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EXTREME INTERDEPENDENCE AND EXTREME CONTAGION BETWEEN EMERGING MARKETS

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Extreme Interdependence and Extreme Contagion Between Emerging Markets

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Abstract

This paper presents a methodology to identify contagion between exchange market pressure events in different countries, based on a set of seemingly unrelated probit equations. This technique allows us to separate the transmission due to broadly defined macroeconomic interdependence, and contagion due to herding, avoiding some of the caveats of the more traditional cross-correlation approach.

We find evidence of pure contagion only for a limited number of country pairs which, with few notable exceptions, belong to the same region. In some instances, a reduction in speculative pressure can be identified between countries located in different regions. This evidence seems to suggests that the spreading of crises can be triggered by sudden shifts in investors expectations after an initial crisis episode and that investors tend to discriminate on the basis of location and common macroeconomic weakness or perceived similarity.

JEL-Codes: C35, F31, F32, F34

Keywords: Currency Crisis, Contagion, Seemingly Unrelated Bivariate Probit

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1 Introduction

The debate on the nature of contagion revolves around a number of issues in international finance, such as the development of a viable International Financial Architecture, the choice of the appropriate International Monetary System, and the role of capital flows in the development of crises. Also, it has important implications for crisis management and for portfolio investment strategies. With respect to the first issue, for example, the identification of contagion is needed to gauge the effectiveness of international rescue plans. For example, during periods of diffused turmoil, intervention is necessary and effective only if targeted to avoid the propagation of mayhem to countries unrelated to the country where the crisis originated. Otherwise intervention would simply slow down the necessary, albeit painful, adjustment process and distort recovery from the crisis over the longer–term. A second backlash of this debate pertains to the effectiveness of investors' diversification strategies, which pursue international diversification on the assumption that international stocks exhibit lower correlation than domestic stocks and that crises are country–specific. If, on the other hand, assets in different countries exhibit higher correlation at times of crisis, and crises in different countries are related, international investors will be left exposed to even more un–hedged risk.

Despite a vast volume of papers produced over the last few years, the literature has reached little consensus on the role of contagion in recent crisis episodes. At the root of this controversy lies the disagreement on what should be interpreted as contagion. Early studies adopted a general definition, which viewed contagion as the increase in the probability of crisis after the occurrence of a crisis elsewhere. According to this definition, it is possible to identify contagion by including the contagious event in an equation traditionally used to predict crises, and use a set of weights to assess the role of alternative channels of transmission. Eichengreen, Rose and Wyplosz (1996) and Glick and Rose (1999), for example, adopted the above definition to investigate the channels of contagion in order to shed some light on the origins of contagious currency crises. That kind of analysis, however, put aside the distinction between interdependence and contagion.

In a recent paper, Forbes and Rigobon (FR henceforth, 2002) have adopted a more restrictive interpretation of contagion as a significant increase in the correlation between international assets (financial stocks in their paper) after a crisis event. This definition introduces a critical distinction between contagion as such and *interdependence*, i.e. a high level of cross–market correlation, which is present in all *states of the world*. According to Forbes and Rigobon, therefore, the transmission of a crisis from one country to another **cannot** be interpreted as contagion if the operation of the channel does not change across regimes. Accordingly, contagion is identified as a structural break in the crisis transmission mechanism, i.e. a *correlation breakdown*. They suggest that studies relying on standard correlation analysis are biased, because an increase in correlation may be due to the large realisation of an idiosyncratic shock.[1] They argue that once the correlation coefficient is corrected for this bias, no contagion, but only interdependence, can be detected during recent episodes of crisis.

The cross–correlation analysis of Forbes and Rigobon has received a mixed reaction in the profession (See, for example, Favero and Giavazzi, 2000, Corsetti, Pericoli and Sbracia 2000, 2001, Dungey and Zhumabekova, 2001, and Caporale, Cipollini and Spagnolo, 2002). One of the main caveats of studies trying to identify a break in the correlation structure is that the separation of tranquil from turbulent periods is often arbitrary, given that the starting and closing dates of turmoil are not always easily identified. Also, in a correlation analysis the correlation coefficient between two assets before the crisis is considered as

[1]A result derived from the Normal Correlation Theorem. See also Boyer, Gibson, and Loretan (Boyer et al. (1999)), and Loretan and English (Loretan and English (2000))

the measurement of the existing linkages between the two countries, and the break in the series is interpreted as evidence of contagion. However, the existing interdependence arising through the interrelation between fundamentals, which may be the root of the transmission mechanism, is not modelled explicitly.

In this paper, we maintain an equivalently strict definition of contagion to the one proposed by Forbes and Rigobon, and interpret contagion as the *increase in the probability of crisis beyond what could be foreseen by the linkages between fundamentals*. Unlike FR, we do not rely on the blurred distinction between different states of the world, as we formulate a more explicit role for fundamentals in the transmission mechanism. Therefore, we try to identify contagion as the transmission beyond what would be expected by the existing interrelation between fundamentals.[2]

In conformity with this interpretation, we rely on the identification of currency crises using exchange market pressure indices and then propose a methodology based on *seemingly unrelated bivariate probit models* in order to test for the presence of extreme contagion between 14 emerging market economies. In order to measure "pure contagion", we exploit the information coming from the cross–country correlation between the residuals of two equations.[3] Using a three stage approach, we try to separate the transmission due to broadly defined macroeconomic interdependence, and contagion due to herding. Finally, our approach allows us to check the properties of the joint and the conditional predicted probabilities of crises between country pairs.

The remainder of this paper is organised as follows. In the next section, we describe where our approach stands in terms of the existing literature on the identification of contagion. Section 3 presents the methodology and section 4

[2]This approach bears the advantage of avoiding some of the caveats of the cross-correlation approach (see Dungey and Zhumabekova, 2001), and in this respect, it is more similar to the one suggested by Favero and Giavazzi (2000), and Caporale, Cipollini and Spagnolo (2002).

[3]This approach extends the more traditional tests of contagion, which rely on the identification of contagion as the impact of a crisis elsewhere beyond the effect of the country's fundamentals. At the same time, it overcomes some of their limitations.

describes the empirical implementation, and comments on the results. Finally, section 5 provides a discussion of the conclusions from the analysis.

2 Tie–Up To The Existing Literature

In this section, we briefly recall some of the main approaches utilised to measure contagion in order to place our methodology in the context of existing tests.[4] A popular approach to detecting contagion is through cross–correlation analysis. FR have pointed to the fact that sudden correlation changes are neither necessary nor sufficient to identify contagion or crisis periods, since an increase (decrease) in correlation does not imply a change in the data generating process. They have implemented a corrected correlation coefficient, which rejects the presence of contagion during recent episodes. This evidence has not, however, been universally accepted.[5] Dungey and Zhumabekova (2001), in particular, have underlined that the results of correlation analysis may be seriously biased by the size of the "non–crisis" compared to the "crisis" periods.[6] Cross–correlation analysis, however, carries two further caveats. Firstly, the problem of distinguishing turbulent from tranquil periods,[7] and, secondly, the lack of an explicit formulation for the role of fundamentals in the data generating process of the joint distribution of returns. This formulation is even more important if currency crises rather than stock market crises are the focus of analysis.

Recently, Chan–Lau, Mathieson, and Yao (2002) have suggested identifying extreme events as those returns exceeding a large threshold value (based on a 95% cut–off point), and using extreme value theory (EVT) methods to quantify contagion as the "... the joint behavior of extremal realizations (or co–exceedances) of financial prices or returns across different markets ...". Chan–Lau, Mathieson,

[4]See Pericoli and Sbracia (2001), Bayoumi, Fazio, Kumar, and MacDonald (2003) for a more thorough discussion of the different tests developed in the literature to measure contagion over recent episodes.

[5]See, for example, Favero and Giavazzi (2000), Corsetti, Pericoli and Sbracia (2000, 2001).

[6]See, also, Caporale, Cipollini and Spagnolo (2002) for a proposed solution to this issue.

[7]Which should be endogenously, rather than exogenously determined.

and Yao refer to EVT measures of contagion as *extreme contagion* measures. This approach differs from the standard cross–correlation analysis, because it marks bullish and bearish periods ex–ante, as the top (bottom) five percent of the return distribution, and then estimates the joint probability of these extreme returns.[8]

Recent evidence suggests that during periods of turmoil contagion is selective, i.e. it spreads to some countries while others remain resilient to international shocks. Correlation analysis does not conceive an explicit role for the transmission mechanism which, on the contrary, has been investigated extensively in probability based studies. This literature can be divided into three main groups depending on the different sources of contagion. The first group analyses trade linkages, such as those highlighted by Gerlach and Smets (1994) and Glick and Rose (1999), as the main source of contagion. If a partner or a competitor country devalues, pressure mounts on the domestic monetary authorities to devalue as well. The second group of papers considers the role of international financial markets as a source of contagion. This channel works through the presence of a *common lender* or via the stock market.[9] This type of contagion is due to liquidity shocks[10] or stock market comovements.[11] Finally, the third group of papers concentrates on *common macroeconomic weaknesses*[12] as a potential explanation for the *speculative selection process*. If currency markets are characterised by multiple-equilibria, a change in investors' expectations can cause a shift from one equilibrium to another. A crisis in one country can trigger speculative pressure on other countries which, in the eyes of international investors, display greater

[8]Chan–Lau, Mathieson, and Yao measure extremal dependence along two dimensions. The first looks at shifts from asymptotic independence to asymptotic dependence from the joint behaviour of the realisations of two series in the limit. The second corresponds to changes in the extremal dependence measured by a given asymptotic tail property.

[9]See, for example, Kaminsky and Reinhart (1999), Caramazza, Ricci and Salgado (2000) and Pesenti and Tille (2000)

[10]See Goldfajn and Valdes (1998)

[11]See Kaminsky and Reinhart (1999), and Kodres and Prisker (2002)

[12]Sachs, Tornell, and Velasco (1996), and Eichengreen, Rose, and Wyplosz (1996) are the seminal papers in this stream of research.

similarity with the hit country.[13] This is also defined by Ahluwalia (2000) as "discriminating contagion". On the other hand, if investors do not discriminate, *flight from risk* will affect all emerging markets alike.

A test of discriminating contagion needs to appraise whether speculative pressure mounts on countries with similarly bad fundamentals to the hit country, and whether this perception of vulnerability is indeed affected by location in a particular region. Ahluwalia, for example, tests for discriminating contagion using standard probit methodologies and three *ad–hoc* measures of similarity. The first of these measures, *fundamentals common weakness discrimination*, is given by the number of countries experiencing a crisis during a contagious episode having at least one vulnerability signal (in the early warning signal terminology) in common with the country under observation. The second, *fundamentals common weakness and common region discrimination*, is given by the number of signals in crisis countries belonging to the same region. The third, *wake-ip call discrimination*, considers the number of signals a country has in common with the country that triggered the wave of contagion (Mexico in 1994–95, Thailand in 1997–98, and Russia in 1998).

Here, we suggest an alternative approach to testing for discriminating contagion, based on the estimation of a series of seemingly unrelated bivariate probit models over a sample of 14 emerging countries observed at monthly frequencies. We choose as fundamental controls a set of indicators commonly used in traditional empirical models to predict currency crises, and test the significance of the cross–equation correlations. The correlation between the disturbances of the two equations represents the correlation between the crisis outcome in each country, once the impact of fundamentals has been accounted for. Hence, we can consider this as the correlation between *omitted factors*. We then test for contagion using

[13]Two countries may seem alike to *information–constrained* international investors, because of perceived common fundamentals weaknesses, or even simply because of geographical location. Location may convey a signal of vulnerability, because countries in the same region usually enjoy stronger trade and financial linkages or because they are perceived as more structurally similar.

standard Likelihood Ratio or Wald tests. If the correlation coefficient is significant, the estimation on the basis of the included own country fundamentals is not sufficient to explain the probability of a crisis, and it is necessary to take into account the information coming from the fundamentals of the other country.

The methodology proposed in this paper can be assimilated to the Extreme Value Theory approach,[14] but it extends it by allowing the parametric estimation of the joint probability of extreme events on the basis of the fundamental controls. Hence, we can make explicit the cross–correlation due to fundamentals in the crisis transmission mechanism. This cross–correlation is likely to originate from common fundamental weakness or from the fact that a shock to the fundamentals of one country is transmitted to the fundamentals of another via one or more of the usual channels. Compared to the approach adopted by Ahluwalia, this methodology does not require the formulation of *ad–hoc* and restrictive measures of similarity, but defines similarity more broadly. It encompasses general macroeconomic interdependence, using all of the information coming from fundamentals. Also, it tests for the correlation between omitted factors, overcoming one of the limitations of traditional tests indicated by Forbes and Rigobon.

At the same time, this alternative formulation is appropriate to a test for contagion resulting from herding behaviour as opposed to transmission due to fundamentals, commonly referred to as interdependence. This form of contagion, which we can refer to as "pure contagion", spreads because international capital markets are characterised by an informational asymmetry arising from the limited ability of international investors to gather all the relevant and correct informa-

[14]In the EVT approach, the joint probability distribution function of two random variables X and Y - $F(x, y) = Pr(X < x, Y < y)$ - is not known, but it can be estimated using a *copula* if the two univariate marginal distributions are known. This copula is the unique function, which relates the marginals to the joint distribution.

$$F(x, y) = C\{F_X(x), F_Y(y)\}$$

The copula function C can either be specified parametrically or estimated empirically.

tion on macroeconomic fundamentals.[15] Finally, since our sample encompasses countries from different regions, we can also draw some inference on whether discriminating contagion operates differently between and within regions.

3 Methodology

The simple idea behind this empirical exploration is to estimate the probability of crisis in one country using the information coming from both its fundamentals and the fundamentals of another country. We do this by estimating a series of bivariate probit models, where the left hand side variable is a 0/1 dummy indicating a crisis, and then testing for the significance of the cross–equation correlation. In the first stage, we identify simple extreme interdependence, which can be due to common factors, such as interest rate shocks in industrialised countries, to macroeconomic interdependence, or to herding. In the second stage, we try to exclude the cross–correlation dependence due to common factors, by introducing the US real interest rate as an explanatory variable in both equations. Finally, we account for a number of fundamentals traditionally considered as good predictors of currency crises in order to draw inference on the cross–equation correlation due to non–foreseeable omitted factors,[16] which we can take as a measure of herding.

In the most general representation, the probability of a crisis in country one and country two will depend on a set of own country fundamentals, common shocks, and normally distributed error terms:

$$y_1^* = \boldsymbol{\beta_1'}\boldsymbol{x_1} + \gamma_1\eta + \epsilon_1,\ y_1 = 1 \text{ if } y_1^* > 0 \text{ and } y_1 = 0 \text{ otherwise ;}$$

[15]This explanation for the contagion mechanism works along the lines of second generation speculative attack models, where multiple equilibria and investors' expectations can precipitate a country into a crisis. Yet, it is consistent with investors' rational behaviour as explained in Calvo (1999), Calvo and Mendoza (2000), and Pritsker (2000). The cost of gathering information in an increasingly globalised world is such that utility maximising investors may decide to adopt the strategy to follow those investors reputed as more informed. If these investors are forced to meet margin calls, this action may be interpreted as a signal of poor returns by the less informed investors, leading to an information cascade of the type described by Banerjee (1992). This view is also complementary to the "wake-up-call" argument presented in Goldstein (1998), where investors reassess one country's creditworthiness after a crisis elsewhere, and with the bank lending contagion introduced by Kaminsky and Reinhart (2000).

[16]See Greene (2003) for a full description of this methodology.

$$y_2^* = \boldsymbol{\beta_2'}\boldsymbol{x_2} + \gamma_2\eta + \epsilon_2,\ y_2 = 1 \text{ if } y_2^* > 0 \text{ and } y_1 = 0 \text{ otherwise } ; \tag{1}$$

$$E[\epsilon_1] = E[\epsilon_2] = 0 \ ;$$

$$Var[\epsilon_1] = Var[\epsilon_2] = 1 \ .$$

Where y_j^* is the latent variable and y_j is the observable for $j = 1, 2$. When each equation is estimated separately, it is implicitly assumed that the errors are independent of one another, i.e.

$$Corr[\epsilon_1, \epsilon_2] = \rho_{12} = 0 \ .$$

Under the null hypothesis the two error components are uncorrelated, i.e. no contagion. In this scenario, it is possible to estimate the two equations separately. However, if the errors in the two equations are correlated, because of the common unobservable component, ω, i.e.

$$\begin{aligned} \epsilon_1 &= \omega + \xi_1 \ , \\ \epsilon_2 &= \omega + \xi_2 \ , \end{aligned} \tag{2}$$

the correct specification is the model in bivariate form.

In order to formulate our contagion test, we develop from the general representation of the set of equations in (1), and proceed using a specific–to–general approach.

Step 1 – $H_0: \ Corr(u_1, u_2) = 0$.

We first estimate a version of the model where each equation includes only a constant. This first specification allows us to perform the equivalent of a test of correlation between extreme events in different currency markets, in the spirit of Chan–Lau, Mathieson and Yao (2002). The two equations take the following form,

$$y_1^* = u_1, \qquad y_1 = 1 \qquad \text{if } y_1^* > 0 \text{ and } y_1 = 0 \text{ otherwise } ;$$

$$y_2^* = u_2, \qquad y_2 = 1 \qquad \text{if } y_2^* > 0 \text{ and } y_1 = 0 \text{ otherwise ;} \tag{3}$$

$$E[u_1] = E[u_2] = 0 \ ;$$

$$Var[u_1] = Var[u_2] = 1 \ .$$

In this specification, the error terms are,

$$u_j = \boldsymbol{\beta_j'} \boldsymbol{x_j} + \gamma_j \eta + \underbrace{\omega + \xi_j}_{\epsilon_j} \quad for \ j = 1, 2.$$

The error terms u_1 and u_2 include the common shock η, the set of fundamental controls $\boldsymbol{x_j}$, an unobservable and normally distributed error term (ω) common to both equations, and a normally distributed error term (ξ), which is specific to each equation. If the cross–correlation between these error terms is significantly different from zero, this can be attributed to any of the three above components.

Step 2 – $H_0: \ Corr(\nu_1, \nu_2) = 0$.

Since the error terms from step one may be significantly correlated because of the inclusion of a common shock, we cannot consider a rejection of the null hypothesis as evidence of contagion, but as a mere test of the correlation between extreme events. In order to formulate a test of contagion,[17] we need to exclude the common common shock from the error terms, $\boldsymbol{u_j}$. We do this by testing the significance of the cross–correlation of the errors after the inclusion of *proxies* for common shocks in the estimation of the two equations. In this second case, the model specification has the following form,

$$y_1^* = \gamma_1 \eta + \nu_1, \ y_1 = 1 \text{ if } y_1^* > 0, \text{ and } y_1 = 0 \text{ otherwise ;}$$

$$y_2^* = \gamma_2 \eta + \nu_2, \ y_2 = 1 \text{ if } y_2^* > 0, \text{ and } y_1 = 0 \text{ otherwise ;} \tag{4}$$

$$E[\nu_1] = E[\nu_2] = 0 \ ;$$

$$Var[\nu_1] = Var[\nu_2] = 1 \ .$$

[17]At this stage, we are still using the term contagion very generally. We will distinguish between contagion and interdependence in the third step.

Where,

$$\nu_j = \boldsymbol{\beta_j'} \boldsymbol{x_j} + \underbrace{\omega + \xi_j}_{\epsilon_j} \ .$$

In this formulation, a cross–correlation between the error terms, $Corr(\nu_1, \nu_2)$, which is significantly different from zero cannot be attributed to the common shock η, but to the correlation between the fundamental controls, $\boldsymbol{\beta_j'} \boldsymbol{x_j}$, or to the unobservable component ω, which is common to the two equations.

If ν_1 and ν_2 are positively correlated, we can define this as negative contagion.[18] If the correlation between ν_1 and ν_2 is smaller than zero, we can define this as positive contagion, i.e. a crisis in one country, reduces the probability of a crisis in another country.

Step 3 $H_0: \ Corr(\epsilon_1, \epsilon_2) = 0$.

In the third step of our methodology we test the correlation between the errors which only include the common unobservable component ω, and the uncorrelated equation specific part of the error. This test can be formulated by including the set of country fundamentals in each respective equation. We, therefore, go back to the original specification in equations (1),

$$\begin{aligned} y_1^* &= \boldsymbol{\beta_1'} \boldsymbol{x_1} + \gamma_1 \eta + \epsilon_1, \ y_1 = 1 \text{ if } y_1^* > 0, \text{ and } y_1 = 0 \text{ otherwise} \ ; \\ y_2^* &= \boldsymbol{\beta_2'} \boldsymbol{x_2} + \gamma_2 \eta + \epsilon_2, \ y_2 = 1 \text{ if } y_2^* > 0, \text{ and } y_1 = 0 \text{ otherwise} \ ; \\ & E[\epsilon_1] = E[\epsilon_2] = 0 \ ; \\ & Var[\epsilon_1] = Var[\epsilon_2] = 1 \ . \end{aligned} \tag{5}$$

Where the error term is,

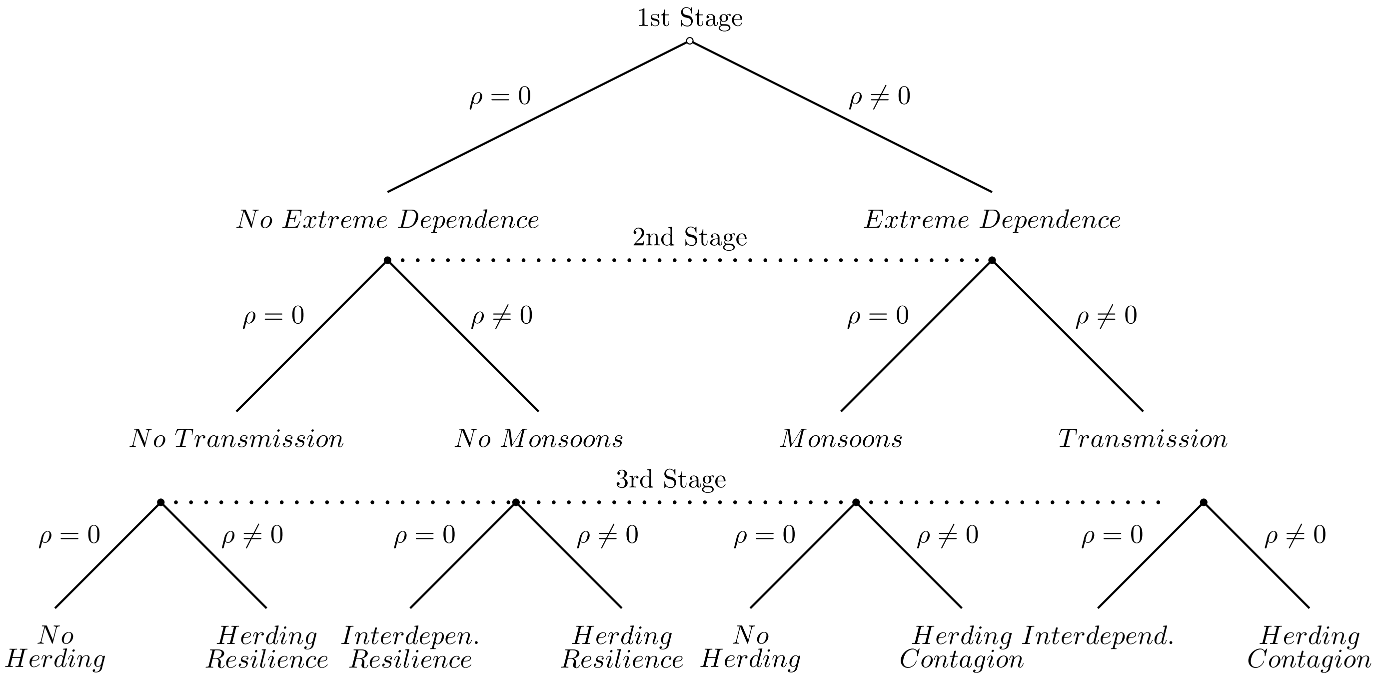
$$\epsilon_j = \omega + \xi_j, \quad for \ j = 1, 2 \ .$$

A test of whether the correlation between ϵ_1 and ϵ_2 significantly differs from zero represents a test of the impact of the unobservable component ω, which we can

[18] Again, a word of caution is necessary. Many authors would argue that this is not contagion, but interdependence. We keep this terminology for the sake of clarity, although the term "transmission" should be more appropriate and maybe more widely accepted.

interpret as *herding*. A significant correlation between the *residual errors* would be commonly accepted in the literature as a test of *pure contagion*.

Figure 1: Estimation Strategy and Scenarios



The bivariate normal cdf is $\Phi_2(x_1, x_2, \rho)$, where the subscript 2 indicates the bivariate nature of the normal distribution. In order to construct the likelihood function, as in Greene, we let $q_{ij} = 2y_{ij} - 1$, so that if $y_{ij} = 1 \Rightarrow q_{ij} = 1$ and if $y_{ij} = 0 \Rightarrow q_{ij} = -1$, where i indicates the observation. Now define,

$$z_{ij} = \boldsymbol{\beta_j' x_{ij}} \quad and \quad w_{ij} = q_{ij} z_{ij}, \quad for\ j = 1, 2\ ,$$

and $\rho_i^* = q_{i1} q_{i2} \rho$. The likelihood function has the following form:

$$\log\ L = \sum_{i=1}^{n} \ln \Phi_2(w_{i1}, w_{i2}, \rho_{i*})\ . \tag{6}$$

As is clear from equation (6), if $\rho = 0$, the log-likelihood of the bivariate model is equal to the sum of the log-likelihoods of the two univariate models. To test the significance of the correlation coefficient, it is possible to perform a simple likelihood ratio test (equivalently a Wald test) on ρ by comparing the full bivariate model and the sum of the two univariate probit regressions.[19]

Rejection of $\rho = 0$ is proof of crisis transmission, once we have accounted for a set of predictors of currency crises, representing the macroeconomic interdependence or the macroeconomic similarity between the two countries. If ρ is significantly different from zero, the omitted factors or the non–fundamental factors from the two equations are correlated. Figure 1 provides an illustration of the different outcomes for each of the three stages.

We can therefore estimate the joint, the marginal and the conditional predicted probabilities from the regressions, which are easily derived from the likelihood function. Recall that the probabilities in the likelihood function are,

$$Prob(Y_1 = y_{i1}, Y_2 = y_{i2}) = \Phi_2(w_{i1}, w_{i2}, \rho_i^*)\ ,$$

which is equal to:

$$\Phi(q_{i1}\boldsymbol{\beta_1'}\mathbf{x_{i1}}, q_{i2}\boldsymbol{\beta_2'}\mathbf{x_{i2}}, \rho_i^*)\ .$$

[19]We perform this analysis in Stata 7, using the biprobit command with the robust option, which automatically produces a Wald test.

Now, we can distinguish the following cases:

$$1. \qquad Pr\ (y_{i1} = 1, y_{i2} = 1) = \Phi_2(\boldsymbol{\beta_1' x_{i1}}, \boldsymbol{\beta_2' x_{i2}}, \rho)\ ;$$

$$2. \qquad Pr\ (y_{i1} = 1, y_{i2} = 0) = \Phi_2(\boldsymbol{\beta_1' x_{i1}}, -\boldsymbol{\beta_2' x_{i2}}, -\rho)\ ;$$

$$3. \qquad Pr\ (y_{i1} = 0, y_{i2} = 1) = \Phi_2(-\boldsymbol{\beta_1' x_{i1}}, \boldsymbol{\beta_2' x_{i2}}, -\rho)\ ;$$

$$4. \qquad Pr\ (y_{i1} = 0, y_{i2} = 0) = \Phi_2(\boldsymbol{\beta_1' x_{i1}}, \boldsymbol{\beta_2' x_{i2}}, \rho)\ .$$

The two marginal probabilities are respectively $\Phi(\boldsymbol{\beta_1' x_{i1}})$ and $\Phi(\boldsymbol{\beta_2' x_{i2}})$. In particular, we are interested in the joint probability of a crisis outcome and in the conditional probabilities:

$$A. \qquad Pr\ (y_{i1} = 1/y_{i2} = 1) = \frac{\Phi_2(\boldsymbol{\beta_1' x_{i1}}, \boldsymbol{\beta_2' x_{i2}}, \rho)}{\Phi(\boldsymbol{\beta_2' x_{i2}})}\ ,$$

and

$$B. \qquad Pr\ (y_{i2} = 1/y_{i1} = 1) = \frac{\Phi_2(\boldsymbol{\beta_1' x_{i1}}, \boldsymbol{\beta_2' x_{i2}}, \rho)}{\Phi(\boldsymbol{\beta_1' x_{i1}})}\ .$$

We can compare the joint, the marginal, and the conditional probabilities in order to draw some inference on the effect that the probability of a crisis in one country has onto the probability of crisis in another. In particular, if the two outcomes are independent it follows that

$$Pr\ (y_{i1} = 1/y_{i2} = 1) = Pr\ (y_{i1} = 1)$$

and

$$Pr\ (y_{i1} = 1/y_{i2} = 1) - Pr\ (y_{i1} = 1) = 0.$$

If the two are correlated,

$$Pr\ (y_{i1} = 1/y_{i2} = 1) - Pr\ (y_{i1} = 1) \lesseqgtr 0.$$

Therefore, we can take the difference between the conditional and the marginal probabilities as a measure of contagion. In the following section, we illustrate the empirical implementation - data, crisis definition and indicators used - and then comment on the results.

4 Empirical Implementation and Results

4.1 Data

We run this empirical exploration on monthly data for the period from January 1990 to December 1999 for fourteen emerging market economies. The choice of this frequency is dictated by the aim of assessing the predictive power of the economic indicators at a time horizon close to the crisis. Whilst a higher frequency could underestimate the role of fundamentals, a lower frequency would not be well suited to capture speculative pressure. Geographically, data come from five Asian economies (Korea, Malaysia, Indonesia, Thailand, Philippines), five Latin American countries (Brazil, Argentina, Chile, Mexico, Venezuela), three Central–Eastern European (Poland, Hungary, and Turkey) and one not belonging to any of the other regions (South Africa).

Crisis Definition

Our crisis definition replicates the measure of speculative pressure proposed by Kaminsky, Lizondo and Reinhart (KLR henceforth, 1998). This is defined as,

$$I_{KLR} = \begin{cases} 1 & \text{if } KLR \geq \mu_{KLR} + 1.5\sigma_{KLR} \quad \text{and} \\ 0 & \text{otherwise} \end{cases}$$

where $KLR = \Delta e_t - (\sigma_e/\sigma_r)\Delta r_t$. Where e is the exchange rate, r is the level of international reserves (both expressed in log form), μ and σ indicate, respectively, the mean and the standard deviation. This definition differs from the one employed by Eichengreen et al. (ERW, henceforth, 1994), because it does not include movements in the interest rate. KLR motivate this because of the lack of data availability for their sample. However, there could be a substantial motivation for not including the interest rate as a measure of speculative pressure.

Indeed, many commentators have argued that the ability of emerging markets to influence the exchange rate using the interest rate is rather limited. Figures 2 and 3 show, respectively, the number of crises identified by this definition over time and their distribution by country.

Right Hand Side

In order to discriminate the impact of contagion from the effect of fundamentals, we use a set of variables, which have been found to have a good track record in terms of predictive ability (See Goldstein, Kaminsky, and Reinhart, 2000). In particular, we use:

Real Interest Rate Differential (RIRD) A high differential between home and foreign money market real interest rates is often associated with a higher probability of crisis.[20] For the entire sample, the US Federal Fund Rate is assumed as the foreign interest rate. The higher the interest spread, the higher the risk of speculative pressure (a prediction associated with the monetary model of exchange rate determination).

Domestic Credit/GDP Growth (DCG) This indicator is positively associated by first generation models of speculative attacks to the build up of a crisis. Hence, we expect it to be positively signed.

M2/ Reserves (MTRG) This indicator is able to capture the effect of a loss of reserves,[21] and it is often introduced in order to measure financial depth. Indeed, many believe that a more appropriate measure of reserves adequacy is obtained by scaling foreign reserves using a liquid asset. The ratio of M2 to reserves should be able to reflect the vulnerability of the Central Bank

[20] Alternative to this indicator might be more able to capture the role of expectations. In this work, however, we prefer to use this as a control variable, following closely Goldstein, Kaminsky and Reinhart (2000).

[21] We use this variable in place of international reserves growth, which we have also used in our "backstage" regressions, because it is more informative. The two are highly correlated and introducing them together would pose problems of multicollinearity.

to potential runs against the currency. We expect a positive association between this ratio and the probability of a crisis.

Industrial Production (IPG) The probability of a currency crisis is often associated with a slowdown in growth. In order to control for this effect, we include the (year to year) changes in the industrial production index as an explanatory variable. Following the predictions of the monetary model, which associates an increase in GDP growth to a currency appreciation, we expect this variable to be negatively associated with the likelihood of a crisis.

Overvaluation (OVER) The excessive appreciation of the real exchange rate has been considered in previous studies as the most important explanation for large currency depreciations, and evidence suggests that devaluations are often associated with overvalued real exchange rates. Other studies, such as Husted and MacDonald (2000) and Chinn (1999), have concentrated on estimating the extent of the misalignment before the crisis using VAR and Panel–VAR methodologies on the monetary or on the PPP versions of exchange rate determination. In this study, the real exchange rate overvaluation is just one of the potential indicators of currency crisis. Hence, we rely on a more rough and ready measure of overvaluation similar to the one adopted by Esquivel and Larraìn (1998), Goldfajn and Valdés (1998) and Kaminsky et al. (2000). We define *overvaluation* as the relative distance of the real exchange rate from its long–run value, computed using the Hodrick–Prescott filter.[22] We expect this variable to be negatively signed. The more the real exchange rate is below its long–run value, the greater the extent of the overvaluation and the quest for a realignment.

[22]We compute the real exchange rate as the $log(S \times P^*/P)$, using the US$ as a reference currency for the Asian countries and South Africa, and the DM for the Central-Eastern European sub–sample.

Exports Growth (EXPG) This variable controls, again, for the potential effect of a current account problem. Higher exports growth lead to increasing levels of reserves, and they are expected to be negatively associated with the probability of crisis. This variable is expressed as the twelve month change in exports.

All of the right hand side variables are transformed in year-to-year log differences, and averaged over three months in order to remove any residual seasonality and to incorporate lagged information without burning degrees of freedom. They are also introduced with a period lag so that the predicted probabilities are one-step-ahead probabilities. The bivariate models are estimated via maximum likelihood. Unfortunately, these models do not easily achieve convergence.[23]

It seems important to highlight some of the potential caveats of this methodology. Firstly, the use of measures of exchange market pressure is very popular in the literature, but is not critique-free[24]. In out study, the use of monthly data reduces, but does not eliminate, some of the problems associated with these indices. Secondly, the use of higher frequency data would be more appropriate to determine the presence of contagion, but it would make it more difficult to model explicitly the role of fundamentals and, consequently, distinguish the crisis transmission due to contagion from that due to interdependence. Thirdly, as for any nonstructural analysis, the choice of the appropriate set of fundamentals can be critical, especially if the test involves the correlation between omitted factors. However, in order to distinguish interdependence from contagion it is not important whether a particular predictor has been omitted, but whether the omitted fundamentals are correlated across equations. Finally, in order to consider all possible interactions, it would be ideal to estimate a seemingly unrelated model of all the countries in the sample. Unfortunately, these models do not reach con-

[23]Hence, we are forced to search for the joint set of fundamentals, which allows each bivariate model to reach convergence, and the included set of fundamentals may vary for each pair.

[24]See Flood and Marion (**?**

vergence easily in their bivariate form and a multi–country analysis remains an impossible challenge. Advances in econometric analysis, however, such as the use of simulated maximum likelihood methods, do not exclude this possibility in the future.

4.2 Results

The correlation coefficient between equations (1) measures the correlation between the disturbances (the omitted factors) of the two equations. We can interpret ρ as the correlation between the outcomes after we have accounted for the influence of the included factors. If this correlation turns out to be statistically significant, we can interpret this as evidence of contagion.

Moreover, from the lower/upper diagonal matrix of bivariate correlation coefficients obtained from the 14 countries in our sample, we can extrapolate further information on the intra and inter–regional nature of this contagion. Location may, indeed, play a role in conveying (misleading?) information on the similarity between fundamentals.

We begin the empirical exploration by running the bivariate probit on all the possible country pairs in the sample. This gives us $n \times (n-1)/2$ correlation coefficients. We follow the empirical strategy outlined in section 3, and begin our empirical exploration by running a first set of regressions using only the constants as regressors. We then add, in a second stage, the US real interest rate in order to include the effect of monetary policy changes in industrialised countries. According to many commentators, these changes may have played an important role in the development of crises in emerging markets.

Stage 1

In the first stage, we compute the most simple of the extreme dependence measures by running a constants-only version of the seemingly unrelated bivariate probit model for each pair of countries in the sample. The constants take care of country-specific mean effects. The cross–equation correlation indicates whether two extreme outcomes are indeed correlated, and whether the two equations should be estimated jointly. At this stage, the omitted factors include factors common to both equations (common shocks) and factors that are country-specific (the fundamentals). Hence, the cross-equation correlation is a simple measure of extremal dependence and provides a first indication of which countries are likely to experience speculative pressure at the same time. However, it cannot be regarded as a test of contagion. Table 1 reports the cross-equation correlation coefficients and the respective p–values for the Wald test of significance. Crisis transmission is selective and tends to occur between specific pairs within the region and across regions, rather than across all emerging markets alike. The correlation coefficients are often negative, rather than positive, indicating that crises in different countries can be negatively related, as in some cases pressure on some countries can ease–off pressure on others. This evidence may be linked to the argument made by Morris and Shin (1998) that in turmoil periods the sheer force of speculation is important and, as suggested by Ahluwalia (2000), investors do tend discriminate during times of crisis.

A first noticeable result from table 1 is that crises between East–Asian economies, in particular between the Asean–4 economies (Indonesia, Malaysia, Philippines, and Thailand), tend to be positively correlated. On the other hand, speculative pressure with respect to South Korea is not significantly correlated to pressure in any of the other Asian countries in sample, except Thailand. A second result worth mentioning is that crises in the Asian countries are either unrelated or negatively related to crises elsewhere in the sample, with the exception of some positive correlation of Indonesia, Malaysia and Thailand with Chile. Indeed, at the time of the Asian crisis, both Thailand and Chile came under severe pressure, as noted by Edwards (2000).

Another interesting piece of evidence from this first set of regressions is that speculative pressure episodes among Latin American countries seem to be negatively related or unrelated (Brazil–Mexico), except for Argentina–Brazil and Argentina–Mexico, which show some positive correlation. Mexico and Brazil exhibit a positive, though insignificant, correlation. This implies that attacks on Brazil and Mexico, both unstable economies in the region, corresponded to attacks on Argentina that, however, managed to hold tightly onto its currency board for most of the 1990s.

In general, correlation between events in countries belonging to different geopolitical regions is either negative or not significant, with few notable exceptions (Argentina–Turkey, and Chile–S.Africa at the 10% significance level). Extreme events are positively correlated within the same region mostly in the case of the Asian countries, whereas most of the crises in L.American countries are negatively correlated. There is little evidence of dependence across regions (Chile–S.E.Asia, Chile–S.Africa, and Argentina–Turkey).

Stage 2

In the second set of regressions, we include the US Federal Fund Rate as a proxy for common shocks, and for industrialised countries' policies.[25] We are still deliberately omitting the own country fundamentals. Table 2 reports the results of this second set of regressions. Interestingly, not much has changed within the Asia sub–sample, where the correlation coefficients have only had a minor reduction in size. This probably suggests that crises in these countries had very little to do with industrial country policies, but originated from troubles borne from within the region. All of the remaining results are also largely unchanged

[25]We have also tried the Japanese and the German Money Market Rates, and the US, Japanese, and German industrial production index, but with no significant change in the results. We feel, however, that the US interest rate is the most adequate proxy, given that the USA is a major lender to the countries under observation.

with the notable exception of the pairs Brazil–Argentina and Mexico–Argentina, which are now insignificantly correlated. Events in Mexico and Brazil, which were previously positively but not significantly correlated, are now negatively, but significantly, correlated. This may be due to the fact that common shocks were at the root of the earlier detected positive correlation and that these countries were greatly affected by interest rate policies in the USA.[26]

Stage 3

In the third and final stage, we include the set of fundamental controls with the aim that the correlation between omitted factors will capture non–fundamental factors only, i.e. herding, or correlation between extreme events *unmotivated* by fundamentals' interdependence. Table 3 presents the cross–equation correlation coefficients of the last set of regressions. The comparison of the results obtained in stage two and the ones obtained in stage three, allows the distinction between extreme interdependence and extreme contagion. In this last stage, the picture depicted by tables 1 and 2 changes quite dramatically. Very few of the correlation coefficients remain significant after the introduction of the own country fundamentals. For example, the top left quadrant of the table suggests that most of the dependence within Asia was due to fundamental interdependence. In the terminology of Masson (1999), this means that for these countries it is more appropriate to talk about *spillovers* rather than pure contagion, with the notable exception of the Malaysia–Philippines pairing, where dependence does not seem to be accounted for by fundamentals' interdependence, and can probably be imputed to herding. The earlier negative interdependence between Asia and the rest of the sample, and Latin America in particular, seems now to have vanished. This indicates that the negative correlation coefficients were probably due to the negative correlation between fundamentals, with the exception of Chile

[26]I.e. change in monetary policy in the USA triggers generalised attacks on these countries. Some commentators would argue that this evidence provides a further case for dollarisation.

which maintains positive, but not significant at standard confidence levels, correlations with some Asian countries. Speculative pressure in Argentina continues to be negatively related to pressure onto Korea and Malaysia, and so it is for Korea with Mexico, Venezuela, and S.Africa, and Hungary and Turkey with the Philippines.

Within Latin America there are two further cases of positive contagion between the pairs Argentina–Mexico and Argentina–Venezuela, both at the 10% significance level. The remaining correlation coefficients within the region are either not significant or negatively related. As before, there is no evidence of contagion from any of the Latin American countries to the rest of the sample, implying that the previously detected (weak) correlation between Chile and S.Africa and Argentina and Turkey was probably due to some form of positive correlation between fundamentals.

In general, table 3 suggests that herding is limited to only a handful of cases between countries belonging to the same region, whereas most of the evidence between countries in different regions is of negative herding.

Joint, Marginal And Conditional Predicted Probabilities

The comparison of the joint, marginal, and conditional probabilities of crises for each country pair provides a measurement of the extent of the transmission. If the crisis outcomes in the two countries are independent, the conditional probability of speculative pressure on one country conditional on speculative pressure on another will not be significantly different from its marginal probability, implying that the informational content descending from the other country is irrelevant.

In order to illustrate this approach we concentrate on some of the most representative cases. Figures 4 and 5 plot, respectively, the joint and the conditional probabilities of crisis of the Asian countries in sample versus Thailand, considered as the crisis originator in 1997. The predicted joint probabilities are all close to zero for most of the period under observation, but increase markedly immediately after the eruption of the Asian crisis. This increase is gradual for the probability predicted from the stage two regressions, but it is captured by a spike for the joint probabilities from the full model. The conditional probabilities exhibit a similar behaviour when computed on the full model in the third stage of regressions, but a distinction emerges from stage two. In stage two, the Malaysia and Philippines probabilities, conditional on an event in Thailand, exhibit an almost identical (albeit with different size) decay during the second part of the 1990s, which counteracts the spikes of the conditional probabilities of stage three. In contrast, the conditional probabilities for Indonesia and Korea go up together in the second half of the 1990s and reach their maximum around 1998. However, these extreme outcomes are significantly correlated only in the first and the second stage, and there is no significant correlation after the inclusion of fundamentals. This means that the correlation coefficient in the first two stages were capturing the correlation between fundamentals, or interdependence. This result is not surprising because it classifies countries as belonging to the same region, and can be interpreted as evidence in support of the spillover effects mentioned by Masson (1999).

Malaysia and Philippines, for example, exhibit significant extreme correlation (according to the Wald test) in all three forms of the bivariate model. Quadrant A of figure 6 plots the predicted joint crisis probability in these two countries computed in each of the three stages. The joint probability from the first two stages is significant, but fairly constant throughout the 1990s. When the fundamentals are included, the joint crisis probability peaks at the time of the Asian crisis, rising to 28% in correspondence to July–August 1997. Quadrants B, C and D show the probability of crisis in the Philippines conditional on a crisis in Malaysia estimated using the three specifications described in section 3. Whereas quadrant C tells us how much the conditional probability differs (increases) with respect to the marginal probability because of the correlation between both the fundamentals and the omitted factors, quadrant D reflects more the change due to the correlation between omitted factors.[27] In all three cases, the conditional probability is considerably and significantly greater than the marginal probability. Quadrant D plots the probabilities predicted from the full model. The marginal probability of a crisis in the Philippines remains generally low throughout the period, with a small peak right at the time of the Asian crisis. The conditional probability from the full model, however, exhibits greater variability than in the other two stages, it rises well before the Asian crisis and drops suddenly just after it, mimicking the exchange market mayhem of that period.

Among the Asian countries, crises in South Korea seem to be influenced only by crises in Thailand, but the correlation disappears when we include the full set of fundamentals. Instead, speculative pressure on South Korea seems to be unrelated to speculative pressure elsewhere in the region. As an example, figure 7 shows the predicted joint, conditional and marginal probabilities of Korea vs. the Philippines. This pair exhibits a very low joint probability of crisis not rising beyond 5% and, as it can be seen from quadrant D, there is no distinction between the conditional and the marginal probabilities, once the full set of fundamentals is introduced in the third stage.

Figure 9 presents the example of Indonesia and Poland, as a case diametrically opposite to that of the Philippines and Malaysia in figure 6. Tables 1 and 2 show that these two countries are characterised by anti–correlated events. The negative correlation coefficient looses its significance when fundamentals are included in the model (see table 3). We can see from figure 9 that these two countries have a minuscule probability of ending up in a crisis at the same time (see quadrant A of

[27]This approach carries the same limitation of any non–structural approach, i.e. it is always possible that some relevant fundamentals will not be included in the analysis. However, in this context, this would represent a limitation only if the excluded fundamentals were correlated across countries

the figure) and the marginal probability of a crisis in Indonesia is always greater than its probability conditional on a crisis in Poland. Quadrant D, in particular, shows that when the events in the two countries are unrelated, as indicated by the the Wald test on the correlation coefficient, the conditional probability is almost impossible to discern from the marginal probability.

It is also interesting to look at the case of Chile, which adopted capital controls during most of the 1990s. Edwards (2000) highlights that Chile fell under intense pressure together with some Asian economies, and Thailand in particular. This evidence is supported by our correlation tables. Figure 8 shows in panel A how Chile and Thailand tended to come under speculative pressure at the same time. The conditional probabilities in quadrant C and D are persistently greater than the marginal probability. However, according to the Wald test, the correlation coefficient is not significant after the inclusion of fundamentals. On the other hand, Chile does not seem to be affected by crises occurring in the same region. For example, figure 11 considers the predicted probabilities of a crisis in Chile vs. Venezuela. These two countries exhibit very small joint probabilities of crisis and the marginal probability of a crisis in Chile is always greater than the probability conditional on a crisis in Venezuela. A similar pattern can be noticed in figure 12, where it is represented the case of Chile and Mexico.

The case of Argentina is also interesting, because it is a country that managed to maintain a currency board throughout the 1990s. Tables 1 to 3 highlight the presence of extreme contagion between Argentina and Mexico. Figure 10 shows that the probability of a crisis in Argentina conditional on a crisis in Mexico, a country often at the center of turmoil, is always greater than its marginal probability. These results show a resilience of the Argentinean currency board to contagion during this period, which contrasts with the instability at the beginning of the 2000s.

5 Conclusions

Identifying contagion is one of the critical issues in the current debate on currency crises. Although the literature on this topic has increased exponentially, little consensus has been reached on the identification of contagion in recent episodes. A common but controversial approach to measuring contagion uses correlation analysis of returns. More recently, extreme value theory methods have been suggested as a way to measure the correlation between extreme events and detect *extreme contagion*. These approaches, however, do not model explicitly the role of fundamentals and do not allow the investigation of the channels of transmission.

In this empirical exercise we interpret contagion as the *increase in the probability of crisis beyond what could be foreseen by the linkages between fundamentals*, and propose an alternative methodology. We are able to estimate an extremal dependence measure and model explicitly the role of fundamentals, allowing the distinction between *extreme interdependence* and *extreme contagion*. This approach consists of estimating a series of seemingly unrelated bivariate probit models between country pairs for a sample of emerging markets observed during the 1990s. Our test of contagion consists of a test of the significance of the correlation between the cross–equation errors, the *omitted factors*. Under the null hypothesis of no contagion, the two country-specific equations can be estimated separately. Rejection of the null hypothesis implies that estimating the model in its bivariate form yields a greater predictive power. Running this test before and after the introduction of a set of fundamental controls, we are able to distinguish the extremal dependence due to the correlation between fundamentals, or interdependence, and the dependence due to the correlation between omitted factors, or "pure contagion".

We find evidence of contagion for few cases and generally between countries belonging to the same region. In some instances, it is possible to identify a reduction of speculative pressure, especially between countries located in different regions. However, it seems that most of the extreme dependence is due to extreme interdependence. On this evidence, it cannot be ruled out that speculators discriminate on the basis of location and common macroeconomic weakness or perceived similarity. This argument supports the view that crises in emerging markets can be generated by sudden shifts in investors' confidence. The cost of gathering information at the global level makes these sudden shifts more likely by increasing the asymmetry between informed and uninformed investors.

These results carry some interesting policy implications. First, in order to assess the vulnerability of country, market participants and policymakers need to discount the state of fundamentals in other countries, in particular those belonging to the same region. Early warning systems need to monitor more carefully those countries with stronger existing linkages. However, contagion can occur without the presence of existing linkages, and international intervention may be required to limit the undue spreading of crises to "innocent" countries.

6 Data Appendix

Exchange Rate Nominal Exchange Rate expressed in national currency unit per US$, line ..AE.. IMF–IFS CD-Rom.

Real Interest Rate Differential The differential between the home and the foreign (US$) money market interest rate, deflated using consumer price inflation. The interest rate is line 60, and the consumer price index is line 64 from the IMF–IFS CD-Rom.

Reserves International reserves are taken from line ..1L.. of IFS-IMF CD-ROM

Industrial Production Industrial production growth. The Industrial Production Index is the line 66 from IFS-IMF CD-Rom.

Overvaluation This is an ad-hoc built measure of misalignment. We define the real exchange rate as rer=log(e)+log(p*)-log(p) computed using the consumer price indices and the USA as a foreign country. We apply an Hodrick-Prescott filter to the real exchange rate in order to compute the "long-run" value and define the misalignment as the relative difference between the actual and the predicted real exchange rate.

Exports Exports (in US$ value) line ..70.. IFS-IMF CD-Rom

M2/Reserves Ratio of M2 to Reserves. M2 is the sum of lines ..34.. and ..35.. (converted in US$) divided by line ..1L.. from IFS-IMF CD-ROM.

Domestic Credit Ratio of Domestic Credit to GDP. Domestic Credit is line ..32..from the IFS-IMF CD-Rom. GDP is interpolated from line ..99B.. from the IMF-IFS CD-Rom and OECD CD-Rom (where missing)

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Table 1: **Stage 1 - Bivariate Probit Correlations**

Constants Only	Korea	Malaysia	Indonesia	Thailand	Philippines	Brazil	Argentina	Chile	Mexico	Venezuela	Poland	Hungary	Turkey
Malaysia	0.631												
	(0.112)	-		SE Asia									
Indonesia	0.603	0.684											
	(0.124)	(0.012)	-										
Thailand	0.992	0.722	0.816										
	(0.000)	(0.009)	(0.002)	-									
Philippines	0.603	0.909	0.643	0.684									
	(0.124)	(0.000)	(0.016)	(0.012)	-								
Brazil	-0.790	-0.831	-0.838	-0.831	0.153								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.615)	-							
Argentina	-0.770	-0.806	-0.817	-0.806	-0.817	0.700			Latin	America			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	-						
Chile	0.603	0.499	0.643	0.684	0.457	-0.838	-0.817						
	(0.124)	(0.081)	(0.016)	(0.012)	(0.103)	(0.000)	(0.000)	-					
Mexico	-0.770	0.309	-0.817	-0.806	-0.817	0.238	0.629	-0.817					
	(0.000)	(0.345)	(0.000)	(0.000)	(0.000)	(0.452)	(0.039)	(0.000)	-				
Venezuela	-0.770	-0.806	-0.817	-0.806	-0.817	-0.824	-0.812	-0.817	-0.812				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	-			
Poland	-0.784	-0.825	-0.832	-0.825	-0.832	0.153	-0.817	-0.832	-0.817	-0.817			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.615)	(0.000)	(0.000)	(0.000)	(0.000)	-	CE Europe	
Hungary	-0.770	-0.806	-0.817	-0.806	-0.817	0.514	0.629	-0.817	0.352	0.352	0.272		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.075)	(0.039)	(0.000)	(0.292)	(0.292)	(0.398)	-	
Turkey	0.555	-0.837	0.121	0.161	-0.843	0.08	0.483	-0.843	0.208	0.208	-0.843	0.208	
	(0.150)	(0.000)	(0.685)	(0.596)	(0.000)	(0.770)	(0.090)	(0.000)	(0.506)	(0.506)	(0.000)	(0.506)	-
S. Africa	-0.770	-0.806	0.272	0.309	-0.817	-0.824	-0.812	0.548	-0.812	0.352	-0.817	0.352	0.208
	(0.000)	(0.000)	(0.398)	(0.345)	(0.000)	(0.000)	(0.000)	(0.061)	(0.000)	(0.292)	(0.000)	(0.292)	(0.506)

Wald Test of $\rho = 0$

p-values in parentheses

Table 2: **Stage 2 - Bivariate Probit Correlations**

Common Shocks	Korea	Malaysia	Indonesia	Thailand	Philippines	Brazil	Argentina	Chile	Mexico	Venezuela	Poland	Hungary	Turkey
Malaysia	0.582												
	(0.180)	-											
Indonesia	0.445	0.676		SE Asia									
	(0.278)	(0.026)	-										
Thailand	0.990	0.698	0.722										
	(0.000)	(0.019)	(0.011)	-									
Philippines	0.581	0.905	0.678	0.696									
	(0.178)	(0.000)	(0.024)	(0.018)	-								
Brazil	-0.799	-0.818	-0.913	-0.865	0.246								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.444)	-		Latin	America				
Argentina	-0.531	-0.787	-0.506	-0.611	-0.801	0.400							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.247)	-						
Chile	0.479	0.426	0.483	0.565	0.410	-0.841	-0.792						
	(0.272)	(0.138)	(0.105)	(0.050)	(0.141)	(0.000)	(0.000)	-					
Mexico	-0.511	0.368	-0.530	-0.611	-0.813	-0.812	0.544	-0.837					
	(0.000)	(0.283)	(0.000)	(0.000)	(0.000)	(0.000)	(0.134)	(0.000)	-				
Venezuela	-0.647	-0.831	-0.695	-0.747	-0.832	-0.806	-0.800	-0.858	-0.805				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	-			
Poland	-0.737	-0.816	-0.803	-0.832	-0.841	0.135	-0.800	-0.821	-0.808	-0.814		CE Europe	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.649)	(0.006)	(0.000)	(0.000)	(0.000)	-		
Hungary	-0.807	-0.841	-0.859	-0.874	-0.837	0.394	0.556	-0.870	0.444	0.381	0.381		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.226)	(0.133)	(0.000)	(0.206)	(0.249)	(0.278)	-	
Turkey	0.580	-0.856	0.022	0.128	-0.852	0.147	0.615	-0.892	0.269	0.202	-0.880	0.289	
	(0.187)	(0.000)	(0.946)	(0.722)	(0.000)	(0.627)	(0.043)	(0.000)	(0.384)	(0.513)	(0.000)	(0.343)	-
S. Africa	-0.877	-0.846	0.101	0.191	-0.839	-0.818	-0.792	0.537	-0.809	0.343	-0.838	0.422	0.215
	(0.000)	(0.000)	(0.777)	(0.584)	(0.000)	(0.000)	(0.000)	(0.050)	(0.000)	(0.306)	(0.000)	(0.203)	(0.475)

Wald Test of $\rho = 0$

p-values in parentheses

Table 3: **Stage 3 - Bivariate Probit Correlations**

Full Model	Korea	Malaysia	Indonesia	Thailand	Philippines	Brazil	Argentina	Chile	Mexico	Venezuela	Poland	Hungary	Turkey
Malaysia	0.375												
	(0.392)	-		SE Asia									
Indonesia	-0.734	0.431											
	(0.423)	(0.502)	-										
Thailand	0.154	-0.358	0.424										
	(0.662)	(0.317)	(0.253)	-									
Philippines	0.085	0.823	0.397	0.519									
	(0.847)	(0.000)	(0.428)	(0.323)	-								
Brazil	-0.843	-0.026	-0.339	-0.413	-0.756								
	(0.105)	(0.985)	(0.394)	(0.116)	(0.110)	-							
Argentina	-0.916	-0.938	0.010	-0.154	-0.010	-0.781		Latin	America				
	(0.000)	(0.000)	(0.961)	(0.573)	(0.984)	(0.118)	-						
Chile	0.081	0.493	0.998	0.879	0.999	-0.980	-0.827						
	(0.889)	(0.166)	(0.146)	(0.223)	(0.106)	(0.030)	(0.000)	-					
Mexico	-0.875	0.787	-0.077	-0.403	-0.267	-0.191	0.645	-0.899					
	(0.000)	(0.752)	(0.793)	(0.206)	(0.125)	(0.140)	(0.066)	(0.352)	-				
Venezuela	-0.963	-0.772	-0.390	-0.473	0.153	-0.424	0.618	-0.972	-0.548				
	(0.000)	(0.127)	(0.537)	(0.230)	(0.902)	(0.177)	(0.096)	(0.000)	(0.026)	-			
Poland	-0.998	-0.689	-0.4651	-0.064	-0.932	0.318	-0.166	-0.925	-0.569	-0.523			
	(0.417)	(0.430)	(0.032)	(0.737)	(0.241)	(0.327)	(0.626)	(0.000)	(0.003)	(0.083)	-	CE Europe	
Hungary	0.997	-0.411	-0.998	-0.948	-0.978	0.999	0.999	-0.968	-0.058	-0.976	-0.130		
	(0.589)	(0.839)	(0.644)	(0.518)	(0.020)	(0.750)	(0.915)	(0.025)	(0.945)	(0.013)	(0.767)	-	
Turkey	0.686	-0.998	-0.715	-0.027	-0.980	-0.969	-0.811	-0.983	0.457	0.494	-0.810	-0.255	
	(0.164)	(0.334)	(0.369)	(0.947)	(0.025)	(0.000)	(0.000)	(0.008)	(0.424)	(0.193)	(0.125)	(0.806)	-
S. Africa	-0.978	-0.999	0.418	0.732	0.295	-0.931	-0.963	0.999	-0.513	0.087	-0.993	0.999	1
	(0.012)	(0.688)	(0.354)	(0.608)	(0.722)	(0.350)	(0.000)	(0.935)	(0.327)	(0.837)	(0.072)	(0.952)	(0.245)

Wald Test of $\rho = 0$

p-values in parentheses

Figure 2: **Number of $\mathbf{I_{KLR}}$ Crises (1990,2-1999,12)**

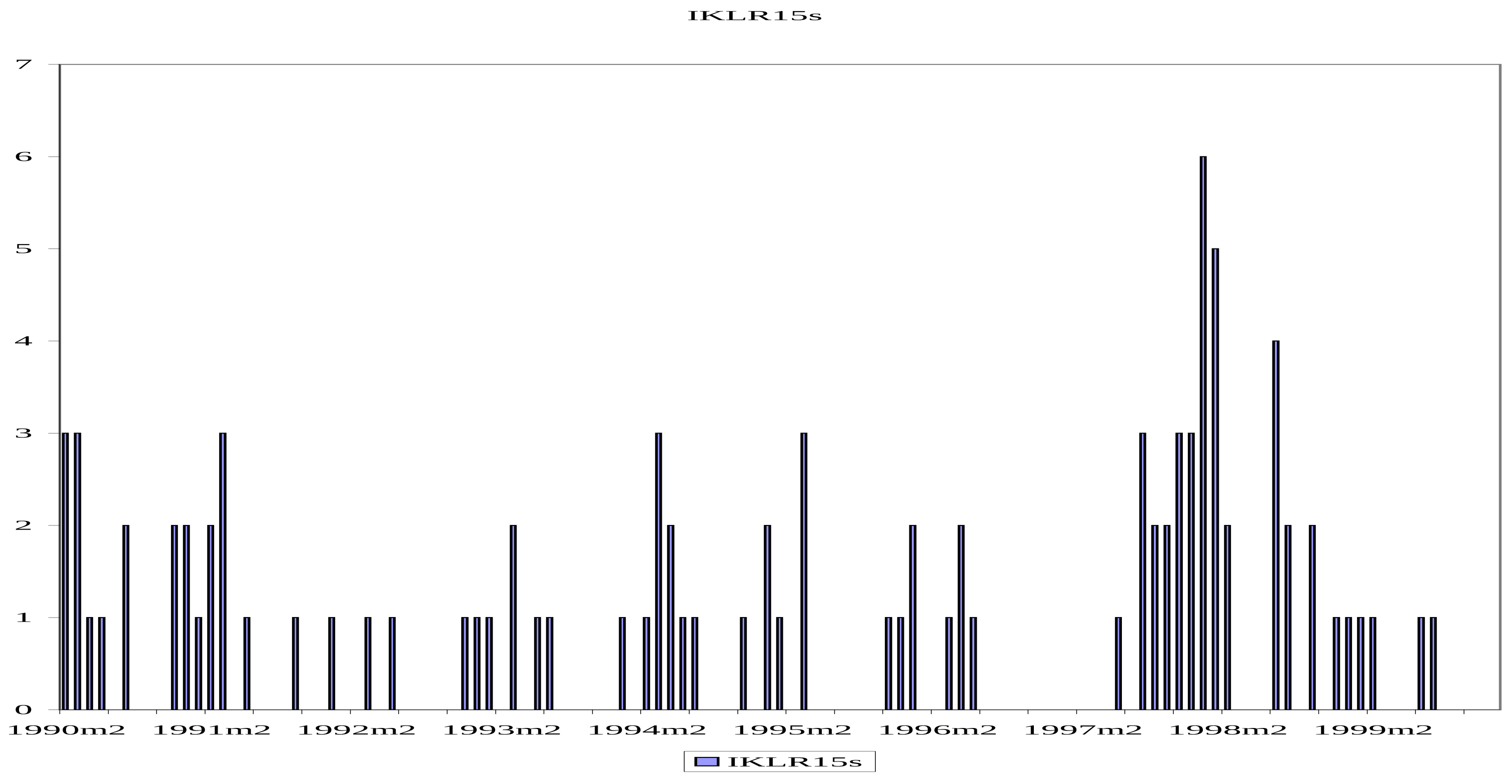


Figure 3: **Number of Crises by Country**

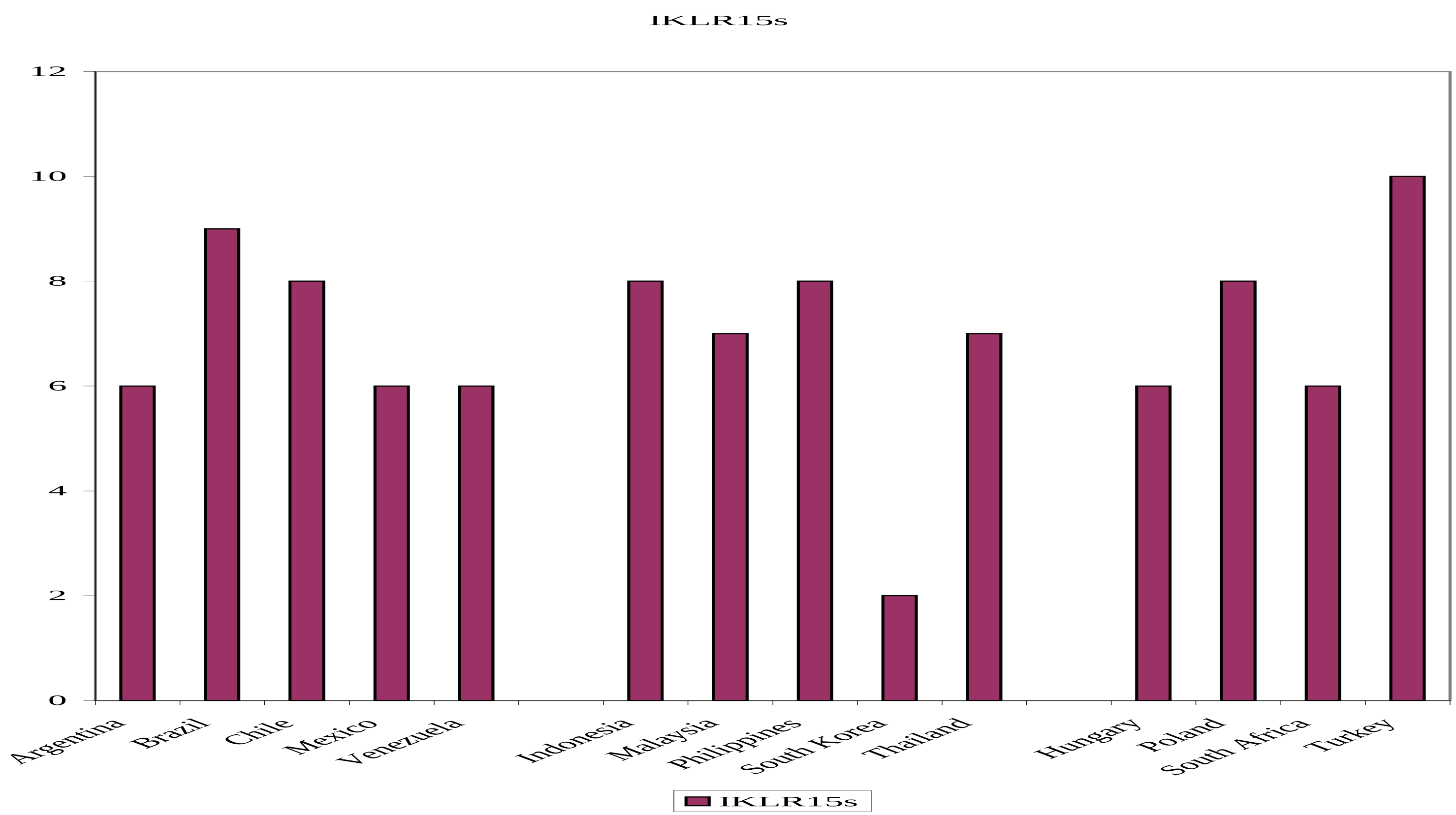


Figure 4: Asian countries vs. Thailand - Joint Probabilities

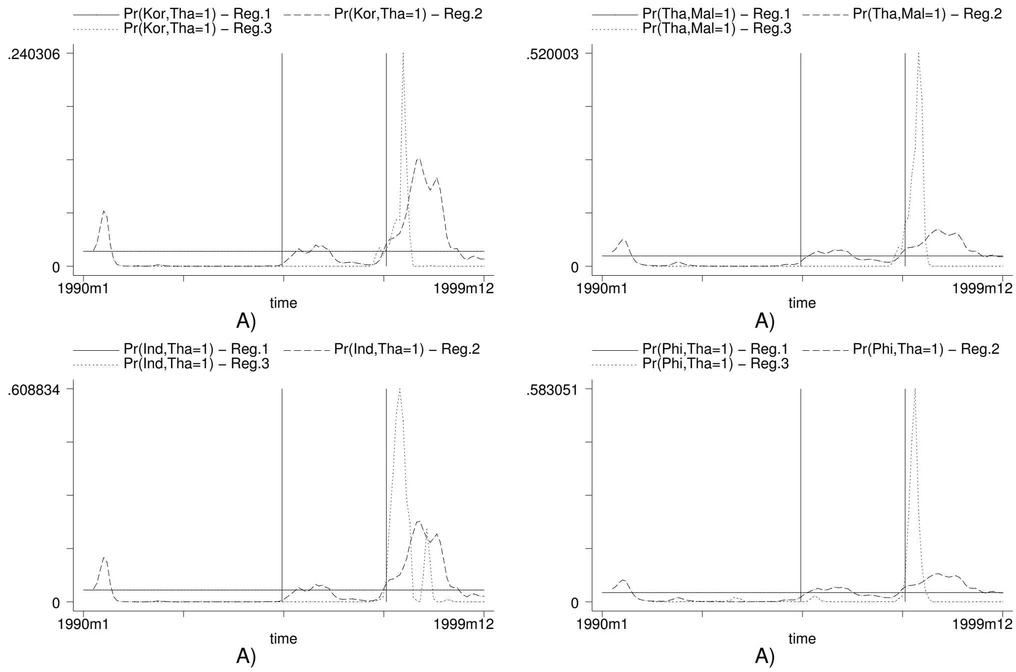


Figure 5: Asian countries vs. Thailand - Conditional Probabilities

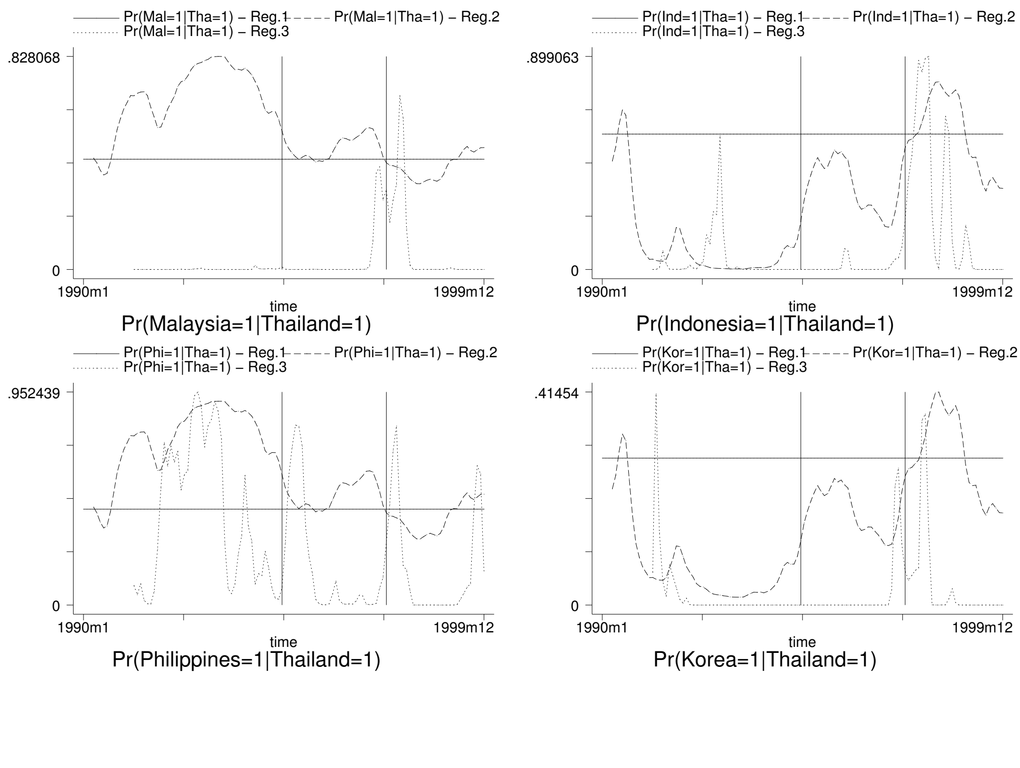


Figure 6: Philippines vs. Malaysia - Joint, Conditional, and Marginal Probabilities

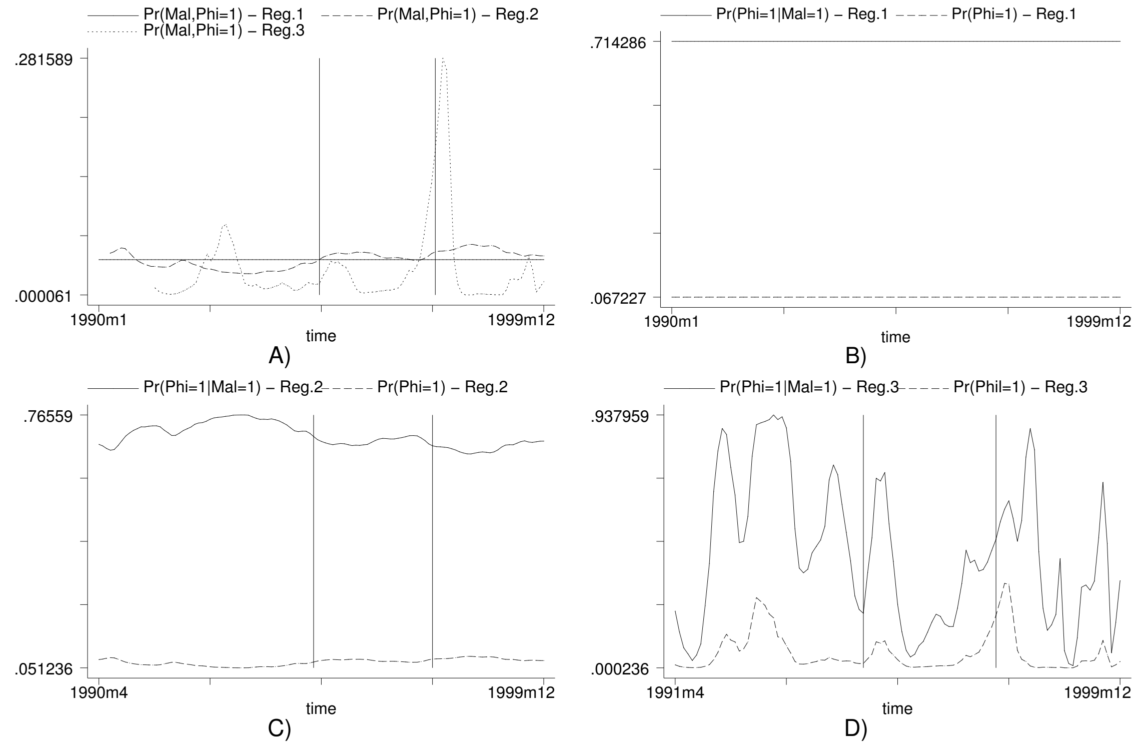


Figure 7: Korea vs. Philippines - Joint, Conditional and Marginal Probabilities

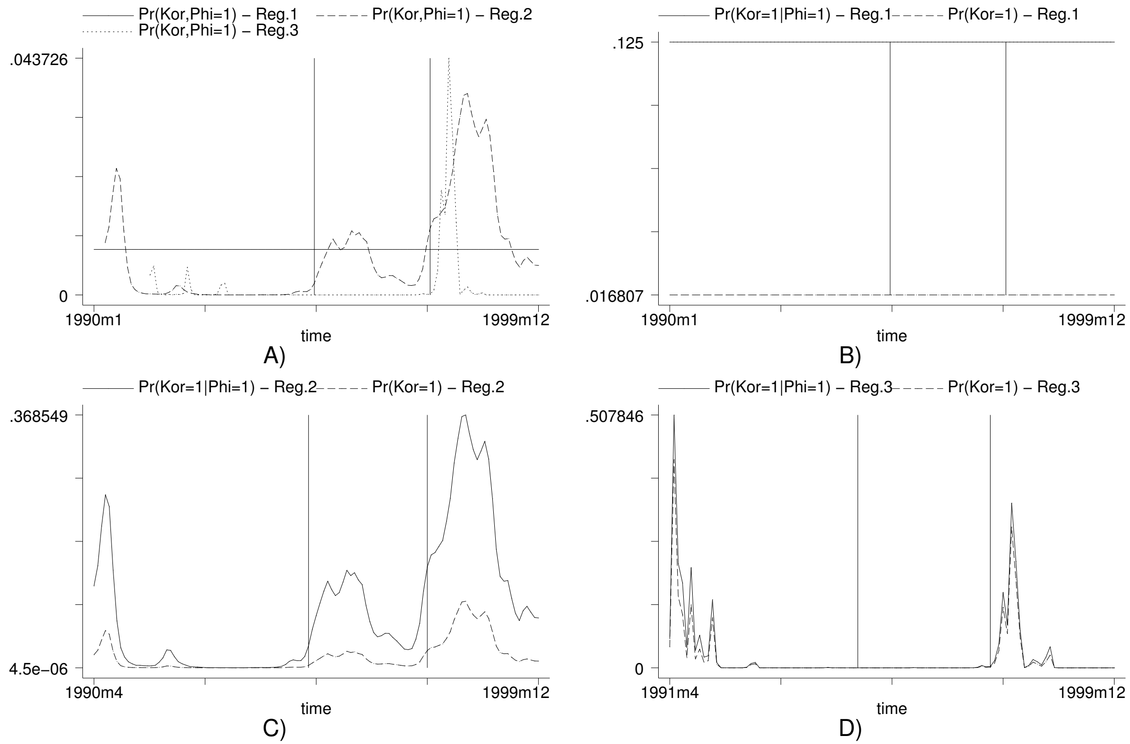


Figure 8: Chile vs. Thailand - Joint, Conditional and Marginal Probabilities

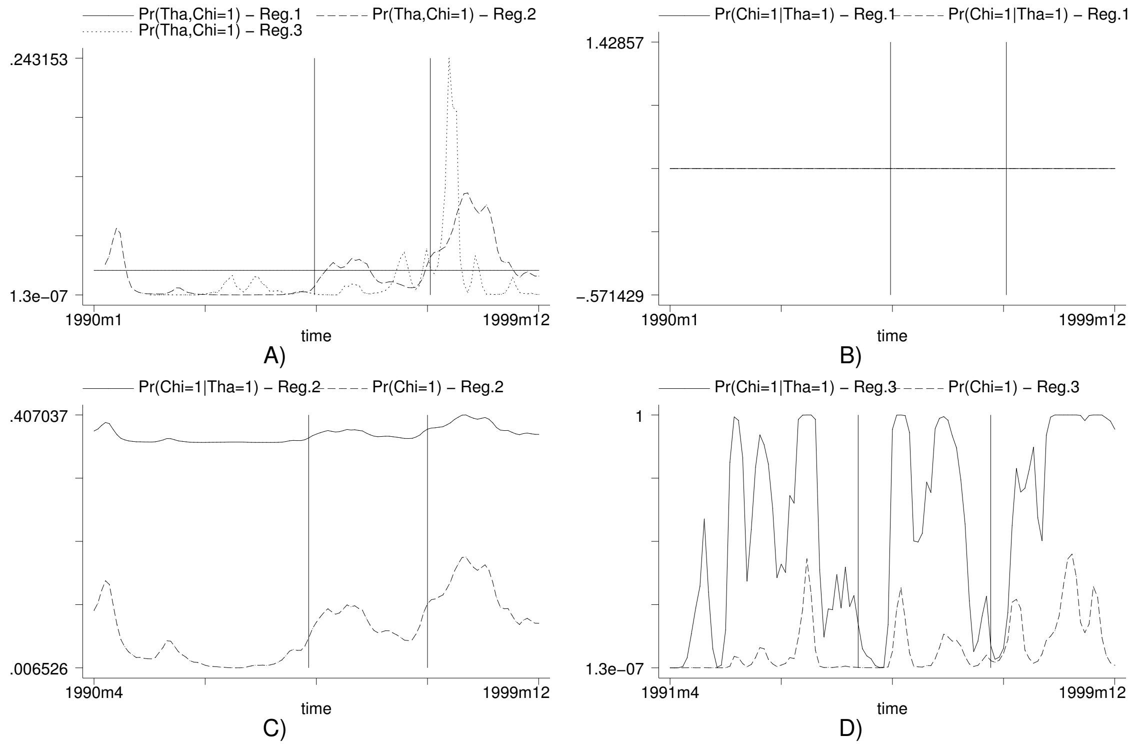


Figure 9: Indonesia vs. Poland - Joint, Conditional and Marginal Probabilities

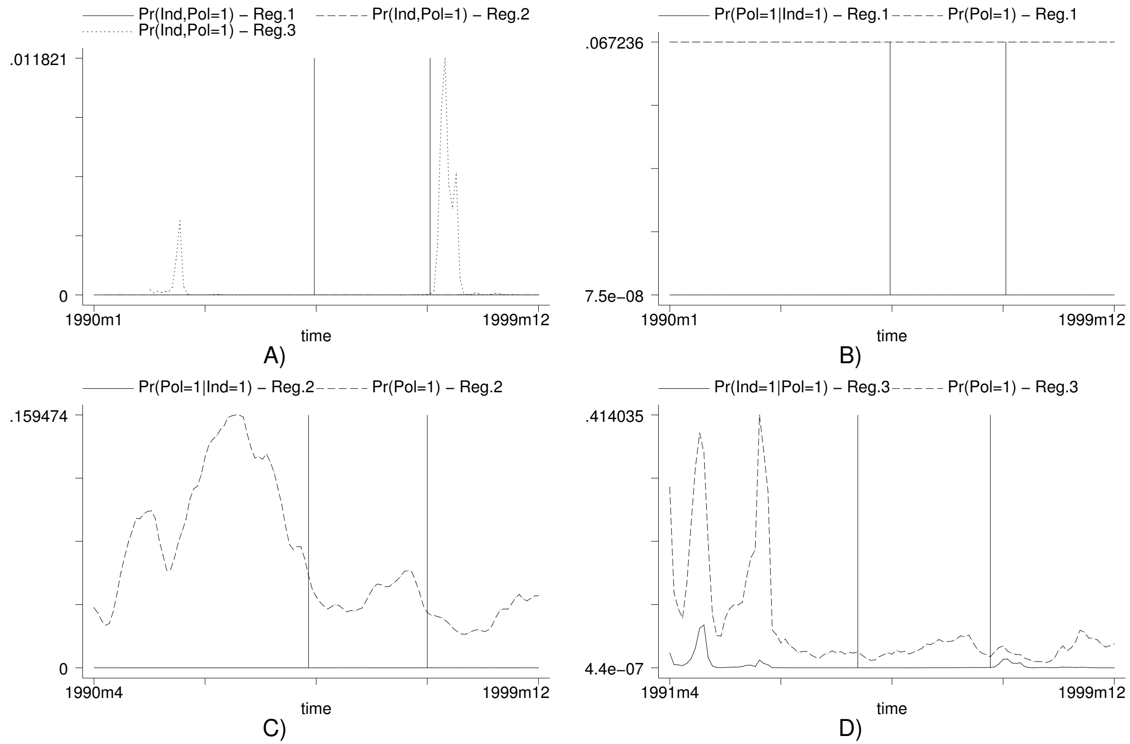


Figure 10: Argentina vs. Mexico - Joint, Conditional and Marginal Probabilities

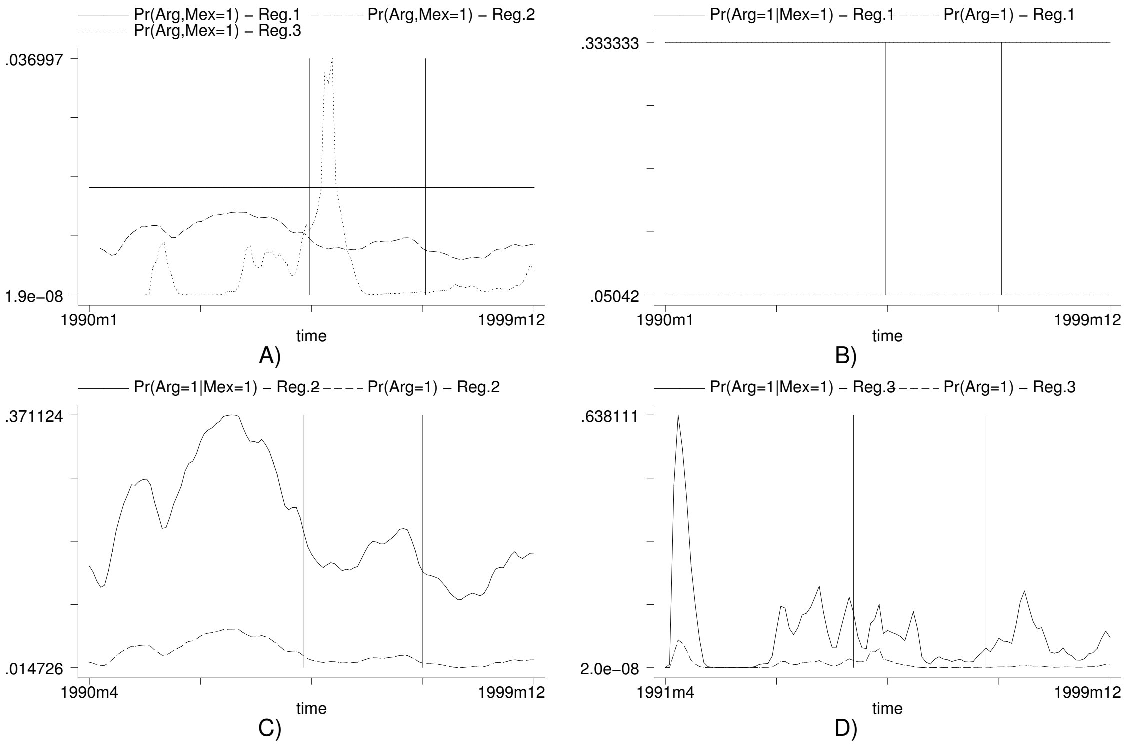


Figure 11: Chile vs. Venezuela - Joint, Conditional, and Marginal Probabilities

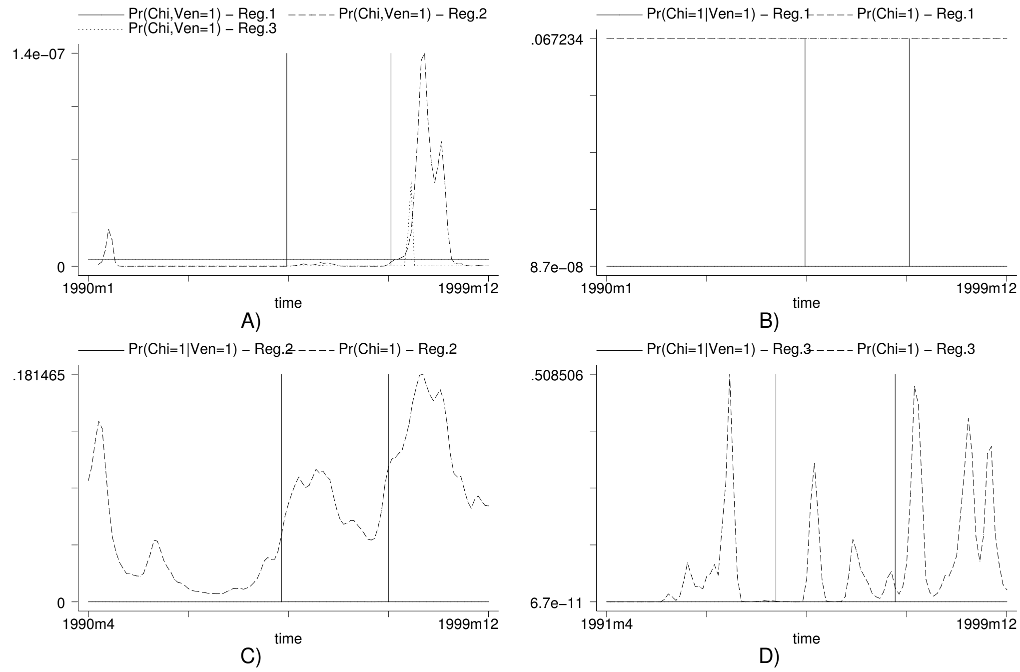
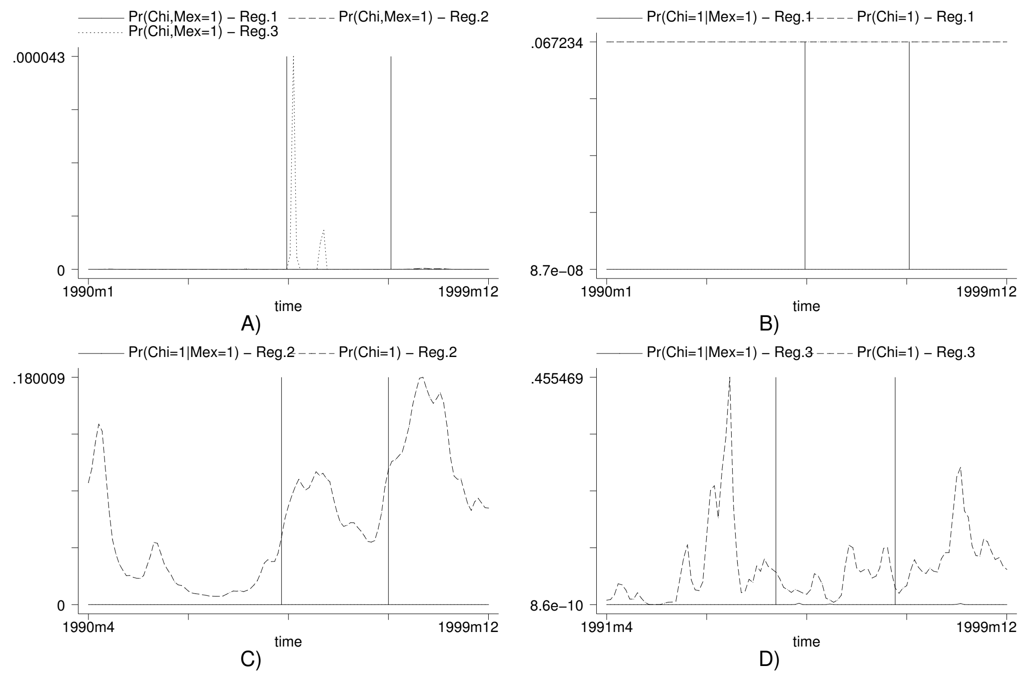


Figure 12: Chile vs. Mexico - Joint, Conditional, and Marginal Probabilities



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