Early Warning Systems for Currency Crises: A Multivariate Extreme Value Approach

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October 29, 2010

Abstract

We apply multivariate extreme value theory to test whether extreme exchange rate depreciations and devaluations are associated with extreme movements in lagged macro economic and financial variables. We find that nearly all fundamental variables have no relation with extreme exchange rate returns, except for the real interest rate. The estimated probability of a currency crisis occurring within twelve months of a positive extreme value of the domestic real interest rate is equal to 30%. Our findings can explain why existing early warning systems for currency crises perform poorly out of sample.

Keywords: Currency crises; Crisis prediction; Emerging markets; Extreme value theory

JEL classification: F31; F47; C10

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1. Introduction

The Mexican peso crisis in 1994, the Asian crisis in 1997-1998, and the Argentinean crisis in 2002 show that currency crises can have a devastating impact on the real economy. To prevent future crises researchers have since tried to identify common factors underlying exchange rate instability[1], and to build early warning systems for predicting currency crises.[2] In this paper we test whether currency crises are associated with extreme movements in lagged economic and financial variables, using multivariate extreme value theory. We find that nearly all fundamental variables commonly used in the literature have no relation with extreme exchange rate returns, except for the real interest rate. These findings may explain why existing early warning models for currency crises perform poorly out of sample, despite impressive in-sample results.[3]

Our main tool for assessing the usefulness of an economic fundamental variable as an indicator for currency turmoil is the concept of asymptotic dependence (Poon, Rockinger and Tawn, 2004). When a currency crisis measure and an economic fundamental variable are asymptotically independent, the conditional currency crisis probability approaches zero in the limit as the value of the economic indicator becomes more extreme. From a crisis prediction perspective, economic fundamentals that have some degree of regular dependence (non-zero correlation) with the currency crisis measures, but *no asymptotic dependence* in the tail area, are most likely poor predictors of currency crises, as the relation between the variables vanishes for the extreme events that matter most.

Our motivation for applying extreme value theory (EVT) is that currency crises are by definition infrequent extreme events that are more suited for specialized techniques that focus exclusively on rare tail events, instead of traditional approaches that are applicable to the entire domain of a distribution. In the currency crisis literature, there is no work yet that applies EVT to model the relation between macroeconomic variables and currency crisis measures. Koedijk, Stork and de Vries (1992) use EVT to study the empirical distribution of foreign exchange rate returns.[4] Related to our work, Pozo and Amuedo-Dorantes (2003) apply EVT to set thresholds for the identification of currency crises, instead of the more common approach that defines a crisis when a foreign exchange rate pressure measure is two or three standard deviations beyond its mean. Pozo and Amuedo-Dorantes (2003) find that the EVT method more accurately identifies actual crises than the conventional method.

Several studies apply EVT to analyze extreme dependence among financial markets, including Longin and Solnik (2001), Embrechts, McNeill and Straumann (2002), Bradley and Taqqu (2003), Poon, Rockinger and Tawn (2004), Hartmann, Straetmans and de Vries (2004), and de Vries (2005). Intriguingly, Embrechts et al. (2002) and de Vries

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[1] Among many fine surveys, the reader is referred to Kaminsky, Lizondo and Reinhart (1998), Flood and Marion (1999), Sarno and Taylor (2002), Krugman (2003) and Kumar, Moorthy and Perraudin (2003).

[2] The research is known as the signaling approach of currency crises. The group of works has been initiated by Kaminsky, Lizondo and Reinhart (1998), accompanied by a series of related works, such as Goldstein (1998), Goldstein, Kaminsky and Reinhart (2000), Kaminsky (1998, 1999, 2006), and Kaminsky and Reinhart (1998, 1999).

[3] See, for instance, Furman and Stiglitz (1998) and Berg and Pattillo (1999a, 1999b).

[4] Koedijk, Stork and de Vries (1992) find that countries with de facto fixed exchange rate regimes tend to have a higher chance of a currency crash than those with floating exchange rate regimes. Before that, with parametric techniques, Westerfield (1977) and Rana (1984) also estimate the unconditional distribution of foreign exchange rate returns and have similar findings.

(2005) demonstrate that variables with a Pearson correlation coefficient of zero may still be dependent in the tail area.[5] Hartmann et al. (2004) in addition show that joint probabilities of extreme stock market and bond market returns are estimated rather inaccurately under the assumption of multivariate normality.

The existing literature on extreme events in financial markets confirms that most economic and financial variables are non-normally distributed and that the dependency between variables in the tail area and in the centre range can be drastically different. Given these empirical facts, and the relevance of currency crisis prevention, in this paper we estimate the tail dependence of currency crises measures and lagged economic variables. Our sample consists of monthly observations on exchange rates and a large number of economic fundamentals for a cross-section of 46 developed and developing countries, spanning the period from January 1974 until February 2008.

Our results provide new insights about the extremal dependence of currency crisis measures and economic indicators that are important for developers of early warning systems in our opinion. First, the distributions of currency crisis measures and most economic variables have very heavy tails. For example, the tails of the monthly exchange rate return distribution are so heavy that the second moment and all higher moments do not exist (the integrals are unbounded). The conventional approach that uses "*x* times the standard deviation" to identify a currency crises is clearly at odds with the non-normal distribution of exchange rate returns.

Second, nearly all pairs of currency crisis measures and economic fundamentals are asymptotically independent. Hence, most economic indicators used in existing early warning models are unlikely to provide good predictions of future currency crises, as the conditional probability of an extreme currency event approaches zero as both variables move deeper into the tail. However, the exchange rate return is asymptotically dependent with the real interest rate and the real interest rate differential (relative to a reference country), at all lags up to 11 months. The limiting conditional probability of an extreme currency crash given an extreme positive real interest rate signal is estimated as 30%.

Last, the information conveyed by the EVT approach is insightful for crisis prediction, even though our approach is non-parametric and it does not rely on optimizing in-sample performance. Within the sample, we find a clear positive link between tail dependency and the success of an economic indicator in predicting currency crises. In our out-of-sample assessment period from July 1995 through February 2008, the EVT methodology correctly identifies all well-known major currency crises, such as the 1997 Asian crisis, the crisis in Russia in 1998 and the crisis in Argentina in 2002. Moreover, the simple real interest rate signals selected by our EVT approach perform better out of sample than competing indicators and crisis probability models.

[5] The Pearson correlation measure gives little weight to tail events and is thus prone to inadequately capture the interdependency in the tail area when the variables are non-normally distributed.

2. Methodology

2.1 Exchange Rates

In this paper we use three measures to identify the occurrence of currency crashes and crises, namely the exchange rate return (*ER*), the exchange market pressure index (*EMP*) and the real exchange market pressure index (*REMP*). The first measure (*ER*) is the simple monthly rate of change of the exchange rate,

$$ER_t = \Delta s_t = \ln s_t - \ln s_{t-1},$$

where s_t denotes the nominal spot exchange rate at time *t*, quoted as the price of foreign currency in terms of domestic currency.[6] The right tail of the distribution represents depreciation (or devaluation) of the domestic currency, while the left tail concerns appreciation (or revaluation). Frankel and Rose (1996) and Kumar, Moorthy and Perraudin (2003) use this measure to identify currency crises. For example, Frankel and Rose (1996) define a currency crash when a depreciation greater than 25% occurs that is also an increase in the rate of devaluation of at least 10%.

A speculative attack with selling pressure may not only result in domestic currency depreciation, but also loss of international reserves and/or an increase of the domestic interest rate by authorities to defend the currency. The exchange market pressure index (EMP_t) can pick up these additional signs of currency pressure:

$$EMP_t = \mathbf{a}\,\Delta s_t + \mathbf{b}\,\Delta \tilde{i}_t - \mathbf{c}\,\Delta DINR_t,$$

where $\tilde{i}_t$ is the monthly domestic-foreign interest rate differential, $DINR_t$ is the logarithmic differential between the monthly domestic and foreign ratios of international reserves to broad money supply (M2), and **a**, **b** and **c** are the inverse of the standard deviation of Δs_t, $\Delta \tilde{i}_t$ and $\Delta DINR_t$, respectively.[7] The definition above follows similar indices in Girton and Roper (1977), Eichengreen, Rose and Wyplosz (1995, 1996), Kaminsky et al. (1998) and Berg and Pattillo (1999a, 1999b). Eichengreen et al. (1996) identify a currency crisis when EMP_t is 1.5 standard deviations above the mean, while Kaminsky et al. (1998) use three standard deviations as the threshold.

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[6] For most countries, the exchange rate is quoted per US$1, while for the group of EMS countries the exchange rate is quoted per DM1.

[7] Country-specific weights are attached to each component to equalize the volatility of the three components within each country like in Kaminsky et al. (1998). The three variables are measured relative to US values, except for the EMS countries for which Germany is used as the base country. Our definition of the *EMP* index closely follows Pozo and Amuedo-Dorantes (2003). However, we use M2 instead of M1 to represent the size of the domestic money market, with the aim to make the series more compatible across countries. We apply a hyperinflation-correction method as in Kaminsky et al. (1998). When constructing the *EMP* series the sample is divided into two groups according to whether annual inflation rates during the previous six months were higher than 125 percent or not. Then, we compute (country-specific) indices for each group separately, using different weights. The purpose is to distinguish the behaviour of these three variables in hyperinflation periods, which may differ strongly from regular periods. After standardizing, the series from the two groups are recombined.

The real exchange market pressure index ($REMP_t$) uses real levels of the exchange rate and the interest rate differential to account for differences in inflation rates across countries and over time:

$$REMP_t = a'\Delta q_t + b'\Delta\tilde{r}_t - c'\Delta DINR_t ,$$

where q_t is the monthly real exchange rate, defined as one unit of foreign goods in terms of domestic goods, $\tilde{r}_t$ is the monthly domestic-foreign real interest rate differential, and a', b' and c' are the inverse of the standard deviation of Δq_t, $\Delta\tilde{r}_t$ and $\Delta DINR_t$, respectively. Bussiere and Fratzscher (2006) define a currency crisis when $REMP_t$ is two standard deviations above the mean.

For ease of exposition, in this paper we do not distinguish between currency crashes (extremes of *ER*) and currency crises (extremes of *EMP* and *REMP*), and from here onwards we use the term 'currency crisis' to refer to extremes of all three measures.

2.2 Economic Indicator Variables

Following the currency crises in Latin America in 1994-1995 and in Asia in 1997-1998, many papers investigate whether currency crisis have common causes and can be predicted with lagged economic and financial data. Kaminsky et al. (1998) and Berg and Pattillo (1999b) build early warning systems (EWS) for predicting the likelihood of currency crises based on a large set of such indicators, as currency crises are usually preceded by a broad range of economic problems that vary over time and across countries. The pioneering work in this area by Kaminsky et al. (1998) of the IMF investigates whether signals issued by economic indicators are followed by currency crises within the next 24 months.

In this paper, we examine 17 economic variables from a consensus selection of successful indicators based on multiple works surveyed by Kaminsky et al. (1998), as well as Kaminsky and Reinhart (1998, 1999), and Kaminsky (1999, 2006). Table 2 lists the 17 indicators used in this study. The second column of Table 2 shows the tail of the indicator (left or right tail) that is expected to give a depreciation signal based on the economic literature. Web Appendix A provides the rationale for the selection of these 17 indicators, and the motivation for the expected sign. Web Appendix B contains details on the definition and data sources for each indicator.

2.3 Thresholds for Currency Crises and Economic Warning Signals

In the EWS for currency crises of Kaminsky et al. (1998) currency crises are defined to occur when the exchange market pressure index (EMP_t) exceeds its mean by three standard deviations. The signal threshold for an economic indicator variable is set by maximizing the in-sample currency crisis prediction performance of the indicator. The economic indicator sends out a currency crisis warning signal whenever it moves beyond the signal threshold.

The "x times the standard deviation" method applied by Kaminsky et al. (1998) and others to identify currency crises implicitly assumes a normal distribution.

Inappropriately imposing the assumption of normality on a fat-tailed distribution will result in underestimation of the likelihood of extreme events. In this paper we apply extreme value theory: we first estimate the tail index of the three currency crisis measures to assess the degree of tail fatness. Second, the tail index estimation procedure also provides a threshold that separates extreme observations in the tail from the centre range of the distribution.[8]

According to extreme value theory, a distribution function $F(x)$ has heavy tails if its tails vary regularly (slowly) at infinity, i.e.

$$\lim_{t\to\infty}\frac{1-F(tx)}{1-F(t)}=x^{-\alpha}, \quad \text{for } x>0 \text{ and } \alpha>0,$$

where α is the tail index.[9] The parameter γ is the inverse of the tail index α ($\gamma=1/\alpha$). The parameter γ governs the shape of the tail, regardless of the precise form of the underlying distribution function $F(x)$.[10] This property is very important, as in practice we rarely know the true distribution function.

When $\gamma>0$ the distribution has heavy tails, and the number of existing moments of the random variable is equal to α. For instance, Pareto and Student's *t* distributions fall in this category: these distribution are heavy tailed, with a finite number of moments. For normally distributed variables the tail shape parameter γ equals zero. If $\gamma = 0$, the distribution has thin tails and an infinite number of existing moments. If $\gamma < 0$, the distribution has a finite upper limit, and therefore no long tail. For example, the uniform distribution is bounded and has a negative tail shape parameter ($\gamma < 0$).

We estimate the tail shape parameter γ non-parametically with the Hill estimator. If we define the ascending order statistics from a random sample of size n as $X_{(1)} \le X_{(2)} \le \ldots \le X_{(n)}$, the estimator proposed by Hill (1975) is

$$\hat{\gamma}=\frac{1}{m}\sum_{i=1}^{m}\left[\log X_{(n+1-i)}/X_{(n-m)}\right],$$

where $\hat{\gamma}$ is the estimator of the inverse tail index and $X_{(n-m)}$ is a high threshold such that there are m observations above the threshold.[11] The estimator asymptotically follows a normal distribution, which can be used to test hypotheses about the tail fatness of a

[8] For details on univariate extreme value theory, the reader is referred to Login (1996) and Embrechts, Kluppelberg and Mikosch (1999).

[9] For the lower tail, $\lim_{t\to\infty}\frac{F(-tx)}{F(-t)}=x^{-\alpha}$, $x>0$ and $\alpha>0$.

[10] Extreme value theory provides, under some conditions, a precise form of the asymptotic distribution of the maximum order statistic, independent of the data generating process of the variable. This is analogous to the central limit theorem. See Mood, Graybill and Boes (1974, p. 261-2) for the derivation of limiting distributions of extreme value statistics and the necessary conditions on the parent distributions.

[11] The analysis of the left tail is analogous, after premultiplying the observations by -1.

variable.[12] The Hill estimator has been shown to be asymptotically unbiased and more efficient than alternative estimators (see, e.g., Koedijk et al., 1992).

An essential step in estimating the tail index is the selection of the threshold, $X_{(n-m)}$, which determines the number of observations m in the tail area used for estimating γ. Using too few observations can enlarge the variance of the estimate, while using too many observations reduces the variance at the expense of biasedness when non-tail observations are included. Several methods have been developed in the literature to deal with this trade-off problem. In this paper we apply two methods for threshold selection: the simulation method of Jansen and de Vries (1991) and the bootstrapping technique of Danielsson, de Haan, Peng and de Vries (2001). Web Appendix C provides implementation details.

In this paper we identify a currency crisis when the exchange rate pressure measure (either *ER, EMP* or *REMP*) is above its EVT threshold $X_{(n-m)}$. The main advantage is that the non-parametric EVT technique identifies extreme observations without making any assumptions about the shape of the unknown population distribution. Pozo and Amuedo-Dorantes (2003) show that the extreme value method signals more episodes of speculative pressure and identifies actual crisis events more accurately than the conventional standard deviation approach.

Further, in this paper we also use the EVT threshold $X_{(n-m)}$ to define when a fundamental indicator takes on extreme values and issues warning signals of potential future currency crises. Our approach focuses on the tail of the economic fundamental distribution to set the thresholds, instead of potentially overfitting the data by setting the signal thresholds to maximize in-sample prediction performance as in Kaminsky et al. (1998). The overfitting problem is relevant, as most early warning systems have poor out-of-sample performance.

2.4 Asymptotic Dependence

We apply multivariate EVT to test whether currency crises and lagged economic variables are truly linked in the tail area of the distribution.[13] We consider a pair of random variables X and Y: Y is a currency crisis measure and X is a lagged economic fundamental. Bivariate extremes occur when $X > \theta_x$ and $Y > \theta_y$, where θ_x and θ_y are the EVT thresholds in the tails of the respective univariate distributions. The conditional probability $P\{Y > \theta_y | X > \theta_x\}$ then measures the probability of a currency crisis conditional on observing a warning signal isssued by the lagged economic variable.

The bivariate distribution function $P\{Y > \theta_y, X > \theta_x\}$ consists of two parts, namely the marginal distributions and the dependence structure between the two variables. To focus solely on the dependence structure of X and Y, the influence of the marginal

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[12] $(\hat{\gamma} - \gamma)m^{1/2}$ is asymptotically normal with mean zero and variance γ^2, see Jansen and de Vries (1991).

[13] For details on multivariate extreme value theory, the reader is referred to Peng (1999), Kotz and Nadarajah (2000), Longin and Solnik (2001), Hartmann, Straetmans and de Vries (2004), Poon, Rockinger and Tawn (2004), Beirlant, Goegebeur, Segers and Teugels (2004), and de Vries (2005).

distributions of X and Y, i.e. F_X and F_Y, can be eliminated by transforming the data. Following Poon et al. (2004), we apply the unit Frechet marginal distribution:

$$S = -1/\log F_X(X) \text{ and } T = -1/\log F_Y(Y).$$

After the data transformation S and T both follow the same marginal distribution function, namely $F(z) = \exp(-1/z)$, while still having the same dependence structure as the original variables X and Y.[14]

Let $P(q)$ denote the conditional probability of $T > F^{-1}(q)$, given that $S > F^{-1}(q)$, where q is a percentile of the distribution:

$$P(q) = P\left[T > F^{-1}(q) \middle| S > F^{-1}(q)\right], \qquad \text{for } 0 < q < 1.$$

Clearly, if the two events are independent, $P(q) = P\left[T > F^{-1}(q)\right] = 1 - q$. If two events are positively dependent, $P(q) > 1 - q$, while $P(q) < 1 - q$ for negative dependence. Given s with $F^{-1}(q) = s$, we can also write $P(q)$ as follows: $P(q) = P\left[T > s \middle| S > s\right]$.

As we are interested in extreme values, we study the dependence function as both variables approach their upper limits, that is, when $q \to 1$. The variables S and T are said to be *asymptotically independent* if $P(q)$ has a limit equal to zero as $q \to 1$. The variables are *asymptotically dependent* if the limit of $P(q)$ is nonzero. Poon et al. (2004) define a pair of measures (χ, $\bar{\chi}$) that fully describe the asymptotic dependence structure of X and Y, using the transformed variables S and T. The first measure of asymptotic dependence defined in Poon et al. (2004) is χ:

$$\chi = \lim_{q \to 1} P(q) = \lim_{q \to 1} P\left[T > F^{-1}(q) \middle| S > F^{-1}(q)\right] = \lim_{s \to +\infty} P\left[T > s \middle| S > s\right] \quad .$$

If $\chi > 0$, S and T are asymptotically dependent. If $\chi = 0$, S and T are asymptotically independent. When a currency crisis measure and an economic fundamental are asymptotically independent, the conditional crisis probability approaches zero in the limit as we move deeper into the tail area and events become more extreme. Asymptotic dependence in the tail can be completely different from regular dependence over the entire domain of the variables. For example, Sibuya (1960) shows that any pair of variables following a bivariate normal distribution with Pearson correlation coefficient $\rho < 1$ is asymptotically independent (i.e. $\chi = 0$), even though the variables are dependent in the usual sense for all $\rho \neq 0$.

For variables that are asymptotically independent ($\chi = 0$), Poon et al. (2004) introduce a second measure of extremal dependence, $\bar{\chi}$, which measures the rate at which the conditional probability $P(T > s | S > s)$ approaches 0:

[14] Beirlant et al. (2004) discuss other choices of marginal distribution transformation and also state that the precise choice of transformation is not so important.

$$\bar{\chi} = \lim_{s \to \infty} \frac{2 \log P(S > s)}{\log P(S > s, T > s)} - 1 .$$

Note that $-1 \le \bar{\chi} \le +1$. Positive and negative values of $\bar{\chi}$ correspond to positive and negative extremal association, respectively. For example, for two variables with a bivariate normal dependence structure $\bar{\chi}$ is equal to the correlation coefficient ρ.

It can be shown that $\bar{\chi}$ = 1 for all asymptotically dependent variables, while $\bar{\chi}$ < 1 for asymptotically independent variables (see Ledford and Tawn, 1996, and Coles, Heffernan and Tawn, 1999). To examine whether a currency crisis measure Y and an economic fundamental variable X are linked in the tail, we estimate $\bar{\chi}$ and test the null hypothesis $\bar{\chi}$ = 1. If we can reject $\bar{\chi} = 1$, the variables X and Y are said to be asymptotically independent with χ = 0. If we cannot reject $\bar{\chi} = 1$, then the variables are asymptotically dependent and we estimate χ: the limiting conditional probability of a currency crisis.

In sum, the dependence measures $\bar{\chi}$ and χ provide a complete description of the asymptotic (in)dependence and the degree of extremal association between the currency crisis measure Y and the lagged economic fundamental X. We refer to Poon et al. (2004) for details on the non-parametric estimation of $\bar{\chi}$ and χ, given time series of observations on X and Y, as well as the asymptotic distribution of the estimators (e.g., for testing $\bar{\chi}$ = 1). The estimation approach is also briefly summarized in Appendix A.

2.5 Empirical Distribution of Extremes

Apart from assessing asymptotic dependence, we also want to calculate the probability of a currency crisis conditional on observing a *particular value* for an economic indicator, as this information is useful for assessing the likelihood of future currency crises. To calculate these conditional crisis probabilities we calibrate a parametric model for the tail dependence structure using estimates of $\bar{\chi}$ and χ, following Poon et al. (2004). When the currency crisis measure and the economic indicator are asymptotically dependent we calibrate a logistic dependence model:[15]

$$P\{S \le s, T \le t\} = \exp\left\{ -\left(s^{-1/\tau} + t^{-1/\tau} \right)^{\tau} \right\}, \text{ with } 0 < \tau \le 1,$$

where $\tau = \log(2 - \chi) / \log 2$.

When the currency crisis measure and the fundamental are asymptotically independent, we model the dependence structure with the Gaussian model:

$$P\{S \le s, T \le t\} = \Phi_2\left(\Phi^{-1}\{\exp(-1/s)\}, \Phi^{-1}\{\exp(-1/t)\}; \rho\right),$$

[15] See Longin and Solnik (2001) and Poon et al. (2004) for applications of this dependence model for financial risk management.

where Φ_2 denotes the bivariate normal distribution with mean vector (0,0) and a variance-covariance matrix with the diagonal elements equal to 1. The covariance parameter ρ is set equal to extremal dependence measure $\bar{\chi}$ ($\rho = \bar{\chi}$).

Hence, we can use estimates of χ and $\bar{\chi}$ to fully calibrate the dependence structure. Studies by Ledford and Tawn (1996) and Dupuis and Tawn (2001) have shown that the precise form of the dependence model is relatively unimportant given proper estimates of $\bar{\chi}$ and χ. More details about model calibration, including estimation of the marginal distribution functions for the Frechet transformations, are in Appendix A.

3. Empirical Results

3.1 Descriptive Statistics

Tail dependence tests require a large number of observations, as they are based on asymptotic theoretical results and extreme events are rare by definition. For this purpose we pool the data across countries. Pooling the data also has a good economic motivation, as the literature on early warning systems for currency crises tries to identify *common* factors underlying exchange rate instability that apply equally across countries.

Table 1 shows descriptive statistics of the pooled data for the three currency crises measures and the 17 fundamental variables. The last column of Table 1 shows the panel unit root test statistic of Breitung (2000). The null hypothesis of a unit root can be rejected for all pooled series.[16] The pooled series have heavy tails, judged by the large excess kurtosis values. The Jarque-Bera test rejects a normal distribution for all series in Table 1 (results not reported to save space).[17]

3.2 Tail Index Estimates

Table 2 shows the tail index estimates for the pooled series, both for the currency crisis measures and the economic signal variables.[18] The left part of the table displays estimates for the depreciation side of the currency crisis measures, while for each fundamental variable the tail expected to give a depreciation signal is shown. The right part of the table contains similar information for the currency appreciation side.

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[16] The null hypothesis of the Breitung (2000) test is that the data generating processes for all countries in the cross-section has a unit root, while controlling for cross-section specific intercepts, trends and autocorrelation. The alternative is that series do not have a common unit root.

[17] Some very large outliers occur in the two real interest rate series, caused by exceptionally high interest rates in Argentina during the country's hyperinflation episode in 1989. Very extreme positive outliers also occur in the lending-to-deposit rate ratio series, as in some cases the deposit rate in the numerator approaches zero. To avoid unboundedness, we cap the ratio of lending-to-deposit rates at the large value of 500 and code all values above 500 as missing. We drop cases with zero deposit rates as well.

[18] In the following sections we report tail index estimates based on Jansen and de Vries (1991) threshold selection method. The estimates do not change materially when applying the Danielsson et al. (2001) bootstrapping algorithm. However, in some cases the bootstrapping technique does not converge to a reasonable threshold value. See Web Appendix C for details.

The exchange rate measures all have heavy tails, much fatter than a normal distribution. The tail index estimates for the two exchange rate pressure indices EMP_t and $REMP_t$ are close to 3, implying that only the first two moments of the distribution are bounded, while the existence of the third moment (skewness) is debatable. The nominal EMP_t index has slightly heavier tails than the real $REMP_t$ index, perhaps because deflating the exchange rate pressure index with the CPI reduces the occurrence of extreme values. The distribution of the monthly exchange rate returns, ER_t, is very heavy tailed: $\hat{\alpha}$=1.3 on the depreciation side and $\hat{\alpha}$=2.5 on the appreciation side, implying that only the first moment is bounded. More extremes occur on the depreciation side than on the appreciation side.

Among the economic signal variables, the right tail of the two real interest rate variables have the lowest tail estimates, $\hat{\alpha}$=1.0 and $\hat{\alpha}$=0.9, respectively, followed by the right tail of the lending-to-deposit rate ratio ($\hat{\alpha}$=1.2). For the two real interest rate series even the existence of the first moment, the mean, is in doubt. Other signal variables with very heavy tails are the excess real money balance (right tail, $\hat{\alpha}$=1.6) and the terms of trade (right tail, $\hat{\alpha}$=1.5). Economic signal variables with relatively thin tails are the short-term debt ratio (right tail, $\hat{\alpha}$=12.2), the ratio of M2 to reserves (right $\hat{\alpha}$=8.8, left $\hat{\alpha}$=8.0) and international reserves (right $\hat{\alpha}$=6.9, left $\hat{\alpha}$=7.0).

Overall, we conclude that the currency crisis measures and most economic signal variables follow heavy-tailed distributions. This reinforces our doubts about the common approach that uses 2 or 3 times the standard deviation to identify currency crises. The extremes for the currency pressure measures that the EVT method identifies include all well-known historical crisis events: the EMS crisis in 1992, Mexico 1994, the Asian crisis of 1997-1998 and the Russian crisis of 1998. To make the crisis identification exercise more stringent, in the Section 4.1 we assess the *out of sample* identification of currency crises by the EVT method, instead of in sample.

3.3 Asymptotic Dependence of Currency Crises and Lagged Fundamentals

Are currency crisis measures and lagged economic fundamentals asymptotically dependent? To answer this question we estimate $\bar{\chi}$ for all pairs of currency crisis measures and 17 economic variables, and we then test the hypothesis $\bar{\chi}$=1. As in practice most economic data is published with delay and warning signals issued well in advance of a crisis are more useful, we lag the economic variables from 4 up to 24 months. We consider only the depreciation/devaluation tail of the exchange rate, as depreciation events are usually much more damaging and disruptive for the real economy than large appreciations. Table 3 shows the largest estimate of $\bar{\chi}$ among all lags from 4 through 24 months for each economic fundamental, and the lag value that maximizes $\bar{\chi}$. For comparison sake, the simple Pearson correlation using all observations (not just the tail) is displayed as well, with the time lag for the fundamental variable chosen from 4 through 24 months to maximize the correlation estimate.

Inspecting the estimation results in Table 3, the most striking conclusion is that nearly all pairs of lagged economic fundamentals and currency crisis measures are asymptotically independent. There are only two exceptions: for the exchange rate return (ER_t) and the

lagged real interest rate we cannot reject asymptotic dependence ($\bar{\chi} = 1$), and the same result also holds for ER_t and the real interest rate differential. The estimates are $\hat{\bar{\chi}} = 1.000$ for the real interest rate (at lag 8 months, p-value=0.497) and $\hat{\bar{\chi}} = 1.019$ for the real interest rate differential (at lag 4 months, p-value = 0.624). The estimates of the limiting conditional crisis probability are $\hat{\chi} = 0.309$ and $\hat{\chi} = 0.305$, respectively. Hence, the probability of a currency crisis after the lagged real interest rate takes on an extreme positive value is about 30%.

Further investigation reveals that the exchange rate return and the real interest rate are also asymptotically dependent at all lags from 1 through 13 months, as well as at lags 16 and 19 months. ER_t and the real interest rate differential are asymptotically dependent at all lags from 1 through 11, and at 13 and 15 months. Hence, the asymptotic dependence is not limited to one particular lag and extends to periods of more than one year before the currency crisis events take place. The estimated limiting conditional probability $\hat{\chi}$ is also always close to 30%, and not sensitive to the time lag.

As a graphic illustration of the tail dependence results, Figure 2 shows the conditional probability $P(q) = P(\ Y > F_Y^{-1}(q) \mid X > F_X^{-1}(q)\ )$, as a function of the percentile q, ranging from 0 to 1.[19] In Panel A the variable Y is the exchange rate return (ER_t) and X is the increase in imports lagged 23 months. Panel A shows that the conditional crisis probability goes to zero as $q \rightarrow 1$: this illustrates the tail independence of ER_t and imports. In Panel B the variable Y is ER_t and X is the real interest rate differential lagged 4 months: in this case the conditional probability approaches 0.30 – 0.40 in the limit, illustrating the asymptotic dependence of these two variables.[20] Finally, Panel C shows the same plot for the lagged decrease in real commercial bank deposits. This is an example of tail independence, but with relatively high extremal dependence ($\hat{\bar{\chi}} = 0.669$).

Although we reject $\bar{\chi} = 1$ for nearly all series, the tail dependence measures for the asymptotically independent pairs of variables are all considerably larger than the Pearson correlation estimates based on the full sample of observations. Thus, large values do occur jointly more often than suggested by the simple correlation measure ρ, but the relation disappears in the limit as we move deeper into the tail area.

3.4 In-Sample Crisis Prediction Performance

We now assess the in-sample crisis prediction performance of the economic variables with two statistics often used in the literature on early warning systems (see Kaminsky et al., 1998). Table 4 shows the 'percentage of currency crises correctly called', which is the percentage of currency crises preceded by at least one fundamental signal during the previous 24 months. Further, Table 4 displays the 'percentage of false alarms', which is the percentage of fundamental signals not subsequently followed by a currency crisis

[19] The discontinuity in the middle of the plots represents a large number of months with no change in the exchange rate, irrelevant for our tail analysis.

[20] The last two dots in the plot do seem to approach zero, but these conditional probabilities are estimated with such a small fraction of the observations (0.1% and 0.2%, respectively) that the estimation error is very large. Therefore, no reliable conclusions can be based on these two point estimates in isolation.

during the next 24 months.[21] In this paper the signaling threshold for each fundamental is equal to the EVT threshold $X_{(n-m)}$, with the number of extremes m determined with the method of Jansen and de Vries (1991).

The in-sample crisis prediction results in Table 4 are poor overall. For crises identified with the nominal and real exchange rate pressure indices, EMP_t and $REMP_t$, the false alarm rate of all indicators is higher than 50%, while the percentage of crises called is less than 42.5%. These results are not surprising, given that all lagged economic indicators are asymptotically independent with EMP_t and $REMP_t$ ($\chi = 0$), and the estimated extremal dependence measures $\bar{\chi}$ are also relatively low ($\bar{\chi} < 0.40$).

The results for the exchange rate return (ER_t) measure are better. The indicators international reserves and real commercial bank deposits have low false alarm rates, 12.5% and 8.1% respectively. However, these two fundamentals call less than 13% of all currency crises, as the number of signals issued is rather low. The indicators real interest rate, real interest differential and terms of trade call more than 70% of the crises defined with ER_t, while having false alarm rates below 50%. Interestingly, these five successful indicators all have relatively high extremal dependence estimates ($\bar{\chi} > 0.40$).

Figure 1 depicts the relation between the tail dependence estimates ($\hat{\bar{\chi}}$) in Table 3 and the in-sample crisis prediction results in Table 4. Figure 1 is a scatter plot, with $\hat{\bar{\chi}}$ on the x-axis and the percentage of crises predicted correctly minus the percentage of false alarms on the y-axis (for each fundamental, with ER_t as the currency crisis measure). The figure shows a strong positive linear relation between extremal dependence estimates and in-sample prediction performance of economic indicators ($r^2 = 0.86$).[22]

Hence, we find evidence that a significant positive relation exists between estimates of the bivariate tail dependency measure $\bar{\chi}$ and the in-sample success of an economic indicator in predicting currency crises without too many false alarms. In the following section we assess out-of-sample prediction results.

4. Prediction of Currency Crises

For the out-of-sample identification and prediction of currency crises we use emerging markets only, to create distinction with the full-sample results in the previous section and because many major currency crises occurred in emerging markets. Further, if crises in emerging and developed markets do not have common antecedents, then separating the two groups can improve prediction accuracy. We set the in-sample period equal to

[21] Please note that the results in Table 4 are not directly comparable, nor competing, with similar figures reported by Kaminsky et al. (1998) and others, as we use signalling thresholds for economic fundamentals that separate extreme values from regular observations, instead of threshold values that are selected to optimize the in-sample prediction performance as in Kaminsky et al. (1998).

[22] We find a similar positive linear association between the 'percentage of crises predicted correctly minus false alarms' and $\hat{\bar{\chi}}$ for the measures EMP_t and $REMP_t$, with correlation estimates r = 0.79 and r = 0.39, respectively. For $REMP_t$ the relation is weaker, but this is likely the result of the lack of variation in $\hat{\bar{\chi}}$, as all extremal dependence estimates are rather low for $REMP_t$.

February 1974 through June 1995, leaving July 1995 through February 2008 as the out-of-sample period. This gives the various models a time-window of 24 months to predict the beginning of the Asian crisis in July 1997. We only evaluate the predictability of currency crises identified with the exchange rate return ER_t, ignoring the two exchange rate pressure measures EMP_t and $REMP_t$, as we expect that risk managers in practice are more concerned about actual currency crashes than unsuccessful speculative attacks.[23]

4.1 Out-of-Sample Identification of Currency Crises

Before we assess the out-of-sample predictability of currency crises, another important issue is whether our extreme value methodology is able to *identify* well-known currency crises in the out-of-sample period, like the Asian crisis in 1997, Russia 1998, Brazil 1999, and Argentina 2002, amongst others. Apart from identifying these major crisis events, our methodology preferably should not flag up many months that are not generally known as major crisis episodes or currency crashes.

We begin by estimating the tail index and the extreme event threshold for the exchange return series ER_t in the in-sample period January 1974 through June 1995, pooling the data from all emerging market countries. The estimated right tail index $\hat{\alpha}$ is 1.24, similar to the full sample result in Table 2, implying that the distribution has a very heavy tail on the depreciation side. The threshold separating extreme events from regular observations, determined with the Jansen and de Vries (1991) method, is equal to 0.0959. In the out-of-sample period 87 monthly exchange rate returns are over the threshold and identified as extreme events (1.75% of the 4975 out-of-sample observations). As currency crises are often characterized by multiple months of extreme exchange rate depreciation or devaluation, for ease of exposition we bundle together all extremes in one country that occur within 12 months of each other. In this way the extreme value approach identifies 37 currency crises out of sample. Table 5 lists the countries, the first and the last month of each currency crisis, and the number of extremes in each episode.

Table 5 demonstrates that the extreme value methodology successfully identifies the following well-known currency crises out of sample: the Asian crisis in 1997, Russia 1998, Brazil 1999, Ecuador 2000, Turkey 2001-2002 and Argentina 2002. Focusing on the Asian crisis, the list of crisis episodes includes Thailand, Indonesia and South Korea, the three countries that were most affected, and Malaysia and Philippines, two countries also experiencing severe disruptions. Less affected Asian countries such as China, India, and Hong Kong are absent in Table 5, and rightly so in our opinion.

Appendix B provides a complete description of all known currency crises in Table 5, as well as a list of extreme events identified in Table 5 that are not associated with a well documented crisis episode. In Appendix B we also compare our out-of-sample identification of currency crises with the method of Kaminsky et al. (1998), implemented for an extended sample by Beckmann, Menkhoff and Sawischlewski (2006). Kaminsky et al. (1998) identify a crisis when the exchange rate market pressure index, EMP_t, is more

[23] Our results in Section 3 also show that the additional information incorporated in the currency pressure indices to identify unsuccessful speculative attacks, namely changes in international reserves and interest rates, might actually reduce the predictability of extreme currency events, given the relatively low tail dependence measures found for EMP_t and $REMP_t$, compared to ER_t.

than three standard deviations above the average. Remarkably, the methodology of Kaminsky et al. (1998) does not identify a currency crisis in Argentina in 2002, and neither in Brazil in 2002.

4.2 Selecting Currency Crisis Signals and Models In-Sample

Before assessing the out-of-sample predictability of currency crises, we first select a number of promising signals and models based on in-sample performance during the period Jan-1974/June-1995.[24] As we expect that tail dependence provides useful information for selecting successful indicators, we estimate the extremal dependence measure $\bar{\chi}$ with ER_t for each fundamental variable in the in-sample period, using all emerging markets data (pooled). Table 6 shows the fundamental variables sorted in descending order based on the in-sample estimate $\hat{\bar{\chi}}$.[25] Asymptotic dependence can be rejected for all fundamentals, except for the two real interest rate variables, as we found before. The estimated extremal dependence for the excess real M1 balances is relatively high at 0.731, but significantly below one.

Table 6 also displays the in-sample performance of the indicators in columns 5-10. Following our extreme value approach, an indicator issues a signal when it is exceeds its extreme value threshold. The two real interest rate indicators perform well: they call more than 80% of the crises correctly by issuing at least one signal in the time window 24 months before the crisis, while in 44% of the cases the signal issued is false (not followed by a crisis within 24 months). Apart from the excess real M1 balance, the other indicators do not perform well: either the fraction of crises called is low and/or the number of false alarms is high.

We follow two approaches to reduce the relatively high false alarm rate of the real interest rate indicators (about 44%). First, we create a combined indicator that only issues a signal when the real interest rate is above its threshold *and* one of the following three variables issues a signal as well: excess real M1 balances, real deposits or the real exchange rate. We choose these three variables based on their relatively low false alarm rate. Inspecting the in-sample performance of the combined indicator, we see that it achieves its goal: the false alarm rate is only 8%, while 2 out of 3 crises are called correctly (66%).

As a second approach for reducing false alarms, we calibrate a logistic dependence structure for the real interest rate and the exchange rate return.[26] We then use the calibrated model to predict the conditional probability of a currency crisis given that the real interest rate has crossed its threshold and has value x.[27] For the 865 extremes of the

[24] If we would simply assess all possible signals and models out of sample, this would undermine the usefulness of the out-of-sample procedure.

[25] The estimation results for the fundamentals terms of trade, the real effective exchange rate and real output growth are not shown, as the number of countries with data available for these variables out of sample is relatively small (7, 15 and 26 out of 31 countries, respectively), making comparisons difficult. Total foreign debt and the short term foreign debt ratio are excluded due to the small number of in-sample observations (775 months for assessing in-sample crisis prediction), making the in-sample performance assessment less useful as the number of signals issued is rather low.

[26] The extremal dependence estimates used to calibrate the logistic dependence function are chosen at lag 7 (months) for the real interest rate, as in Table 6.

[27] We do not use the tail dependence model when the real interest rate is below its extreme value threshold, as the dependence structure of the two variables outside of the extreme value domain might be different.

real interest rate in the in-sample period, the predicted probability of a currency crisis ranges from 19.7% to 92.0%, with an average of 35.9%. To reduce the number of false alarms, we set a minimum threshold for this predicted crisis probability. We chose two different thresholds: 25% and 35%, reducing the number of signals by roughly 1/3 and 2/3, respectively. Table 6 shows the in-sample crisis prediction performance with these two thresholds: the false alarm rate indeed decreases, to 34.2% and 18.9%, respectively, while the number of crises called is 79% and 74%.

Finally, for comparison sake, we adopt a standard approach from the literature and estimate a probit model for crisis prediction. We create a dummy variable by coding all months that are followed within 24 months by at least one currency crisis by 1, and all other months by 0. We then estimate a probit model for this crisis dummy, including as explanatory variables all fundamentals with at least 5,000 pooled observations. Insignificant explanatory variables are removed stepwise with a significance level of 5%. We remove any explanatory variables with estimated coefficients that do not have the sign expected based on theory. We end up with an estimated probit model that includes the following variables: the real interest rate, excess M1 balances, the M2 multiplier, bank deposits, international reserves and exports (McFadden $R^2 = 0.11$).

We use the probit model to generate fitted crisis probabilities, conditional on the current values of the fundamentals, and arbitrarily set the threshold for issuing a crisis signal at a probability level of 50%.[28] Table 6 shows that with this threshold the probit model calls 91% of the crises correctly, while issuing false alarms at a rate of only 30%. As a second alternative, we set the probability threshold at 75%: this further reduces the false alarm rate to only 9%, while the model still calls more than 66% of the crises correctly.

4.3 Out-of-Sample Crisis Prediction Performance

Table 7 shows the prediction performance of selected indicators, the combination signal and the probit models in the out-of-sample period from July 1995 through February 2008. We assess the predictions with an adjusted evaluation window ranging from 4 months until 24 months after the signal, to take into account that most macroeconomic data is published with a considerable time lag. Overall, the results show that prediction performance deteriorates tremendously out of sample.

The probit model with a probability threshold of 50% has a false alarm rate of 72% out of sample, while calling only 30% of the crises correctly. The second probit model (with 75% threshold) fares equally poor, with a false alarm rate of 53% and only 8% of crises correctly called. The combination signal also disappoints strongly, with 73% of the signals false and merely 20% of the crises called. In comparison, the real interest rate differential indicator performs relatively well: 63% of the crises are called correctly, with a false alarm rate of 68%. The empirical efficient frontier consists of the real interest rate differential signal and the tail dependence model for the real interest rate with threshold probability of 35%.

The tail dependence structure is calibrated using the estimated extremal dependence measures $\overline{\chi}$ and χ , and in our opinion it is not correct to apply this function to non-extreme observations without further validation.

[28] We also tried a 25% threshold, but this resulted in a rather large number of signals, and hence also a relatively high frequency of false alarms. Results not reported to save space.

It is remarkable that the simple real interest rate signals selected by our EVT approach perform better out of sample than a multivariate probit model constructed from all possible indicators. The probit model probably fits the in-sample data too closely, reducing its robustness. Although the real interest rate signals perform well compared to other models, the false alarm rate is rather high for risk management purposes.[29] Importantly, though, this information was already available among the in-sample EVT estimation results: the limiting probability of a crisis occurring after a real interest rate signal is 30% (about 70% false alarms predicted). The information conveyed by the non-parametric EVT tail dependence measures seems robust, while the traditional approaches show a large discrepancy between in-sample and out-of-sample results. Further, the false alarm rate of the real interest rate signal can be reduced by using the calibrated logistic dependence model with a higher threshold for issuing signals (e.g., 35%, see Table 7).

5. Conclusions

In this paper we apply extreme value theory to test whether currency crises are associated with extremes in lagged economic and financial variables. Using monthly data for a cross-section of 46 countries during the period 1974–2008, we find that nearly all economic fundamentals are asymptotically independent with currency crisis measures. Asymptotic independence means that the conditional crisis probability approaches zero in the limit as events become more extreme, implying that the relation between the currency crisis measure and the lagged fundamental vanishes in the tail. There are only two economic variables in our dataset for which we cannot reject tail dependence with the exchange rate return: the domestic real interest rate, and the real interest rate differential (measured relative to a reference country).

We evaluate various economic indicators and competing crisis prediction models during an out-of-sample assessment period from July 1995 through February 2008, using a sample of 33 emerging markets. The out-of-sample crisis prediction results are poor for all indicators and probability models. This especially holds true for models and approaches that rely on in-sample optimization of model fit, like a standard probit model. The non-parametric extreme value approach developed in this paper on the other clearly indicates that currency crises and most economic fundamentals are not linked in the tail in the in-sample period, in line with the poor out-of-sample prediction results. Further, the two real interest rate indicators identified by the extreme value approach perform better out of sample than alternative models.

Our results show that positive extremes of the two real interest rate variables are common currency crisis indicators, potentially useful as warning signals for authorities and risk managers. In the economic literature, the two real interest rate indicators are considered as crisis symptoms that reflect various types of weak economic and financial conditions

[29] Simulation results show that if we draw 1,000 random variables that issue the same number of signals as the real interest rate differential in the out-of-sample period, but completely random, the real interest rate indicator does have a significantly lower false alarm rate (95% confidence interval: {76%, 84%}). The percentage of crises called is not significantly different.

preceding currency turmoil.[30] The real interest rate on deposits is an indicator associated with issues such as overlending cycles, possible financial sector problems, a potential cause of future economic recession and a sign of a liquidity crunch. The domestic-foreign real interest rate differential is an indicator that captures a heightened risk premium for holding domestic currency assets and a potential cause of economic slowdown, bank fragility and the burst of asset price bubbles.

References

Beckmann, D., Menkhoff, L., and K. Sawischlewski, 2006, Robust Lessons about Practical Early Warning Systems, *Journal of Policy Modeling* 28, 163-193.

Beirlant, J., Y. Goegebeur, J. Segers, and J. Teugels, 2004, *Statistics of Extremes: Theory and Application*, Chichester: Wiley.

Berg, A., Borensztein, E., and C. Pattillo, 2005, Assessing Early Warning Systems: How Have They Worked in Practice?, *IMF Staff Papers* 52, 462-502.

Berg, A., and C. Pattillo, 1999a, Predicting Currency Crises: The Indicators Approach and an Alternative, *Journal of International Money and Finance* 18, 561–586.

Berg, A., and C. Pattillo, 1999b, Are Currency Crises Predictable? A Test. *IMF Staff Papers* 46, 107–138.

Bradley, B., and M. Taqqu, 2003, Financial Risk and Heavy Tails, in S.T. Rachev (ed.), *Handbook of Heavy-Tailed Distributions in Finance*, Amsterdam: Elsevier.

Breitung, J., 2000, The Local Power of Some Unit Root Tests for Panel Data, in B. Baltagi (ed.), *Advances in Econometrics*, *Vol. 15: Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, Amsterdam: JAI Press, 161-178.

Bussiere, M., and M. Fratzscher, 2006, Towards a New Early Warning System of Financial Crises, *Journal of International Money and Finance* 25, 953-973.

Coles, S.G., J. Heffernan, and J.A. Tawn, 1999, Dependence Measures for Extreme Value Analyses, *Extremes* 3, 5-38.

Danielsson, J., L. de Haan, L. Peng, and C.G. de Vries, 2001, Using a Bootstrap Method to Choose the Sample Fraction in Tail Index Estimation, *Journal of Multivariate Analysis* 76, 226-248.

Dupuis, D.J., and J.A. Tawn, 2001, Effects of Misspecification in Bivariate Extreme Value Problems, *Extremes* 4, 315-330.

Eichengreen, B., A.K. Rose, and C. Wyplosz, 1995, Exchange Market Mayhem: The Antecedents and Aftermath of Speculative Attacks, *Economic Policy* 21, 249-312.

Eichengreen, B., A. Rose, and C. Wyplosz, 1996, Contagious Currency Crises: First Tests, *Scandinavian Journal of Economics* 98, 463-484.

Embrechts, P., C. Kluppelberg, and T. Mikosch, 1999, *Modelling Extremal Events for Insurance and Finance*, Berlin: Springer-Verlag.

Embrechts, P., A. McNeill, and D. Straumann, 2002, Correlation and Dependence Properties in Risk Management: Properties and Pitfalls, in M. Dempster (ed.), *Risk Management: Value at Risk and Beyond*, Cambridge: Cambridge University Press, 176–223.

Flood, R.P., and N.P. Marion, 1999, Perspectives on the Recent Currency Crisis Literature, *International Journal of Finance and Economics* 50, 245-268.

[30] See the discussion about the roles of the real interest rate and the real interest rate differential as crisis indicators in Kaminsky et al. (1998), Kaminsky and Reinhart (1998, 1999), and Kaminsky (1999, 2006), amongst others.

Frankel, J.A., and A.K. Rose, 1996, Currency Crashes in Emerging Markets: An Empirical Treatment, *Journal of International Economics* 41, 351-366.

Furman, J., and J.E. Stiglitz, 1998, Economic Crises: Evidence and Insights from East Asian, World Bank (unpublished).

Girton, L., and D. Roper, 1977, A Monetary Model of Exchange Market Pressure Applied to the Postwar Canadian Experience, *American Economic Review* 67, 537-548.

Goldfajn, I., and R.O. Valdés, 1998, Are Currency Crises Predictable?, *European Economic. Review* 42, 873-885.

Goldstein, M., 1998, Early Warning Indicators and the Asian Financial Crisis, Institute for International Economics, unpublished.

Goldstein, M., G.L. Kaminsky, and C.M. Reinhart, 2000, *Assessing Financial Vulnerability: An Early Warning System for Emerging Markets*, Institute for International Economics, Washington, DC.

Hartmann, P., S. Straetmans, and C.G. de Vries, 2004, Asset Market Linkages in Crisis Periods, *Review of Economics and Statistics* 86, 313-326.

Hill, B., 1975, A Simple General Approach to Inference about the Tail of a Distribution, *Annals of Mathematical Statistics 3*, 1163-1174.

Jansen, D.W., and C.G. de Vries, 1991, On the Frequency of Large Stock Returns, Putting Boom and Busts into Perspective, *Review of Economics and Statistics* 73, 18-24.

Kaminsky, G.L., 1998, Currency and Banking Crisis: A Composite Leading Indicator, Mimeo, Board of Governors of the Federal Reserve System.

Kaminsky, G.L., 1999, Currency and Banking Crises: The Early Warning of Distress, Working Paper WP/99/178, International Monetary Fund.

Kaminsky, G.L., 2006, Currency Crises: Are They All the Same?, *Journal of International Money and Finance* 25, 503-527.

Kaminsky, G.L., S. Lizondo, and C.M. Reinhart, 1998, Leading Indicators of Currency Crises, *International Monetary Fund Staff Paper* 45, March.

Kaminsky, G.L., and C.M. Reinhart, 1998, Financial Crises in Asia and Latin America: Then and Now, *American Economic Review* 88, 444-448.

Kaminsky, G.L., and C.M. Reinhart, 1999, The Twin Crises: The Causes of Banking and Balance-of-Payments Problems, *American Economic Review* 89, 473-500.

Koedijk, K.G., P.A. Stork, and C.G. de Vries, 1992, Differences between Foreign Exchange Rate Regimes: the View from the Tails, *Journal of International Money and Finance* 11, 462-473.

Kotz, S., and S. Nadarajah, 2000, *Extreme Value Distributions: Theory and Applications*, London: Imperial College Press.

Krugman, P., 2003, Crises: The Next Generation?, in E. Helpman and E. Sadka (eds.), *Economic Policy in the International Economy: Essays in Honor of Assaf Razin*, Cambridge: Cambridge University Press, 15-33.

Kumar, M., U. Moorthy, W. Perraudin, 2003, Predicting Emerging Market Currency Crashes, *Journal of Empirical Finance* 10, 427-454.

Ledford, A., and J.A. Tawn, 1996, Statistics for Near Independence in Multivariate Extreme Values, *Biometrika* 83, 169-187.

Ledford, A., and J.A. Tawn, 1998, Concomitant Tail Behaviour for Extremes, *Advances in Applied Probability* 30, 197-215.

Longin, F.M., 1996, The Asymptotic Distribution of Extreme Stock Market Returns, *Journal of Business* 69, 383-408.

Longin, F.M., and B. Solnik, 2001, Extreme Correlation of International Equity Markets, *Journal of Finance* 56, 649-676.

Mood, A.M., T.A. Graybill, and D.C. Boes, 1974, *Introduction to the Theory of Statistics*, New York: McGraw-Hill.

Peng, L., 1999, Estimation of the Coefficient of Tail Dependence in Bivariate Extremes, *Statistics & Probability Letters* 43, 399-409.

Poon, S., M. Rockinger, and J. Tawn, 2004, Extreme-Value Dependence in Financial Markets: Diagnostics, Models and Financial Implications *Review of Financial Studies* 17, 581-610.

Pozo, S., and C. Amuedo-Dorantes, 2003, Statistical Distributions and the Identification of Currency Crises, *Journal of International Money and Finance* 22, 591-609.

Rana, P.B., 1984, Fixed Versus Flexible Exchange Rates and Measurement of Exchange Rate Instability: Comment, *Journal of International Economics* 20, 307-310.

Sarno, L., and M.P. Taylor, 2002, *The Economics of Exchange Rates*, Cambridge: Cambridge Press.

Sibuya, M., 1960, Bivariate Extreme Statistics I, *Annals of the Institute of Statistical Mathematics* 11, 195-210.

Vries, de, C.G., 2005, The Simple Economics of Bank Fragility, *Journal of Banking and Finance* 29, 803-825.

Westerfield, J.M., 1977, An Examination of Foreign Exchange Risk under Fixed and Floating Rate Regimes, *Journal of International Economics* 7, 181-200.

Appendix A: Estimation of Extremal Dependence

To estimate the pair of bivariate extremal dependence measures $\bar{\chi}$ and χ, recall that after applying the unit Frechet transformation to the original pair of variables X and Y, the transformed variables S and T have the same distribution function, i.e. $F(z) = \exp(-1/z)$, and possess the same dependence structure as the original pair (X, Y).[31] Under the condition of regular variation, the joint cumulative distribution function of the Frechet transformed variables S and T can be writen as

$$P(S > s, T > s) \sim L(s)s^{-1/\xi}; s \to \infty,$$

where $\xi \in (0,1]$ and $L(s)$ is a slowly varying function.

Following from Poon et al. (2004), the parameter ξ can be estimated as a tail index of the univariate variable Z, with $Z = \min(S, T)$. Mathematically,

$$\begin{aligned} P(S > z, T > z) &= P\{\min(S,T) > z\} \\ &= P(Z > z) \\ &= L(z)z^{-1/\xi} \quad \text{for } z > u, \end{aligned}$$

where u is a sufficiently high threshold, such that the limit result for the joint probability $P(S > s, T > s)$ approximately holds with equality. The Hill (1975) estimator, described earlier, can be used to estimate the tail index ξ of Z.

Given the estimate $\hat{\xi}$ and the tail threshold $u = Z_{(n-m)}$, with $Z_{(n-m)}$ the m-th largest observation from a sample of size n, the estimator for $\bar{\chi}$ is

$$\hat{\bar{\chi}} = 2\hat{\xi} - 1,$$

$$\text{with } Var(\hat{\bar{\chi}}) = (\hat{\bar{\chi}} + 1)^2 / m.$$

Using the fact that the Hill estimator follows a normal distribution asymptotically, we then test the null hypothesis $\bar{\chi} = 1$. In case that the null hypothesis cannot be rejected, i.e. the variables are asymptotically dependent, we then proceed to estimate χ.

The maximum likelihood estimator of χ and its variance are (Poon et al., 2004):

$$\hat{\chi} = \frac{m}{n} Z_{(n-m)}$$

[31] For full details, we refer to Ledford and Tawn (1996, 1998) and Poon et al. (2004).

$$Var(\hat{\chi}) = \frac{\left[Z_{(n-m)}\right]^2 m(n-m)}{n^3}.$$

The non-parametric estimates $\hat{\bar{\chi}}$ and $\hat{\chi}$ together provide all necessary information regarding the extremal dependence of the pair of variables X and Y. For asymptotically independent variables (for which we can reject $\bar{\chi} = 1$, and hence $\chi = 0$) the estimate $\hat{\bar{\chi}}$ captures the degree of extremal dependence, which is inversely related to the speed at which the limit probability χ approaches 0. For asymptotically dependent variables (for which we cannot reject $\bar{\chi} = 1$), the estimate $\hat{\chi}$ gives the limiting conditional probability of an extreme value in Y, given an extreme value in X.

In estimation practice, as a first step we require a functional form for the univariate distribution functions $F_X(X)$ and $F_Y(Y)$, so we can transform the marginal distributions to unit Frechet marginals via $S = -1/\log F_X(X)$ and $T = -1/\log F_Y(Y)$. Following Poon et al. (2004), we use the empirical distribution, denoted by $\tilde{F}_X(X)$, for non-extreme observations below the threshold θ_x, as we have more observations for this part of the distribution. Above extreme value threshold θ_x data is scarcer and a generalized Pareto distribution is estimated to model the tail area. The univariate distribution function of X is, therefore,

$$F_X(x) = \begin{cases} \tilde{F}_X(x) & if \quad x < \theta_x \\ 1 - \left\{1 - \tilde{F}_X(\theta_x)\right\}\left(1 + \gamma_x \dfrac{(x - \theta_x)}{\sigma_x}\right)^{-1/\gamma_x} & if \quad x \geq \theta_x \end{cases}.$$

where θ_x is a given high threshold, and γ_x and σ_x are the shape and scale parameters of the generalized Pareto distribution, respectively.

If we would like to calculate the probability of a currency crisis conditional on a given value of the economic signal (not a limiting value), we need to calibrate a parametric tail dependence function. Following Poon et al. (2004), for asymptotically dependent variables we calibrate the logistic tail dependence structure with the estimate of χ, i.e. $P\{S \leq s; T \leq t\} = \exp\left\{-\left(s^{-1/\hat{\tau}} + t^{-1/\hat{\tau}}\right)^{\hat{\tau}}\right\}$, with $\hat{\tau} = \log(2 - \hat{\chi}) / \log 2$. For asymptotically independent variables we fit the Gaussian dependence structure using the estimate of $\bar{\chi}$, i.e. $P\{S \leq s; T \leq t\} = \Phi_2\left(\Phi^{-1}\{\exp(-1/s)\}, \Phi^{-1}\{\exp(-1/t)\}; \hat{\rho}\right)$, with $\hat{\rho} = \hat{\bar{\chi}}$.

Appendix B: Identification of Currency Crisis Episodes

Table 5 shows that the EVT methodology identifies the following well-known currency crises out-of-sample: the Asian crisis in 1997, Russia 1998, Brazil 1999, Ecuador 2000, Turkey 2001-2002 and Argentina 2002. Other crises correctly identified in Table 5 occurred in Brazil and Uruguay in the summer of 2002, following the severe currency crisis in neighboring Argentina. The currency crisis in Ecuador identified in 2000 is widely documented, resulting in the abandonment of the national currency (dollarization). Venezuela went through a severe banking crisis in 1994, followed by a currency crisis in 1995, identified correctly. Venezuela further experienced a severe economic crisis in 2002 and 2003, accompanied by large currency devaluations. From 2003 onwards Zimbabwe went through a prolonged crisis period, a mix of political instability, hyperinflation, and other economic woes, identified by two episodes in Table 5.

Mexico experienced two extreme currency events according to Table 5, in October 1995 and August 1998. We consider the disruption in October 1995 part of the Mexican Peso crisis that started in 1994 (the year 1994 itself is not included in the out-of-sample window). We classify the extreme depreciation in Mexico in August 1998 as a spillover effect of the 1998 crisis originating in Russia. The spillover may have been triggered by increased risk aversion among investors and a simultaneous reassessment of countries with weak fundamentals. Similarly, we consider the extreme depreciation in Israel in October 1998 as spillover effect of the LTCM liquidity crisis and the Russian crisis in August 1998. The extreme events identified in South Africa in June 1998 and in Zimbabwe from November 1997 through September 1998, can similarly be classified as spillover effects of the Asian crisis and Russian crisis.

Two extreme currency events identified in Table 5 are not easily associated with known crises, but were still quite disruptive and a big concern for authorities, namely South Africa in 2001 and Hungary in 2003. South-Africa went through a period of currency turmoil and sharp depreciations in November and December 2001, being so disruptive that the government later officially investigated the causes.[32] Hungary experienced severe currency turmoil in June 2003, the result of a string of speculative attacks.[33] Other events identified in Table 5 are the result of adjustments of the official exchange rate regime or large devaluations: the floating of the Pakistani rupee in May 1999, the floating of the Egyptian currency in January 2003 (which was followed by a depreciation of more than 17%), large devaluations in Venezuela in February 2004 and April 2005, and the devaluation of the Zimbabwean dollar in August 2000.

Table 5 also contains a number of extreme depreciations of floating currencies that were large, beyond the 9.59% threshold, but rather isolated and to the best of our knowledge not part of a well documented crisis or currency crash: Brazil May 2006, Colombia August 2007, Indonesia April 2001, Pakistan September 2000, Pakistan June 2002, South Africa May 2003, South Africa May 2005 and Turkey May 2006.

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[32] See the final report of the "Commission of Inquiry into the Rapid Depreciation of the Exchange Rate of the Rand and Related Matters". http://www.polity.org.za/polity/govdocs/commissions/2002/

[33] The speculative attack is described in a report on Hungary by the European Commission's Directorate-General for Economic and Financial Affairs: ECFIN Country Focus, Volume 1, Issue 9 (Date: 12.05.2004). http://ec.europa.eu/economy_finance/publications/publication1409_en.pdf

We now compare the out-of-sample identification of currency crises using EVT with the method of Kaminsky et al. (1998), referred to as KLR, implemented for an extended sample by Beckmann, Menkhoff and Sawischlewski (2006). KLR define a crisis when the exchange rate market pressure index, EMP_t, is more than three standard deviations above the sample mean. The standard deviation and mean are calculated within each country, that is, the threshold is set relative to each country's own history. In contrast, our extreme value approach pools all data and sets an absolute threshold for the exchange rate return that applies to all countries in the sample.

Beckmann et al. (2006) implement the KLR method in the period January 1970 through December 2002 with an extended number of 21 emerging countries, which are also part of our cross-section of 33 emerging countries. We check whether the extreme events identified by our methodology for these 21 countries are also identified as 'currency crises' in Beckmann et al. (2006, see Table A.1). In Table 5 column 4 indicates whether the data for a particular crisis episode was also included in the sample of Beckmann et al. (2006), and if so, column 5 shows whether the KLR methodology identified at least one month in the episode as a currency crisis event.

Among all 37 crisis episodes identified by our methodology, 17 episodes involve countries and/or periods not included in the sample of Beckmann et al. (2006) and hence are not relevant for a comparison. Among the remaining 20 crisis episodes that can be compared, 12 are also identified as a currency crisis by the KLR methodology in Beckmann et al. (2006), while 8 are not. The 8 crisis episodes *not* identified by the KLR methodology are: Argentina Jan-02/May-02, Brazil Jun-02/Sept-02, Indonesia April-02, Mexico Oct-95, Mexico Aug-98, Pakistan May-99, Pakistan Sept-00 and Philippines Oct-02. Remarkably, the KLR methodology does not identify a currency crisis in Argentina in 2002, and neither in Brazil in 2002.

The KLR methodology also identifies a number of currency crises that our EVT approach does not detect: Colombia Sept-98/Aug-99, Colombia Jul-02, Singapore Dec-97/May-98, Sri Lanka Jul-98 and South Africa April-96. Colombia Sept-1998 can be tracked back to a banking crisis (see Reinhart and Rogoff, 2009) and Singapore was affected by the Asian crisis in 1997-98, so these two episodes are potentially currency crises not identified correctly by the EVT method. We cannot find any information in the literature and other sources about the remaining three crises called by the KLR methodology, so we are not convinced about their relevancy.

Table 1 Descriptive Statistics, Pooled Data: Currency Crisis Measures and Economic Indicators

Variable	Mean	Median	Std.dev.	Skew	Kurt.	Max	Min	Obs.	Panel unit root test
Exchange rate pressure index	0.17	0.05	1.66	1.1	15.4	18.8	-17.4	14576	-63.1***
Real exchange rate pressure index	-0.02	-0.05	1.45	0.0	18.6	13.3	-22.2	14532	-47.7***
Exchange rate return (%, monthly)	1.17	0.04	6.92	16.4	457.9	272.2	-59.7	17092	-72.7***
International reserves (Δ%)	11.31	10.53	36.43	0.0	6.9	264.7	-263.8	15868	-10.1***
Imports (Δ%)	8.95	9.81	23.08	-0.4	7.6	221.9	-196.3	16233	-7.7***
Export (Δ%)	9.05	9.62	21.45	-0.5	10.6	156.7	-191.6	16292	-11.3***
Terms of trade (Δ%)	-0.02	-0.06	13.24	2.4	54.6	213.9	-198.1	4787	-6.9***
Real exchange rate, (% deviation)	0.43	-0.07	19.48	1.2	11.8	238.4	-98.1	16017	-4.8***
Real effective exchange rate (Δ%)	-0.95	-0.01	11.58	-2.1	60.5	183.5	-243.7	8416	-9.3***
Real interest rate (%, monthly)	3.43	0.28	119.45	73.5	6403.7	11584.4	-102.3	14821	-8.1***
Real interest rate differential (%, monthly)	3.24	0.09	119.34	73.6	6414.4	11583.8	-102.5	14847	-9.4***
Excess real M1 balances (%)	7.95	2.49	67.92	39.7	2147.7	4445.9	-1190.6	13964	-2.4***
M2 multiplier (Δ%)	2.28	2.21	18.33	-0.3	16.0	157.6	-139.3	14668	-6.4***
Domestic credit to GDP (Δ%)	1.58	1.58	15.93	-0.3	42.0	208.2	-334.6	14434	-8.9***
Ratio of lending-to-deposit rates	2.48	1.47	11.80	34.4	1389.4	500.0	0.2	11647	-1.9**
Real commercial bank deposits (Δ%)	6.10	5.94	15.62	-0.6	29.8	172.8	-208.0	14592	-7.5***
Ratio of M2 to reserves (Δ%)	-1.34	-0.26	36.34	-0.2	7.6	221.6	-253.8	14838	-8.2***
Output (Δ%)	3.44	3.64	11.44	0.5	79.7	214.3	-205.7	11817	-8.5***
Stock market (Δ%)	13.66	14.52	40.58	0.5	16.2	567.5	-331.9	11407	-8.4***
Total foreign debt (Δ%)	7.58	8.00	19.04	0.2	6.7	200.8	-77.7	7533	-7.9***
Short term foreign debt ratio (Δ%)	0.21	-0.03	12.16	-0.3	5.5	56.2	-95.6	7533	-9.6***

*,**,*** Denotes significance at the 10%, 5% and 1% level, respectively. The last column shows the panel unit root test of Breitung (2000). The null hypothesis is that the data generating processes for all countries in the cross-section has a unit root.

Table 2 Tail Index Estimates

Variable	l / r tail	$\hat{\gamma}$	$\hat{\alpha}$	Obs. in the tail	% of total	l / r tail	$\hat{\gamma}$	$\hat{\alpha}$	Obs. in the tail	% of total
Currency crisis measures	*Depreciation of currency*					*Appreciation of currency*				
Exchange rate pressure index	r (+)	0.36	2.8	151	1.0%	l (−)	0.32	3.1	151	1.0%
Real exchange rate pressure index	r (+)	0.33	3.0	151	1.0%	l (−)	0.27	3.7	82	0.6%
Exchange rate return (%, monthly)	r (+)	0.80	1.3	655	3.8%	l (−)	0.40	2.5	242	1.4%
Economic Indicators	*Depreciation signal*					*Appreciation signal*				
International reserves (Δ%)	l (−)	0.15	6.9	24	0.2%	r (+)	0.14	7.0	24	0.2%
Imports (Δ%)	r (+)	0.18	5.4	39	0.2%	l (−)	0.24	4.1	92	0.6%
Export (Δ%)	l (−)	0.39	2.6	230	1.4%	r (+)	0.20	5.0	57	0.3%
Terms of trade (Δ%)	l (−)	0.41	2.5	111	2.3%	r (+)	0.68	1.5	266	5.6%
Real exchange rate, (% deviation)	l (−)	0.15	6.7	39	0.2%	r (+)	0.30	3.3	159	1.0%
Real effective exchange rate (Δ%)	r (+)	0.44	2.3	149	1.8%	l (−)	0.36	2.8	149	1.8%
Real interest rate (%, monthly)	r (+)	1.03	1.0	1203	8.1%	l (−)	0.77	1.3	613	4.1%
Real interest rate differential (%, monthly)	r (+)	1.09	0.9	1203	8.1%	l (−)	0.72	1.4	613	4.1%
Excess real M1 balances (%)	r (+)	0.62	1.6	594	4.3%	l (−)	0.37	2.7	210	1.5%
M2 multiplier (Δ%)	r (+)	0.25	3.9	82	0.6%	l (−)	0.25	4.0	82	0.6%
Domestic credit to GDP (Δ%)	r (+)	0.38	2.6	151	1.0%	l (−)	0.42	2.4	224	1.6%
Ratio of lending-to-deposit rates	r (+)	0.87	1.2	503	4.3%	l (−)	---	---	---	---
Real commercial bank deposits (Δ%)	l (−)	0.19	5.3	37	0.3%	r (+)	0.38	2.7	224	1.5%
Ratio of M2 to reserves (Δ%)	r (+)	0.11	8.8	23	0.2%	l (−)	0.13	8.0	23	0.2%
Output (Δ%)	l (−)	0.46	2.2	295	2.5%	r (+)	0.39	2.6	189	1.6%
Stock market (Δ%)	l (−)	0.19	5.3	50	0.4%	r (+)	0.29	3.4	71	0.6%
Total foreign debt (Δ%)	r (+)	0.30	3.3	62	0.8%	l (−)	0.26	3.9	62	0.8%
Short term foreign debt ratio (Δ%)	r (+)	0.08	12.2	11	0.1%	l (−)	0.19	5.4	39	0.5%

Table 3 Asymptotic Dependence of Currency Crisis Measures and Economic Signals

Variable	l / r tail	$\hat{\bar{\chi}}$	Lag	Correl.	$\hat{\bar{\chi}}$	Lag	Correl.	$\hat{\bar{\chi}}$	Lag	Correl.
Economic Indicators		EMP_t			$REMP_t$			ER_t		
International reserves (Δ%)	l (–)	0.262	4	0.035	0.214	23	0.018	0.456	8	0.055
Imports (Δ%)	r (+)	0.198	17	0.022	0.158	22	0.027	0.200	23	-0.017
Export (Δ%)	l (–)	0.169	4	0.058	0.131	7	0.031	0.278	4	0.057
Terms of trade (Δ%)	l (–)	0.323	18	0.027	0.263	9	0.034	0.611	24	0.008
Real exchange rate, (% deviation)	l (–)	0.122	4	0.045	0.016	6	0.021	0.440	24	0.060
Real effective exchange rate (Δ%)	r (+)	0.245	11	0.054	0.229	21	0.032	0.402	9	0.089
Real interest rate (%, monthly)	r (+)	0.348	6	0.025	0.193	15	0.014	**1.000**[†]	8	0.137
Real interest rate differential (%, monthly)	r (+)	0.365	4	0.025	0.217	7	0.014	**1.019**[†]	4	0.137
Excess real M1 balances (%)	r (+)	0.260	4	0.010	0.129	24	0.029	0.568	16	0.142
M2 multiplier (Δ%)	r (+)	0.153	24	0.030	0.073	24	0.023	0.463	16	0.029
Domestic credit to GDP (Δ%)	r (+)	0.051	24	0.020	0.027	4	0.024	0.202	11	-0.021
Ratio of lending-to-deposit rates	r (+)	-0.086	20	0.035	-0.117	16	-0.001	0.125	8	-0.009
Real commercial bank deposits (Δ%)	l (–)	0.113	7	0.019	0.175	6	0.000	0.669	4	0.125
Ratio of M2 to reserves (Δ%)	r (+)	0.293	7	0.029	0.222	23	0.023	0.467	8	0.029
Output (Δ%)	l (–)	0.207	24	0.032	0.132	7	0.025	0.371	7	0.057
Stock market (Δ%)	l (–)	0.204	4	0.013	0.149	6	0.022	0.565	4	0.026
Total foreign debt (Δ%)	r (+)	0.243	18	0.027	0.215	18	0.016	0.074	4	-0.004
Short term foreign debt ratio (Δ%)	r (+)	0.044	19	0.041	0.129	14	0.009	-0.105	18	0.014

The table shows the estimated extremal dependence ($\hat{\bar{\chi}}$) of 17 lagged fundamentals with EMP_t, $REMP_t$, and ER_t, respectively. Estimate standard errors and p-values for the test are available, but not reported to save space. *Lag*: the lag of the fundamental, chosen between 4 to 24 months to maximize the tail dependence estimate. *Correl.*: Pearson correlation of the two series.

[†]: denotes that the null hypothesis of asymptotic dependence ($\bar{\chi} = 1$) cannot be rejected at the 5% level.

Table 4 In-Sample Crisis Prediction Performance of Economic Signals

Variable	l / r tail	Num. of signals	% crises called	% false alarms	Num. of signals	% crises called	% false alarms	Num. of signals	% crises called	% false alarms
Economic Indicators			EMP_t			$REMP_t$			ER_t	
International reserves (Δ%)	l (–)	15	4.4	60.0	15	3.0	66.7	24	3.7	12.5
Imports (Δ%)	r (+)	33	2.9	78.8	32	3.8	56.3	39	3.1	69.2
Export (Δ%)	l (–)	158	12.5	80.4	157	13.8	79.6	229	17.8	55.0
Terms of trade (Δ%)	l (–)	108	39.4	65.7	95	18.8	77.9	109	71.7	49.5
Real exchange rate, (% deviation)	l (–)	19	0.0	94.7	19	3.7	63.2	31	6.0	38.7
Real effective exchange rate (Δ%)	r (+)	118	4.5	83.1	118	7.6	83.9	147	19.2	49.0
Real interest rate (%, monthly)	r (+)	1131	36.9	74.4	1138	37.0	75.6	1195	70.9	41.6
Real interest rate differential (%, monthly)	r (+)	1122	42.3	74.0	1117	40.9	76.5	1185	70.1	44.9
Excess real M1 balances (%)	r (+)	524	18.5	77.7	523	16.4	81.1	537	45.1	54.2
M2 multiplier (Δ%)	r (+)	76	2.4	88.2	76	2.5	85.5	77	12.5	57.1
Domestic credit to GDP (Δ%)	r (+)	133	4.0	78.2	133	1.7	95.5	151	5.3	70.9
Ratio of lending-to-deposit rates	r (+)	414	1.4	99.5	415	3.4	98.1	439	6.9	95.0
Real commercial bank deposits (Δ%)	l (–)	23	0.0	100.0	23	5.1	73.9	37	12.3	8.1
Ratio of M2 to reserves (Δ%)	r (+)	16	2.3	81.3	16	3.2	81.3	23	2.8	52.2
Output (Δ%)	l (–)	203	10.7	82.3	213	13.9	80.3	293	25.1	54.9
Stock market (Δ%)	l (–)	39	6.7	71.8	39	7.2	82.1	50	14.3	20.0
Total foreign debt (Δ%)	r (+)	59	2.6	84.7	59	0.0	100.0	62	1.3	77.4
Short term foreign debt ratio (Δ%)	r (+)	6	0.0	100.0	6	0.0	100.0	11	1.9	90.9

The table shows the in-sample crisis prediction performance of the 17 economic fundamentals, for crisis measures EMP_t, $REMP_t$, and ER_t, respectively.
% crises called: denotes the percentage of all crises preceded by at least one signal in the preceding 24 months.
% false alarms: denotes the percentage of all fundamental signals not followed by at least one currency crisis in the following 24 months.

Table 5 Crises Identified – Emerging Markets, July-1995 / Feb-2008

Country	Begin / End of crisis episode	Months identified as crisis	In BMS'06 sample (Y/N)	Identified by BMS'06 (Y/N)
Argentina	Jan-02 / May-02	4	Y	N
Brazil	Jan-99	1	Y	Y
Brazil	June-02 / Sept-02	3	Y	N
Brazil	May-06	1	N	---
Colombia	Aug-07	1	N	---
Ecuador	Sept-98 / Jan-00	7	N	---
Egypt	Jan-03	1	N	---
Hungary	Jun-03	1	N	---
Indonesia	Aug-97 / Sep-99	8	Y	Y
Indonesia	Apr-01	1	Y	N
Israel	Oct-98	1	N	---
Korea	Nov-97 / Dec-97	2	Y	Y
Malaysia	Aug-97 / Jan-98	3	Y	Y
Mexico	Oct-95	1	Y	N
Mexico	Aug-98	1	Y	N
Pakistan	May-99	1	Y	N
Pakistan	Sep-00	1	Y	N
Paraguay	Jun-02	1	N	---
Philippines	Sep-97 / Dec-97	2	Y	Y
Philippines	Oct-00	1	Y	N
Russia	Aug-98 / Dec-98	4	N	---
South Africa	Jun-98	1	Y	Y
South Africa	Nov-01 / Dec-01	2	Y	Y
South Africa	May-03	1	N	---
South Africa	May-05	1	N	---
Thailand	Jul-97 / Jan-98	3	Y	Y
Turkey	Feb-01 / Sep-01	4	Y	Y
Turkey	May-06	1	N	---
Uruguay	Jun-02 / Aug-02	3	Y	Y
Venezuela	Dec-95 / Apr-96	2	Y	Y
Venezuela	Feb-02 / Jan-03	4	Y	Y
Venezuela	Feb-04	1	N	---
Venezuela	Apr-05	1	N	---
Zimbabwe	Nov-97 / Sep-98	4	N	---
Zimbabwe	Aug-00	1	N	---
Zimbabwe	Mar-03 / Apr-04	4	N	---
Zimbabwe	May-05 / Aug-06	8	N	---

The table shows months identified as a currency crises in the out-of-sample period July-1995 until Feb-2008 by the EVT approach. Column 4 indicates whether this country & period are also included in the sample studied by Beckmann, Menkhoff and Sawischlewski (2006). Column 5 indicates whether BMS (2006) identified at least one month in this crisis episode as a currency crisis event.

Table 6 In-Sample Tail Dependence and Crisis Prediction – Emerging Markets, Jan-1974 / June-1995

Variable	l / r tail	$\hat{\alpha}$	$\hat{\bar{\chi}}$	Lag	Num. signals	% crises called (A)	% false alarms (B)	(A -B)	P(crisis | signal)	P(crisis | no signal)
Economic Indicators	*Tail information & dependence*				*In-sample performance*					
Real interest rate differential	r (+)	1.3	1.119	-4	850	83.9	44.1	39.8	55.9	27.4
Real interest rate, ***signal 1***	r (+)	1.3	1.105	-7	856	85.0	43.3	41.7	56.7	27.2
Excess real M1 balances, ***signal 2***	r (+)	0.7	0.713	-12	271	66.6	31.4	35.2	68.6	32.2
Stock market return	l (–)	19.3	0.562	-8	8	3.0	37.5	-34.5	62.5	22.2
M2 multiplier (Δ%)	r (+)	2.8	0.558	-8	84	32.2	47.6	-15.4	52.4	33.6
Real bank deposits (Δ%), ***signal 3***	l (–)	5.0	0.543	-21	34	19.7	5.9	13.8	94.1	33.8
Real exchange rate deviation, ***signal 4***	l (–)	9.1	0.533	-19	10	8.9	0.0	8.9	100.0	32.5
Ratio of M2 to reserves (Δ%)	r (+)	8.1	0.393	-22	16	3.0	68.8	-65.7	31.3	34.0
International reserves (Δ%)	l (–)	7.6	0.335	-8	22	3.8	18.2	-14.4	81.8	33.6
Ratio of lending-to-deposit rates	r (+)	2.7	0.169	-4	65	10.4	50.8	-40.4	49.2	29.7
Export (Δ%)	l (–)	5.3	0.157	-7	26	1.8	69.2	-67.4	30.8	32.6
Imports (Δ%)	r (+)	5.3	0.151	-23	37	4.0	81.1	-77.0	18.9	32.5
Domestic credit to GDP (Δ%)	r (+)	8.6	0.118	-10	8	0.4	87.5	-87.1	12.5	34.0
Combined Signals and Probability Models					*In-sample performance*					
Signal 1 *and* signal 2, 3 or 4	---	---	---	---	140	65.7	7.9	57.9	92.1	31.4
Signal 1 *and* crisis probability > 25%	---	---	---	---	617	78.8	34.2	44.6	65.8	27.5
Signal 1 *and* crisis probability > 35%	---	---	---	---	333	73.4	18.9	54.4	81.1	28.7
Probit model, with 50% threshold	---	---	---	---	532	90.7	30.3	60.4	69.7	27.9
Probit model, with 75% threshold	---	---	---	---	170	68.4	8.8	59.6	91.2	30.7

% crises called: denotes the percentage of all crises preceded by at least one signal in the preceding 24 months.
% false alarms: denotes the percentage of all fundamental signals not followed by at least one currency crisis in the following 24 months.
P(crisis | signal): conditional probability of a currency crisis occurring during the next 24 months, given that the fundamental has issued a signal.

Table 7 Out-of-Sample Crisis Prediction Performance – Emerging Markets, July-1995 / Feb-2008

	Num. of signals	% crises called (A)	% false alarms (B)	(A -B)	P(crisis | signal)	Num. of signals	% crises called (A)	% false alarms (B)	(A -B)	P(crisis | signal)
Economic Indicators	*In-sample performance*					*Out-of-sample performance*				
Real interest rate differential	850	83.9	44.1	39.8	55.9	373	63.1	68.9	-5.8	31.1
Real interest rate, ***signal 1***	856	85.0	43.3	41.7	56.7	351	57.1	68.1	-10.9	31.9
Excess real M1 balances, ***signal 2***	271	66.6	31.4	35.2	68.6	343	28.4	84.8	-56.5	15.2
Stock market return	8	3.0	37.5	-34.5	62.5	47	21.5	40.4	-18.9	59.6
M2 multiplier (Δ%)	84	32.2	47.6	-15.4	52.4	43	0.0	100.0	-100.0	0.0
Real bank deposits (Δ%), ***signal 3***	34	19.7	5.9	13.8	94.1	0	0.0	---	---	0.0
Real exchange rate deviation, ***signal 4***	10	8.9	0.0	8.9	100.0	25	11.9	52.0	-40.1	48.0
Combined Signals and Probability Models	*In-sample performance*					*Out-of-sample performance*				
Signal 1 *and* signal 2, 3 or 4	140	65.7	7.9	57.9	92.1	60	20.3	73.3	-53.1	26.7
Signal 1 *and* crisis probability > 25%	617	78.8	34.2	44.6	65.8	157	44.0	65.6	-21.6	34.4
Signal 1 *and* crisis probability > 35%	333	73.4	18.9	54.4	81.1	10	11.9	30.0	-18.1	70.0
Probit model, with 50% threshold	532	90.7	30.3	60.4	69.7	170	29.7	71.8	-42.1	28.2
Probit model, with 75% threshold	170	68.4	8.8	59.6	91.2	19	7.8	52.6	-44.8	47.4

% crises called: denotes the percentage of all crises preceded by at least one signal in the preceding 24 months.
% false alarms: denotes the percentage of all fundamental signals not followed by at least one currency crisis in the following 24 months.
P(crisis | signal): conditional probability of a currency crisis occurring during the next 24 months, given that the fundamental has issued a signal.

Figure 1 Scatter Plot: % (Crises Called – False Alarms) versus Estimated Extremal Dependence ($\hat{\bar{\chi}}$)

This figure shows a scatter plot of the in-sample crisis prediction performance measure '(% crisis called – % false alarms)' on the y-axis versus the estimated extremal dependence measure with ER_t on the x-axis, for each economic indicator variable.

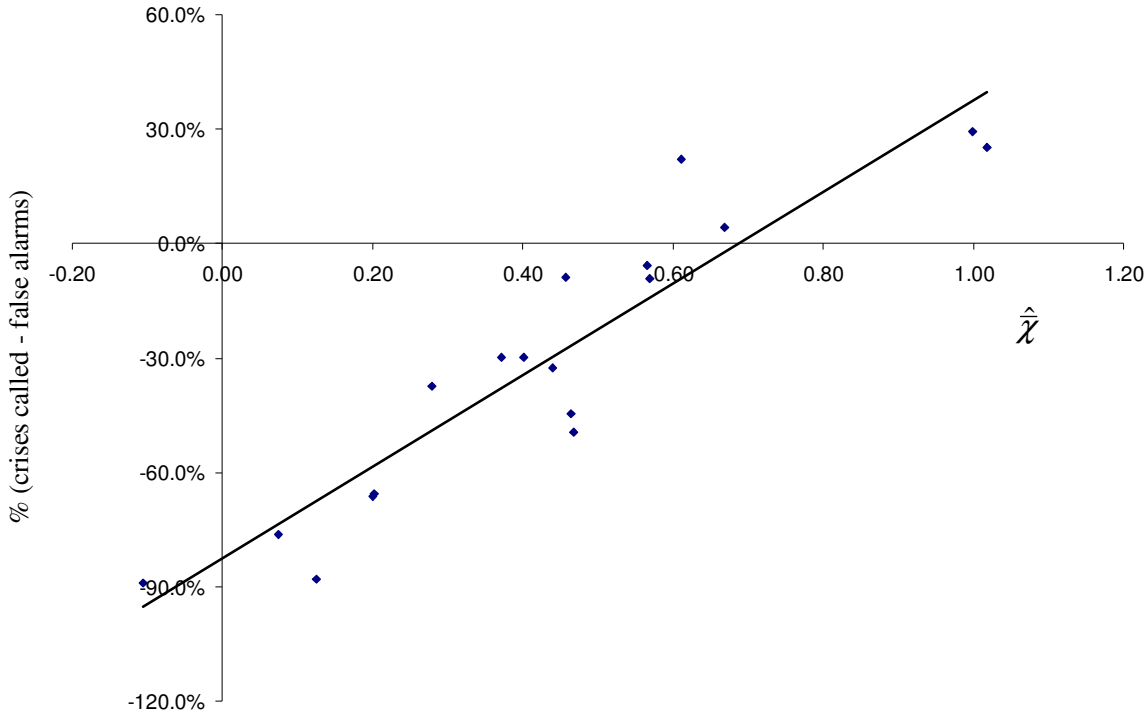
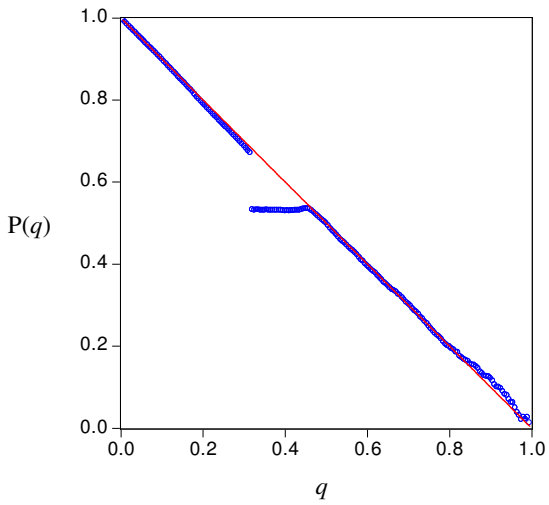


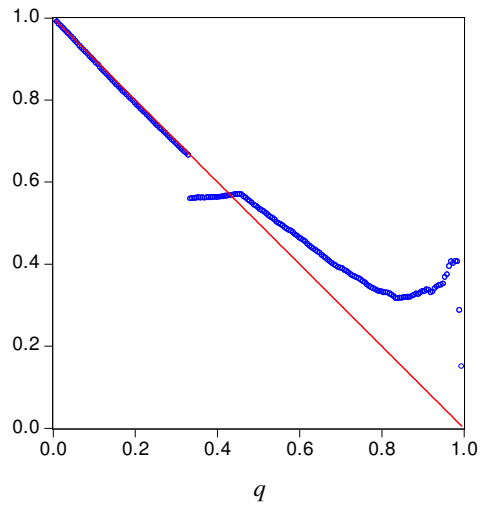
Figure 2 Conditional Probability Plots

The plots show the conditional probability $P(q) = P(\ Y > F_Y^{-1}(q) \mid X > F_X^{-1}(q)\ )$, as $q \rightarrow 1$. In all plots variable Y is the exchange rate return in month t (ER_t). Panel A: variable X is the lagged increase in imports at month t-23. Panel B: variable X is the lagged real interest rate differential at month t-4. Panel C: variable X is the decrease in real commercial bank deposits at month t-4. The probability $P(q)$ is shown on the y-axis, and the percentile q on the x-axis.

Panel A: Imports



Panel B: Real interest rate differential



Panel C: Real commercial bank deposits