THE BREADTH OF CURRENCY CRISES

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ABSTRACT. We study the breadth of crises in global foreign exchange markets, covering major industrial country currencies and emerging market currencies. We use new statistics based on multivariate extreme value theory and estimate them semi-parametrically. This approach to measuring extreme co-movements does not make any distributional assumptions for return processes and it can account for nonlinearities that are typical for financial crisis situations. We can also derive a "contamination function" that indicates the likelihood of crises in an arbitrarily large number of markets conditional on (contemporaneous or lagged) crises in one, a few or many other markets. First results contradict a number of widely held beliefs about currency contagion. While emerging market currencies crash more frequently than major industrial country currencies, those crashes do not spread more widely and frequently than the case among major currencies. Moreover, there is little evidence of frequent spillovers of crises in emerging market currencies to major currencies and even less so in the reverse direction. Finally, we can identify a few specific currencies that seem to constitute "hot spots" in the foreign exchange market.

1. INTRODUCTION

Analyses of financial crises have increasingly paid attention to the spreading of instability across corporations, markets or countries. The recent literature on financial contagion has provided some theoretical models and a number of empirical techniques to assess the occurrence of failures of one financial corporation spilling over to another financial corporation or steep crashes of one financial market spilling over to another financial market (see e.g. De Bandt and Hartmann (2000) for a broad survey, Claessens and Forbes (2001) for a collection of recent essays or Goodhart and Illing (2002) for a selection of classic articles). A limitation, however, of much of the empirical literature on financial market crises is that most techniques only allow for the direct estimation of spillovers of relatively limited breadth, usually two markets of the same asset class. Financial crises that reach systemic dimensions, however, would have to (i) cut across different asset classes and (ii) affect many more than two markets. In Hartmann, Straetmans and de Vries (forthcoming) we addressed the former problem, by presenting an analysis of joint crashes in stock and bond markets and of the "flight-to-quality" phenomenon. In the present paper we are turning to the latter problem, by proposing a new approach how to analyze crises spreading across many markets.

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In an important recent paper Bae, Karolyi and Stulz (forthcoming), inspired by the medical epidemiology literature, have proposed the application of the multinomial logistic regression model to the issue of widespread equity market spillovers. Using daily returns of stock indices for 17 Asian and Latin American countries as well as the US and Europe between 1996 and 1999, they estimate probabilities that a certain number of stock markets experience a large return (defined as either lower than or equal to the 5th percentile or higher than or equal to the 95th percentile), given that a smaller number of stock markets experience a large return. With this approach they find evidence of cross-region contagion between emerging markets but a relative isolation of the US market from Asian events. In the present paper, we develop a different approach to widespread market spillovers based on multivariate extreme-value theory (EVT). We derive two different measures of extreme market spillovers and estimate them semi-parametrically. One extends our previous bivariate EVT technique to estimate the conditional expected value of the number of crashes (see Hartmann et al., forthcoming and 2003) to the general multivariate case. The other directly estimates, to some extent similar to Bae et al. (forthcoming), the conditional probability that a certain number of markets crash given that some lower number of (explicitly specified) markets crash. There are at least three important differences between our approach and logit analysis. First of all, EVT allows to focus on crash phenomena that are more severe than the ones mainly captured by more standard econometric techniques such as logit models. This makes sure that there cannot be any doubt about the fact that the estimation results refer to market linkages in crisis situations. Second, the semi-parametric approach ensures that no single specific parametric distribution is imposed on the returns of a wide range of very different markets, which would consirably enhance the risk of misspecification. Third, as our second measure is conditioning on specific markets, and not simply on a not further specified number of markets, we can gain a more informative geographical picture of global crisis spillovers.

In this paper we focus on foreign exchange markets. We study extreme currency market spillovers for a sample of 10 East Asian and Latin American as well as 5 major industrial country exchange rates during the period 1987 to 2003. The economic questions we are trying to answer include the following. How likely is it that exchange market crises affect a larger number of currencies? Are certain currencies more instrumental in widespread exchange market crises than others? In particular, are the major currencies less prone to crisis propagation than emerging market currencies, and can these two groups of currencies contaminate each other or not? Finally, are contemporaneous crisis spillovers stronger or weaker than spillovers that propagate over time?

EVT is particularly well designed to address those issues, as it is concerned with the tail behavior of distributions. In univariate and bivariate settings EVT has been used in the past to assess the severity of extreme market movements and extreme market spillovers. For example, Koedijk, Schafgans and de Vries (1990), Hols and de Vries (1991), Koedijk, Stork and de Vries (1992) as well as Hartmann et al. (2003) study the fat tails of exchange rate returns. Jansen and de Vries (1991), Longin (1996) and Lux (1996) address booms and busts in stock markets. Hartmann et al. (forthcoming) cover, inter alia, extreme up and downturns in government bond markets. Bivariate EVT has been applied to extreme stock market spillovers by Straetmans (2000) and Poon, Rockinger and Tawn (2001), semi-parametrically, and by Longin and Solnik (2001), parametrically. Hartmann et al. (forthcoming) address various forms of stock-bond spillovers. Hartmann et al. (2003) apply it to currency markets. We are not aware of any attempt so far to study market spillovers in a fully multivariate setting using EVT.

Financial theory explains market contagion phenomena with asymmetric information and related signal-extraction problems for traders (King and Wadhwani, 1990), with herding when international diversification leads to less information acquisition about local markets (Calvo and Mendoza, 2000), with the implications of wealth effects on cross-market "convergence" traders (Kyle and Xiong, 2001) and with cross-market portfolio rebalancing in response to idiosyncratic shocks when macroeconomic risks are shared and there is asymmetric information (Kodres and Pritsker, 2002). More macroeconomically oriented "third generation" models advocate country exposures (Buiter, Corsetti and Pesenti, 1997), asymmetric information about governments' commitments (Drazen, 1998) and shifts between multiple equilibria when expectations are self-fulfilling (Masson, 1999) as explanations for contagious crises in fixed exchange rate regimes. Morris and Shin (2000), however, make the point that self-fulfilling currency attacks need not be associated with multiple equilibria when fundamentals are not entirely common knowledge. Moreover, the joint occurrence of crises may be related to common shocks rather than to idiosyncratic shocks propagating across markets.

There is also an empirical literature about the propagation of speculative attacks on pegged currencies. This literature, however, often uses an index of speculative attacks that not only measures exchange rate returns but also reserve losses and interest rate increases. This implies that also the propagation of unsuccessful attacks is captured, whereas our examination of realized returns only looks at actual market crises. In a pioneering paper Eichengreen, Rose and Wyplosz (1996) estimate a binary probit model, in which the probability of currency attacks are explained by economic fundamentals and by contemporaneous attacks on other currencies. Attacks elsewhere in the world turn out to be an economically and statistically significant explanatory variable. Also Caramazza, Ricci and Salgado (2000) use the probit approach. Kaminsky and Reinhart (2000) compare the probability of currency attacks, conditional on macroeconomic fundamentals, with the probability of currency attacks, conditional on macro fundamentals and the contemporaneous occurrence of attacks elsewhere in the world. A lower quadratic probability score of the latter compared to the former is indicative of contagion. Van Rijckeghem and Weder (2001). Fratzscher (forthcoming) uses a Markov-switching vectorautoregression model and a random effects panel regression.

Finally, in the equity market literature also bivariate regime-switching models have been used to study spillovers. For example, Ramchand and Susmel (1998) estimate a bivariate regime-switching ARCH model, where estimated correlations in the high-variance state are 2.5 to 3 times higher compared to the low-variance state. Ang and Bekaert (2002) fit a regime-switching model on equity returns (without conditional heteroskedasticity) and argue that the high variance, high correlation state exhibits correlations close to the ones estimated by Longin and Solnik (2001). Nevertheless, it is an issue to which extent the high-correlation regimes found, hardly statistically significant in Ang and Bekaert, are associated with market crises or not. Forbes and Rigobon (2002). Corsetti, Pericoli and Sbracia (2003).

The rest of our paper is structured as follows. The next section introduces the two measures of multivariate extreme market spillovers and the following one derives how they can be estimated. Sections 4, 5, 6 and 7 then examine the breadth of currency crises among major markets, among emerging markets and between major currencies and emerging markets. The final section concludes. Data are discussed in Appendix A.

2. Multivariate market linkage measures

The probability that different asset prices (such as nominal exchange rates) fluctuate simultaneously above (or below) a given large quantile (or crash level; "exceedance probability") seems a natural measure of the systemic breadth of market crises. In this paper we use two alternative measures of such *multivariate* (or *multilateral*) market dependence during crisis periods, which provide us with complementary information. One is based on the concept of conditional expectation and therefore shows how widely market turbulence can reach. The other is based on the concept of conditional probability, indicating how likely crises of a certain breadth are. We will further differentiate the two measures by conditioning the latter on specific extreme events, while the former − like multinomial logit − is conditioned on the number of extreme events (without further specification which markets experience the extreme returns). This differentiation will allow for a more refined economic analysis of international financial stability in sections 4f.

Both measures can be expressed in terms of marginal (univariate) and joint (multivariate) exceedance probabilities. They can be applied to any asset market (or even non-economic phenomena). As the present paper focuses on currency markets, the inputs are returns on nominal exchange rates. In the empirical applications below exchange rates will be expressed as the price of the domestic currency per unit of foreign currency. Hence, as a crisis of the domestic currency is defined by a large depreciation of it, crashes will show up as large *increases* in the exchange rate.

Our first measure is the multivariate generalization of the two-dimensional conditional "co-crash indicator" presented in Hartmann, Straetmans and de Vries (forthcoming). Consider an N-dimensional currency block, i.e., a set of currencies that originate from the same region or that face similar exchange rate policies or regimes. Denote the log first differences of the exchange rates as random variables X_i $(i = 1, \cdots, N)$, with accompanying crisis levels (or extreme quantiles) r_i $(i = 1, \cdots, N)$.[1] If κ stands for the number of currencies whose returns simultaneously cross extreme quantile barriers, then our first extreme linkage indicator is the conditional expectation $E[\kappa|\kappa \geq 1]$. The crash number κ is defined as the sum of N indicator variables:

$$\kappa = \sum_{i=1}^{N} \mathbf{1}\left\{X_i > r_i(p_i)\right\}, \tag{2.1}$$

where $\mathbf{1}\{\cdot\}$ equals one for a crashing currency and zero otherwise. The inverse marginal quantile function $r_i = r_i(p_i)$ relates the excess probability $p_i = P\{X_i > r_i\}$ to the corresponding extreme return quantile r_i.

[1] Alternatively, one can interpret these crisis levels as Value-at-Risk (VaR) levels, corresponding to an exceedance probability p_i such that $P\{X_i > r_i\} = p_i$.

From elementary probability theory (starting from the standard definition of conditional expectation) we have the following equalities:

$$E[\kappa|\kappa \geq 1] = \frac{E[\kappa]}{P\{\kappa \geq 1\}} = \frac{\sum_{i=1}^{N} P\{X_i > r_i\}}{P\left\{\bigcup_{i=1}^{N} X_i > r_i\right\}}, \tag{2.2}$$

where $P\left\{\bigcup_{i=1}^{N} X_i > r_i\right\} = P\{X_1 > r_1 \text{ or } \cdots X_i > r_i \cdots \text{or } X_N > r_N\}$
$= 1 - P\{X_1 \leq r_1, \ \cdots X_i \leq r_i \cdots, \ X_N \leq r_N\}$; see e.g. Straetmans (1998). Hence, here we measure the expected number of market crashes, given a lower (but positive) number of markets crash. This statistic is simply the ratio of the sum of marginal crash probabilities and the probability that one or more of the markets considered crash.

The expectational linkage measure in (2.2) assumes that any (or any subset) of the currencies considered can play the role of the conditioning crash or crisis, without specifying it (much like the logit model). The advantage of this perspective is that it provides a very general view on multivariate dependence during crisis periods. This advantage, however, also constitutes its main drawback. With the expectational linkage measure it is not possible to condition on *specific* crash or depreciation scenarios, to achieve greater precision on the issue which currencies are more often at the origin of widespread crises. This type of refinement is, however, valuable both for risk managers and for supervisory authorities. For example, risk managers can exploit such refined information for stress testing. Similarly, knowing the “hot spots” in currency is useful for the supervisory surveillance of international financial markets.

Therefore, as a complement to the expectational linkage measure in (2.2) we also consider a probability measure of multivariate linkages that is conditioned on a subset $M < N$ *explicitly specified* crashing currencies:

(2.3)

$$P_{N|M} = P\left\{\bigcap_{i=1}^{N} X_i > r_i(p_i) \middle| \bigcap_{j=1}^{M} X_j > r_j(p_j)\right\} = \frac{P\left\{\bigcap_{i=1}^{N} X_i > r_i(p_i)\right\}}{P\left\{\bigcap_{j=1}^{M} X_j > r_j(p_j)\right\}}.$$

Clearly, the right-hand side immediately follows from the definition of conditional probability. This measure is defined by the probability that an arbitrarily large number of markets crash, given that a specifically chosen set of markets crash. So, another advantage of it is that it can be easily used as an extreme linkage measure across currency blocks. The conditioning currencies j in the denominator of (2.3) can be selected outside the currency block i. Finally, this measure also allows to study crisis propagation through time, as the conditioning variables X_j can be lagged. Again, this was not possible with the expectational linkage measure. In the now following section we describe how both measures of multivariate market spillovers can be estimated with EVT.

3. Estimation of multivariate crisis linkage measures

A preliminary step to applying our extreme linkage measures is to decide whether in defining a crisis we fix the extreme quantiles and leave percentiles open or fix exceedance probabilities and leave the quantiles open. Thoughout this paper, and without loss of generality, we will assume that the marginal crisis levels or quantiles used as inputs in (2.2) and (2.3) are associated with a common significance level (or percentile) p of the empirical return distribution. The value of p determines the severity of the currency crises, i.e., how far we go into the multivariate tail of the currency block in order to evaluate our pair of multivariate linkage measures. By definition of the inverse marginal quantile function $r_i = r_i(p)$, the lower the significance level p the higher the corresponding quantile or Value-at-Risk (VaR) level. Notice that a common marginal exceedance probability p still permits the corresponding quantiles to differ across currencies ($r_i \neq r_j$, $i \neq j$), because the probability distribution functions (pdfs) of the currency returns will generally be different across markets. By the aim of focusing on crisis situations, we are typically interested in calculating our linkage measures in the vicinity of the sample boundary or sometimes even outside the historical sample range, i.e., $p \leq n^{-1}$, with n the sample size.[2]

How can we then estimate $P_{N|M}$ and $E[\kappa|\kappa \geq 1]$? As all marginal probabilities are set equal to p it suffices to estimate the joint probabilities in the denominators of (2.2) and (2.3). Within the framework of a parametric probability law, the calculation of the proposed multivariate probability measures is straightforward, because one can estimate the distributional parameters by, e.g., Maximum Likelihood (ML) techniques. However, if one estimates the linkage measures on the basis of the wrong distributional assumptions, the estimates may be severely biased due to misspecification. Such model risk can be expected to be high in the case at hand, when markets of many very different currencies are compared.[3] We therefore decided to renege from making very specific distributional assumptions for currency returns and to pursue a semi-parametric EVT approach.

Notice that both types of multivariate probabilities occurring in the denominators of (2.2) and (2.3) are conditioned on different failure regions. In order to estimate the first type of joint tail probability $P\left\{\bigcup_{i=1}^{N} X_i > r_i\right\}$, as included in the expectational measure, a standard approach in extreme value analysis can be used that decomposes the joint extreme value behavior of the variables X_i into their marginal (univariate) tail behavior and a description of the extremal dependence structure. More specifically, this "decomposition" can be written as

$$\begin{aligned} & P\{X_1 > r_1 \text{ or } \cdots X_i > r_i \cdots \text{or } X_N > r_N\} \\ \approx\ & \ell\left(P\left(X_1 > r_1\right), \cdots, P\left(X_i > r_i\right), \cdots, P\left(X_N > r_N\right)\right) \\ =\ & \ell\left(p, \cdots, p, \cdots, p\right) \end{aligned} \tag{3.1}$$

with $\ell(\cdot)$ being the so called "stable tail dependence function" (Huang (1992)).[4] The curvature of $\ell(\cdot)$ completely determines the dependency structure between the X_i components in the tail area. A basic property of $\ell(\cdot)$ constitutes the inequality

$$p \leq \ell\left(p, \cdots, p, \cdots, p\right) \leq Np.$$

[2] Notice that this amounts to estimating a VaR quantile beyond the 1% significance levels required by supervisory authorities.

[3] For example, it can be easily shown that the application of a multivariate normal law to extreme linkage measures like (2.2) and (2.3) leads to a dramatic underestimation of the true degree of linkage regardless of the forex regime or the currency block considered.

[4] The tail dependence function is formally defined as $\ell(\cdot) = \lim_{t \to 0} \frac{1}{t} P\{X_1 > r_1(tp_1) \text{ or } \cdots X_i > r_i(tp_i) \cdots \text{ or } X_N > r_N(tp_N)\}$.

Equality holds on the left-hand side if the exchange rate returns are completely mutually dependent in the tail area, while equality on the right hand side obtains if the return series are mutually independent in the tail area. Notice that independence over the full range of the joint return pdf implies that

$$\begin{aligned} & P\left\{X_1 < r_1, \cdots, X_i < r_i, \cdots, X_N < r_N\right\} \\ (3.2) \qquad = \; & P\left\{X < r_1\right\} \times \ldots \times P\left\{X_i < r_i\right\} \times \cdots \times P\left\{X_N < r_N\right\} \end{aligned}$$

for *all* quantiles r_i $(i = 1, \cdots, N)$, irrespective of their magnitudes. *Tail* independence only requires this factorization to hold in the multivariate tail of the joint distribution, i.e., for large values of r_i. Thus it may well be that non-extreme return pairs are dependent, although their extremes are asymptotically independent. The multivariate normal distribution with $\rho_{ij} \,\epsilon\, (-1, 1)$ and $\rho_{ij} \neq 0$ for all $i \neq j$ constitutes such a case for example. Estimation of the probability of multiple extreme events exploits a homogeneity property of the tail dependence function: $\ell(tp, \cdots, tp) = t\ell(p, \cdots, p)$. More specifically, this implies that we can exploit the approximate equality

$$\begin{aligned} & P\left\{X_1 > r_1(p) \text{ or } \cdots X_i > r_i(p) \cdots \text{or } X_N > r_N(p)\right\} \\ \approx \; & tP\left\{X_1 > r_1\left(\frac{p}{t}\right) \text{ or } \cdots X_i > r_i\left(\frac{p}{t}\right) \cdots \text{or } X_N > r_N\left(\frac{p}{t}\right)\right\}, \end{aligned}$$

since for small t the right hand side can be estimated using the empirical distribution function. This tail dependence approach has already been succesfully applied in finance in order to identify *bivariate* extreme linkages.[5]

However, there are two complications with this tail dependence function method. First, the $\ell(\cdot)$ function cannot be used to evaluate joint tail probabilities of the type $P\left\{\bigcap_{i=1}^{N} X_i > r_i\right\}$, except in the bivariate case. Indeed, for the bivariate case we could exploit that the two types of joint tail probabilities under consideration are related through the equality

$$\begin{aligned} & P\left\{X_1 > r_1 \text{ or } X_2 > r_2\right\} \\ (3.3) \qquad = \; & P\left\{X_1 > r_1\right\} + P\left\{X_2 > r_2\right\} - P\left\{X_1 > r_1, X_2 > r_2\right\}, \end{aligned}$$

so that it suffices to estimate the LHS of (3.3) by using the $\ell-$function; but this complementary relationship breaks down for higher dimensions. A second complication constitutes the fact that the stable tail dependence function approach requires currency returns to be asymptotically dependent. More specifically, if data are asymptotically independent, the homogeneity property of the $\ell(\cdot)$ function does no longer apply. Moreover, the limiting distribution of estimators for $\ell(\cdot)$ can be shown to be degenerate, which precludes proper hypothesis testing.[6]

Before solving these two issues it is instructive to remove the influence of marginal aspects on the joint tail probabilities by transforming the original variables to a

[5] Longin (2001) uses a parametric approach towards estimating the stable tail dependence function (and thus joint crash probabilities) for assessing bilateral stock market linkages during crisis periods, whereas Hartmann, Straetmans and de Vries (forthcoming) use a non-parametric measure for estimating $\ell(\cdot)$ in order to study bilateral crisis linkages between stock and bond markets and the contagion vs. flight-to-quality issue. Hartmann et al. (2003) also applied the latter methodology in order to assess bilateral extremal currency linkages.

[6] In our previous paper on extreme stock-bond market linkages we pre-test for the presence of asymptotic dependence before going ahead with estimating the $\ell-$function. Use of this method was justified by the fact that we were not able to reject the null hypothesis of asymptotic dependence.

common marginal distribution, see e.g. Ledford and Tawn (1996) and Draisma et al. (2001). After such a transformation differences in joint tail probabilities across currency blocks are solely attributable to dependence aspects. Thus our dependence measures, unlike e.g. correlation, are no longer influenced by the differences in marginal distribution shapes. In this spirit we transform the currency returns $(X_1, \cdots, X_i, \cdots, X_N)$ to unit Pareto marginals by:

$$\widetilde{X}_i = \frac{1}{1 - F_i(X_i)}, \ i = 1, \cdots, N,$$

with $F_i(\cdot)$ representing the marginal cumulative distribution function (cdf) for X_i. However, since the marginal cdfs are unknown, we have to replace them with their empirical counterparts. For each X_i this leads (with a small modification to prevent division by 0) to:

$$\widetilde{X}_i = \frac{n+1}{n+1-R_{X_i}}, \ i = 1, \cdots, N,$$

where $R_{X_i} = rank(X_{ij}, j = 1, \cdots, n)$. Using this variable transform, we can rewrite the two types of joint tail probabilities we are interested in

$$\begin{aligned} P\left\{\bigcap\nolimits_{i=1}^{N} X_i > r_i\right\} &= P\left\{\bigcap\nolimits_{i=1}^{N} \widetilde{X}_i > s\right\} \text{ and} \\ P\left\{\bigcup\nolimits_{i=1}^{N} X_i > r_i\right\} &= P\left\{\bigcup\nolimits_{i=1}^{N} \widetilde{X}_i > s\right\}, \end{aligned}$$

where $s = 1/p$. The multivariate estimation problem can now be reduced to estimating a univariate exceedance probability for the cross-sectional minimum or maximum of the N currency return series, i.e., it is always true that:

$$P\left\{\bigcap\nolimits_{i=1}^{N} \widetilde{X}_i > s\right\} = P\left\{\min_{i=1}^{N}\left(\widetilde{X}_i\right) > s\right\} = P\left\{T_{\min} > s\right\} \text{ and} \tag{3.4}$$

$$P\left\{\bigcup\nolimits_{i=1}^{N} \widetilde{X}_i > s\right\} = 1 - P\left\{\bigcap\nolimits_{i=1}^{N} \widetilde{X}_i < s\right\} = 1 - P\left\{\max_{i=1}^{N}\left(\widetilde{X}_i\right) < s\right\} = P\left\{T_{\max} > s\right\}. \tag{3.5}$$

The marginal tail probabilities at the right-hand side can now be easily calculated by making an additional assumption on the univariate tail behaviors of $T_{\min}$ and $T_{\max}$. Ledford and Tawn (1996) impose a regularly varying (or heavy) tail for the auxiliary variable $T_{\min}$ in a bivariate framework. This assumption can be justified by referring to the stylized fact of heavy-tailed foreign exchange returns. Consequently, the transformed series $\widetilde{X}_i$ and the time series of the cross-sectional minima should inherit this property. Now, our methodological contribution is to generalize the Ledford-Tawn approach to estimating probabilities of type (3.4) and for more than 2 dimensions.

Assuming that $T_{\min}$ and $T_{\max}$ exhibit heavy tails with tail indexes $\alpha_{\min}$ and $\alpha_{\max}$, respectively, the regular variation assumption for the auxiliary variables implies that the univariate probabilities have a tail descent of the Pareto type:

$$\begin{aligned} P\left\{T_{\min} > s\right\} &\approx s^{-\alpha_{\min}} \\ P\left\{T_{\max} > s\right\} &\approx s^{-\alpha_{\max}}, \end{aligned} \tag{3.6}$$

with s large (p small). Univariate excess probabilities for fat-tailed random variables can be estimated by using the semi-parametric probability estimator from De Haan et al. (1994):

$$\widehat{p}_s = \frac{m}{n}\left(\frac{T_{n-m,n}}{s}\right)^{\alpha}, \tag{3.7}$$

where the "tail cut-off point" $T_{n-m,n}$ is the $(n-m)$-th ascending order statistic (or loosely speaking the m-th smallest return) from a sample of size n. An important aspect of the estimator $\widehat{p}_s$ is that it can extend the empirical distribution function outside the domain of the sample by means of its asymptotic Pareto tail from (3.6). The estimator (3.7) is conditional upon the tail index α. We estimate the tail index by means of the popular Hill (1975) estimator:

$$\widehat{\gamma} = \frac{1}{m}\sum_{j=0}^{m-1}\ln\left(\frac{T_{n-j,n}}{T_{n-m,n}}\right), \tag{3.8}$$

where m has the same value and interpretation as in (3.7) and $\widehat{\alpha} = 1/\widehat{\gamma}$ stands for the estimated tail index. Further details are provided in Jansen and De Vries (1991) and, e.g., the monograph by Embrechts, Klüppelberg and Mikosch (1997).

With all these tools at hand, we can now turn to the empirical analysis of systemic instability in global foreign exchange markets. The next section focuses on the (relatively unspecific) expectational measure introduced above, and the subsequent sections exploit in depth the (more specific) probability measure.

4. Isolated and widespread currency crises

We start our analysis of widespread extreme exchange rate linkages with a brief rehearsal of the univariate properties of extreme exchange rate returns. The second sub-section then discusses the results from the expectational multivariate linkage measure for all three currency blocks considered.

4.1. **Exchange rate data and univariate properties.** In this paper we study the joint occurrence of extreme exchange rate depreciations for the major industrial country currencies and a number of emerging market countries. For comparability we build three groups, or currency blocks, of equal size; major industrial currencies, East Asian currencies and Latin American currencies. The five major currencies we cover are the Deutsche mark (DEM, and since January 1999 the euro (EUR)), the Japanese yen (JPY), the pound sterling (GBP), the Swiss franc (CHF) and the Australian dollar (AUD). The second block includes five East Asian emerging market currencies, namely the Hong Kong dollar (HKD), the Indonesian rupiah (IRD), the Malaysian ringgit (MYR), the Philippine peso (PHP) and the Thai baht (THB). Five Latin American emerging market currencies constitute the last block; Bolivian boliviano (BOB), Chilean peso (CLP), Columbian peso (COP), Mexican peso (MXN) and Venezuelan bolivar (VEB).

In order to focus on more sustained crises and to significantly alleviate time zone problems we use weekly exchange rate returns. They are calculated as first log differences (Monday to Monday), with the United States dollar (USD) serving as the common base currency. Our sample ranges from January 1987 to February 2003, which yields about 850 return observations for each exchange rate. Appendix A provides further details on the choice and treatment of data.

[TABLE 1 ABOUT HERE]

The occurrence of booms and busts in foreign exchange markets has been the subject of a rather extensive univariate literature (see, e.g., Koedijk et al. (1990), Hols and de Vries (1991) or Koedijk et al. (1992)). Therefore, we recall only briefly some of the extreme properties of exchange rate returns. Table 1 displays the three largest depreciations and appreciations in the sample for each of the 15 currencies. Most but not all maxima and minima are larger for emerging market returns than for major currency returns. (One "outlier", of course, being the atypical Hong Kong dollar.) The picture becomes somewhat clearer in table 2, which displays on the left-hand side the estimated (right) tail indexes (for currency crashes). Major currencies' indexes are all relatively close to 3, wherease emerging market indexes vary between 1 and 2. So, as in Hartmann et al. (2003), we can confirm the "conventional wisdom" that emerging market currencies have fatter tails than industrial country currencies and therefore they tend to crash more often. This can be explained with more frequent political instability, partly related to greater difficulties in domestic macroeconomic management, their relatively smaller size in relation to international capital flows, a greater inclination to use fixed exchange-rate arrangements that can be attacked and intermediate levels of domestic financial development (see Aghion, Bacchetta and Banerjee, 1999).[7]

[TABLE 2 ABOUT HERE]

On the right-hand side, table 2 also shows the extreme quantiles that can be derived from the common marginal exceedance probability (percentile) $p = n^{-1}$. As a consequence of the tail index estimates, they tend to be larger for emerging markets (with a few exceptions). The implied weekly depreciations are clearly of critical magnitude.

4.2. **The breadth of currency crises: evidence from the expectation measure.** As a first step to assess the breadth of turmoil in currency markets, we consider unconditional probabilities of having many currencies crash (i.e., the unconditional version of our probability measure of systemic currency risk (2.3)) and our expectational measure of systemic currency risk (2.2). The results are reported on the left and right-hand sides of table 3, respectively. We distinguish extreme linkages within our three blocks (upper panel) and across currency blocks (lower panel). Recall the exceedance probabilities are set equal to the inverse of the sample size, but they could be easily shifted more inside or outside.

Obviously, the joint probability of all currencies in a block crashing by such an amount is extremely low. This reflects well that systemic risk is associated with disastrous but very low probability events. Perhaps more informative is the relative importance of such risk across blocks. Interestingly, the risk of all five major industrial currencies (DEM, JPY, GBP, CHF and AUD) crashing together is statistically higher than the risk of the five East Asian currencies crashing together or the risk of the five Latin American currencies crashing. In terms of the different emerging market blocks, East Asia looks more risky than Latin America. (A detailed application of the conditional version of the probability measure (2.3) follows in sections 5, 6 and 7.)

[TABLE 3 ABOUT HERE]

These relations are confirmed with the expectational linkage measure. The expected number of crashing major industrial currencies, given at least one of them

[7] See Hartmann et al. (2003) for a more detailed discussion of the issues addressed in this subsection, in particular relating the extreme returns displayed in table 1 to major crisis episodes.

crashes, is higher than for East Asia, which itself is higher than for Latin America. One should, however, also note that the differences are not very large. For example, $E = 1.8$ for industrial currencies and $E = 1.5$ for East Asian emerging market currencies.

Unconditional systemic currency crisis probabilities are lower across blocks, as now 10 currencies are included, not only five. The least unlikely is a crisis cutting across the industrial and East Asian block. Similarly, the expected number of crashes among all these currencies, given there is a crisis in at least one of them, is the highest, with $E = 2.1$. For the other two pairs of blocks, industrial and Latin American currencies as well as East Asian and Latin American currencies, the expected number of crashes is around 1.7.

5. Widespread crises among the major currencies

In the next step, we study in greater detail the structure of extreme linkages among the major industrial currencies. We apply the conditional probability measure (2.3) introduced in sections 2 and 3, for a large number of conditioning events. We examine both contemporaneous and lagged spillover probabilities.

Table 4 describes the estimations we undertake and summarizes the results. As we are interested in crises that can reach systemic dimensions, we calculate the probabilities that all five exchange rates crash. We condition on crashes in one currency (panel A), two currencies (panel B), three currencies (panel C) and four currencies (panel D). In each case we consider all possible combinations of the respective currencies and document the average spillover probability across those combinations. The left-hand column shows the contemporaneous spillover probabilities from (2.3) and the right-hand column the spillover probability with the conditioning crash lagged by one period (i.e., by one week).

All probabilities are expressed in per cent. Let us give an example, involving the Japanese yen and the Australian dollar. Going to the column "contemporaneous" and the row "X_3, X_5", we see that the probability that all five major currencies crash, given that the JPY and the AUD crash in the same week, is an astonishingly high 41%. In other words, an extreme depreciation of both these currencies would almost every other time be associated with a widespread currency crisis among the major industrial countries. Moving on to lagged extreme spillovers on the right-hand side, we see that propagation over time is weaker than the immediate impact. If the yen and the Australian dollar crash in a given week, the probability of having a full-scale industrialized country currency crisis in the next week is, however, still a non-negligible 14%.

[TABLE 4 ABOUT HERE]

We have not chosen this example by coincidence. The case of JPY and AUD reflects a number of more general results for the major currencies. First, the probabilities across the table indicate that systemic risk among the major currencies may be quite high, as soon as one considers more than one conditioning crash. For example, if any single one of the remaining three other major currencies joins the JPY and the AUD, then the probability of a full-scale systemic event doubles to around 80%. The block of major currencies appears, however, quite resilient to single crashes, as extreme spillover probabilities for those are below 1%. Second, propagation over time tends to generally be weaker than contemporaneous propagation. This can be easily seen by comparing the left with the right column of table 4. Third, the AUD − in particular in combination with the JPY − seems to constitute a "hot spot" in the industrial currency block. The largest entries in panels A, B, C and D relate to crashes occuring for the AUD in combination with the JPY.

The first two main results for industrial country currencies are well illustrated in figure 1, which plots the probability of having a crisis in all five industrial currencies against the conditioning events of a crisis in one, two, three or four of them. Points of the graphs inserted in the figure describe the average probabilities in each of the panels in table 4. The bold graph links contemporaneous extreme spillover probabilities and the thin graph lagged probabilities. Both lines are quite high in the figure and increase relatively steeply, reflecting the relatively high systemic risk found for those five currencies. The bold line is consistently above the thinner one, indicating the stronger contemporaneous risk. We denote the functions underlying those graphs as "contamination functions", and we will use their illustrative power throughout the discussion of most of our results. These contamination functions are the EVT equivalent to the "co-exceedance response curves" derived by Bae et al. (forthcoming) from a multinomial logit model. (For the main differences between our approach and the multinomial logit approach, refer to the introduction.)

[FIGURE 1 ABOUT HERE]

6. Widespread crises among emerging market currencies

We now turn to the analysis of the breadth of emerging market currency crises. Extreme depreciations of emerging market currencies, often but not always in relation to the breadown of a fixed exchange rate regime, are a recurrent theme in international financial crisis episodes. "Conventional wisdom", at least partly based on economic analysis but also based on market views, holds that emerging market currencies are particularly vulnerable to crises in other emerging market currencies. This has been highlighted in the context of the Asian financial crisis of 1997 as well as the Mexican crisis of 1994 and other Latin American crises. Therefore, in the next sub-section we study the (regionally) systemic currency risk in five East Asian currencies and in the following one such risk for five Latin American currencies.

6.1. **East Asia.** Table 5 shows the results derived from our conditional joint crash probability measure (2.3) for the five East Asian currencies (Indonesian rupiah, Malaysian ringgit, Thai baht, Hong Kong dollar and Philippine peso), in analogy to table 4 for major industrial currencies in the previous section. Figure 2 plots the contemporaneous and lagged contamination functions for that region, in analogy to figure 1.

[TABLE 5 ABOUT HERE]

Again, the probability that all five Asian currencies crash, given that two or more of them crash, is quite high and also the slope of the contamination function is quite steep. (The probabilities seem, however, slightly lower than for major currencies in section 5; see the comparison of major and emerging currencies in the third subsection.) The second feature of major currencies is also reproduced in East Asia, as the lagged spillovers are lower than the contemporaneous ones.

[FIGURE 2 ABOUT HERE]

Where should we locate the East Asian "hot spots"? The picture is not as clear as it was for the industrial currencies. Most often crises conditioned on the PHP, in particular in conjunction with the MYR, have the highest probabilities. This emerges most clearly from panels C and D of table 5 for contemporaneous spillovers. (For crises conditioned contemporaneously on two crashes, also the HKD seems to play some special role; see panel B.) Similar patterns emerge for lagged spillovers, but they are even more blurred.

6.2. **Latin America.** The results for the Latin American currency block (Mexican peso, Bolivian boliviano, Venezuelan bolivar, Chilean peso and Columbian peso) are summarized in table 6 and figure 3. In many respects Latin America seems to be similar to Asia. Again, regional systemic risk is not low (although probably somewhat lower than risk in the major currency block). Lagged spillovers are generally weaker than immediate ones.

[TABLE 6 AND FIGURE 3 ABOUT HERE]

Regarding our interest in finding “hot spots”, the structure of extreme linkages seems clearer than in Asia. The MXN seems to be a special source of systemic risk in Latin America, and also the VEB (particularly also both together). In particular, for lagged spillovers sometimes the CLP in conjunction with other currencies implies (mild) above average risk.

6.3. **Comparing emerging market currencies with major currencies.** We can now compare more systematically the risks of widespread crises among emerging market currencies with the ones among major industrial currencies. Figure 4 plots the contemporaneous contamination functions for all three blocks in one picture. The figure confirms the surprising finding from section 4 (table 3) that the spreading of currency crises among major currencies is not more contained than among emerging markets. If anything, contemporaneous currency crises within the developed world seem more likely to be broad than either within Asia or Latin America. The main finding is not reversed either when looking at the plot of the three lagged contamination curves (figure 5). The intertemporal propagation of currency crashes seems very much the same in any of the blocks.

[FIGURES 4 AND 5 ABOUT HERE]

How can it be that the emerging market currencies are not more contagion-prone than the major industrial currencies? First of all, we have to make sure we interpret our multivariate extreme linkage probabilities correctly. Recall from sub-section 3.1 (table 2) and Hartmann et al. (2003) that, univariately, emerging market currencies (with few exceptions) crash much more frequently than industrial country currencies. The fact that the conditional multi-crash probabilities discussed in the present section are not higher than the ones in the previous one does not necessarily mean that widespread emerging market crises are overall less frequent than widespread major currency crises. What it means is rather that once a crisis, or several crises have occurred industrial country currencies are not less likely to be affected widely than emerging market currencies. Once instability has struck them, emerging market currencies are not affected more broadly than major currencies. If anything, the breadth of crises in this sense is fairly comparable between the two groups of currencies.

One reasons for this, on the surface, surprising result may be that industrial countries tend to be more economically and financially integrated with each other than many emerging market economies with each other. For this reason, a crisis in one may affect in a similar way another, with implications for the propagation of extreme currency movements. Another reason may be that traders’ crisis behavior is fairly similar across currencies. So, once an extreme crisis has occurred somewhere, the same "cross-country panic selling" happens, irrespective of the exact character of the respective currencies. A crisis is a crisis, irrespective of where it occurs. The two explanations for our finding do not exclude each other, but may well be responsible for it together. The next section, however, will show that multivariate extreme market linkages are not identical everywhere.

7. Crisis spillovers between major and emerging market currencies

An important question for the assessment of global systemic currency risk is to which extent the three blocks − major industrial, East Asian and Latin American − are interlinked with each other in crisis situations. This is the subject of this section. We first present estimations of our probability measure (2.3) for widespread crises in emerging market countries, conditional on crises of varying size in major industrial currencies. Second, we reverse the order, analyzing widespread crises among the major currencies, conditional on crises of varying breadth in emerging market currencies.

The results about spillovers from major currencies to emerging markets are displayed in table 7 and figure 6. The first observation is how much lower the spillover probabilities are, compared to the ones observed within currency blocks. Looking for "hot spot" currencies, the contemporaneous probabilities highlight the Australian dollar as a conditioning currency that has often the strongest impact. For the lagged probabilities, the AUD is sometimes joined by the Japanese yen. It is, of course, unsurprising that among all five industrial currencies the Asian and the Oceanian one have the biggest impact on other East Asian currencies. Finally, the weaker character of lagged spillovers is also preserved in the present case.

[TABLE 7 AND FIGURE 6 ABOUT HERE]

As to Latin America, this region is affected by even less than East Asia from turmoil originating in the major currencies. (Of course, this has also to do with the fact that the US dollar is the base currency, and therefore dollar crashes are not covered by our spillover measures.) Interestingly, the AUD remains a "hot spot", even for Latin America (in particular, together with the DEM).

In table 8 and figure 7 conditioning and conditioned currency blocks are reversed. Most surprisingly, spillover probabilities are higher than the ones discussed above. This means that our data suggest that emerging markets are a more dangerous source of systemic currency risk for industrial countries than a multi-currency crash in industrial countries for emerging markets. Contamination curves for East Asia and Latin America are almost identical in figure 7, so the two emerging market blocks involve about the same risk for major markets. Regarding "hot spots" from Asia, the Philippine peso figures again relatively highly, together this time with the Hong Kong dollar (and for lagged probabilities with the Malaysian ringgit). Regarding Latin America, the Mexican peso in conjunction with the Venezuelan bolivar seems to be a source of higher risk for major currencies. For lagged probabilities again the VEB plays a somewhat special role, may be sometimes together with the Colombian peso.

[TABLE 8 AND FIGURE 7 ABOUT HERE]

8. Summary and conclusions

In this paper we have presented a new approach to assess systemic market risk, based on multivariate extreme value theory. We derived two measures of the breadth of violent currency depreciations and developed semi-parametric estimators for them. The minimization of model risk implicit in this approach is particularly important, as − by the nature of the problem we are addressing − many different markets have to be covered. One general measure of widespread currency risk is based on conditional expectations. The other measure is based on conditional probabilities and has the distinct advantage that one can condition on very specific events. From the latter, we also derive a neat graphical representation of the breadth of currency crises, the "contamination function".

With 17 years of exchange rate data for 5 major industrial currencies and 10 emerging market curencies, we find a number of interesting results. Some of them do not necessarily correspond to the "conventional wisdom" about international financial instabilities. First, the spreading of extreme depreciations among major industrial currencies, if they occur, is not less severe than among emerging market currencies. Quite the contrary, extreme spillover probabilities rather tend to be somewhat larger, perhaps related to the greater integration of the economies underlying those currencies. Alternatively, this finding can be indicative of a certain generality of crisis propagation.

Second, extreme currency linkages in a multivariate context seem to be generally quite strong within currency blocks. We distinguish three blocks: major industrial currencies, East Asian emerging market currencies and Latin American emerging market currencies.

Third, across the three blocks spillovers are much weaker. Again surprisingly, however, the probability of a widespread crisis among major currencies, conditional on two or more crisis events among emerging market currencies, is higher than the probability of a widespread crisis among emerging market currencies, conditional on crisis events among the major industrial currencies. According to this result, industrial countries are more at risk from emerging markets than emerging markets are from industrial countries.

Fourth, lagged extreme spillover probabilities are systematically smaller than contemporaneous spillover probabilities. As we use weekly returns, this probably means that crises propagate very fast. Most of an extreme shock will have its main effects on other currencies within the same week.

Finally, we identify a few currencies that play a larger role than the other currencies in crisis propagation. We denote them as "hot spots", as they are of particular interest for international financial surveillance and risk management. Among the major currencies, we identified particularly the Australian dollar. From East Asia, the Philippine peso often seems to have a strong effect. And from Latin America, less surprisingly, the Mexican peso emerges as a source of risk, but also the Venezuelan bolivar.

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Appendix A. Data description and discussion

Data were obtained from Datastream inc. We downloaded daily nominal bilateral spot exchange rates against the Pound sterling (GBP), because this renders the largest rectangular panel data set (largest cross section of currencies over the longest possible time span). Next, exchange rates against the US dollar (USD) were calculated by applying the no triangular arbitrage condition. Hence, the USD is taken as the numéraire. The full sample covers January 1987 through February 2003.

Exchange rate returns were calculated as log first differences, Monday to Monday. So, for each series we have about 850 observations. Weekly data have the advantage that one significantly reduces the typical time zone problems encountered with international data at the intradaily or daily frequencies. Moreover, they capture more sustained crash phenomena than one would usually pick up with daily returns, which can be expected to have more significant effects on financial institutions and the real economy. An even longer holding period was not possible due to the limited length of the emerging market currency data available to us. The number of currencies within each currency block (major industrial, East Asian, Latin American) is chosen equal to 5 in order to make the estimates of our multivariate linkage measure comparable across currency blocks.

Major industrial currencies were selected with an eye on their turnover in global foreign exchange trading (see BIS, 2002). They are listed with the following abbreviations: German mark (DEM), Japanese yen (JPY), Pound sterling (GBP), Swiss franc (CHF) and Australian dollar (AUD). The DEM is taken as a representative currency for what is now the euro area. Before January 1999 it played a central role in the European Monetary System. Since then it is irrevocably fixed to the euro (EUR), by a conversion rate of 1.9558 DEM/EUR, so that euro and mark returns are basically identical. (The AUD was included among the major currencies, instead of the Canadian dollar, as the latter is relatively close to the USD.)

The choice of *emerging market currencies* covered was determined by geographical coverage, data availability and data reliability. East Asian emerging market currencies are: Indonesian rupiah (IDR), Malaysian ringit (MYR), Thai baht (THB), Hong Kong dollar (HKD) and Philippine peso (PHP). Latin American emerging market currencies are: Mexican peso (MXN), Bolivian boliviano (BOB), Venezuelan bolivar (VEB), Chilean peso (CLP) and Colombian peso (COP). (The Hong Kong dollar might not be considered an emerging market currency like the others, e.g., because of its currency board arrangement against the US dollar. We may replace it in future revisions by the Korean Won.)

Table 1. Extremal weekly depreciations/appreciations w.r.t. USD (1987-2003)

	extreme depreciations (%)			extreme appreciations (%)		
	$X_{n,n}$	$X_{n-1,n}$	$X_{n-2,n}$	$X_{1,n}$	$X_{2,n}$	$X_{3,n}$
	(Date)	(Date)	(Date)	(Date)	(Date)	(Date)
Panel A: developed currency returns						
GBP	10.02	7.04	5.57	-4.77	-4.42	-4.37
	(21/9/92)	(1/2/93)	(22/4/91)	(7/12/92)	(4/11/91)	(8/10/90)
DEM	5.84	5.80	5.32	-4.66	-4.63	-4.59
	(15/5/95)	(14/9/92)	(22/4/91)	(4/12/00)	(26/7/99)	(4/11/91)
JPY	5.57	5.44	4.71	-12.80	-6.97	-6.74
	(21/6/93)	(9/11/98)	(12/6/89)	(12/10/98)	(7/9/98)	(12/5/97)
CHF	7.29	6.54	5.07	-5.79	-5.21	-5.19
	(15/5/95)	(12/10/92)	(14/9/92)	(24/8/92)	(29/5/95)	(6/3/95)
AUD	8.09	5.50	5.17	-4.96	-4.19	-3.68
	(20/2/89)	(27/10/97)	(15/10/90)	(12/10/98)	(19/1/98)	(4/12/00)
Panel B: Asian currency returns						
IDR	35.62	33.11	27.66	-35.37	-16.64	-13.88
	(26/1/98)	(15/12/97)	(12/1/98)	(2/2/98)	(12/10/98)	(25/5/98)
MYR	35.69	11.25	10.27	-13.38	-11.83	-11.08
	(2/11/98)	(12/1/98)	(9/3/98)	(5/4/99)	(31/5/99)	(19/1/98)
THB	13.41	12.77	10.70	-10.49	-9.24	-7.10
	(15/12/97)	(12/1/98)	(7/7/97)	(16/3/98)	(10/11/97)	(2/2/98)
HKD	1.73	1.72	1.68	-1.73	-1.62	-1.34
	(23/8/93)	(20/7/92)	(2/2/87)	(29/6/87)	(26/1/87)	(27/7/92)
PHP	12.94	12.76	7.81	-7.96	-7.37	-6.85
	(15/12/97)	(14/7/97)	(14/9/92)	(6/7/87)	(6/11/00)	(13/10/97)
Panel C: Latin American currency returns						
MXN	32.38	29.75	10.13	-17.01	-7.84	-6.28
	(30/11/87)	(26/12/94)	(30/1/95)	(6/2/95)	(10/4/95)	24/4/95)
BOB	21.09	6.71	4.63	-20.03	-3.91	-3.03
	(9/3/87)	(1/8/88)	(8/6/87)	(16/3/87)	(16/1/89)	(30/3/87)
VEB	67.01	16.05	15.67	-18.45	-14.36	-9.77
	(4/12/95)	(30/5/94)	(18/2/02)	(10/2/03)	(11/7/94)	(25/3/96)
CLP	8.58	5.57	5.44	-8.51	-5.50	-4.52
	(22/2/88)	(24/6/91)	(11/1/88)	(15/2/88)	(3/9/90)	(5/12/94)
COP	25.10	9.83	9.59	-9.86	-8.57	-8.22
	(30/11/92)	(5/12/88)	(16/12/91)	(23/12/91)	(28/11/88)	(28/10/91)

Table 2. Tail index and extreme quantile (VaR) estimates for weekly currency returns (1987-2003)

	$\widehat{\alpha}(m)$	$\widehat{q} = X_{n-m}\left(\frac{m}{np}\right)^{\frac{1}{\widehat{\alpha}}}$ (%)
	($m = 75$)	
Panel A: Major industrial block		
DEM	3.10	7.77
JPY	3.03	7.73
GBP	2.46	9.91
CHF	2.95	8.57
AUD	3.17	7.33
Panel B: East Asian block		
IDR	1.18	84.61
MYR	1.15	33.43
THB	1.33	29.33
HKD	1.57	4.22
PHP	1.84	18.46
Panel C: Latin American block		
MXN	1.59	24.03
BOB	1.80	9.23
VEB	1.37	58.88
CLP	1.97	12.72
COB	2.07	13.80

Table 3. Systemic currency risk within and across currency blocks: unconditional probability and expectation measure

	$P\left\{\bigcap_{i=1}^{N} X_i(t) > Q_i(p)\right\},\ p = \frac{1}{n}$	$E = \frac{Np}{P\left\{\bigcup_{i=1}^{N} X_i(t)>Q_i(p)\right\}},\ p = \frac{1}{n}$
	($m = 75$)	($k = 75$)
Currency block	Panel A: within blocks	
Major IC	2.13E-6	1.752
($\widehat{\alpha}$)	(0.550)	
East Asia	1.42E-8	1.512
($\widehat{\alpha}$)	(0.387)	
Latin America	2.02E-10	1.263
($\widehat{\alpha}$)	(0.308)	
	Panel B: across blocks	
IC-EA	4.83E-16	2.066
($\widehat{\alpha}$)	(0.192)	
IC-LA	9.79E-18	1.744
($\widehat{\alpha}$)	(0.174)	
EA-LA	1.68E-17	1.693
($\widehat{\alpha}$)	(0.176)	
	(probability for 10 curr.)	

TABLE 4. Extreme spillovers among major industrial country currencies (1987-2003)

Cond. events	Contemporaneous (%) $(m = 75)$	Lagged (%) $(m = 75)$
	Panel A: 1 conditioning market $(j = 1)$	
X_1		0.76
X_2		0.54
X_3		1.17
X_4		0.81
X_5		1.30
average	0.18	0.92
	Panel B: 2 conditioning markets $(j = 2)$	
X_1, X_2	16.00	2.28
X_1, X_3	33.11	7.42
X_1, X_4	18.10	3.26
X_1, X_5	35.67	7.65
X_2, X_3	30.03	6.29
X_2, X_4	9.67	1.56
X_2, X_5	42.10	8.71
X_3, X_4	26.51	5.54
X_3, X_5	41.05	14.46
X_4, X_5	43.15	7.57
average	29.54	6.47
	Panel C: 3 conditioning markets $(j = 3)$	
X_1, X_2, X_3	40.36	9.47
X_1, X_2, X_4	20.32	7.77
X_1, X_2, X_5	57.17	13.46
X_1, X_3, X_4	39.67	9.73
X_1, X_3, X_5	80.27	36.71
X_1, X_4, X_5	61.26	15.58
X_2, X_3, X_4	31.86	9.05
X_2, X_3, X_5	74.73	30.57
X_2, X_4, X_5	47.88	14.03
X_3, X_4, X_5	80.74	35.57
average	53.42	18.19
	Panel D: 4 conditioning markets $(j = 4)$	
X_1, X_2, X_3, X_4	43.51	27.97
X_2, X_3, X_4, X_5	82.63	51.46
X_3, X_4, X_5, X_1	93.88	48.15
X_4, X_5, X_1, X_2	64.19	25.87
X_5, X_1, X_2, X_3	94.89	46.51
average	75.82	39.99
$X_1 : GBP$	$X_2 : DEM$	$X_3 : JPY$
$X_4 : CHF$	$X_5 : AUD$	
Contemp.	$P\left\{\bigcap_{i=1}^{5} X_i(t) > Q_i(p) \,\middle|\, \bigcap_{j<5} X_j(t) > Q_j(p)\right\},\ p = \frac{1}{n}$	
Lagged	$P\left\{\bigcap_{i=1}^{5} X_i(t) > Q_i(p) \,\middle|\, \bigcap_{j<5} X_j(t-1) > Q_j(p)\right\},\ p = \frac{1}{n}$	

Table 5. Extreme spillovers among East Asian emerging market currencies (1987-2003)

	Contemporaneous (%)	Lagged (%)
Cond. events	($m = 75$)	($m = 75$)
	Panel A: 1 conditioning market ($j = 1$)	
X_1		0.06
X_2		0.13
X_3		0.20
X_4		0.03
X_5		0.28
average	0.001	0.14
	Panel B: 2 conditioning markets ($j = 2$)	
X_1, X_2	14.84	2.21
X_1, X_3	7.57	1.72
X_1, X_4	15.80	1.94
X_1, X_5	14.84	2.06
X_2, X_3	13.39	2.35
X_2, X_4	7.95	0.81
X_2, X_5	15.99	2.15
X_3, X_4	19.76	4.15
X_3, X_5	10.61	3.13
X_4, X_5	15.99	2.43
average	13.76	2.29
	Panel C: 3 conditioning markets ($j = 3$)	
X_1, X_2, X_3	35.72	12.27
X_1, X_2, X_4	36.04	16.28
X_1, X_2, X_5	48.42	12.86
X_1, X_3, X_4	38.01	13.14
X_1, X_3, X_5	25.56	11.05
X_1, X_4, X_5	40.03	12.73
X_2, X_3, X_4	32.60	10.16
X_2, X_3, X_5	48.04	18.26
X_2, X_4, X_5	38.67	12.27
X_3, X_4, X_5	44.29	13.54
average	38.74	13.26
	Panel D: 4 conditioning markets ($j = 4$)	
X_1, X_2, X_3, X_4	58.67	42.45
X_2, X_3, X_4, X_5	70.64	39.36
X_3, X_4, X_5, X_1	64.03	37.41
X_4, X_5, X_1, X_2	73.10	42.66
X_5, X_1, X_2, X_3	70.64	40.05
average	67.42	40.39
$X_1 : IDR$	$X_2 : MYR$	$X_3 : THB$
$X_4 : HKD$	$X_5 : PHP$	
Contemp.	$P\left\{ \bigcap_{i=1}^{5} X_i(t) > Q_i(p) \middle| \bigcap_{j<5} X_j(t) > Q_j(p) \right\}, p = \frac{1}{n}$	
Lagged	$P\left\{ \bigcap_{i=1}^{5} X_i(t) > Q_i(p) \middle| \bigcap_{j<5} X_j(t-1) > Q_j(p) \right\}, p = \frac{1}{n}$	

Table 6. Extreme spillovers among Latin American emerging market currencies (1987-2003)

	Contemporaneous (%)	Lagged (%)
Cond. events	($m = 75$)	($m = 75$)
	Panel A: 1 conditioning market ($j = 1$)	
X_1		0.07
X_2		0.02
X_3		0.08
X_4		0.02
X_5		0.01
average	0.00002	0.04
	Panel B: 2 conditioning markets ($j = 2$)	
X_1, X_2	13.20	3.51
X_1, X_3	11.39	2.73
X_1, X_4	8.43	2.49
X_1, X_5	9.35	1.53
X_2, X_3	7.23	1.43
X_2, X_4	7.81	1.40
X_2, X_5	6.36	1.59
X_3, X_4	14.08	5.56
X_3, X_5	8.43	2.67
X_4, X_5	7.34	2.24
average	9.36	2.52
	Panel C: 3 conditioning markets ($j = 3$)	
X_1, X_2, X_3	39.61	14.60
X_1, X_2, X_4	33.34	15.10
X_1, X_2, X_5	33.67	15.21
X_1, X_3, X_4	38.15	18.40
X_1, X_3, X_5	37.79	17.41
X_1, X_4, X_5	29.26	13.88
X_2, X_3, X_4	36.03	14.96
X_2, X_3, X_5	23.17	9.64
X_2, X_4, X_5	28.08	20.17
X_3, X_4, X_5	29.56	18.54
average	32.87	15.79
	Panel D: 4 conditioning markets ($j = 4$)	
X_1, X_2, X_3, X_4	71.77	43.02
X_2, X_3, X_4, X_5	54.05	50.01
X_3, X_4, X_5, X_1	65.30	44.80
X_4, X_5, X_1, X_2	55.43	47.17
X_5, X_1, X_2, X_3	62.73	42.02
average	61.86	45.40
$X_1 : MXN$	$X_2 : BOB$	$X_3 : VEB$
$X_4 : CLP$	$X_5 : COP$	
Contemp.	$P\left\{\bigcap_{i=1}^{5} X_i(t) > Q_i(p) \middle\vert \bigcap_{j<5} X_j(t) > Q_j(p)\right\},\ p = \frac{1}{n}$	
Lagged	$P\left\{\bigcap_{i=1}^{5} X_i(t) > Q_i(p) \middle\vert \bigcap_{j<5} X_j(t-1) > Q_j(p)\right\},\ p = \frac{1}{n}$	

Table 7. Extreme spillovers from major industrial currencies to emerging market currencies (1987-2003)

	East Asia		Latin America	
	Cont.	Lagged	Cont.	Lagged
Cond. events	(all for $m = 75$)			
	Panel A: 1 conditioning market ($j = 1$)			
X_1		0.0004		0.0000
X_2		0.0004		0.0002
X_3		0.0018		0.0002
X_4		0.0005		0.0000
X_5		0.0005		0.0000
average	4E-11	0.0007	8E-13	0.0001
	Panel B: 2 conditioning markets ($j = 2$)			
X_1, X_2	0.41	0.01	0.15	0.00
X_1, X_3	0.07	0.16	0.02	0.01
X_1, X_4	0.05	0.01	0.02	0.00
X_1, X_5	0.51	0.07	0.19	0.00
X_2, X_3	0.22	0.17	0.07	0.03
X_2, X_4	0.31	0.00	0.11	0.00
X_2, X_5	0.76	0.08	0.30	0.01
X_3, X_4	0.01	0.09	0.00	0.01
X_3, X_5	0.87	0.22	0.35	0.06
X_4, X_5	0.81	0.09	0.32	0.00
average	0.40	0.09	0.15	0.01
	Panel C: 3 conditioning markets ($j = 3$)			
X_1, X_2, X_3	0.69	0.22	0.27	0.04
X_1, X_2, X_4	0.72	0.05	0.28	0.01
X_1, X_2, X_5	5.18	0.48	2.48	0.03
X_1, X_3, X_4	0.10	0.18	0.03	0.03
X_1, X_3, X_5	2.39	1.55	1.05	0.27
X_1, X_4, X_5	1.96	0.49	0.85	0.03
X_2, X_3, X_4	0.37	0.25	0.13	0.03
X_2, X_3, X_5	5.27	1.22	2.52	0.39
X_2, X_4, X_5	4.22	0.14	1.98	0.02
X_3, X_4, X_5	1.18	1.50	0.48	0.27
average	2.21	0.61	1.01	0.11
	Panel D: 4 conditioning markets ($j = 4$)			
X_1, X_2, X_3, X_4	0.90	5.49	0.36	2.51
X_2, X_3, X_4, X_5	5.63	2.24	2.72	0.34
X_3, X_4, X_5, X_1	2.73	2.42	1.22	0.57
X_4, X_5, X_1, X_2	8.37	0.87	4.21	0.14
X_5, X_1, X_2, X_3	9.73	2.79	4.07	0.90
average	5.47	2.76	2.52	0.89
	Panel E: 5 conditioning markets ($j = 5$)			
X_1, X_2, X_3, X_4, X_5	9.73	5.49	4.97	2.51
$X_1 : GBP$	$X_2 : DEM$	$X_3 : JPY$	$X_4 : CHF$	$X_5 : AUD$
Y : Emerging market currencies				
Contemp.	$P\left\{\bigcap_{i=1}^{5} Y_i(t) > Q_i(p) \middle| \bigcap_{j<5} X_j(t) > Q_j(p)\right\}$			
Lagged	$P\left\{\bigcap_{i=1}^{5} Y_i(t) > Q_i(p) \middle| \bigcap_{j<5} X_j(t-1) > Q_j(p)\right\}$			

Table 8. Extreme spillovers from emerging market currencies to major industrial currencies (1987-2003)

	East Asia		Latin America	
	Cont.	Lagged	Cont.	Lagged
Cond. events	(all for $m = 75$)			
	Panel A: 1 conditioning market ($j = 1$)			
X_1		0.002		0.0003
X_2		0.001		0.0003
X_3		0.000		0.0002
X_4		0.000		0.0002
X_5		0.001		0.0003
average	4E^{-11}	0.001	8E^{-13}	0.0003
	Panel B: 2 conditioning markets ($j = 2$)			
X_1, X_2	0.59	0.49	0.67	0.28
X_1, X_3	0.15	0.05	0.52	0.17
X_1, X_4	0.67	0.11	0.30	0.10
X_1, X_5	0.59	0.18	0.37	0.10
X_2, X_3	0.48	0.05	0.23	0.11
X_2, X_4	0.17	0.09	0.27	0.05
X_2, X_5	0.69	0.41	0.18	0.15
X_3, X_4	1.05	0.03	0.76	0.31
X_3, X_5	0.30	0.10	0.30	0.15
X_4, X_5	0.69	0.27	0.24	0.11
average	0.54	0.18	0.38	0.15
	Panel C: 3 conditioning markets ($j = 3$)			
X_1, X_2, X_3	3.47	2.04	4.74	2.04
X_1, X_2, X_4	3.54	2.14	3.49	2.14
X_1, X_2, X_5	6.41	3.07	3.55	3.07
X_1, X_3, X_4	3.94	0.47	4.43	0.47
X_1, X_3, X_5	1.77	0.58	4.36	0.58
X_1, X_4, X_5	4.37	1.72	2.77	1.72
X_2, X_3, X_4	2.89	0.93	4.00	0.93
X_2, X_3, X_5	4.20	4.04	1.83	4.04
X_2, X_4, X_5	2.21	3.50	2.57	3.50
X_3, X_4, X_5	4.51	1.72	2.82	1.72
average	2.88	2.02	3.45	2.02
	Panel D: 4 conditioning markets ($j = 4$)			
X_1, X_2, X_3, X_4	6.83	3.85	13.61	9.41
X_2, X_3, X_4, X_5	12.74	11.44	8.22	6.88
X_3, X_4, X_5, X_1	8.26	4.34	11.50	7.47
X_4, X_5, X_1, X_2	12.74	9.63	8.60	5.53
X_5, X_1, X_2, X_3	9.71	7.29	10.71	10.04
average	10.13	7.31	10.53	7.86
	Panel E: 5 conditioning markets ($j = 5$)			
X_1, X_2, X_3, X_4, X_5	18.51	20.86	24.52	24.91
E.Asia: $X_1 : IDR$	$X_2 : MYR$	$X_3 : THB$	$X_4 : HKD$	$X_5 : PHP$
L.Am.: $X_1 : MXN$	$X_2 : BOB$	$X_3 : VEB$	$X_4 : CLP$	$X_5 : COP$
Major currencies	Y			
Contemp.	$P\left\{ \bigcap_{i=1}^{5} Y_i(t) > Q_i(p) \middle| \bigcap_{j<5} X_j(t) > Q_j(p) \right\}$			
Lagged	$P\left\{ \bigcap_{i=1}^{5} Y_i(t) > Q_i(p) \middle| \bigcap_{j<5} X_j(t-1) > Q_j(p) \right\}$			

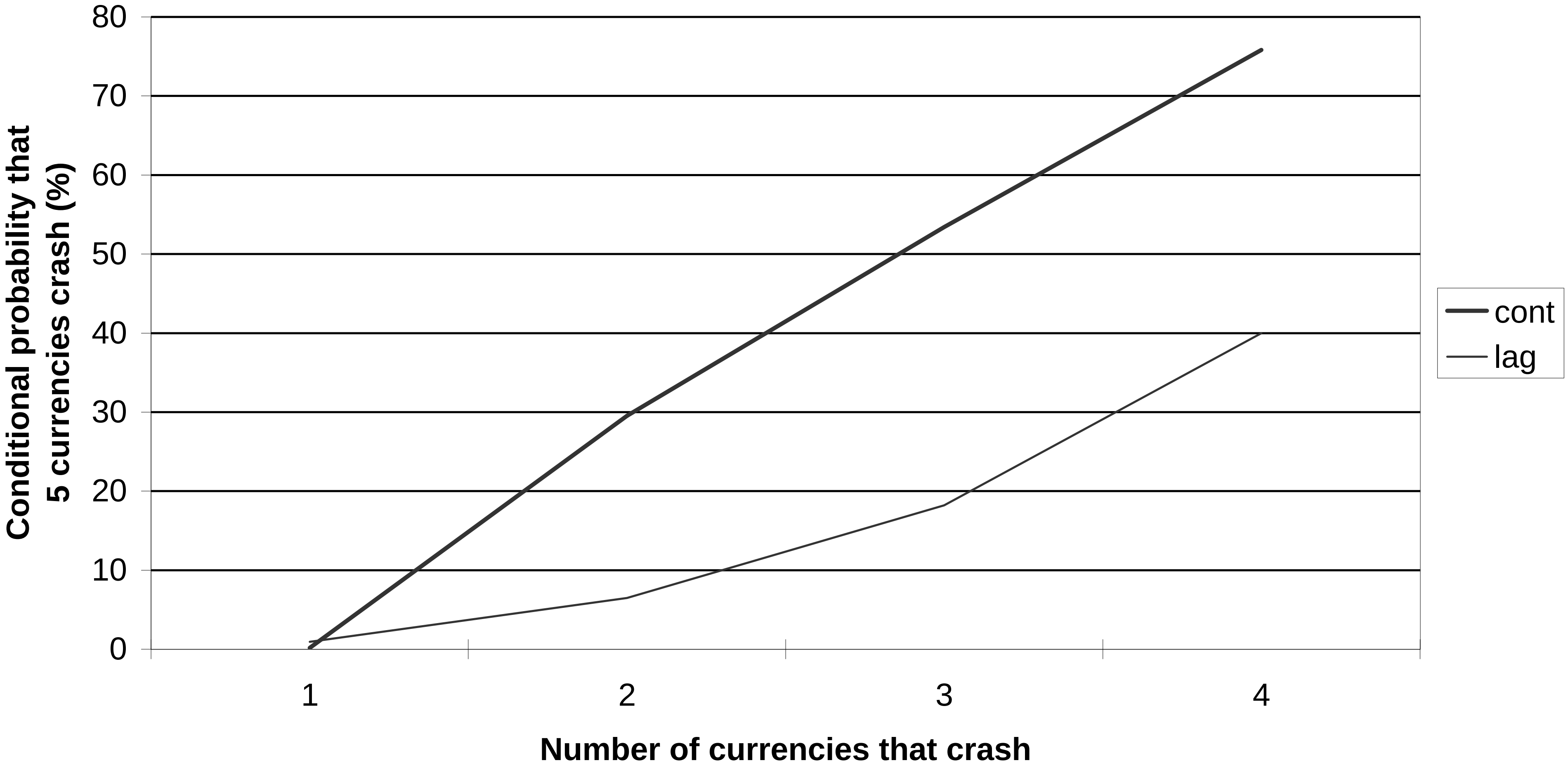


Figure 1: Contamination functions for major industrial currencies, contemporaneous and lagged

Figure 2: Contamination functions for East Asian currencies, contemporaneous and lagged

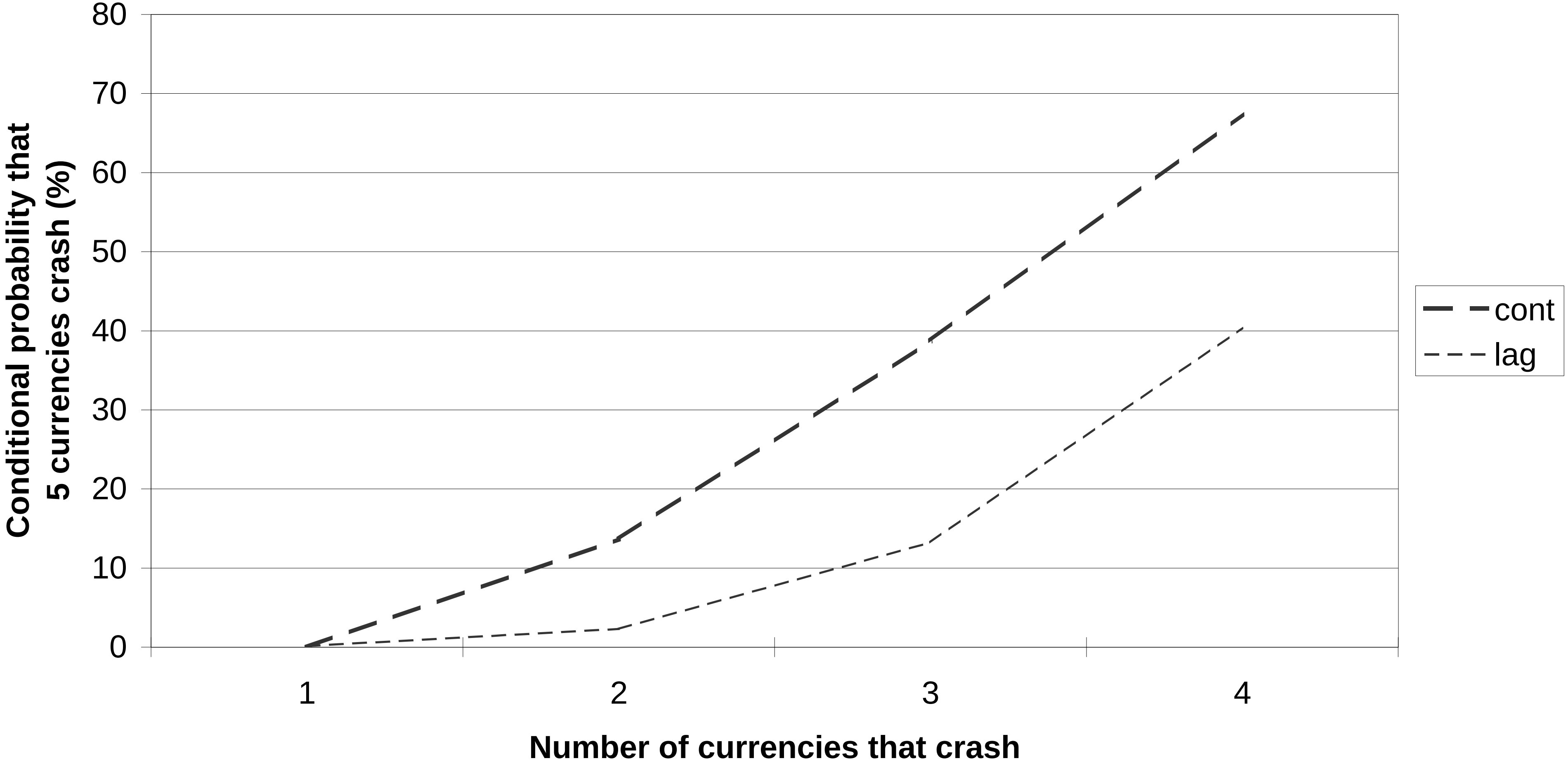


Figure 3: Contamination functions for Latin American currencies, contemporaneous and lagged

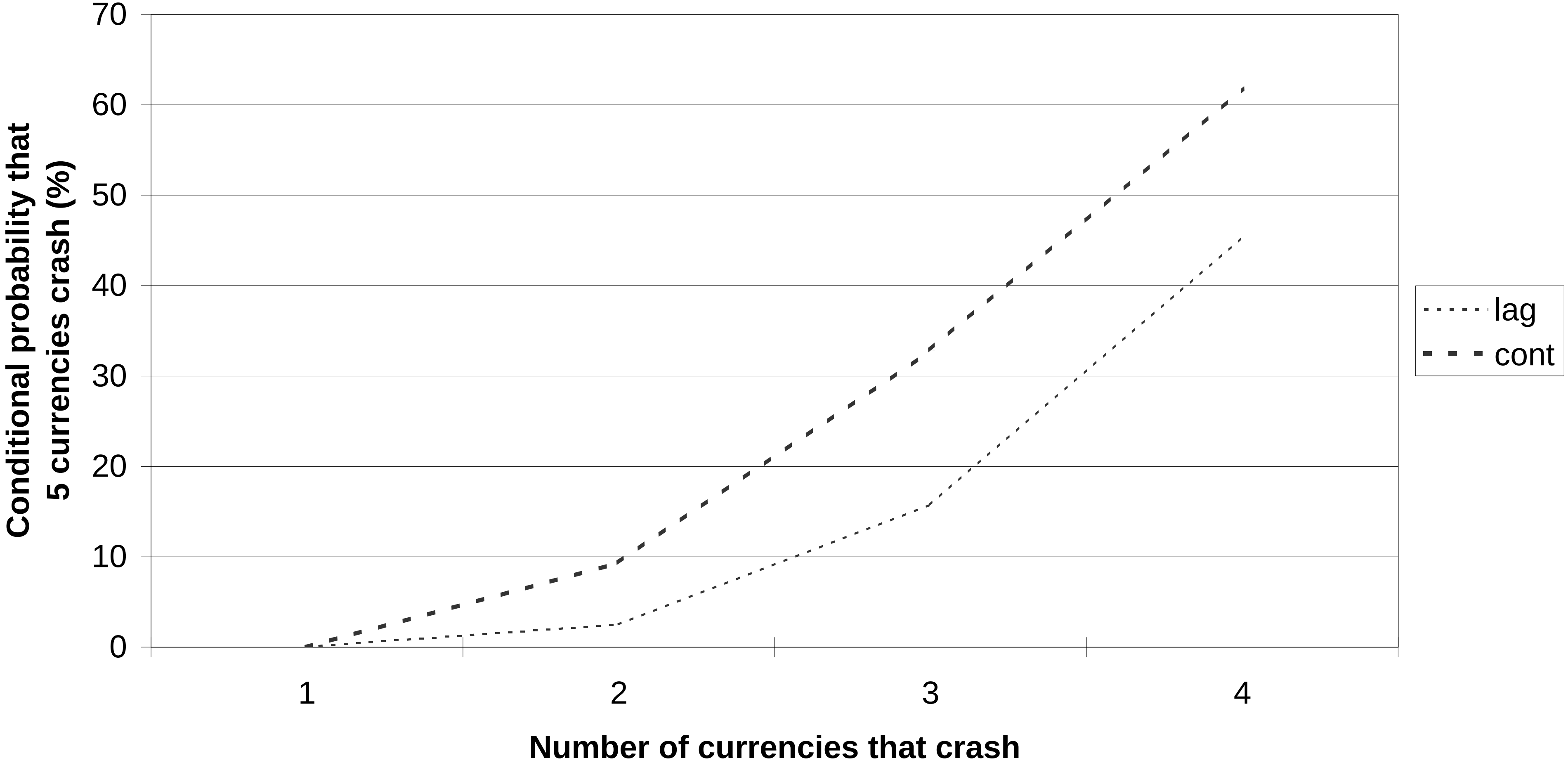


Figure 4: Contemporaneous contamination function for each currency block

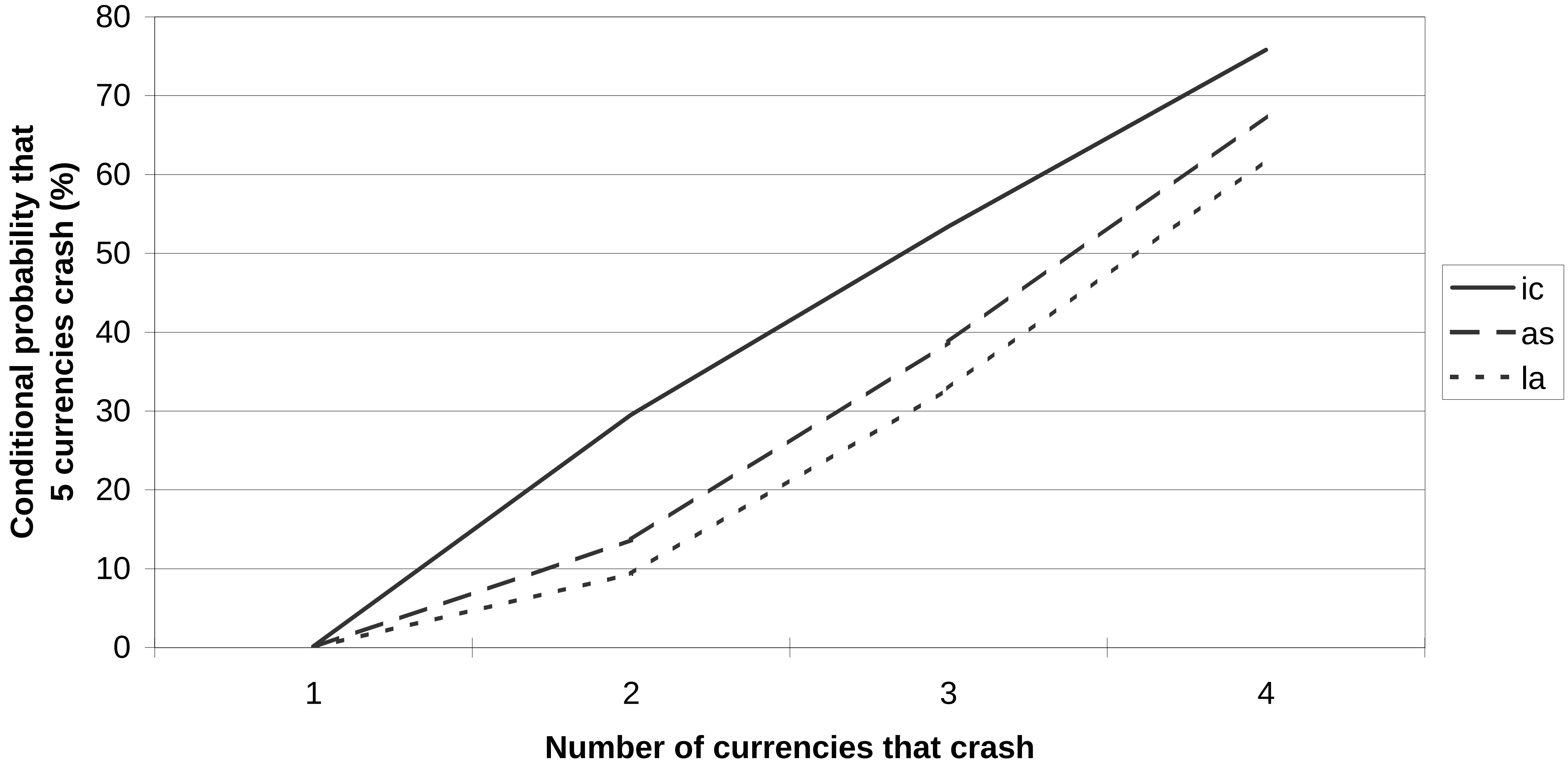


Figure 5: Lagged contamination function for each currency block

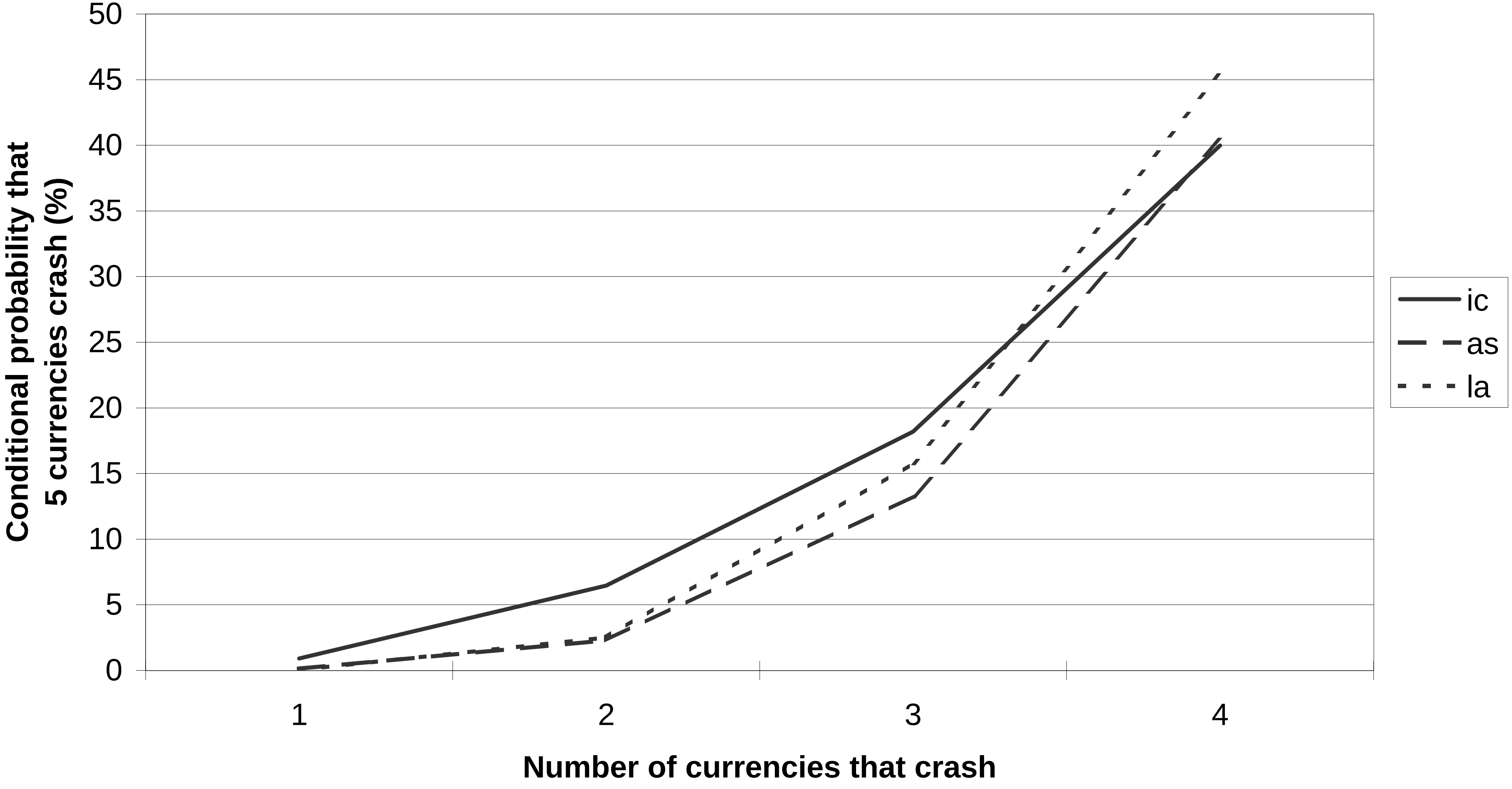


Figure 6: Contamination functions from major industrial currencies to emerging market currencies

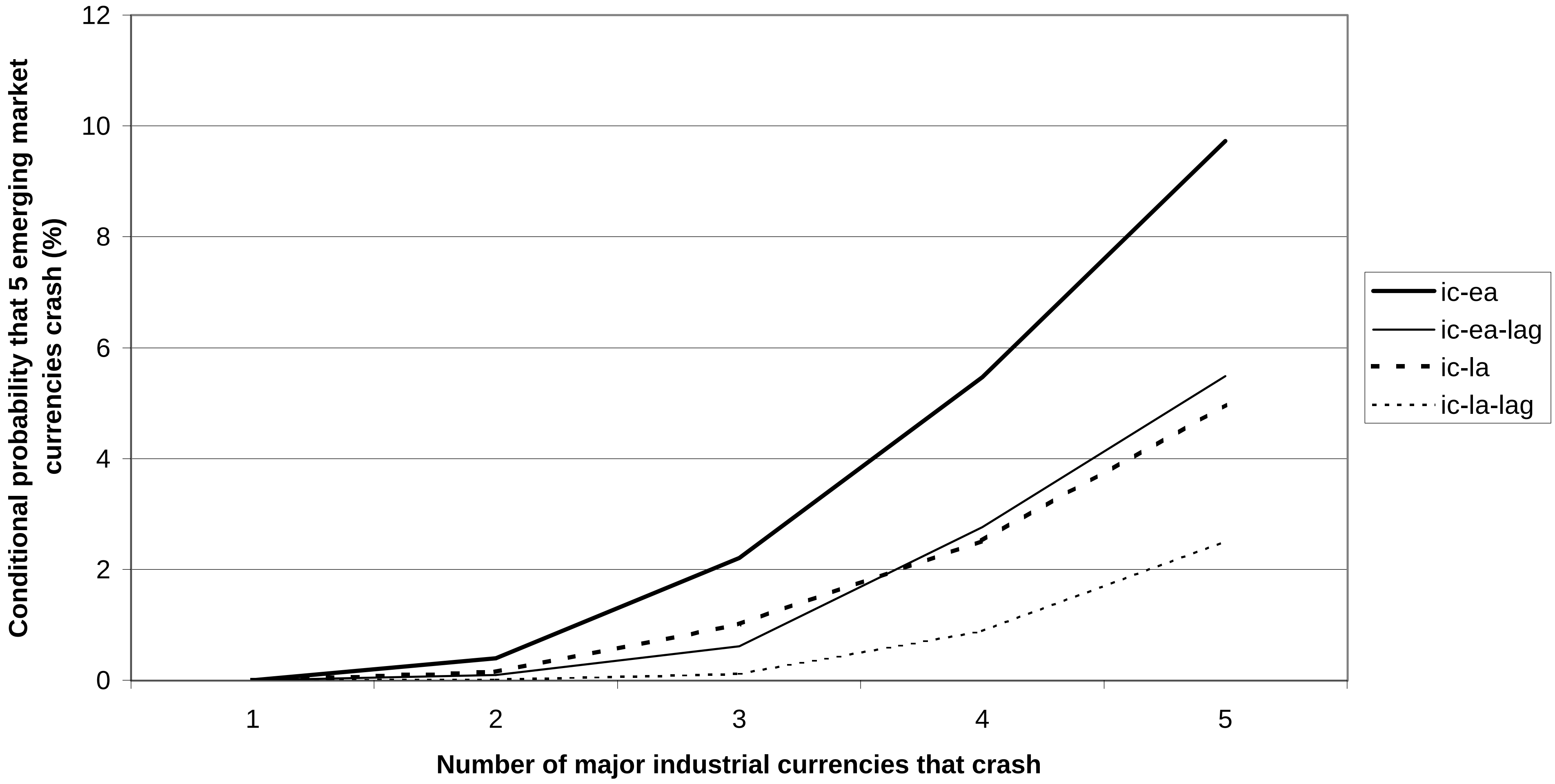
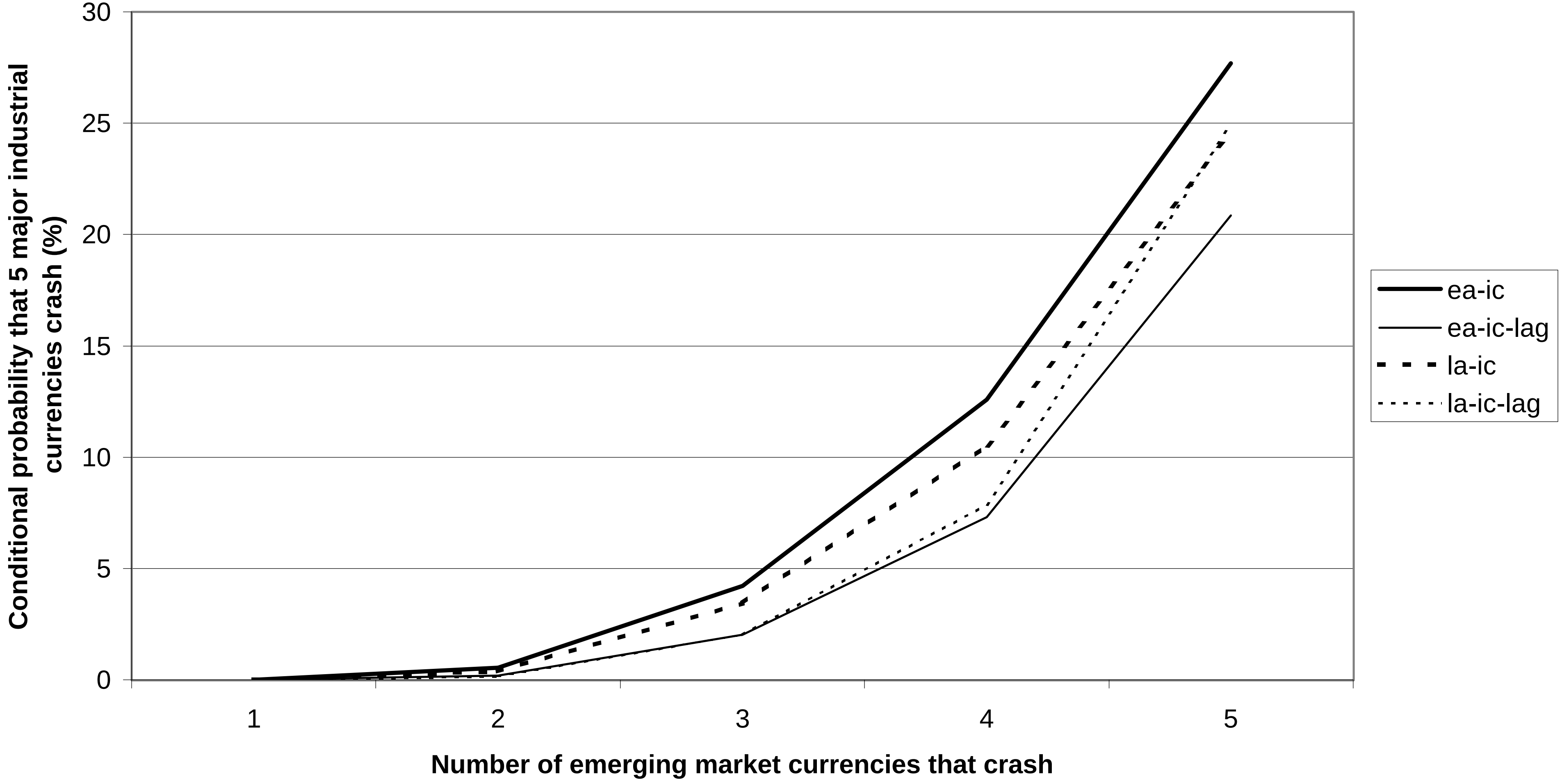


Figure 7: Contamination functions from emerging market currencies to major industrial currencies



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