Early warning systems for currency crises:
A multivariate extreme value approach

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Abstract

We apply extreme value theory to assess the tail dependence between three currency crises measures and 18 economic indicators commonly used for predicting crises. In our pooled sample of 46 countries in the period 1974-2008, we find that nearly all pairs of variables are asymptotically independent: in the limit, extreme values of economic indicators are not followed by severe currency crashes. Our findings may explain the poor performance of existing early warning systems for currency crises. However, we do find that economic variables with stronger extremal association with the exchange rate have better crisis prediction performance, both in-sample and out-of-sample.

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1. Introduction

Currency crises can have a devastating impact on the real economy, as shown by the Mexican peso crisis in 1994-1995, the Asian crisis in 1997-1998, and the Argentinean crisis in 2002.[1] To prevent future crises researchers have since tried to identify common factors underlying exchange rate instability[2], and to build early warning systems.[3] However, existing early warning models fail to predict crises out of sample (Furman and Stiglitz, 1998, Berg and Pattillo, 1999, and Berg, Borensztein and Pattillo, 2005), despite impressive in-sample results. In this paper we test whether currency crises and extreme movements in lagged economic and financial variables are truly linked in the tail, using multivariate extreme value theory (EVT). Further, we investigate whether EVT measures can provide useful information for building an early warning system.

Our motivation for applying 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. We employ extremal dependence measures developed by Poon, Rockinger and Tawn (2004) that are non-parametric, providing unbiased information about the extremal relation between currency crises measures and lagged fundamentals, without making assumptions about the unknown shape of the distribution. Existing methods for predicting crises in the literature, such as the signaling approach and probit models, rely on maximizing in-sample prediction performance, putting them at risk of overfitting the data. The poor out-of-sample results of existing early warning systems also justify an investigation of alternative methodologies such as EVT. [4]

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[1] See, Krugman (2010), for the decline in GDP during these crises. Bussière, Saxena and Tovar (2012) provide more empirical evidence on the effect of currency crises on economic growth.

[2] For a survey of the literature, see Kaminsky, Lizondo and Reinhart (1998), Flood and Marion (1999) and Kumar, Moorthy and Perraudin (2003).

[3] This line of research is known as the signaling approach: see Kaminsky, Lizondo and Reinhart (1998), Kaminsky (1999, 2006), Kaminsky and Reinhart (1998, 1999), Goldstein, Kaminsky and Reinhart (2000).

[4] Other modelling techniques have also been considered in the literature. For example, Lin, Khan, Chang and Wang (2008) use a combination of neural networks and fuzzy logic to predict currency crises.

Using monthly observations on exchange rates for a cross-section of 46 developed and developing countries in the period 1974-2008, we assess the asymptotic dependence of three currency crisis measures and 18 lagged economic indicators commonly used in early warning models. Asymptotic dependence means that in the limit, as the condition of the economic fundamental deteriorates and the variable moves deeper into the tail, more extreme currency depreciations (or devaluations) tend to follow with positive probability. Out of 54 pairs of variables, we find only two pairs that are asymptotically dependent: increases in the real interest rate and the real interest rate differential are asymptotically dependent with currency crashes. The other pairs are asymptotically independent, which means that the relation disappears as we move deeper into the tail. Lack of asymptotic dependence may explain why early warning systems perform so poorly in practice.

Apart from asymptotic dependence, which is defined in the limit, we also estimate an EVT measure of extremal association for all pairs, which can be interpreted as the association in the tail between two variables. We assess the usefulness of this measure for predicting currency crises, both in sample and out of sample. First, we find that the extremal association in the tail between currency crises measures and lagged economic fundamentals is stronger than suggested by a standard Pearson correlation measure. Second, we find a strong positive link between our extremal association measure and the success of an economic indicator in predicting currency crises in-sample. Third, we find that our in-sample extremal association estimate also has a positive relation with the out-of-sample indicator prediction performance.

In the out-of-sample period (emerging markets, 1995-2008), we compare crisis prediction performance with standard approaches from the literature, such as a probit model and the signaling approach. Unfortunately, out-of-sample crisis prediction performance is poor for all methods, including the EVT method. However, in contrast to other methods, the EVT approach foreshadowed this poor outcome based on the lack of asymptotic dependence between fundamentals and currency crises measures. In addition, for the two asymptotically dependent real interest rate indicators, our EVT method implies a false alarm rate of 70% in-sample, close to the actual out-of-sample rate.

In the currency crisis literature, there is no empirical work yet that applies EVT to estimate the relation between fundamentals and currency crisis measures. Koedijk, Stork and de Vries (1992) use EVT to study the univariate distribution of exchange rate returns. 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 measure of foreign exchange market pressure 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. Hartmann, Straetmans and de Vries (2010) demonstrate how joint currency crises can occur through shared fundamental linkages, and they estimate the tail dependence of exchange rate pairs.

Several studies apply EVT to analyze extreme dependence among financial markets, including Longin and Solnik (2001), Embrechts, McNeill and Straumann (2002), Poon, Rockinger and Tawn (2004), Hartmann, Straetmans and de Vries (2004, 2010), Jondeau and Rockinger (2006) and Ning (2010). The 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 the relevance of currency crisis prevention and the well-documented poor performance of existing early warning systems out of sample, in this paper we apply extremal dependence measures to test whether currency crises measures and lagged economic fundamentals are truly linked in the tail.

2. Methodology

2.1. Currency crisis measures

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,

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

where s_t denotes the nominal spot exchange rate at time *t*, quoted as the price of foreign currency in terms of domestic currency.[5] 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 depreciation 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 in 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:

$$EMP_t = \mathbf{a}\,\Delta s_t + \mathbf{b}\,\Delta\tilde{i}_t - \mathbf{c}\,\Delta DINR_t\,, \tag{2}$$

[5] 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.

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.[6] The definition above follows similar indices in Girton and Roper (1977), Eichengreen, Rose and Wyplosz (1996), Kaminsky et al. (1998) and Berg and Pattillo (1999). 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.

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:

$$REMP_t = a'\Delta q_t + b'\Delta\tilde{r}_t - c'\Delta DINR_t, \tag{3}$$

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. Bussière and Fratzscher (2006) define a currency crisis when $REMP_t$ is two standard deviations above the mean.

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[6] Country-specific weights are attached to each component to equalize the volatility of the three components within each country as 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), but use M2 instead of M1 to represent the size of the domestic money market, with the aim of making the series more compatible across countries. We apply a hyperinflation-correction method as in Kaminsky et al. (1998).

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 Mexico in 1994-1995 and in Asia in 1997-1998, many papers investigate whether currency crises have common causes and can be predicted with lagged economic and financial data. Kaminsky et al. (1998) and Berg and Pattillo (1999) build early warning systems (EWS) based on a large set 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 18 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 1 lists the 18 indicators used in this study, with the eighth column showing 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 indicators, and the motivation for the expected sign. Web Appendix B contains details on the definition and data sources for each indicator.

2.3. Extremal dependence

We use two extremal dependence measures from multivariate EVT to investigate whether currency crises and lagged economic variables are linked in the tail area of the distribution.[7] Let random variable Y denote a currency crisis measure and X denote a lagged economic fundamental variable, with cumulative distribution function $F_Y(y)$ and $F_X(x)$. The conditional probability $P(q) = P\left[Y > F_Y^{-1}(q) \middle| X > F_X^{-1}(q)\right]$ then measures the probability that the currency return is above the q-th percentile of its distribution, conditional on the lagged economic variable being above the q-th percentile.

Poon, Rockinger and Tawn (2004) define a pair of measures ($\chi, \overline{\chi}$) that fully characterise the extremal dependence of X and Y. The first measure is χ:

$$\chi = \lim_{q \to 1} P(q) = \lim_{q \to 1} P\left[Y > F_Y^{-1}(q) \middle| X > F_X^{-1}(q)\right]. \tag{4}$$

The variables X and Y 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.[8] Asymptotic dependence means that as the lagged fundamental moves deeper into the tail, more extreme currency depreciations (or devaluations) tend to follow with positive probability. In the case of asymptotic independence the conditional probability approaches zero in the limit, implying that the relation eventually disappears as we move deeper into the tail. Asymptotic independence casts doubt on the existence of a causal link between extreme lagged fundamental values and currency crises, and on whether the fundamental is a robust indicator for crisis prediction.

As asymptotic dependence is defined in the limit and could be too strict for crisis prediction in practice, we also estimate a measure of extremal association in the tail, $\overline{\chi}$.

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[7] For details on multivariate EVT, the reader is referred to Coles, Heffernan and Tawn (1999), Kotz and Nadarajah (2000), Poon, Rockinger and Tawn (2004), and Beirlant, Goegebeur, Segers and Teugels (2004).
[8] 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 $\rho \neq 0$.

We assess the usefulness of this measure for predicting currency crises, both in sample and out of sample. The extremal association measure $\bar{\chi}$ is intended for variables that are asymptotically independent ($\chi = 0$), and is inversely related to the rate at which the conditional probability $P(q)$ approaches 0:

$$\bar{\chi} = \lim_{q \to 1} \frac{2 \log P\left[X > F_X^{-1}(q)\right]}{\log P\left[Y > F_Y^{-1}(q), X > F_X^{-1}(q)\right]} - 1. \tag{5}$$

Note that $-1 \leq \bar{\chi} \leq +1$. The interpretation of $\bar{\chi}$ is similar to correlation, but applied to the tail area: positive and negative values of $\bar{\chi}$ correspond to positive and negative extremal association, respectively. For two variables with a Gaussian dependence structure (e.g., a bivariate normal distribution) $\bar{\chi}$ is *equal* to the correlation coefficient ρ. When the dependence structure is non-Gaussian, however, the correlation coefficient ρ and the extremal association measure $\bar{\chi}$ can be markedly different.

Ledford and Tawn (1996) show that $\bar{\chi}$ = 1 for all asymptotically dependent variables, while $\bar{\chi}$ < 1 for asymptotically independent variables. To examine whether a currency crisis measure and a fundamental are asymptotically dependent, we estimate $\bar{\chi}$ and test the null hypothesis $\bar{\chi}$ = 1. If we can reject $\bar{\chi} = 1$, then the variables are asymptotically independent with χ = 0. If we cannot reject $\bar{\chi} = 1$, then the pair is asymptotically dependent and we estimate the limiting probability χ. We refer to Poon et al. (2004) for details on the non-parametric estimation of $\bar{\chi}$ and χ, as well as the asymptotic distribution of the estimators (for testing $\bar{\chi}$ = 1). The estimation approach is also briefly summarized in Appendix B.

3. Empirical results

3.1. Descriptive statistics and tail indices

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 18 fundamental variables. 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).[9] We have also tested whether these series are stationary using the panel unit root test statistic of Breitung (2000): the null hypothesis of a unit root can be rejected for all series.[10]

To further characterize the tail fatness and shape, we estimate the tail index α with the Hill estimator (details are in Appendix A). When $1/\alpha > 0$ the distribution has heavy tails, and the number of existing moments of the random variable is equal to the integer value of α (e.g., the Pareto and Student's *t* distributions fall in this category). If $1/\alpha = 0$, the distribution has thin tails and an infinite number of existing moments (e.g., the normal distribution). If $1/\alpha < 0$, the distribution has a finite upper limit and therefore no long tail (e.g., the uniform distribution).

[9] 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.

[10] 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.

Table 1 shows the tail index estimates $\hat{\alpha}$ for the pooled series.[11] The estimates are 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 exchange rate measures all have heavy tails ($\hat{\alpha} \leq 3$), much fatter than a normal distribution. For the exchange rate returns $\hat{\alpha}$ is 1.3, implying that only the first moment is bounded. Among the economic signal variables, the two real interest rate variables have the lowest tail index estimates, $\hat{\alpha}$ =1.0 and $\hat{\alpha}$ =0.9, respectively. Other fundamentals with heavy tails are the lending-to-deposit rate ratio ($\hat{\alpha}$ =1.2), the excess real money balance ($\hat{\alpha}$ =1.6) and the terms of trade ($\hat{\alpha}$ =1.5). Fundamentals with relatively thin tails are the short-term debt ratio, the ratio of M2 to reserves and international reserves.

3.2. Extremal dependence of currency crises and lagged fundamentals

We estimate the extremal association measure $\bar{\chi}$ for all pairs of currency crisis measures and 18 economic variables, and we then test the hypothesis $\bar{\chi}$ =1 to assess asymptotic dependence. We lag the economic variables from 4 up to 24 months, as in practice most economic data is published with delay and warning signals issued well in advance of a crisis are more useful. 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 2 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, the simple Pearson correlation *r* using all observations is displayed as well, with the time lag for the fundamental variable chosen from 4 through 24 months to maximize the

[11] 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. See Web Appendix C for details.

correlation estimate. In nearly all cases the extremal association measure is considerably larger than the correlation. Thus, extreme currency depreciations and large values of lagged fundamentals do occur jointly more often than correlation estimates suggest.

However, the relation between currency extremes and fundamental extremes also tends to disappear in the limit as we move deeper into the tail area: nearly all pairs of lagged economic fundamentals and currency crisis measures are asymptotically independent. There are only two exceptions: we cannot reject asymptotic dependence between the exchange rate return (ER_t) and the lagged real interest rate, and the same result 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, *p*-value = 0.624). The estimated limiting probabilities are $\hat{\chi} = 0.309$ and $\hat{\chi} = 0.305$, respectively. Hence, when the lagged real interest rate takes on more extreme positive values, the probability of more severe currency depreciations is 30%. The relation is persistent, at lags from 1 to 15 months, extending to more than one year before the extreme currency crashes take place.[12]

To better illustrate and contrast the difference between the concepts of asymptotic dependence and independence, Figure 1 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.[13] In all panels the variable *Y* is the exchange rate return (ER_t) and *X* is a lagged fundamental. Panel A shows an example of tail independence, while Panel B is a case of tail dependence, and Panel C & D are cases of tail independence with high extremal association.

[12] ER_t and the real interest rate are asymptotically dependent at all lags from 1 to 13 months, and at lags 16 and 19. ER_t and the real interest rate differential are asymptotically dependent at lags 1 to 11, and at 13 and 15 months. The estimated limiting probability is always close to 30%; it is not sensitive to the time lag.

[13] 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.

In Panel A the fundamental X is the lagged increase in imports, which is asymptotically independent with the exchange rate return Y. Panel A shows that the conditional probability $P(q)$ of more extreme currency crashes goes to zero in the limit as $q \rightarrow 1$. In Panel B the fundamental is the lagged real interest rate differential, a variable that is asymptotically dependent with Y. In this case the conditional probability does not go to zero in the limit, but to a stable value between 0.3 and 0.4.[14]

Finally, Panel C and D shows two examples of tail independence, but with relatively high extremal association ($\hat{\bar{\chi}} = 0.669$ and $\hat{\bar{\chi}}$=0.565), namely the lagged decrease in bank deposits and the stock market decline. In these two plots the conditional probability does approach zero in the limit, but at a relatively slow speed. At finite thresholds q=0.90 and q=0.95 the conditional probability of extreme currency crashes is still high, and above the straight line denoting statistical independence.

In sum, we learn that association in the tail area between currency crises measures and lagged fundamentals, assessed by $\bar{\chi}$, is usually considerably larger than suggested by the simple correlation r. However, in the limit, as both the currency crises measure and the lagged fundamental move deeper into the tail, the association eventually disappears (asymptotic independence). Only the real interest rate is asymptotically dependent with the exchange rate return. In the next sections we investigate whether the extremal dependence measures contain useful information for currency crisis prediction.

4. In-sample prediction of currency crises

To assess currency crisis prediction performance, we evaluate the conditional crisis probability and the performance measure "% of crises correctly called - % of false

[14] 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.

alarms" for all 18 indicators. However, we first need to define precisely when a currency crisis occurs. A common approach in the literature is to define a currency crisis when a measure of exchange rate market pressure (either *ER*, *EMP* or *REMP*) exceeds its mean by x standard deviations: x = 1.5 in Eichengreen et al. (1996), x = 3 in Kaminsky et al. (1998), and x = 2 in Bussière and Fratzscher (2006). Alternatively, Pozo and Amuedo-Dorantes (2003) identify a currency crisis when the exchange rate measure is above its extreme value threshold, determined as part of the tail index estimation procedure. The EVT threshold separates extremes from regular observations (see Appendix A).

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 "x standard deviations" approach. The advantage of the EVT approach is that it includes only observations in the tail area (i.e., truly extreme), without making assumptions about the shape of the unknown population distribution. Pescatori and Sy (2007) report that the EVT threshold method accurately defines emerging market debt crises, while Dridi, El Ghourabi and Limam (2012) show that an EVT-based method tracks episodes of stress in the banking sector more closely then ad-hoc approaches based on the standard deviation.

In this paper we follow Pozo and Amuedo-Dorantes (2003) and define a currency crisis when the measure of exchange rate market pressure is above its EVT threshold, determined with the method of Jansen and de Vries (1991).[15] For example, for the exchange rate measure *ER* the threshold is a depreciation of 7.4% and 655 observations are identified as extreme events (3.83% of total). The currency crises identified in this manner include all well-known historical crisis events: the EMS crisis in 1992, Mexico in 1994, the Asian crisis of 1997-1998 and the Russian crisis of 1998.

[15] See Web Appendix C for more details about implementation of the Jansen and de Vries (1991) method.

4.1. Conditional crisis probability

The extremal dependence measures χ and $\bar{\chi}$ are both defined as limiting values as the percentile q approaches its upper value of 1, that is, as the currency crisis measure and the lagged fundamental both move deeper into the tail. In early warning systems, however, a currency crisis is a discrete event that occurs once the exchange rate measure passes the fixed crisis threshold value θ_y.[16] To assess whether economic fundamentals are good crisis predictors, the following conditional crisis probability is also relevant: $P^*(q_x)$ = $P\left[Y > \theta_y \middle| X > F_X^{-1}(q_x)\right]$, while varying only the percentile q_x of the economic variable.

Figure 2 shows $P^*(q_x)$ as a function of the fundamental percentile q_x, ranging from 0 to 1. The solid straight line in all plots is the *unconditional* crisis probability. In Panel A the fundamental variable is the lagged increase in imports, a variable with low extremal association with the exchange rate ($\hat{\bar{\chi}}$=0.2). In Panel A the conditional crisis probability $P^*(q_x)$ is low and close to the unconditional probability, regardless of the value of the imports variable. In Panel B the predictor variable is the real interest rate differential (lagged 4 months), which is asymptotically dependent with the exchange rate ($\hat{\bar{\chi}}$=1.0). In this case the conditional crisis probability increases steadily and steeply as the real interest rate differential becomes more extreme ($q_x \rightarrow 1$): $P^*(q_x)$=31%, 67% and 72%, at q_x =0.95, 0.99 and 0.995, respectively.

Panel C shows an example of tail independence, but with high extremal association ($\hat{\bar{\chi}} = 0.669$): the lagged decrease in bank deposits. The crisis probability rises substantially as the decrease in bank deposits becomes more extreme: $P^*(q_x)$=17%, 34% and 44%, at q_x =0.95, 0.99 and 0.995. However, the increase of the crisis probability is less pronounced than in Panel B. Finally, Panel D shows the stock market decline,

[16] In other words, for the exchange rate the percentile q is fixed at a given high value $q^* = F_Y(\theta_y)$.

another fundamental with relatively high extremal association ($\hat{\hat{\chi}}$=0.565). The conditional crisis probabilities, $P^*(q_x)$= 10%, 11% and 17%, at q_x =0.95, 0.99 and 0.995, are all considerably higher than the unconditional crisis probability of 2.4%, but lower than in Panel C (bank deposits) and Panel B (interest rate).

A clear pattern emerges in Figure 2: the stronger the extremal association measure $\hat{\hat{\chi}}$ of the fundamental with the exchange rate, the higher the conditional currency crisis probability $P^*(q_x)$. Indeed, the correlation between $\hat{\hat{\chi}}$ and $P^*(q_x)$ among our set of 18 fundamental variables is strong: r =94.4%, 94.9% and 90.7%, at q_x=0.95, 0.99 and 0.995. Figure 3 illustrates these relations with a scatter plot, showing how the conditional crisis probability $P^*(q_x)$ increases as a function of $\hat{\hat{\chi}}$. These results clearly suggest that the estimated extremal association measure $\hat{\hat{\chi}}$ contains relevant information about crisis prediction perfomance.

4.2. In-sample crisis prediction performance

We assess the in-sample crisis prediction performance of the economic variables more in detail with two statistics often used in the literature on early warning systems (see Kaminsky et al., 1998). In Table 3 Column A 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. Column B displays the 'percentage of false alarms', which is the percentage of fundamental signals not subsequently followed by a currency crisis in the next 24 months.[17]

[17] Please note that the results in Table 3 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).

In Kaminsky et al. (1998), the signal threshold for an economic indicator variable is set by maximizing the in-sample crisis prediction performance of the indicator. In this paper we instead use the EVT threshold to define when a fundamental variable takes on extreme values and issues warning signals of future currency crises. Our approach focuses on the tail of the distribution to set the signal threshold, instead of potentially overfitting the data by maximizing in-sample prediction performance. The overfitting problem is relevant, as most early warning systems have poor out-of-sample performance. Just for comparison, we have also implemented the signalling approach of Kaminsky et al. (1998), and evaluate results later on.

The in-sample crisis prediction results are rather poor for EMP_t and $REMP_t$. For crises identified with these nominal and real exchange rate pressure indices, the false alarm rate of all indicators is higher than 50%, while the percentage of crises called is less than 42.5%.[18] We note that the estimated extremal association measures $\overline{\chi}$ of the fundamentals with EMP_t and $REMP_t$ are also relatively low ($\overline{\chi} < 0.40$).

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

Figure 4 depicts the relation between the tail association estimates ($\hat{\overline{\chi}}$) and the in-sample crisis prediction results in Table 3. Figure 4 is a scatter plot, with $\hat{\overline{\chi}}$ 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 currency crisis measure). The figure shows a strong positive linear relation between the extremal association estimates and in-sample prediction performance of economic indicators ($r = 0.93$).[19] Hence, a significant and strong positive relation exists between our extremal association estimates and the in-sample success of economic indicators in predicting currency.

Finally, we have also implemented the KLR method (Kaminsky, Lizondo and Reinhart, 1998). KLR set the signaling threshold for fundamental variables by maximizing the noise-to-signal ratio, searching over percentiles from 80% to 90% of the fundamental distribution *within* each country. KLR rank indicators on the noise-to-signal ratio, from low (best) to high (worst). We find that the KLR methodology selects different indicators than our EVT method: the correlation is only +0.352 between the indicator rankings of the two methods (our ranking is based on $\hat{\bar{\chi}}$). Moreover, the real interest rate variables are ranked 6 and 9 by the KLR method (but ranked 1 & 2 by EVT). In sum, the EVT and KLR methods lead to different conclusions about which fundamentals are good indicators, and thus do not provide the same information.

5. Out-of-sample prediction of currency crises

For the out-of-sample prediction of currency crises we use emerging markets only, to create a distinction with the full-sample results 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 January 1974 through June 1995, leaving July 1995 through February 2008 as the out-of-sample period. This gives the various

[18] The results for $REMP_t$ are not shown in Table 3 to save space, but available, and very similar to EMP_t.

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, focusing only on actual currency crashes, and ignoring unsuccessful speculative attacks picked up by the two exchange rate pressure measures.

After bundling together all extremes in one country that occur within 12 months of each other, the extreme value approach identifies 37 currency crises out of sample, including the Asian crisis in 1997, Russia in 1998, Brazil in 1999, Ecuador in 2000, Turkey in 2001-2002 and Argentina in 2002. Web Appendix D provides a complete description of all crises identified, as well as a comparison with the "3 standard deviations" method of Kaminsky et al. (1998). Remarkably, the method of Kaminsky et al. (1998) does not identify a currency crisis in Argentina in 2002, nor in Brazil in 2002.

In Section 5.1 we select economic signals and models for prediction in sample, and in Section 5.2 we evalute out-of-sample prediction performance.

5.1. Selection of currency crisis signals and models

To select signals for out-of-sample prediction we first rank all economic fundamentals based on extremal dependence with the exchange rate in the in-sample period (1974-95), selecting only a small number of promising variables. We then try to reduce the false alarm rate of these indicators by combining them, and by calibrating a logistic dependence model that gives predicted crisis probabilities. For comparison with the existing literature, we also estimate a standard probit model in-sample, exploiting information of all 18 fundamental variables.

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[19] The results for EMP_t and $REMP_t$, are similar, with correlation estimates $r = 0.79$ and $r = 0.39$, respectively, for the relation between prediction performance and $\hat{\bar{\chi}}$. For $REMP_t$ the relation is weaker, but likely the result of the lack of variation in $\hat{\bar{\chi}}$, as all extremal dependence estimates are low for $REMP_t$.

Table 4 shows the fundamentals sorted in descending order based on in-sample estimate $\hat{\hat{\chi}}$.[20] Only the two real interest rate variables are asymptotically dependent with the exchange rate, as we found before. In addition, the extremal association estimate is relatively high ($\hat{\hat{\chi}}$ > 0.5) for excess M1 balances, stock market declines, increases in the money multiplier, declines in bank deposits and the real exchange rate deviation from trend. Table 4 also displays the in-sample crisis prediction performance of indicators in Column A and B (indicators issue a signal when above the EVT threshold). The two real interest rate variables perform well, calling more than 80% of the crises, with 44% false alarms. The M1 balance, declines in bank deposits and the real exchange rate deviation from trend also have reasonable performance. The other indicators all perform poorly.

We try to reduce the relatively high false alarm rate of the real interest rate indicators (about 44%) by two approaches. 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 and high $\hat{\hat{\chi}}$. The combined indicator has a false alarm rate of only 8%, while calling 2 out of 3 crises correctly (66%).

Second, we calibrate a logistic dependence structure for the exchange rate return and the real interest rate (lagged 7 months) to predict the conditional crisis probability given that the interest rate has crossed its EVT threshold.[21] For the 865 extremes of the real interest rate in sample, the predicted crisis probability ranges from 19.7% to 92.0%, with an average of 35.9%. To reduce the false alarm rate we set two different minimum

[20] Estimation results for the 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).

thresholds for the predicted crisis probability: 25% and 35%, reducing the number of signals by roughly 1/3 and 2/3. With these two thresholds, the number of crises called is 79% and 74%, while the false alarm rate decreases to 34.2% and 18.9%, respectively.

Finally, for comparison, 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 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 also remove variables with estimated coefficient with signs not expected based on theory. The final model includes the following six variables: the real interest rate, M1 balances, the M2 multiplier, bank deposits, international reserves and exports (McFadden $R^2 = 0.11$). We generate predicted crisis probabilities, conditional on the fundamental values, and arbitrarily set the threshold for a crisis signal at 50%.[22] Table 4 shows that with this threshold the probit model calls 91% of the crises, with a false alarm rate of 30%. As a second alternative, we set the probability threshold at 75%: this reduces the false alarm rate to only 9%, while the model still calls 68% of the crises correctly.

5.2. Out-of-sample crisis prediction performance

Table 5 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

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[21] 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.
[22] 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.

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 poorly, with a false alarm rate of 53% and only 8% of crises 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 real interest rate differential signal and the tail dependence model for the real interest rate with a threshold probability of 35% are on the empirical efficient frontier, meaning that these two predictors have the lowest false alarm rate for a given level of crises correctly called.

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 relatively well, the false alarm rate is rather high for risk management purposes.[23] Importantly, though, this information was already available among the in-sample EVT estimation results: the limiting probability of extreme currency depreciations following extreme real interest rate signals is 30% (about 70% false alarms predicted). The information conveyed by the non-parametric EVT tail association measures seems robust, while the traditional approaches show a large discrepancy between in-sample and out-of-sample results.

[23] 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.

We have also compared with the out-of-sample performance of the KLR method, based on setting a signal threshold that minimizes the in-sample noise-to-signal ratio. Out of sample we find that the KLR method does not perform much worse or better than the EVT method, due to the overall poor results for all indicators. What is remarkable, though, is that KLR's in-sample noise-to-signal ratio of the indicators has a correlation of -0.177 with out-of-sample KLR indicator performance: again, a large discrepancy between in-sample and out-of-sample results. On the other hand, the in-sample EVT estimate $\hat{\bar{\chi}}$ has a correlation of +0.474 with out-of-sample KLR indicator performance. Thus, $\hat{\bar{\chi}}$ predicts the out-of-sample performance of the KLR indicators better than the KLR method's own noise-to-signal ratio.

6. Conclusions

In this paper we apply extreme value theory to test whether currency crises are linked with extremes in lagged economic and financial variables. Using monthly data for a cross-section of 46 countries in the period 1974–2008, we first show that nearly all economic fundamentals are asymptotically independent with currency crisis measures. Asymptotic independence means that as the values of the economic indicator become more extreme, the conditional probability of more extreme currency events approaches zero in the limit, casting doubt on whether a causal link exists. 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.

Asymptotic dependence is a concept defined in limit, as events become more and more extreme, and it could be too strict for crisis prediction in practice. We therefore also estimate a measure of extremal association that can be interpreted as the strength of the relation in the tail for pairs of asymptotically independent variables. We assess the value of this measure for predicting currency crises, both in sample and out of sample. We find that in most cases the extremal association between currency crashes and lagged economic fundamentals in the tail is higher than a simple correlation measure (based on all observations) suggests. Moreover, the extremal association measure has a strong link (r = 0.92) with the in-sample crisis prediction performance of economic indicators.

We also evaluate various economic indicators and competing crisis prediction models in an out-of-sample assessment period (1995-2008) in 33 emerging markets. All indicators and models perform poorly out of sample, and much worse than in sample. This especially holds true for approaches that maximize in-sample model fit, like a probit model. Our non-parametric extreme value approach on the other hand clearly indicated that currency crisis measures and most economic fundamentals are not asymptotically dependent in the in-sample period, in line with the poor out-of-sample prediction results. Moreover, the two real interest rate indicators selected by the extreme value method perform better out of sample than alternative models.

Our results show that positive extremes of the two real interest rate variables are potentially useful as warning signals for authorities and risk managers. In the literature, high real interest rates are considered as symptoms that reflect weak economic and financial conditions. The real interest rate on deposits is an indicator associated with issues such as overlending cycles, financial sector problems, liquidity crunch, and a potential cause of future economic recessions. 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

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

Berg, A., Borensztein, E., Pattillo, C., 2005. Assessing early warning systems: How have they worked in practice? IMF Staff Papers 52, 462–502.

Berg, A., Pattillo, C., 1999, Predicting currency crises: The indicators approach and an alternative. Journal of International Money and Finance 18, 561–586.

Breitung, J., 2000. The local power of some unit root tests for panel data, in Baltagi, B. (Ed.), Advances in Econometrics, Vol. 15: Nonstationary Panels, Panel Cointegration, and Dynamic Panels. JAI Press, Amsterdam, 161–178.

Bussière, M., Fratzscher, M., 2006. Towards a new early warning system of financial crises. Journal of International Money and Finance 25, 953–973.

Bussière, M., Saxena, S.C., Tovar, C.E., 2012. Chronicle of currency collapses: Re examining the effects on output. Journal of International Money and Finance 31, 680–708.

Coles, S.G., Heffernan, J., Tawn, J.A., 1999. Dependence measures for extreme value analyses. Extremes 3, 5–38.

Danielsson, J., de Haan, L., Peng, L., de Vries, C.G., 2001. Using a bootstrap method to choose the sample fraction in tail index estimation. Journal of Multivariate Analysis 76, 226–248.

Dupuis, D.J., Tawn, J.A., 2001. Effects of misspecification in bivariate extreme value problems. Extremes 4, 315–330.

Dridi, A., El Ghourabi, M., Limam, M., 2012. On monitoring financial stress index with extreme value theory. Quantitative Finance 12, 329–339.

Eichengreen, B., Rose, A.K., Wyplosz, C., 1996. Contagious currency crises: First tests. Scandinavian Journal of Economics 98, 463–484.

Embrechts, P., McNeill, A. Straumann, D., 2002. Correlation and dependence properties in risk management: Properties and pitfalls, in Dempster, M. (Ed.), Risk Management: Value at Risk and Beyond. Cambridge University Press, Cambridge, 176–223.

Frankel, J.A., Rose, A.K., 1996. Currency crashes in emerging markets: An empirical treatment. Journal of International Economics 41, 351–366.

Furman, J., Stiglitz, J.E., 1998. Economic crises: Evidence and insights from East Asia. World Bank, unpublished report.

Girton, L., Roper, D., 1977. A monetary model of exchange market pressure applied to the postwar Canadian experience. American Economic Review 67, 537−548.

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

Hartmann, P., Straetmans, S., de Vries, C.G., 2004. Asset market linkages in crisis periods. Review of Economics and Statistics 86, 313−326.

Hartmann, P., Straetmans, S., de Vries, C.G., 2010. Heavy tails and currency crises. Journal of Empirical Finance 17, 241−254.

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., de Vries, C.G., 1991. On the frequency of large stock returns: Putting boom and busts into perspective. Review of Economics and Statistics 73, 18−24.

Jondeau, E., Rockinger, M., 2006. The Copula-GARCH model of conditional dependencies: An international stock market application, Journal of International Money and Finance 25, 827-853.

Kaminsky, G.L., 1999. Currency and banking crises: The early warning of distress. IMF Working Paper WP/99/178.

Kaminsky, G.L., 2006. Currency crises: Are they all the same? Journal of International Money and Finance 25, 503−527.

Kaminsky, G.L., Lizondo, S., Reinhart, C.M., 1998. Leading indicators of currency crises, International Monetary Fund Staff Paper 45.

Kaminsky, G.L., Reinhart, C.M., 1998. Financial crises in Asia and Latin America: Then and now. American Economic Review 88, 444−448.

Kaminsky, G.L., Reinhart, C.M., 1999. The twin crises: The causes of banking and balance-of-payments problems. American Economic Review 89, 473−500.

Koedijk, K.G., Stork, P.A., de Vries, C.G., 1992. Differences between foreign exchange rate regimes: The view from the tails. Journal of International Money and Finance 11, 462−473.

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

Kumar, M., Moorthy, U., Perraudin, W., 2003. Predicting emerging market currency crashes. Journal of Empirical Finance 10, 427−454.

Krugman, P., 2010. Crises. Nobel Lecture at the Annual Meeting of the American Economic Association, Atlanta.

Ledford, A., Tawn, J.A., 1996. Statistics for near independence in multivariate extreme values. Biometrika 83, 169−187.

Lin, C.S., Khan, H.A., Chang, R.Y., Wang, Y.C., 2008. A new approach to modeling early warning systems for currency crises: Can a machine-learning fuzzy expert system predict the currency crises effectively? Journal of International Money and Finance 27, 1098–1121.

Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. Journal of Finance 56, 649−676.

Ning, C., 2010. Dependence structure between the equity market and the foreign exchange market–A copula approach. Journal of International Money and Finance 29, 743-759.

Pescatori, A., Sy, A.N.R., 2007. Are debt crises adequately defined? IMF Staff Papers 54, 306–337.

Poon, S., Rockinger, M., Tawn, J., 2004. Extreme-value dependence in financial markets: Diagnostics, models and financial implications. Review of Financial Studies 17, 581−610.

Pozo, S., Amuedo-Dorantes, C., 2003. Statistical distributions and the identification of currency crises. Journal of International Money and Finance 22, 591−609.

Sibuya, M., 1960. Bivariate extreme statistics I. Annals of the Institute of Statistical Mathematics 11, 195−210.

Appendix A. Estimation of tail indices

Consider a stationary sequence $\{X_1, X_2,..., X_n\}$ of independent and identically distributed random values of a variable X with a cumulative distribution function F. Suppose we are interested in the upper tail. Let M_n denote the maximum order statistic among the first n random values of a variable X, i.e.

$$M_n \equiv \max\{X_1, X_2,..., X_n\}. \tag{A1}$$

Analogous to the central limit theorem, extreme value theory provides under some conditions the precise form of the asymptotic distribution of M_n, independent of the data generating process of the variable X:

$$P\{a_n(M_n - b_n) \leq x\} \rightarrow G(x); \text{ as } n \rightarrow \infty, \text{ with} \tag{A2}$$

$$G(x) = \begin{cases} \exp\left(-(1+\gamma((x-\mu)/\sigma))^{-1/\gamma}\right) & \text{for} \quad \gamma \neq 0 \\ \exp(-\exp(-((x-\mu)/\sigma))) & \text{for} \quad \gamma = 0 \end{cases} \tag{A3}$$

where a_n and b_n are appropriate normalizing constants which may depend on the sample size n, $G(x)$ is the cumulative distribution function of the generalized extreme value distribution, and μ, σ (>0) and γ are location, scale and shape parameters, respectively. The parameter γ is the inverse tail index (and $\alpha = 1/\gamma$ is the tail index). It governs the shape of the tail, regardless of the precise form of the underlying distribution *F*.

We estimate γ non-parametically with the Hill estimator. Define the ascending order statistics from a sample of size n as $X_{(1)} \leq X_{(2)} \leq ... \leq X_{(n)}$. The Hill (1975) estimator is

$$\hat{\gamma} = \frac{1}{m}\sum_{i=1}^{m}\left[\log X_{(n+1-i)} / X_{(n-m)}\right], \tag{A4}$$

where $X_{(n-m)}$ is a high threshold such that there are m observations above the threshold. The Hill estimator $\hat{\gamma}$ 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, $X_{(n-m)}$, that 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 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 full implementation details.

Appendix B. Estimation of extremal dependence

The bivariate distribution function $P\{Y > \theta_y, X > \theta_x\}$ consists of two parts, namely the marginal distributions and the dependence structure of X and Y. To estimate the extremal dependence measures $\overline{\chi}$ and χ, we first apply the unit Frechet transformation to normalize X and Y:

$$S = -1/\log F_X(X) \text{ and } T = -1/\log F_Y(Y). \tag{B1}$$

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

Under the condition of regular variation, the joint cumulative distribution function of the Frechet transformed variables S and T can be writen as

$$P(S > s, T > s) \sim L(s)s^{-1/\xi}; s \to \infty, \tag{B2}$$

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,

$$\begin{aligned} P(S > z, T > z) &= P\{\min(S,T) > z\} \\ &= P(Z > z) \\ &= L(z)z^{-1/\xi} \quad \text{for } z > u, \end{aligned} \tag{B3}$$

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. We use the Hill estimator, described in Appendix A, 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 $\overline{\chi}$ is

$$\hat{\overline{\chi}} = 2\hat{\xi} - 1, \tag{B4}$$

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

Using the fact that the Hill estimator follows a normal distribution asymptotically (see Jansen en de Vries, 1991), we then test the null hypothesis $\overline{\chi} = 1$. 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):

$$\hat{\chi} = \frac{m}{n} Z_{(n-m)} \tag{B5}$$

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

The non-parametric estimates $\hat{\bar{\chi}}$ and $\hat{\chi}$ together provide all necessary information regarding the extremal dependence of the pair of variables

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.

$$P\{S \le s; T \le t\} = \exp\left\{-\left(s^{-1/\hat{\tau}} + t^{-1/\hat{\tau}}\right)^{\hat{\tau}}\right\}, \text{ with } \hat{\tau} = \log(2-\hat{\chi})/\log 2. \tag{B6}$$

For asymptotically independent variables we fit the Gaussian dependence structure using the estimate of $\bar{\chi}$, i.e.

$$P\{S \le s; T \le t\} = \Phi_2\left(\Phi^{-1}\{\exp(-1/s)\}, \Phi^{-1}\{\exp(-1/t)\}; \hat{\rho}\right), \text{ with } \hat{\rho} = \hat{\bar{\chi}}. \tag{B7}$$

where Φ_2 is the bivariate standard normal distribution with covariance parameter ρ. Ledford and Tawn (1996) and Dupuis and Tawn (2001) show that the precise form of the dependence model is relatively unimportant given proper estimates of $\bar{\chi}$ and χ.

In estimation practice, as a first step we require a functional form for the univariate distribution functions $F_X(X)$ and $F_Y(Y)$ to transform the marginal distributions to unit Frechet marginals. 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,

$$F_X(x) = \begin{cases} \tilde{F}_X(x) & if \quad x < \theta_x \\ 1 - \{1 - \tilde{F}_X(\theta_x)\}\left(1 + \gamma_x \dfrac{(x-\theta_x)}{\sigma_x}\right)^{-1/\gamma_x} & if \quad x \ge \theta_x \end{cases}. \tag{B8}$$

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.

Table 1 Descriptive statistics of currency crisis measures and economic indicators

Variable	Mean	Median	Std.dev.	Skew	Kurt.	Obs.	l / r tail	Tail index $\hat{\alpha}$	Obs. in the tail	% of total
Currency crisis measures							*Depreciation of currency*			
Exchange rate pressure index, EMP_t	0.17	0.05	1.66	1.1	15.4	14576	r (+)	2.8	151	1.0%
Real exchange rate pressure index, $REMP_t$	-0.02	-0.05	1.45	0.0	18.6	14532	r (+)	3.0	151	1.0%
Exchange rate return (%, monthly), ER_t	1.17	0.04	6.92	16.4	457.9	17092	r (+)	1.3	655	3.8%
Economic fundamentals							*Depreciation signal*			
International reserves (Δ%)	11.31	10.53	36.43	0.0	6.9	15868	l (−)	6.9	24	0.2%
Imports (Δ%)	8.95	9.81	23.08	-0.4	7.6	16233	r (+)	5.4	39	0.2%
Export (Δ%)	9.05	9.62	21.45	-0.5	10.6	16292	l (−)	2.6	230	1.4%
Terms of trade (Δ%)	-0.02	-0.06	13.24	2.4	54.6	4787	l (−)	2.5	111	2.3%
Real exchange rate, (% deviation)	0.43	-0.07	19.48	1.2	11.8	16017	l (−)	6.7	39	0.2%
Real effective exchange rate (Δ%)	-0.95	-0.01	11.58	-2.1	60.5	8416	r (+)	2.3	149	1.8%
Real interest rate (%, monthly)	3.43	0.28	119.45	73.5	6403.7	14821	r (+)	1.0	1203	8.1%
Real interest rate differential (%, monthly)	3.24	0.09	119.34	73.6	6414.4	14847	r (+)	0.9	1203	8.1%
Excess real M1 balances (%)	7.95	2.49	67.92	39.7	2147.7	13964	r (+)	1.6	594	4.3%
M2 multiplier (Δ%)	2.28	2.21	18.33	-0.3	16.0	14668	r (+)	3.9	82	0.6%
Domestic credit to GDP (Δ%)	1.58	1.58	15.93	-0.3	42.0	14434	r (+)	2.6	151	1.0%
Ratio of lending-to-deposit rates	2.48	1.47	11.80	34.4	1389.4	11647	r (+)	1.2	503	4.3%
Real commercial bank deposits (Δ%)	6.10	5.94	15.62	-0.6	29.8	14592	l (−)	5.3	37	0.3%
Ratio of M2 to reserves (Δ%)	-1.34	-0.26	36.34	-0.2	7.6	14838	r (+)	8.8	23	0.2%
Output (Δ%)	3.44	3.64	11.44	0.5	79.7	11817	l (−)	2.2	295	2.5%
Stock market (Δ%)	13.66	14.52	40.58	0.5	16.2	11407	l (−)	5.3	50	0.4%
Total foreign debt (Δ%)	7.58	8.00	19.04	0.2	6.7	7533	r (+)	3.3	62	0.8%
Short term foreign debt ratio (Δ%)	0.21	-0.03	12.16	-0.3	5.5	7533	r (+)	12.2	11	0.1%

The table shows descriptive statistics of the pooled data. *Kurt.*: kurtosis. *l/r tail*: r(+) denotes the right tail and l(-) the left tail of the distribution. The tail index α is estimated with the Hill estimator. *Obs in the tail*: number of observations in the tail over the extreme value threshold.

Table 2 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 18 lagged fundamentals with EMP_t (exchange market pressure index), $REMP_t$ (real EMP), and ER_t (exchange rate return), 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 3 In-sample crisis prediction performance of economic signals

Variable	l / r tail	$\hat{\chi}$	Num. signals	% crises called (A)	% false alarms (B)	(A - B)	$\hat{\chi}$	Num. signals	% crises called (A)	% false alarms (B)	(A - B)
Economic Indicators		EMP_t *(FX market pressure)*					ER_t *(FX rate depreciation)*				
Real interest rate differential (%, monthly)	r (+)	0.365	1122	42.3	74.0	-31.7	1.019	1185	70.1	44.9	25.2
Real interest rate (%, monthly)	r (+)	0.348	1131	36.9	74.4	-37.5	1.000	1195	70.9	41.6	29.3
Real commercial bank deposits (Δ%)	l (–)	0.113	23	0.0	100.0	-100.0	0.669	37	12.3	8.1	4.2
Terms of trade (Δ%)	l (–)	0.323	108	39.4	65.7	-26.3	0.611	109	71.7	49.5	22.1
Excess real M1 balances (%)	r (+)	0.260	524	18.5	77.7	-59.2	0.568	537	45.1	54.2	-9.1
Stock market (Δ%)	l (–)	0.204	39	6.7	71.8	-65.1	0.565	50	14.3	20.0	-5.7
Ratio of M2 to reserves (Δ%)	r (+)	0.293	16	2.3	81.3	-79.0	0.467	23	2.8	52.2	-49.4
M2 multiplier (Δ%)	r (+)	0.153	76	2.4	88.2	-85.8	0.463	77	12.5	57.1	-44.6
International reserves (Δ%)	l (–)	0.262	15	4.4	60.0	-55.6	0.456	24	3.7	12.5	-8.8
Real exchange rate, (% deviation)	l (–)	0.122	19	0.0	94.7	-94.7	0.440	31	6.0	38.7	-32.7
Real effective exchange rate (Δ%)	r (+)	0.245	118	4.5	83.1	-78.5	0.402	147	19.2	49.0	-29.8
Output (Δ%)	l (–)	0.207	203	10.7	82.3	-71.6	0.371	293	25.1	54.9	-29.9
Export (Δ%)	l (–)	0.169	158	12.5	80.4	-67.9	0.278	229	17.8	55.0	-37.2
Domestic credit to GDP (Δ%)	r (+)	0.051	133	4.0	78.2	-74.2	0.202	151	5.3	70.9	-65.6
Imports (Δ%)	r (+)	0.198	33	2.9	78.8	-75.8	0.200	39	3.1	69.2	-66.2
Ratio of lending-to-deposit rates	r (+)	-0.086	414	1.4	99.5	-98.2	0.125	439	6.9	95.0	-88.1
Total foreign debt (Δ%)	r (+)	0.243	59	2.6	84.7	-82.1	0.074	62	1.3	77.4	-76.1
Short term foreign debt ratio (Δ%)	r (+)	0.044	6	0.0	100.0	-100.0	-0.105	11	1.9	90.9	-89.0

The table shows the in-sample crisis prediction performance of the 18 economic fundamentals, for crisis measures EMP_t and ER_t, respectively.
Num. signals: the number of crisis signals issued by the indicator. *% crises called*: 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 4 In-sample tail dependence and crisis prediction: Emerging markets, 1974-1995

Variable	l / r tail	$\hat{\alpha}$	$\hat{\hat{\chi}}$	Lag	Num. signals	% crises called (A)	% false alarms (B)	(A - B)
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
Real interest rate, ***signal 1***	r (+)	1.3	1.105	-7	856	85.0	43.3	41.7
Excess real M1 balances, ***signal 2***	r (+)	0.7	0.713	-12	271	66.6	31.4	35.2
Stock market return	l (−)	19.3	0.562	-8	8	3.0	37.5	-34.5
M2 multiplier (Δ%)	r (+)	2.8	0.558	-8	84	32.2	47.6	-15.4
Real bank deposits (Δ%), ***signal 3***	l (−)	5.0	0.543	-21	34	19.7	5.9	13.8
Real exchange rate deviation, ***signal 4***	l (−)	9.1	0.533	-19	10	8.9	0.0	8.9
Ratio of M2 to reserves (Δ%)	r (+)	8.1	0.393	-22	16	3.0	68.8	-65.7
International reserves (Δ%)	l (−)	7.6	0.335	-8	22	3.8	18.2	-14.4
Ratio of lending-to-deposit rates	r (+)	2.7	0.169	-4	65	10.4	50.8	-40.4
Export (Δ%)	l (−)	5.3	0.157	-7	26	1.8	69.2	-67.4
Imports (Δ%)	r (+)	5.3	0.151	-23	37	4.0	81.1	-77.0
Domestic credit to GDP (Δ%)	r (+)	8.6	0.118	-10	8	0.4	87.5	-87.1
Combined Signals and Probability Models					*In sample performance*			
Signal 1 *and* signal 2, 3 or 4	---	---	---	---	140	65.7	7.9	57.9
Signal 1 *and* crisis probability > 25%	---	---	---	---	617	78.8	34.2	44.6
Signal 1 *and* crisis probability > 35%	---	---	---	---	333	73.4	18.9	54.4
Probit model, with 50% threshold	---	---	---	---	532	90.7	30.3	60.4
Probit model, with 75% threshold	---	---	---	---	170	68.4	8.8	59.6

The table shows crisis prediction performance (crises based on ER_t) of economic indicators with data during the in-sample period 1974-1995, in emerging markets. The performance of combined signals and probit models is also shown. *Num. signals*: the number of crisis signals issued.
% crises called: the percentage of all crises preceded by at least one signal in the preceding 24 months.
% false alarms: the percentage of all fundamental signals not followed by at least one currency crisis in the following 24 months.

Table 5 Out-of-sample crisis prediction performance: Emerging markets, 1995-2008

Variable	Num. signals	% crisis called (A)	% false alarm (B)	(A - B)	Num. signals	% crisis called (A)	% false alarm (B)	(A - B)
Economic Indicators	*In-sample performance*				*Out-of-sample performance*			
Real interest rate differential	850	83.9	44.1	39.8	373	63.1	68.9	-5.8
Real interest rate, ***signal 1***	856	85.0	43.3	41.7	351	57.1	68.1	-10.9
Excess real M1 balances, ***signal 2***	271	66.6	31.4	35.2	343	28.4	84.8	-56.5
Stock market return	8	3.0	37.5	-34.5	47	21.5	40.4	-18.9
M2 multiplier (Δ%)	84	32.2	47.6	-15.4	43	0.0	100.0	-100.0
Real bank deposits (Δ%), ***signal 3***	34	19.7	5.9	13.8	0	0.0	0.0	0.0
Real exchange rate deviation, ***signal 4***	10	8.9	0.0	8.9	25	11.9	52.0	-40.1
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	60	20.3	73.3	-53.1
Signal 1 *and* crisis probability > 25%	617	78.8	34.2	44.6	157	44.0	65.6	-21.6
Signal 1 *and* crisis probability > 35%	333	73.4	18.9	54.4	10	11.9	30.0	-18.1
Probit model, with 50% threshold	532	90.7	30.3	60.4	170	29.7	71.8	-42.1
Probit model, with 75% threshold	170	68.4	8.8	59.6	19	7.8	52.6	-44.8

The last 4 columns of the table show the crisis prediction performance (crises based on ER_t) of economic indicators in the out-of-sample period 1995-2008, in emerging markets. For comparison, the in-sample crisis prediction performance in the period 1974-1995 is shown in column 2 to 5. The prediction performance of combined signals and probit models is also shown. *Num. signals*: the number of crisis signals issued by the indicator. *% 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.

Figure 1 Limiting probability plots

The plots show the conditional crisis 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 ER_t in month t. Panel A: variable X is the lagged increase in imports (month t-23). Panel B: variable X is the lagged real interest rate differential (t-4). Panel C: X is the decrease in real commercial bank deposits (t-4). Panel D: X is the negative stock market return (t-4). The conditional probability P(q) is shown on the y-axis, and the percentile q on the x-axis.

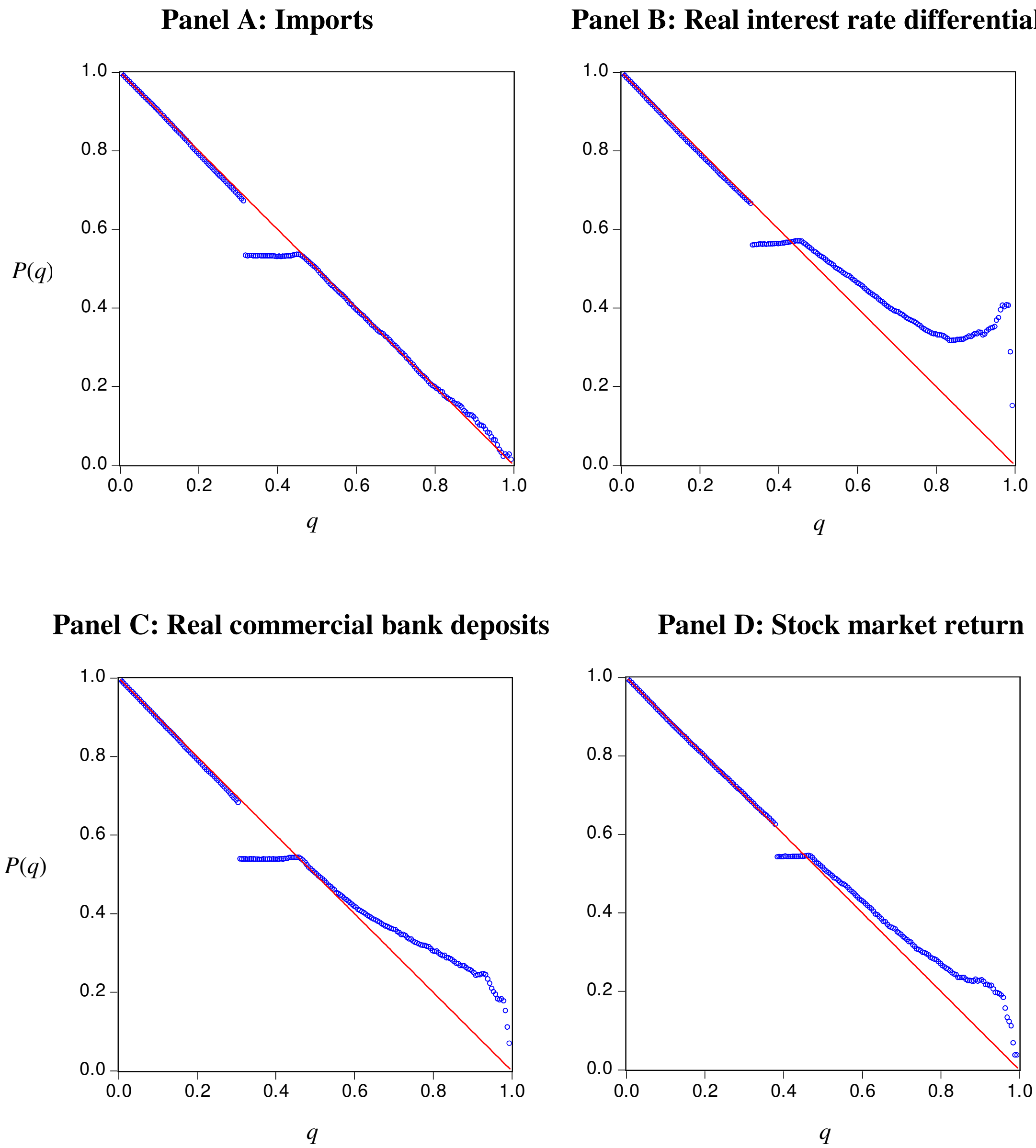


Figure 2 Conditional crisis probability plots

The plots show the conditional currency crisis probability $P^*(q_x) = P(Y > \theta_y \mid X > F_X^{-1}(q_x))$ on the y-axis, as $q_x \rightarrow 1$. In these plots the threshold (percentile) of the exchange rate is fixed at the crisis value θ_y. The percentile q_x of the economic fundamental varies, and is shown on the x-axis. In all plots variable Y is the exchange rate return ER_t in month t. Panel A: variable X is the lagged increase in imports (month t-23). Panel B: variable X is the lagged real interest rate differential (t-4). Panel C: variable X is the decrease in real commercial bank deposits (t-4). Panel D: X is the negative stock market return (t-4). The straight line in all plots is the unconditional crisis probability.

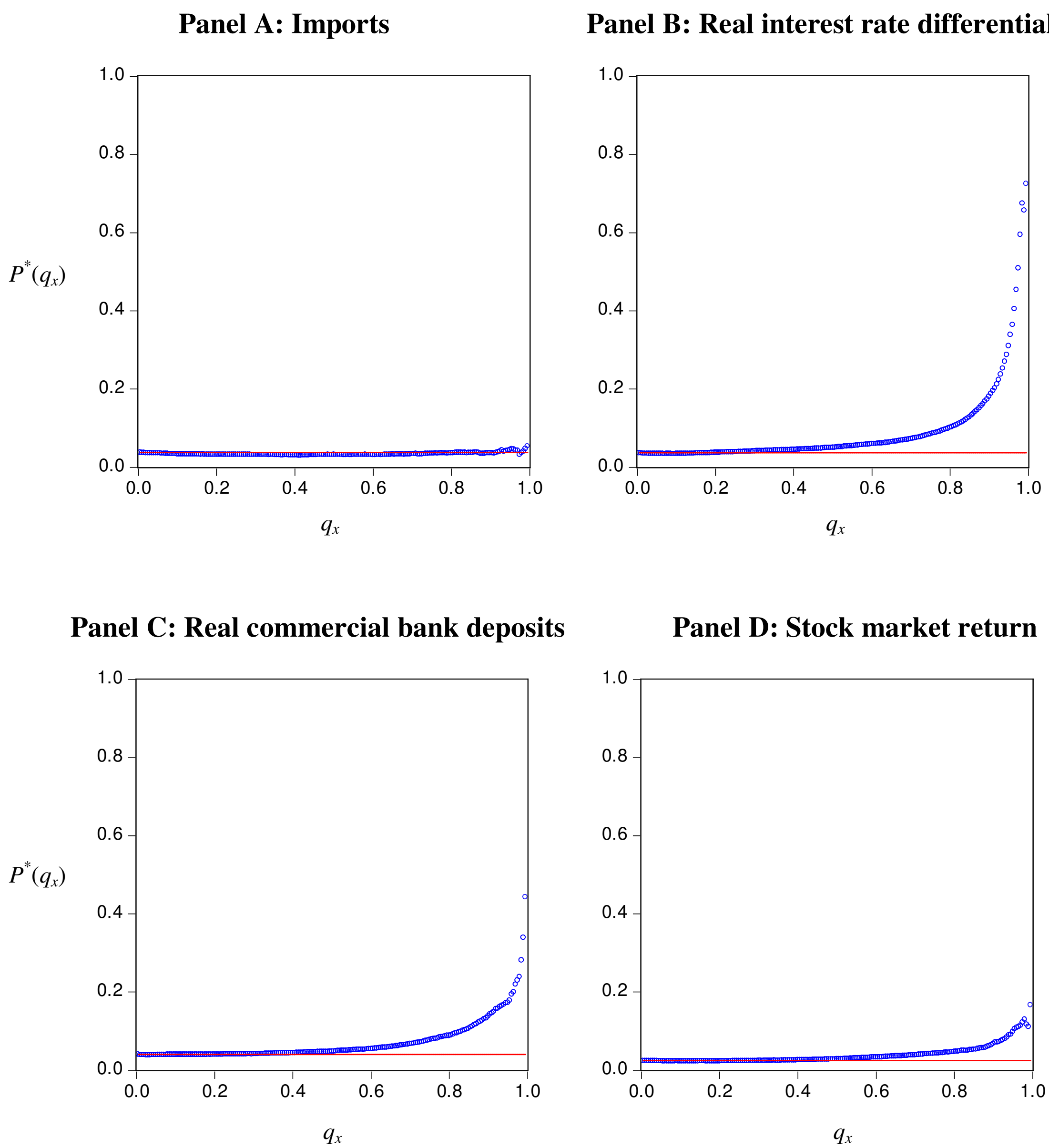


Figure 3 Scatter plot of conditional crisis probability versus estimated extremal association ($\hat{\hat{\chi}}$)

This figure shows a scatter plot of the conditional currency crisis probability $P^*(q_x) = P(Y > \theta_y \mid X > F_X^{-1}(q_x))$ on the y-axis, versus the estimated extremal association measure $\hat{\hat{\chi}}$ with ER_t (exchange rate return) on the x-axis, for each economic indicator. Each marker represents one indicator variable X: the conditional crisis probability $P^*(q_x)$ when X exceeds q_x is shown on the y-axis, and the estimated extremal association $\hat{\hat{\chi}}$ of X with ER_t is on the x-axis. The diamond markers (♦) and the bold quadratic fit line show the conditional crisis probability given that the fundamental variable X is greater than the 95% percentile (q_x = 0.95). The square markers (■) and the dashed fit line are for the 99% percentile (q_x = 0.99), while the triangular markers (▲) and the dotted line are for the 99.5% percentile (q_x = 0.995).

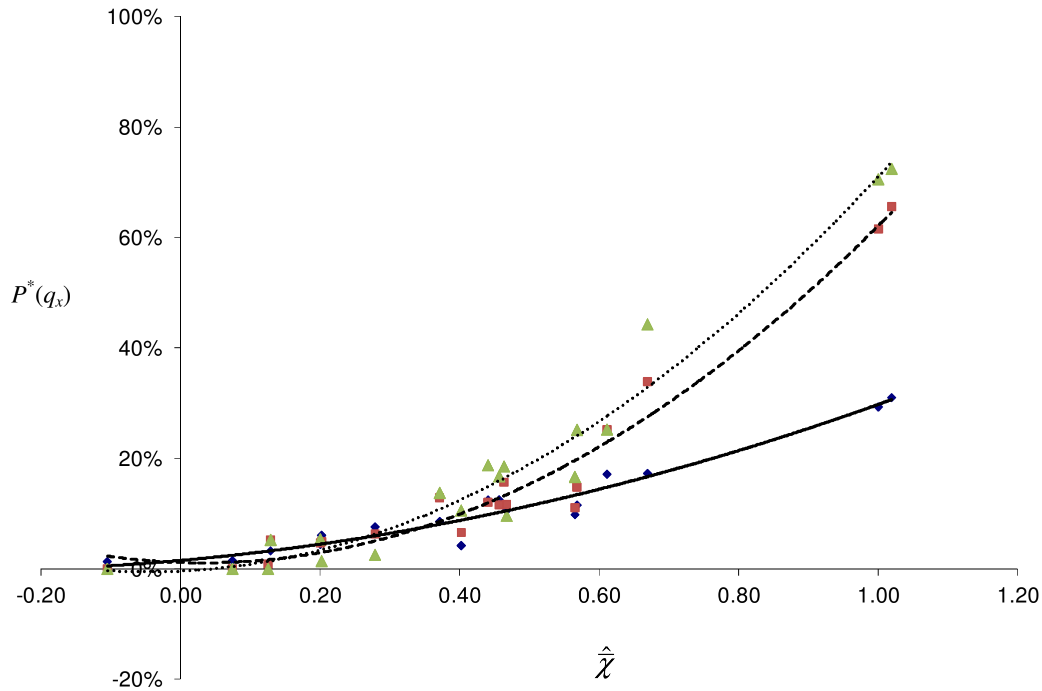
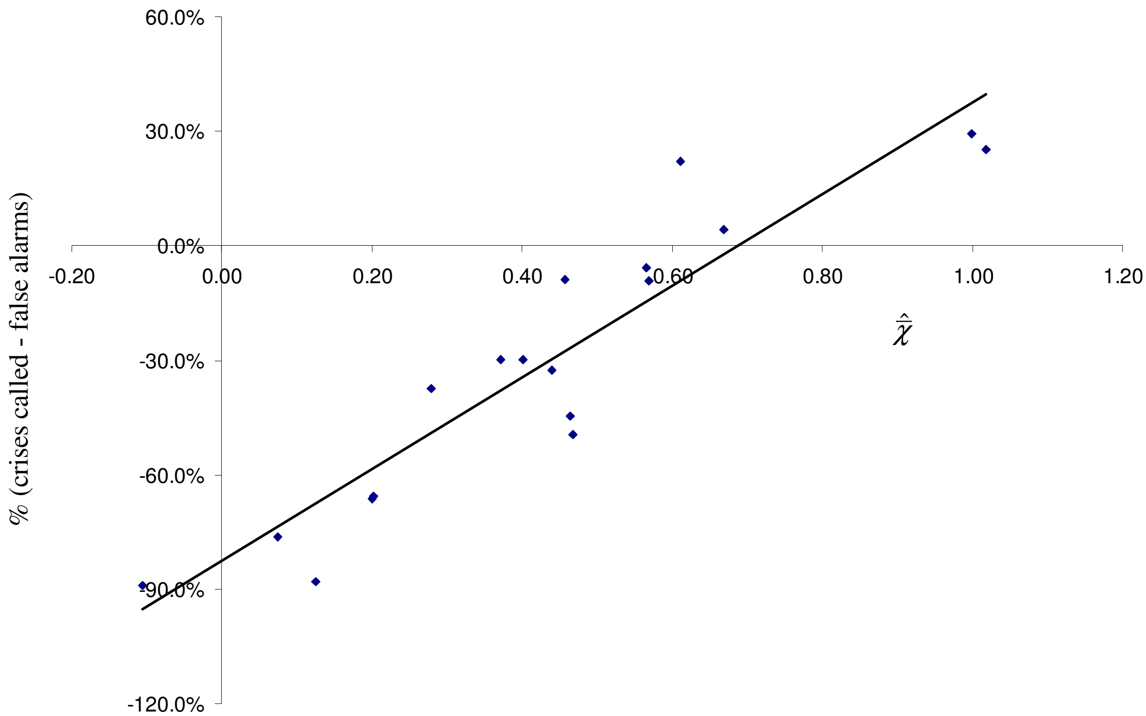


Figure 4 Scatter plot of crises prediction success versus estimated extremal association ($\hat{\hat{\chi}}$)

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 association measure $\hat{\hat{\chi}}$ with ER_t (exchange rate return) on the x-axis, for each economic indicator. Each dot represents one economic indicator variable X: the in-sample crisis prediction performance of the indicator is on the y-axis, while the estimated extremal association $\hat{\hat{\chi}}$ of X with ER_t is on the x-axis.



Web Appendix A. Economic indicators

We examine 18 macroeconomic and financial variables from the literature as potential indicators for predicting currency crises. The economic indicators considered have been used before in Kaminsky, Lizondo and Reinhart (1998), Kaminsky and Reinhart (1998, 1999), and Kaminsky (1999, 2006), amongst others.[24] Below we briefly describe each of the 18 variables, as well as the motivation for selecting them as currency crisis indicators, and we specify the expected relation with the currency crises measures. For details about the definition of each indicator, as well as data sources, we refer to Web Appendix B.[25]

1) International reserves in US dollars

Foreign exchange reserves of the central bank have been used as a capital account indicator in Kaminsky and Reinhart (1998, 1999), and a symptom of sudden stops in Kaminsky (2006). Largely declines in the international reserves may reveal abnormal capital outflows and reduce the credibility of the central bank in maintaining the exchange rate. Thus, a **negative** relationship between the annual percentage change of international reserves and the crisis measures is expected.

2) Imports in US dollars

In Kaminsky and Reinhart (1998, 1999), the value of imports is one of the current account problem indicators. A weak external sector may induce business failures and a decline in the quality of loans. This eventually may lead to vulnerabilities in the banking sector and an economic recession, especially in export-oriented countries. Large positive shocks to imports can be interpreted as a symptom of financial crises.

In Kaminsky (2006), increases in the value of imports are considered as a symptom of the second generation model type of crises. According to the second generation models of currency crises, countercyclical government policies lead to real appreciation of the domestic currency, reduced competitiveness and current account problems. Thus, for the value of imports a **positive** relationship is expected with the currency crisis measures.

3) Exports in US dollars

In Kaminsky and Reinhart (1998, 1999) and Kaminsky (2006), declines in exports signal potential problems in the current account. A weak external sector may eventually trigger an economic slowdown, potentially a banking crisis or a debt crisis, and finally a real economic crisis. Thus, a **negative** relation between the annual growth rate of exports and the crisis measures is expected.

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[24] Kaminsky et al. (1998) summarize indicators used in the literature and consolidate them into categories. Based on the empirical results presented in 17 papers they also show the most successful indicators for each paper individually, as well as a consensus selection of successful indicators based on multiple works.

[25] For all variables we analyze the annual percentage change, except for the deviation of the real exchange rate from trend, the excess real M1 balance and the variables based on interest rates. According to Kaminsky et al. (1998), filtering the data with the 12-month percentage change ensures that the units are comparable across countries and that the transformed variables are stationary, with well-defined moments and free from seasonal effects.

4) Terms of trade

Similar to imports and exports, the terms of trade is an indicator of current account problems and a symptom of the second generation type of currency crises. Terms of trade measures the price of a country's exports in terms of its imports. Kaminsky and Reinhart (1998, 1999) and Kaminsky (2006) expect a **negative** relationship between terms of trade and the currency crisis measures.

5) Real exchange rate

When the domestic currency appreciates in real terms, domestic products become more expensive relative to foreign products. In Kaminsky and Reinhart (1998, 1999) and Kaminsky (2006), excessive real appreciations of the domestic currency indicate misalignment of the domestic currency and loss of competitiveness. These problems eventually induce current account deterioration, a trigger of the second generation crises.

As in Kaminsky et al. (1998), the real exchange rate is defined on a bilateral basis with respect to the German mark for the European countries that experienced the European Monetary System (EMS) crisis, and with respect to the US dollar for all other countries. A decline in the real exchange rate denotes a real appreciation. Thus, the downward deviation of the real exchange rate from its trend measures overvaluation. We expect the relation between the real exchange rate and the crisis measures to be **negative**.

6) Real effective exchange rate

For countries that the data permits, we also examine the annual rate of change of the real effective exchange rate, a trade-weighted average of a basket of foreign currencies. As these rates are quoted indirectly, we expect a **positive** relationship between the real effective rate and the currency crisis measures.

7) Domestic real interest rate

In Kaminsky and Reinhart (1998, 1999), the real interest rate on deposits is an indicator associated with financial liberalization. It is used to capture overlending cycles. An increase in the real interest rate may signal possible financial sector problems. In Kaminsky (2006), following the second generation crisis models, a high real interest rate resulting from contradictory government policies may lead to an economic recession. Kaminsky (1999) states that high real interest rates can be a sign of a liquidity crunch leading to economic slowdown and banking fragility. Thus, for the domestic real interest rate a **positive** relationship is expected.

8) Real interest rate differential

In Kaminsky and Reinhart (1998, 1999), the domestic-foreign real interest rate differential is used as a capital account indicator. A rise in the real interest rate differential signals future problems in the capital account, as it may reflect a heightened risk premium for holding domestic currency assets. While maintaining capital inflows, the high real interest rate differential, especially at the time of high world interest rates, may cause an economic recession and the burst of asset price bubbles that often precede financial crises. Hence, a **positive** relationship is expected.

9) Excess real M1 balances

The variable "excess real M1 balances" is used as a financial indicator in Kaminsky and Reinhart (1998, 1999) to capture loose monetary policy. In Kaminsky (2006), the variable is considered as a symptom of the first generation currency crisis in which the fiscal budget deficit is largely monetized. In Kaminsky (1999), expansionary monetary policy is likely to fuel currency crises and can cause banking crises. Thus, a **positive** relationship between the variable and the crisis measures is expected.

10) M2 multiplier

The M2 multiplier, defined as the ratio of M2 to the monetary base, is another variable used to signal overlending problems due to financial liberalization, see Kaminsky and Reinhart (1998, 1999). Rapid growth in the money multiplier, which might be influenced by liberalization of the domestic financial system, is considered in Kaminsky (2006) as one of the reasons for the third generation currency crises caused by financial excesses. The relationship between the annual rate of change of the M2 multiplier and the currency crisis measures is expected to be **positive**.

11) Domestic credit to GDP

The ratio of domestic credit to GDP (in real terms) is an indicator with similar role as the M2 multiplier. It is used to capture excessive credit expansion within a country compared to the country's own national income or production, which is a main cause of asset price bubbles and banking fragility. Like the M2 multiplier, a **positive** relationship to the currency crisis measures is expected for domestic credit to GDP.

12) Ratio of lending to deposit interest rates

The ratio of lending to deposit interest rates is used to capture problems caused by overlending and financial liberalization in Kaminsky and Reinhart (1998, 1999). In Kaminsky (1999) an increase in the lending-to-deposit ratio signals a decline in the quality of loans, which may make the banking sector more vulnerable to shocks in the future. A **positive** relationship between the lending-to-deposit ratio and the crisis measures is, therefore, anticipated.

13) Real commercial bank deposits

In Kaminsky and Reinhart (1998, 1999) deposits at commercial banks are used as a financial indicator to assess whether there are bank runs that often precede banking and currency crises. In Kaminsky (2006), bank runs are considered as a symptom of the third generation currency crises. Abnormal declines in the stock of commercial bank deposits in real terms may indicate bank runs and raise the probability of a currency crisis. Thus, a **negative** relationship is expected.

14) M2 to international reserves

The ratio of M2 (in US dollars) to international reserves in US dollars is used in Kaminsky and Reinhart (1998, 1999) as a financial indicator to assess to what extent the liabilities of the banking system are backed up by international reserves. The higher the ratio of M2 to international reserves, the lower the ability of the central bank to manage the exchange rate and to meet the demand of people trying convert their domestic currency deposits into foreign currency in the event of currency turmoil.

In Kaminsky (1999) this variable is an indicator of capital account problems, while it is also associated with third generation currency crises in Kaminsky (2006). Rapid growth in credit is likely to raise the ratio of M2 to international reserves and lower the credibility of the central bank in maintaining the value of domestic currency, which may result in capital outflows and speculative attacks. A **positive** relationship is expected.

15) Output

In Kaminsky and Reinhart (1998, 1999), output is a real sector indicator of economic recessions that often precede financial crises. In Kaminsky (2006) the variable is considered as a symptom of the second generation type of currency crises, in which countercyclical policies lead to overvaluation of the domestic currency and/or high real interest rates that are followed by losses in competitiveness and recession. A **negative** relationship between economic growth and the currency crisis measures is anticipated.

16) Stock market index

In Kaminsky and Reinhart (1998, 1999), an index of stock prices in US dollars is used as an indicator of fragility in the real sector. Declines in stock prices may indicate ongoing or expected economic slowdown, whereas stock market crashes signal impending crises. In Kaminsky (2006) stock prices are used as a monitor of third generation currency crises, in which financial excesses fuel asset price bubbles. The burst of an asset price bubble may lead to other types of financial crises. A **negative** relationship is, thus, expected.

17) Total foreign debt

In Kaminsky (1999, 2006) total foreign debt has been used as a signal for potential capital account problems. A large increase in foreign debt may raise issues with debt refinancing in the future. If the debt burden is suspected to be unsustainable, it may lead to capital flight and capital account problems. Therefore, the relationship between the annual rate of change of total foreign debt and the currency crisis measures is expected to be **positive**.

18) Short-term foreign debt ratio

The ratio of short-term foreign debt to total foreign debt is also employed in Kaminsky (1999, 2006) as an indicator of capital account problems. Concentration on short-term foreign debt increases the chance of maturity mismatches, especially in the banking industry, and raises the vulnerability of an economy to external shocks. The relationship between the annual rate of change of the ratio and the currency crisis measures is expected to be **positive**.

Web Appendix B. Data sources and time series construction

The data used in this paper are monthly observations from 48 countries, including Germany and the US as the reference countries, from the IMF International Financial Statistics (IFS). Observations are from January 1974 to March 2008, depending on availability. However, there are some exceptions. For European countries that are considered relative to Germany, observations are only available until December 1998. To obtain monthly real GDP series, we interpolate quarterly GDP data when available, or otherwise annual GDP (IFS line: 99). For stock market indices, the total return data are from S&P/IFC when available, and MSCI otherwise. The data for short-term foreign debt and total foreign debt are from BIS.

For the three currency crisis measures, we generally use the exchange rate from IFS line: AE. The international reserves (in US$) are from IFS line: 1L.D. The monetary aggregate M2 is a sum of IFS lines: 34 and 35, except for some countries, e.g., the UK, IFS line: 59 is applied. For the short-term interest rate, we mostly use the deposit interest rate (IFS line: 60L). If not available, our choice would be the money market rate (IFS line: 60B) or the bank (discount) rate (IFS line: 60), respectively. The consumer price index (IFS line: 64) is used for the price level. For some countries the CPI is not available, e.g. Ireland, and then we use the producer price index (IFS line: 63).

For the 18 economic fundamentals, the data sources and the construction of the series are explained below.

1) International reserves in US dollars

If INR_t (IFS line: 1L.D) is the monthly international reserves (in US$) at time t for the country in consideration, the annual percentage change of international reserves at time t can be defined as

$$\Delta INR_{t,12} = \ln INR_t - \ln INR_{t-12}. \qquad \text{(A1)}$$

2) Imports in US dollars

If IM_t (IFS line: 71) is the monthly import value (in US$) at time t of the country in consideration, its annual growth rate at time t is

$$\Delta IM_{t,12} = \ln IM_t - \ln IM_{t-12}. \qquad \text{(A2)}$$

3) Exports in US dollars

If EX_t (IFS line: 70) is the monthly value of exports (in US$) at time t of the country in consideration, its annual growth rate at time t is

$$\Delta EX_{t,12} = \ln EX_t - \ln EX_{t-12}. \qquad \text{(A3)}$$

4) Terms of trade

Terms of trade at time *t* (TOT_t) is defined as the unit value of exports (IFS line: 74) over the unit value of imports (IFS line: 75), i.e.

$$TOT_t = \frac{\text{unit value of exports at time t}}{\text{unit value of imports at time t}}.$$

The annual rate of change of the terms of trade at time *t* is

$$\Delta TOT_{t,12} = \ln TOT_t - \ln TOT_{t-12}. \text{------------------ (A4)}$$

5) Real exchange rate

Real exchange rate q_t is derived from a nominal exchange rate s_t and the consumer price indices at home p_t and abroad p^*_t (IFS line: 64). In equation,

$$q_t = \ln s_t + \ln p^*_t - \ln p_t.$$

For most countries, s_t denotes the spot exchange rate at time *t*, quoted as the price of a US dollar in terms of domestic currency (IFS line: AE), while p^*_t is the US consumer price index (CPI). For European countries that experienced the EMS crisis, s_t is the price of a German mark in terms of domestic currency, while p^*_t is the German CPI.

The real exchange rate q_t measures the relative price of foreign products (in domestic currency) to the price of domestic products. A decline in the real exchange rate denotes a real appreciation. It implies that the domestic products become relatively more expensive.

For each country, the deviation of the real exchange rate from a deterministic time trend denoted ε_t can be derived from the ordinary least squares estimation of the real exchange rate q_t on a constant c and a time trend $@trend$, i.e. $q_t = ls(c, @trend) + \varepsilon_t$. Therefore,

$$\varepsilon_t = q_t - ls(c, @trend),$$

where $ls(\bullet)$ is an ordinary least squared estimate.

The deviation of the real exchange rate from trend in percentage terms $q(trend)_t$ is

$$q(trend)_t = \frac{\varepsilon_t}{ls(c, @trend)}. \text{---------------------------- (A5)}$$

6) Real effective exchange rate

For countries that the data permits, we also examine the annual rate of change of the real effective exchange rate, based on a trade-weighted basket of currencies. If q^*_t (IFS line: REC or REU) is the monthly real effective exchange rate, its annual rate of change is defined as

$$\Delta q^*_t = \ln q^*_t - \ln q^*_{t-12} \text{ .------------------------------ (A6)}$$

7) Domestic real interest rate

From the monthly deposit interest rate at time t i_t (IFS line: 60L divided by 1200) and the consumer price index at time t p_t (IFS line: 64), the real interest rate at time t r_t is derived from

$$r_t = i_t - \Delta p_{t+1}, \text{-- (A7)}$$

where $\Delta p_{t+1} = \ln p_{t+1} - \ln p_t$. Note that i_t, r_t and Δp_{t+1} are the levels of the monthly rates expressed in percentage points and cover from time t to $t+1$.

8) Real interest rate differential

The domestic-foreign real interest rate differential at time t is

$$\tilde{r}_t = r_t - r^*_t, \text{--- (A8)}$$

where the foreign real interest rate r^*_t is defined as in equation (A7). In most countries, the US is treated as a foreign country. However, for the European countries that participated in the EMS crisis Germany is a foreign reference country.

9) Excess real M1 balances

Excess real money balances are the residuals from a real money demand equation. The real money demand, i.e. M1 denoted by M^1_t (IFS line: 34) deflated by consumer price index P_t (IFS line: 64), is estimated as a function of real GDP Y_t (interpolated IFS line: 99), domestic consumer price inflation $\Delta P_{t,12}$ (the annual rate of change of consumer price index (IFS line: 64)) and a time trend ($@\,trend$).[26]

For each country, we estimate the regression equation

$$\ln M^1_t - \ln P_t = ls(c, \ln Y_t, \Delta P_{t,12}, @\,trend) + \xi_t,$$

where c is a constant term and $ls(\bullet)$ is an ordinary least squared estimate. The residual ξ_t represents excess real M1 balances EM_t, i.e.

$$EM_t = \xi_t \text{.---(A9)}$$

It measures the percentage point difference between actual M1 in real terms and its estimated demand.

[26] As stated in Kaminsky (1999), domestic inflation was used instead of nominal interest rates, as the observations on market-determined interest rates were often incomplete, while the time trend is used as a proxy for financial innovations and/or currency substitution.

10) M2 multiplier

M2 multiplier at time t mm_t is the ratio of M2 at time t M_t (IFS lines: 34+35) to monetary base at time t MB_t (IFS line: 14), i.e.

$$mm_t = \frac{M_t}{MB_t}.$$

The annual growth rate of the M2 multiplier at time *t* is

$$\Delta mm_{t,12} = \ln mm_t - \ln mm_{t-12}. \text{-----------------------} \quad (A10)$$

11) Domestic credit to GDP

Domestic credit to GDP is derived from the ratio of domestic credit in real terms at time t DC_t, which is the nominal domestic credit (IFS line: 52) deflated using consumer price index (IFS line: 64), to real GDP at time t Y_t (interpolated IFS line: 99). Its annual rate of change at time *t* is then

$$\Delta(DC/Y)_{t,12} = \Delta DC_{t,12} - \Delta Y_{t,12}, \text{----------------} \quad (A11)$$

where $\Delta DC_{t,12} = \ln DC_t - \ln DC_{t-12}$ and $\Delta Y_{t,12} = \ln Y_t - \ln Y_{t-12}$.

12) Lending to deposit interest rates

The lending-to-deposit ratio at time t LD_t for the country in consideration is a monthly domestic lending interest rate at time t $i^L{}_t$ (IFS line: 60P divided by 1200) divided by a monthly domestic deposit interest rate at time t i_t (IFS line: 60L divided by 1200), i.e.

$$LD_t = \frac{i^L{}_t}{i_t}. \text{---} \quad (A12)$$

13) Real commercial bank deposits

Real commercial bank deposits at time t B_t is commercial bank deposits (in national currency) at time *t* (IFS line: 24+25) divided by consumer price index at time t P_t (IFS line: 64). The annual growth rate of the stock of bank deposits in real terms at time t $\Delta B_{t,12}$ is then

$$\Delta B_{t,12} = \ln B_t - \ln B_{t-12}. \text{-----------------------------} \quad (A13)$$

14) M2 to international reserves

The ratio of M2 to international reserves is M2 in national currency (IFS line: 34+35) converted into US dollars (using IFS line: AE) divided by international reserves in US dollars (IFS line: 1L.D). Suppose $M^{US\$}{}_t$ is the domestic money supply M2 in US dollars and INR_t denotes international reserves in US dollars. The annual growth rate of the ratio $MINR_t$, which is equal to $M^{US\$}{}_t / INR_t$, is

$$\Delta MINR_{t,12} = \ln MINR_t - \ln MINR_{t-12}. \text{-------------- (A14)}$$

15) Output

The measure of output is industrial production (IFS line: 66), if the data is available. For countries that the data on industrial production is not available, we use the data on manufacturing production (IFS line: 66EY). The annual growth rate of industrial or manufacturing production X_t at time *t* is

$$\Delta X_{t,12} = \ln X_t - \ln X_{t-12}. \text{-------------- (A15)}$$

16) Stock market index

IFC global indices are used as a measure for total stock returns in US dollars, when available, and we use MSCI total return indices otherwise. Suppose H_t is the monthly stock price index (total return index, including dividends) at time *t* for the country in consideration, the annual log-return of the stock price index is

$$\Delta H_{t,12} = \ln H_t - \ln H_{t-12}. \text{------------------------ (A16)}$$

17) Total foreign debt

Suppose TD_t represents total foreign debt, measured as total liabilities of domestic residents to BIS reporting banks, the annual rate of change of the stock of foreign debts is

$$\Delta TD_{t,12} = \ln TD_t - \ln TD_{t-12}. \text{------------------------ (A17)}$$

18) Short-term foreign debt ratio

If SD_t is the short-term foreign debt ratio, which is liabilities of domestic residents to BIS reporting banks with maturities up to one year divided by total liabilities of domestic residents to BIS reporting banks, its annual rate of change is

$$\Delta SD_{t,12} = \ln SD_t - \ln SD_{t-12}. \text{------------------------ (A18)}$$

Web Appendix C. Threshold selection methods

In this web appendix we provide details regarding the selection of the threshold $X_{(n-m)}$, separating extreme events from regular observations and determining the number of observations m used to estimate the tail index α. Using too few observations may enlarge the variance of the estimate, while using too many observations can reduce the variance at the expense of biasedness when non-tail observations are included. We have applied two methods for selecting *m*: the simulation method of Jansen and de Vries (1991) and the bootstrap technique of Danielsson, de Haan, Peng and de Vries (2001).

Gomes and Oliveira (2001) analyze the performance of the subsample bootstrap technique of Danielsson et al. (2001). Gomes and Oliveira (2001, p. 344) note that the method of Danielsson et al. (2001) sometimes led to non-admissible values of *m* in their simulation tests (for example, values of *m* less than 1). To mitigate this problem Gomes and Oliveira (2001) propose two auxiliary statistics that can be used to construct alternative, but asymptotically equivalent, estimators of the optimal threshold *m*. We have implemented these two alternative estimators, in addition to the original bootstrap estimator of Danielsson et al. (2001). We use 5,000 bootstrap replications. Apart from the number of bootstrap resamples, the method has one other free parameter that has to be set in advance: the bootstrap resample size n_1. We follow Gomes and Oliveira (2001, p. 347) who use the choice $n_1 = n^{0.95}$, where n is the sample size of the time series. To assess the sensitivity of our results to the choice of n_1, we also repeat the bootstrap procedure with sub-sample size $n_1 = n^{0.925}$ and $n_1 = n^{0.975}$.

For the three exchange rate crisis measures (EMP_t, $REMP_t$ and ER_t) we find that the bootstrap method using the 1st auxiliary statistic defined in Gomes and Oliveira (2001) gives robust estimates of the threshold number of observations *m*. The thresholds based on two other statistics, the 2nd auxiliary statistics in Gomes and Oliveira (2001) and the original statistic from Danielsson et al. (2001), have more problems with convergence and sensitivity to the sub-sample size n_1 for our data.

As part of the estimation of the bi-variate tail dependence measures χ and $\bar{\chi}$ we need to determine the extreme value threshold m and inverse tail index γ of a series that is the minimum of two variables, both Frechet transformed. The estimation process needs to be repeated at 24 different time-lags (number of months that the signal precedes the exchange rate measure), for the 18 macro-economic signal variables. Unfortunately, in this setting none of the three alternative implementations of the bootstrap method delivered robust results consistently. To try to increase robustness, we chose three resample sizes n_1 covering a much wider range ($n_1 = n^{0.75}$, $n_1 = n^{0.85}$ and $n_1 = n^{0.95}$) and then took the median of the three resulting threshold values *m*. As still none of the three implementations of the bootstrap method consistently performed well, we finally took the median of the three estimates across methods.

We also implemented a Monte Carlo simulation method, following Jansen and de Vries (1991) and Longin and Solnik (2001). The idea is to simulate a large number of random samples of size n from a given distribution function with known tail index value α and then to calculate the threshold number of observations m that minimizes the mean squared error (MSE) of the Hill estimator $\hat{\gamma}$ for the inverse tail index $\gamma = 1/\alpha$. The MSE is estimated by the average squared error, $(\hat{\gamma} - \gamma)^2$, over all simulated samples at a given threshold level m. This results in a series of simulated MSE values $MSE(m)$, as a function of the chosen threshold value m. The optimal threshold value m^* is selected by minimizing $MSE(m)$ over m.

This simulation procedure is repeated for several distributions with different levels of tail thickness, for example a Student t-distribution with k degrees of freedom for $k = 1$ through $k = 10$. As a result, we can construct a table with a series of inverse tail indices $\gamma(j)$ ranging from large to small for $j = 1, 2, \ldots, J$ in the 1st column (for example, $\gamma(1) = 1$, $\gamma(2) = 1/2$, …, $\gamma(10) = 1/10$) and the corresponding optimal number of tail observations $m^*(j)$ in the 2nd column. Obviously, the optimal number of tail observations $m^*(j)$ decreases monotonically as $\gamma(j)$ gets smaller, that is, as the tail of the distribution gets thinner.

To determine the tail threshold for a given actual time series of length n, we proceed by estimating the inverse tail index γ with the Hill estimator, repeating the estimation J times using the threshold levels $m^*(j)$, for $j = 1, 2, \ldots, J$. This results in a series of J Hill estimates: $\hat{\gamma}(j)$, for $j = 1, 2, \ldots, J$. Finally, we set the optimal threshold m^{**} by selecting the Hill estimate for the observed time series that is closest to the corresponding tail index of the theoretical distribution: we find the j value that minimizes the squared error $(\hat{\gamma}(j) - \gamma(j))^2$, and select the corresponding $m^*(j)$ value as the optimal threshold m^{**} for the observed series.[27]

When selecting the tail threshold for the exchange rate indices and economic variables with the Monte Carlo simulation method procedure, the distributions employed are as follows (in decreasing order based on tail thickness): an inverted chi-square distribution with $\alpha = 0.5$, an inverted chi-square distribution with $\alpha = 0.75$ and Student t-distributions with degrees of freedom k equal to k = 1, 1.5, 2, 2.5, 3, 4, 5, 6, 8 and 12. Note that for a Student t-distribution the tail index α equals k. As an example, Table C.1 displays the optimal threshold values $m^*(j)$ that minimized the MSE for these distributions at a sample size of n = 14,550 (similar to the pooled sample size of the monthly exchange rate pressure time series). We used 100,000 simulation replications to estimate the MSE.

As part of the estimation of the bi-variate tail dependence measures χ and $\bar{\chi}$ we need to estimate the extreme value threshold m and the inverse tail index γ of a series that is the minimum of two positive variables (both Frechet transformed). We apply the simulation method to find the optimal threshold values $m^*(j)$ for the following distributions: an inverted chi-square distribution with α equal to 1, 1.111, 1.25, 1.429, 1.667, 2, 3, 4, 5 and 10 (corresponding to γ equal to 1, 0.9, 0.8, 0.7, 0.6, 0.5, 0.333, 0.25, 0.2 and 0.1). We prefer an inverse chi-square distribution over a Student t-distribution for this

[27] Longin and Solnik (2001) divide the difference ($\hat{\gamma}(j) - \gamma(j)$) by the standard error of the estimate $\hat{\gamma}(j)$ and transform the resulting z-statistic to a p-value with the cumulative normal distribution. They select m^{**} by maximizing the p-value (over $j = 1, 2, \ldots, J$). We initially followed this approach, but we found that the standard error of $\hat{\gamma}(j)$ sometimes becomes very large at the smallest threshold value $m^*(J)$. This then leads the p-value criterion to select $m^{**} = m^*(J)$, solely due to the large standard error, even though the corresponding difference ($\hat{\gamma}(J) - \gamma(J)$) may be very large compared to other j values. We circumvent this problem by minimizing $(\hat{\gamma}(j) - \gamma(j))^2$, without considering the standard error.

application, as the minimum of the two Frechet transformed variables is always positive and skewed heavily to the right, resembling a non-negative chi-square distribution more closely than a *t*-distribution. Further, we also have a clear rationale for choosing this particular set of γ values, as the inverse tail index γ of the minimum series is related to $\overline{\chi}$ as follows: $\overline{\chi} = 2\gamma - 1$, with $0 < \gamma \leq 1$. Theoretically γ has an upper bound of 1, corresponding to the case of asymptotic dependence ($\overline{\chi} = 1$). Further, as we will be testing for positive asymptotic dependence (economic signal variables with an expected negative relation with the depreciation side of the exchange rate will be multiplied by -1 before the analysis), we expect $\overline{\chi} > 0$ and hence $1/2 < \gamma \leq 1$. Therefore the distributions chosen for the Monte Carlo simulation were selected to have a relatively fine-grained grid of values $\gamma(j)$ in the area $1/2 < \gamma \leq 1$, while also having some values $\gamma(j)$ <1/2 for cases with potential negative extremal association ($\overline{\chi} < 0$).

As an example, Table C.2 displays the optimal threshold values $m^*(j)$ that minimize the MSE for the chosen distributions at a sample size of n = 14,000 (similar to the pooled sample size of the bivariate distribution of the exchange rate series and the real interest rate indicator). We used 100,000 simulation replications to estimate the MSE.

Web Appendix D. Identification of currency crisis episodes

We estimate 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. The threshold separating extreme events from regular observations, determined with the Jansen and de Vries (1991) method, is equal to 9.6%. In the out-of-sample period 87 monthly exchange rate returns are over the threshold and identified as extreme events (1.75% of 4975 observations). After bundling together all extremes in a country that occur within 12 months of each other, we identify 37 currency crises. Table D.1 shows the countries, the first and the last month of each currency crisis, and the number of extremes in each episode.

The EVT methodology identifies the following well-known currency crises out-of-sample: the Asian crisis in 1997, Russia in 1998, Brazil in 1999, Ecuador in 2000, Turkey in 2001 and 2002, and Argentina in 2002. Other crises correctly identified in Table D.1 occurred in Brazil and Uruguay in the summer of 2002, following the severe currency crisis in neighboring Argentina. The crisis identified in Ecuador in 2000 is also 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 problems, identified by two episodes in Table D.1.

Mexico experienced two extreme currency events according to Table D.1, 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 D.1 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.[28] Hungary experienced severe currency turmoil in June 2003, the result of a string of speculative attacks.[29] Other events identified in Table D.1 are the result of adjustments of the official exchange rate regime or large devaluations: the floating of the Pakistani rupee in May

[28] 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/

[29] 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

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 D.1 also contains a number of extreme depreciations of floating currencies that were 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 in May 2006, Colombia in August 2007, Indonesia in April 2001, Pakistan in September 2000, Pakistan in June 2002, South Africa in May 2003, South Africa in May 2005 and Turkey in May 2006.

We 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 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 D.1 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 in 2002, Brazil in 2002, Indonesia in 2002, Mexico in 1995, Mexico in 1998, Pakistan in 1999 and in 2000, and the Philippines in 2002. Remarkably, the KLR methodology does not identify a currency crisis in Argentina in 2002, nor in Brazil in 2002.

The KLR methodology also identifies a number of currency crises that our EVT approach does not detect: Colombia in 1998-1999, Colombia in 2002, Singapore in 1997-1998, Sri Lanka in 1998 and South Africa in 1996. Colombia 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.

References for web appendices

Beckmann, D., Menkhoff, L., Sawischlewski, K., 2006. Robust lessons about practical early warning systems. Journal of Policy Modeling 28, 163−193.

Danielsson, J., de Haan, L., Peng, L., de Vries, C.G., 2001. Using a bootstrap method to choose the sample fraction in tail index estimation. Journal of Multivariate Analysis 76, 226−248.

Gomes, M.I., Oliveira, O., 2001. The bootstrap methodology in statistics of extremes – Choice of the optimal sample fraction. Extremes 4, 331−358.

Jansen, D.W., de Vries, C.G., 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., 1999. Currency and banking crises: The early warning of distress. IMF Working Paper WP/99/178.

Kaminsky, G.L., 2006. Currency crises: Are they all the same? Journal of International Money and Finance 25, 503−527.

Kaminsky, G.L., Lizondo, S., Reinhart, C.M., 1998. Leading indicators of currency crises, IMF Staff Paper 45.

Kaminsky, G.L., Reinhart, C.M., 1998. Financial crises in Asia and Latin America: Then and now. American Economic Review 88, 444−448.

Kaminsky, G.L., Reinhart, C.M., 1999. The twin crises: The causes of banking and balance-of-payments problems. American Economic Review 89, 473−500.

Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. Journal of Finance 56, 649−676.

Reinhart, C.M., Rogoff, K.S., 2009. The aftermath of financial crises. American Economic Review 99, 466−472.

Table C.1 Optimal threshold values

j	*distribution*	$\alpha(j)$	$\gamma(j)$	$m^*(j)$	$m^*(j) / n$
1	*inverted chi-square*	0.500	2.000	3174	0.218
2	*inverted chi-square*	0.750	1.333	1823	0.125
3	*t-distribution*	1.000	1.000	1152	0.079
4	*t-distribution*	1.500	0.667	601	0.041
5	*t-distribution*	2.000	0.500	349	0.024
6	*t-distribution*	2.500	0.400	224	0.015
7	*t-distribution*	3.000	0.333	151	0.010
8	*t-distribution*	4.000	0.250	82	0.006
9	*t-distribution*	5.000	0.200	53	0.004
10	*t-distribution*	6.000	0.167	37	0.003
11	*t-distribution*	8.000	0.125	24	0.002
12	*t-distribution*	12.000	0.083	12	0.001

Note: the table displays the optimal threshold values $m^*(j)$ that minimize the mean square error (MSE) for the distributions shows in column 2, with tail index given in column 3, using the simulation method of Jansen and de Vries (1991). The sample size is n = 14,550. MSE is estimated with 100,000 simulation replications.

Table C.2 Optimal threshold values

j	*distribution*	$\alpha(j)$	$\gamma(j)$	$m^*(j)$	$m^*(j) / n$
1	*inverted chi-square*	1.000	1.000	1159	0.083
2	*inverted chi-square*	1.111	0.900	953	0.068
3	*inverted chi-square*	1.250	0.800	755	0.054
4	*inverted chi-square*	1.429	0.700	560	0.040
5	*inverted chi-square*	1.667	0.600	425	0.030
6	*inverted chi-square*	2.000	0.500	325	0.023
7	*inverted chi-square*	3.000	0.333	165	0.012
8	*inverted chi-square*	4.000	0.250	103	0.007
9	*inverted chi-square*	5.000	0.200	71	0.005
10	*inverted chi-square*	10.000	0.100	33	0.002

Note: the table displays the optimal threshold values $m^*(j)$ that minimize the mean square error (MSE) for the distributions shows in column 2, with tail index given in column 3, using the simulation method of Jansen and de Vries (1991). The sample size is n = 14,000. MSE is estimated with 100,000 simulation replications.

Table D.1 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 crisis in the out-of-sample period July-1995 until Feb-2008 by the EVT approach. Column 4 indicates whether this country and 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.