\hat{u}^i,\hat{u}^m;\theta_1\right)=\frac{(\theta_1-1)\left[\left(-\log\hat{u}^i\right)^{\theta_1}+\left(-\log\hat{u}^m\right)^{\theta_1}\right]^{(2-3\theta_1)/\theta_1}\exp\left\{-\left[\left(-\log\hat{u}^i\right)^{\theta_1}+\left(-\log\hat{u}^m\right)^{\theta_1}\right]^{1/\theta_1}\right\}}{\hat{u}^i\left(\hat{u}^m\right)^2\left(-\log\hat{u}^i\right)^{1-\theta_1}\left(-\log\hat{u}^m\right)^{2(1-\theta_1)}}, \tag{9}$$

which has been used in finance to model dependence at the right tail of the marginal distributions;

ii) the Clayton copula $C\left(\hat{u}^i,\hat{u}^m;\theta_2\right)=\max\left[\left(\left(\hat{u}^i\right)^{-\theta_2}+\left(\hat{u}^m\right)^{-\theta_2}-1\right)^{-1/\theta_2},0\right]$ with density function:

$$c\left(\hat{u}^i,\hat{u}^m;\theta_2\right)=\frac{1+\theta_2}{\left(\left(\hat{u}^i\right)^{-\theta_2}+\left(\hat{u}^m\right)^{-\theta_2}-1\right)^{2+1/\theta_2}\left(\hat{u}^i\hat{u}^m\right)^{1+\theta_2}}, \tag{10}$$

which has been used to model dependence at the left tail of the marginal distributions; and

iii) the Frank copula $C\left(\hat{u}^i,\hat{u}^m;\theta_3\right)=\dfrac{1}{\theta_3}\log\left[1-\dfrac{\left(1-e^{\theta_3 u^i}\right)\left(1-e^{\theta_3 u^m}\right)}{1-e^{\theta_3}}\right]$ with density function:

[10] Moreover as shown in Chen and Fan (2006), the limiting distribution of the copula parameters also depend on the estimation of the unknown marginals.

$$c\left(\hat{u}^{i},\hat{u}^{m};\theta_{2}\right)=\frac{1+\theta_{2}}{\left(\left(\hat{u}^{i}\right)^{-\theta_{2}}+\left(\hat{u}^{m}\right)^{-\theta_{2}}-1\right)^{2+1/\theta_{2}}\left(\hat{u}^{i}\hat{u}^{m}\right)^{1+\theta_{2}}}, \tag{11}$$

representing symmetric dependence in the mid region of the marginal distributions. The derivations of the respective likelihood functions are omitted for space considerations.[11]

Step 2: Mixed copula weights

Given that the mixed copula is rooted in a mixture of models approach, in the second stage of the estimation procedure, we compute the vector of weights $\hat{\boldsymbol{\pi}}$ for all the copulas included in the mixed copula function using the estimated parameters from the first stage and the sequential version of the EM algorithm, which is explained in detail in the online technical appendix. As a robustness check, we include the Chen et al. (2003) kernel-smoothing non-parametric goodness of fit test using as benchmark a Gaussian copula function.

Step 3: DAG representation of the BBN

The third and final step in the econometric estimation procedure is the statistical identification of the BBN. Given the mixed copula function parameterizations obtained in the previous step, we recover the best (maximally data oriented) graph representation of the BBN using the PC algorithm. In the absence of hidden latent variables, the PC algorithm searches for the best data oriented causal model making queries about conditional independence between each node in the network using Bayes' rule.[12] Given some pre-specified significance level, the statistically significant causal links are identified using Fisher's Z statistic, which is distributed asymptotically as a standard normal variate. For robustness purposes, we also run the FCI algorithm to control for the presence of a hidden common latent variable in the network.

[11] However, they can be obtained via request to the authors.

[12] We restricted the DAG to prevent the possibility that innovations in financial markets of relatively larger economies can be caused by those of relatively smaller regional economies.

C. Empirical results

Summary statistics of the returns included in the empirical analysis are provided in Table 1. Note that most of the asset returns in the financial network under study are characterized by extreme volatility, high skewness, and excessive kurtosis, as expected from the asset pricing financial literature in the area of emerging markets (see, e.g., Bekaert et al. 2003).

The test results for potential dynamic misspecification in the marginals are provided in Table 2. Based on these results, we cannot reject the null hypothesis of serial independence for most of the estimated marginals with a 5% significance level, except for the foreign exchange markets of Argentina, Bolivia, and Uruguay, and the money markets of Argentina, Bolivia, and Paraguay. With the exception of Argentina, these are the smallest economies in the region with under-developed and segmented financial markets. The results for Argentina reflect the pseudo-currency board implemented during most of the period under analysis with a fixed 1:1 FOREX rate between the Argentinian peso (ARS) and the American dollar (USD). Hence, using an alternative autoregressive specification for the GARCH(1,1) filter would have little incremental explanatory.

Table 1. Summary statistics

Variable	Argentina	Bolivia	Brazil	Chile	Paraguay	Uruguay	Venezuela	EASEA	Mexico	Russia
EMBI										
Mean	0.0035	-	0.0087	0.0108	-	-0.0027	0.0043	0.0016	0.0094	0.0350
Std. Dev.	0.0943	-	0.0856	0.0746	-	0.1429	0.0838	0.0788	0.0663	0.2969
Kurtosis	4.6406	-	10.4191	7.4440	-	6.1387	11.0273	2.6818	2.1432	18.8370
Skewness	1.4743	-	2.5258	2.1622	-	1.5681	2.0134	0.8269	1.0858	-0.3722
Min	-0.2396	-	-0.1203	-0.1291	-	-0.3228	-0.2016	-0.2129	-0.1044	-1.4309
Median	-0.0184	-	-0.0057	-0.0077	-	-0.0099	-0.0007	-0.0040	0.0034	0.0121
Max	0.4415	-	0.4661	0.3872	-	0.6578	0.4965	0.3148	0.2624	1.3875
Aut. Coef.	-0.0818	-	-0.1437	-0.0551	-	-0.0757	-0.1388	0.1102	0.3026	-0.4454
FOREX										
Mean	0.5246	0.0520	0.4163	0.1589	0.3384	0.0710	0.8964	-	-	-
Std. Dev.	3.5116	0.1609	3.3532	0.8953	0.9137	0.7757	3.2119	-	-	-
Kurtosis	60.8215	1.5347	17.5297	0.7349	5.9783	11.4918	8.4403	-	-	-
Skewness	7.4965	0.0003	1.7113	0.1365	1.9598	0.8467	2.0456	-	-	-
Min	-1.8804	-0.4621	-12.1249	-2.5140	-2.1177	-2.9002	-10.2890	-	-	-
Median	0.0000	0.0417	0.1216	0.1179	0.1359	0.0904	0.2188	-	-	-
Max	31.1754	0.5206	21.3514	2.6733	4.2750	4.3573	14.2174	-	-	-
Aut. Coef.	-0.0896	-0.5250	-0.1083	-0.0946	0.0416	-0.5654	-0.0734	-	-	-
INTEREST										
Mean	0.1178	0.0034	-0.0046	0.0241	0.0108	0.0022	0.0411	-	-	-
Std. Dev.	0.3004	0.0681	0.2059	0.1560	0.1042	0.0952	0.3283	-	-	-
Kurtosis	1.1287	1.3994	48.1336	-0.1571	21.0129	37.3331	3.6573	-	-	-
Skewness	0.5184	0.1366	-5.6364	-0.1480	2.4462	3.6102	-0.4674	-	-	-
Min	-0.7368	-0.1923	-1.7188	-0.3901	-0.3950	-0.4020	-1.3328	-	-	-
Median	0.0882	0.0044	0.0039	0.0285	0.0060	0.0097	0.0399	-	-	-
Max	1.0775	0.2198	0.4498	0.3914	0.6827	0.7325	1.1074	-	-	-
Aut. Coef.	-0.3731	-0.4863	-0.0351	-0.1678	0.1033	-0.2103	0.0332	-	-	-
STOCK										
Mean	0.0001	-	0.0112	0.0011	-	-0.0045	0.0058	0.0025	-0.0002	0.0058
Std. Dev.	0.0524	-	0.0526	0.0285	-	0.0322	0.0568	0.0182	0.0480	0.0956
Kurtosis	2.7394	-	3.0308	5.6199	-	12.6067	2.0202	0.7820	2.7339	2.9073
Skewness	0.4105	-	-0.1094	-1.2022	-	1.5972	-0.0947	-0.6586	-1.2604	-0.9293
Min	-0.1633	-	-0.1999	-0.1430	-	-0.1034	-0.2201	-0.0586	-0.1821	-0.4042
Median	0.0026	-	0.0130	-0.0005	-	-0.0025	-0.0008	0.0046	0.0075	0.0119
Max	0.1855	-	0.1673	0.0710	-	0.1850	0.1420	0.0417	0.0761	0.2072
Aut. Coef.	0.0265	-	0.1323	-0.0474	-	0.1080	-0.1594	-0.0628	0.0404	0.1401

Notes: Table 1 reports the summary statistics of the innovations in monthly returns of 27 different financial assets included in the study after filtering them using a GARCH (1,1) specification as is standard in the copula empirical literature. The sample period is from 02/1994 to 06/2002.

Table 2. Test results for serial independence

Test (*n+1=100*)	Argentina	Bolivia	Brazil	Chile	Paraguay	Uruguay	Venezuela
EMBI							
$S^{\tau}_{\{1,2\},n}$	0.0361	-	0.1348	0.0378	-	0.1555	0.1552
p-value	(0.8804)	-	(0.3053)	(0.8708)	-	(0.3306)	(0.2435)
$S^{CVM}_{\{1,2\},n}$	0.1256	-	0.2318	0.0891	-	0.1844	0.2465
$S^{KS}_{\{1,2\},n}$	0.7803	-	0.8707	0.6715	-	0.9658	1.1266
FOREX							
$S^{\tau}_{\{1,2\},n}$	1.5265	0.6802	0.2572	0.0504	0.1592	0.5763	0.0590
p-value	(0.0001)	(0.0001)	(0.0616)	(0.6503)	(0.2325)	(0.0001)	(0.7588)
$S^{CVM}_{\{1,2\},n}$	0.6177	2.7830	0.2229	0.0979	0.1289	2.2858	0.1583
$S^{KS}_{\{1,2\},n}$	1.4197	2.6082	0.8209	0.5260	0.7885	2.3504	0.9963
INTEREST							
$S^{\tau}_{\{1,2\},n}$	0.5773	0.6152	0.0740	0.1913	05758	0.1262	0.1546
p-value	(0.0001)	(0.0001)	(0.6808)	(0.1571)	(0.0001)	(0.4410)	(0.3336)
$S^{CVM}_{\{1,2\},n}$	1.4217	2.5613	0.0185	0.3718	11.4040	0.5385	0.1808
$S^{KS}_{\{1,2\},n}$	1.8349	2.3961	0.2634	1.1196	5.4031	1.3354	1.1663
STOCK							
$S^{\tau}_{\{1,2\},n}$	0.0539	-	0.1654	0.0709	-	0.2298	0.1433
p-value	(0.7847)	-	(0.2981)	(0.6967)	-	(0.1382)	(0.2786)
$S^{CVM}_{\{1,2\},n}$	0.0571	-	0.2918	0.0925	-	0.2724	0.2777
$S^{KS}_{\{1,2\},n}$	0.5048	-	1.272	0.7761	-	0.9631	0.8916

Notes: Table 2 includes the S-*tau* statistic based on Kendall's measure $\tau_{\{1,2\},n}$, which rejects the null hypothesis of serial independence if the ratio $S^{\tau}_{\{1,2\},n} = \left|\tau_{\{1,2\},n} + 2/3n\right| \Big/ \sqrt{\left(20n^3 - 14n^2 - 34n + 148\right) / \left(45n^2(n-1)^2\right)}$ is sufficiently large. It also Includes the value of the Cramér-von Mises statistic S-*CVM* where the null of serial independence is rejected if $S^{CVM}_{\{1,2\},n} = n/2 + (1/n) \times \sum_{i=1}^{n-1} N_i^2 \left\{K_{|\{1,2\}|}((i+1)/n) - K_{|\{1,2\}|}(i/n)\right\} - \sum_{i=1}^{n-1} N_i \left\{K^2{}_{|\{1,2\}|}((i+1)/n) - K^2{}_{|\{1,2\}|}(i/n)\right\} > A^{CVM}_{n+1,cl}$, where *N* is the number of observations that are less than or equal to i/n, $K_{\{1,2\},n}(t) = (1/n)\sum_{i=1}^{n} I\left(\Pi_{\{1,2\},n} \leq t\right)$ with joint density Π, and $A^{CVM}_{n+1=100,cl=95} = 0.311$ is the critical value at a 95% confidence level taken from Genest et al. (2002). Includes the value of the Kolmogorov-Smirnov statistic S-*KS* where the null of serial independence is rejected if $S^{KS}_{\{1,2\},n} = \sup_{t \in \Re} \sum_{i=1}^{n-1} \sqrt{n} \left|K_{|\{1,2\}|}(t + 7/12n) - K_{|\{1,2\}|}(t)\right| > A^{KS}_{n+1,cl}$, where $A^{KS}_{n+1=100,cl=95} = 1.142$ is the critical value at a 95% confidence level taken from Genest et al. (2002).

Table 3 provides the results of the Chen et al. (2003) goodness of fit tests. At a 95% confidence level we cannot reject the null hypothesis that the Gaussian copula function would have been at least as good as the mixed copula functions for only 11.93% of the cases under analysis using the consistent version of the test (12.87% using the non-consistent version of the test). These results are not surprising given the observed high skewness, excessive volatility, and kurtosis in the returns under analysis as shown in Table 1.

Table 3. Goodness of fit test results

Panel A. Consistent test

Test statistic	Two-sided 5% critical region	
% Rejections	(-0.3135,0.3135)	88.07
% Non-Rejections	(-0.3135,0.3135)	11.93
Test result: Reject the null hypothesis that a normal copula function would have been at least as good as the mixed copula function.		

Panel B: Non-consistent test

Test statistic	Two-sided 5% critical region	
% Rejections	(-0.3135,0.3135)	87.13
% Non-Rejections	(-0.3135,0.3135)	12.87
Test result: Reject the null hypothesis that a normal copula function would have been at least as good as the proposed mixed copula function.		

Notes: Panel A reports the results of Chen et al. (2003) consistent non-parametric test of the null hypothesis $H_0 : \Pr(g(Z_1,\ldots,Z_d)=1)=1$ if C_0 is the Gaussian copula, where $g(\cdot)$ is the joint density function, and $Z_1 \equiv U_1$, $Z_d \equiv C_{0j}(U_0;\alpha_0|U_1,\ldots,U_{j-1})$ for $j=1,\ldots,d$,; versus the alternative $H_1 : \Pr(g(Z_1,\ldots,Z_d)=1)<1$, otherwise. The test $T_{nd} \equiv (nh^{d/2}i\hat{I}_n - c_{dn})/\sigma_d \Rightarrow N(0,1)$ under the null, where $\hat{I}_n = \int_0^1 \cdots \int_0^1 [\hat{g}(z_1,\ldots,z_d)-1]^2 dz_1 \cdots dz_d$, $\hat{g}(\cdot)$ is a kernel estimator of $g(\cdot)$, $c_{dn} = h^{d/2}\left[(h^{-1}-2)\int_{-1}^1 k^2(w)dw + 2\int_0^1\int_{-1}^{z} k_z^2(y)dydz\right]^d$ and $\sigma_d^2 = 2\left\{\int_{-1}^1\left[\int_{-1}^1 k(u+v)k(v)dv\right]^{2d} du\right\}^d$.

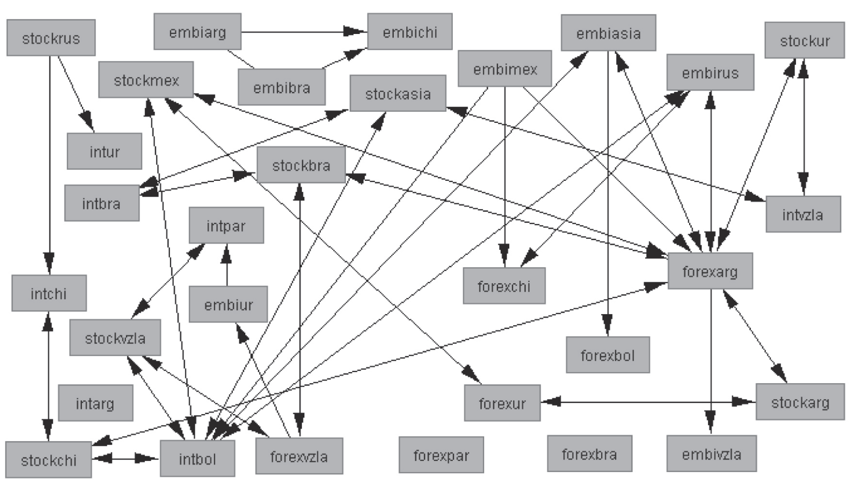
Panel B reports the results of Chen et al. (2003) non-consistent test when the dimension of d is large based on $\hat{J}_n = \int_0^1 [\hat{g}_W(w)-1]^2 dw$, where $\hat{g}_W(\cdot)$ is the density function of $F_{\chi^2_{[d]}}(w)$. Under regular conditions, $T_{n1} \equiv (nh^{1/2}\hat{J}_n - c_{1n})/\sigma_1 \Rightarrow N(0,1)$ under the null, where $c_{1n} = h^{1/2}\left[(h^{-1}-2)\int_{-1}^1 k^2(w)dw + 2\int_0^1\int_{-1}^{z} k_z^2(y)dydz\right]$ and $\sigma_1^2 = 2\int_{-1}^1\left[\int_{-1}^1 k(u+v)k(v)dv\right]^2 du$. We reject the null at a 5% significance level if $T_{nd} > z_{0.05} = 0.3531$.

In the online appendix we include Tables A1-A6 that report the pseudo-ML estimates of the three copula functions included in the mixed copula function with their respective standard errors. Tables A7, A8, and A9 include the weights of these copulas in the mixed copula functions. Figures A1, A2, and A3 illustrate a selected group of copula functions in Mercosur. Clearly, the degree of dependence within the region is higher across sovereign debt and equity markets than across money and FOREX markets. Also, the degree of dependence within the regional network is not significantly higher than with the external markets included in the analysis. Note the asymmetric intensity of dependence across returns. One should expect an increase in the degree of dependence in all markets during a crisis. The question now is what happens with the direction of causality in the network?

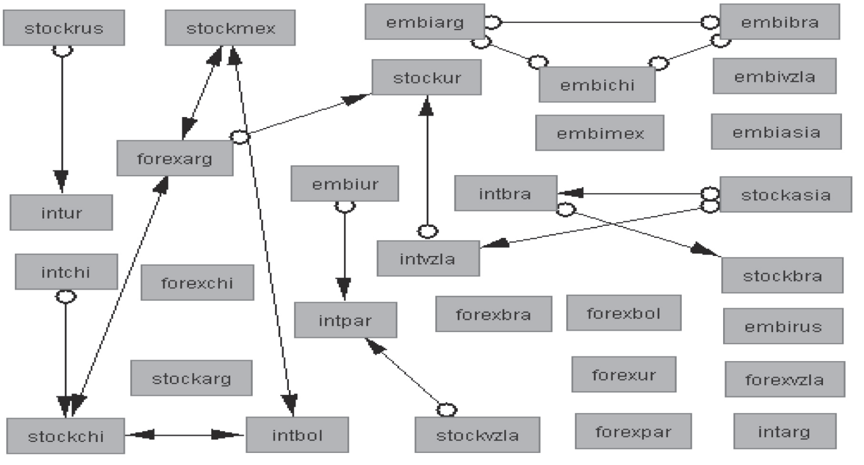
Figures 1 and 2 plot the corresponding empirical DAG representations of the BBN for the status-quo and crisis regimes, respectively, from 1994 to 2002. Testing for DAG isomorphism reduces to comparing both DAGs at a 5% significance level. We proceed now to discuss the test results under each international crisis chronologically.

Figure 1. BBN: Crisis regime

Panel A. DAG Using PC Algorithm



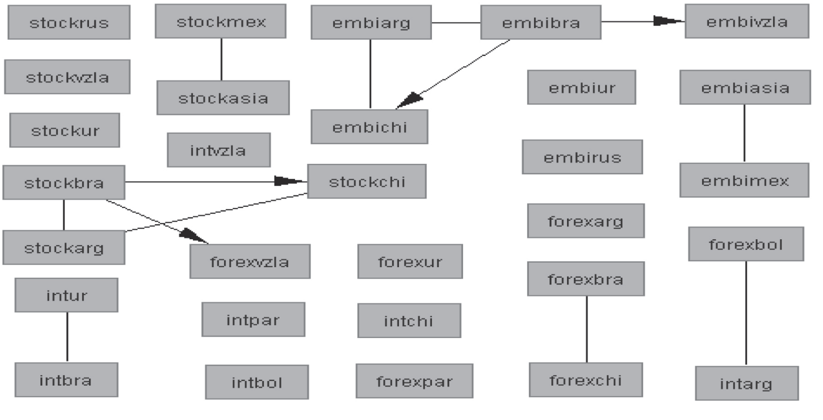
Panel B. DAG Using FCI Algorithm



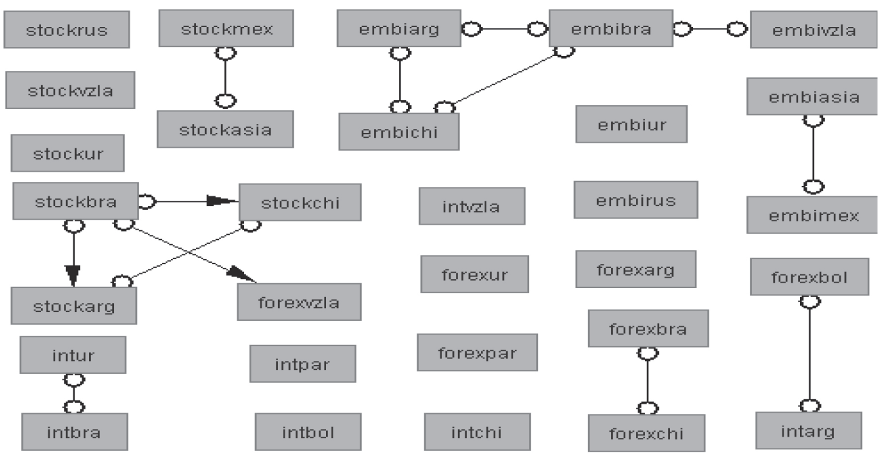
Note: This figure shows the BBN for the complete set of financial markets under analysis during the crisis regime. Panel A shows the best data oriented DAG recovered using a PC search algorithm, and panel B shows the best data oriented DAG recovered using a FCI search algorithm. The sample period under analysis is 02/1994-06/2002.

Figure 2. BBN: Status-quo regime

Panel A. DAG Using PC Algorithm



Panel B. DAG Using FCI Algorithm



Note: This figure shows the DAG for the set of financial markets under analysis during the status-quo regime. Panel A shows the best data oriented DAG using a PC search algorithm, and panel B shows the best data oriented DAG recovered using a FCI search algorithm. The sample period under analysis is 02/1994-06/2002.

The Tequila crisis: Monsoonal effects

Comparing Figures 1 and 2, there is statistical evidence of a causal transmission channel opening between the Mexican sovereign debt market acting as a source of the negative news in contemporaneous time and the foreign exchange markets of Argentina and Chile as well as the money market of Bolivia at a 5% level of significance during the crisis. There is also statistical evidence of a causal transmission channel opening between the Mexican stock market acting as a source of the negative news in contemporaneous time and the foreign exchange markets of Argentina and Uruguay as well as the money market of Bolivia, which behaved as sinks. Such causal relations are not present in the status-quo regime as shown in Figure 2.

The results for the stock market transmission channel are robust to the search method used to reconstruct the best data oriented DAGs. The results for the sovereign debt transmission channel are not robust to the search method used. The weak evidence for the sovereign debt transmission channel might be the result of the presence of a hidden latent factor in the network. In this regard, the Mexican crisis of 1994 was preceded by a shift in the monetary policy stance of the Federal Reserve increasing interest rates in the international money markets. For the case of Argentina, Bolivia, and Uruguay, the results may be also affected by dynamic misspecification as explained before.

Hence, we cannot reject the null hypothesis of only interdependence in the sovereign debt markets (i.e., DAG isomorphism) at a 5% significance level. The result is consistent with previous work about the Mexican crisis and its effects on other emerging markets (see e.g., Masson 1998; and Forbes and Rigobon 2001, 2002). The sovereign market acted as the transmission channel of the "moonsonal effect" from the Fed.

However, we are able to reject the null of only interdependence at a 5% significance level in the stock markets. That is, there is evidence of pure financial contagion effects in the stock markets possibly triggered by the actions of global institutional investors (mutual and hedge funds) acting as carriers of the bad news elsewhere.

The Asian crisis: Wake-up call and capital controls

Figures 1 and 2 show that there is evidence of a causal transmission channel opening between the sovereign debt markets of Asia as a source of bad news in contemporaneous time and the foreign exchange markets of Argentina, and Bolivia, as well as the money market of Bolivia, which behaved as sinks during the crisis regime at a 5% significance level. There is also evidence of a causal transmission channel opening between the stock markets of Asia as a source of bad news in contemporaneous time, and the money markets of Brazil, Bolivia, and Venezuela, which behaved as sinks during the crisis regime at the same significance level. Note that there is also an intra-Mercosur transmission channel opening between the money markets of Brazil and Venezuela as a source of bad news in contemporaneous time, and the stock markets of Brazil and Uruguay, which behaved as sinks during the crisis regime. Such causal relations across markets are not present during the status-quo regime as shown in Figure 2.

Only the results for the stock market transmission channel are robust to the search method used to reconstruct the DAGs. So we reject the null hypothesis of only interdependence in favor of both interdependence and pure contagion effects in the stock market transmission channel during the Asian crisis at a 5% significance level.

These results seem to support the role of the Asian crisis as a wake-up call to other emerging markets (Baig and Goldfajn 1998; Corsetti et al. 2005; Bekaert et al. 2005; and Chiang et al. 2007). The economic intuition of the argument relies on the role of the stock market as a forward looking signal of future fundamentals affecting money and foreign exchange markets. Furthermore, wake-up calls seem to affect more markets that are perceived by investors as relatively riskier possibly because of capital controls. This was the case for Brazil and Venezuela at the time of the Asian crisis.

The Russian crisis: Wall Street as a carrier of bad news

As shown in Figures 1 and 2, there is evidence of a causal transmission channel opening between the sovereign debt market of Russia, which behaved as a source in contemporaneous time, and the foreign exchange markets of Argentina, and Chile, as well as the money market of Bolivia, which behaved as sinks at a 5% significance level. There is also statistical evidence of a causal transmission channel opening between the stock market of Russia, which behaved as a source in contemporaneous time, and the money markets of Chile and Uruguay, which behaved as sinks. Such causal transmission channels do not show up during normal economic times.

After robustness checks, the results leave us with strong evidence of pure contagion only in the stock market transmission channel. The relatively small number of markets affected in contemporaneous time seem to be because of the confounding effect of Wall Street as a carrier of bad news. Anecdotically, the Russian crisis of 1998 triggered a liquidity crunch in Wall Street with the consequent fall of long term capital management (LTCM), which was heavily invested in the Russian markets. In turn, Brazil enters into a crisis after a “sudden stop” in the flow of capital.

The structure of Mercosur regional interdependence

The Brazilian and Argentine crises are important because they provide insights about the structure of regional interdependence in Mercosur. In particular, the sovereign debt and stock markets of Brazil behave as a source of negative news to other relatively small markets in the region such as Chile and Venezuela. However, because such causal transmission channels were present during the status-quo regime, we cannot reject the null hypothesis of only interdependence at a 5% significance level. Surprisingly, Brazil's crisis did not have a major contemporaneous effect on its major trading partner in the region– Argentina. One might argue that the reason for the weak contemporaneous effect was the pseudo-currency board of Argentina.

The crisis did have a major effect on Argentina's large deflation cumulative adjustment process that ended with the collapse of the pseudo-currency board in 2001. Unlike Brazil, Argentina did not seem to act as a source of bad news in the region as the transmission channels opened are not robust to the search method used to reconstruct the DAGs. Thus, we cannot reject the null of only interdependence (DAG-isomorphism) at a 5% significance level after the Brazilian and Argentinian crises.

IV. Conclusion

We test for the presence of pure contagion effects in Mercosur for each major financial crisis that plagued emerging markets between 1994 and 2002. For this purpose, we introduce a novel semi-parametric econometric test that is capable of detecting changes in the causal structural relations of a (regional) network of financial markets. Besides strong evidence in favor of market interdependence, we cannot rule out the presence of pure contagion effects in the stock market transmission channel associated with the Mexican, Asian, and Russian financial crises.

References

Ang, Andrew, and Geert Bekaert (2002). International asset allocation with regime shifts. *Review of Financial Studies* 15: 1137-87.

Ang, Andrew, and Joseph Chen (2002). Asymmetric correlations of equity portfolios. *Journal of Financial Economics* 63: 443-94.

Arcidiacono, Peter, and John B. Jones (2003). Finite mixture distributions, sequential likelihood and the EM algorithm. *Econometrica* 71: 933-46.

Baig, Taimur, and Ilan Goldfajn (1998). Financial market contagion in the Asian crisis. Working Paper 98/155, International Monetary Fund.

Baig, Taimur, and Ilan Goldfajn (2000). The Russian default and the contagion to Brazil. Working Paper 00/160, International Monetary Fund.

Bekaert, Geert, Campbell R. Harvey, and Angela Ng (2005). Market integration and contagion. *Journal of Business* 78: 39-70.

Bessler, David A., and Jian Yang (2003). The structure of interdependence in international stock markets. *Journal of International Money and Finance* 22: 261-87.

Brennan, Michael J. (1990). Latent assets. *Journal of Finance* 45: 709-30.

Chang, Roberto., and Giovanni Majnoni (2002). Financial crises, fundamentals, beliefs, and financial contagion. *European Economic Review* 46: 801-8.

Chen, Xiaohong, Yanqin Fan, and Andrew J. Patton (2003). Simple tests for models of dependence between financial time series: With applications to U.S. equity returns and exchange rates. Discussion Paper 483, Financial Markets Group, New York University, Vanderbilt University, and London School of Economics.

Chen, Xiaohong, and Yanqin Fan (2006). Estimation and model selection of semi parametric copula-based multivariate dynamic models under copula misspecification. *Journal of Econometrics* 135: 125-54.

Cherubini, Umberto, Elsa Luciano, and Walter Vecchiato (2005). *Copula methods in finance*. Wiley, New York.

Chiang, Thomas C., Bang N. Jeon, and Huimin Li (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance* 26: 1206-28.

Connor, Gregory (1984). A unified beta pricing theory. *Journal of Economic Theory* 34: 13-31.

Corsetti, Giancarlo, Marcello Pericoli, and Massimo Sbracia (2005). Some contagion, some interdependence: More pitfalls in tests of financial contagion. *Journal of International Money and Finance* 24: 1177-99.

Dempster, Arthur P., Nan M. Laird, and Donald B. Rubin (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society Series B* 39: 1-38.

Dornbusch Rudiger, Yung C., Park, and Stijn Claessens, 2000. Contagion: Understanding how it spreads. *The World Bank Research Observer* 15: 177-97.

Dungey, Mardi, Renée Fry, Brenda González-Hermosillo, and Vance Martin (2005). Empirical modelling of contagion: A review of methodologies. *Quantitative Finance* 5: 9-24.

Engle, Robert F., and Kenneth F. Kroner (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory* 11: 122-50.

Engle, Robert F., and Kevin K. Sheppard (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. Working paper 2001-15, University of California at San Diego.

Forbes, Kristin J., and Roberto Rigobon (2001). Measuring contagion: Conceptual and empirical issues. In S. Claessens, and K. Forbes, editors. *International Financial Contagion*. New York: Kluwer Academic Publishers.

Forbes, Kristin J., and Roberto Rigobon (2002). No contagion, only interdependence: Measuring stock market co-movements. *Journal of Finance* 47: 2223-61.

Froot, Kenneth A., David S. Scharfstein, and Jeremy C. Stein (1992). Herd on the street: Informational efficiencies in a market with short-term speculation. *Journal of Finance* 47: 1461-84.

Gagliardini, Patrick, and Christian Gouriéroux (2007). An efficient nonparametric estimator for models with nonlinear dependence. *Journal of Econometrics* 137: 189-229.

Genest, Christian, Jean-François Quessy, and Bruno Rémillard (2002). Tests of serial independence based on Kendall's process. *Canadian Journal of Statistics* 30: 1-21.

Hamao, Yasushi, Ronald W. Masulis, and Victor K. Ng (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies* 3: 281-307.

Hong, Yongmiao (1999). Hypothesis testing in time series via the empirical characteristic function: A generalized spectral density approach. *Journal of the American Statistical Association* 84: 1201-20.

Hu, Ling (2006). Dependence patterns across financial markets: A mixed copula approach. *Journal of Applied Financial Economics* 16: 717-29.

Kaminsky, Graciela L., Carmen Reinhart, and Carlos A., Végh (2002). The unholy trinity of financial contagion. *Journal of Economic Perspectives* 17: 51-74.

King, Mervyn A., and Sushil Wadhwani (1990). Transmission of volatility between stock markets. *Review of Financial Studies* 3: 5-33.

Kroner, Kenneth F., and Victor K. Ng (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies* 11: 817-44.

Lee, Sang-bin, and Kwang-jung (1993). Does the October 1987 crash strengthened the co-movement among national stock markets? *Review of Financial Economics* 3: 89-102.

Masson, Paul R. (1998). Contagion: Monsoonal effects, spillovers, and jumps between multiple equilibria. Working Paper 98/142, International Monetary Fund.

Masson, Paul R. (1999). Contagion: Macroeconomic models with multiple equilibria. *Journal of International Money and Finance* 18: 587-602.

Masson, Paul R. (2007). *Lectures in international finance: Crisis, coordination, currency unions, and debt*. Singapore, World Scientific Publishing Co..

Pericoli, Marcello, and Massimo Sbracia (2003). A primer on financial contagion. *Journal of Economic Surveys* 17: 571-608.

Reisman, Haim (1992). Reference variables, factor structure, and the approximate multibeta representation. *Journal of Finance* 47: 1303-14.

Richardson, Matthew P., and Tom Smith (1993). A test of multivariate normality of stock returns. *Journal of Business* 66: 295-321.

Robinson, Peter M. (1987). Asymptotically efficient estimation in the presence of heteroskedasticity of unknown form. *Econometrica* 55: 875-91.

Ross, Stephen A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13: 341-60.