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An alternative view of exchange market pressure episodes in emerging Europe: an analysis using Extreme Value Theory (EVT)

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Abstract

Using extreme value theory tools, we demonstrate that the distributions of the exchange market pressure (EMP) series for most of twelve emerging Europe countries have heavy tails, and disregarding their tail properties may lead to substantial underestimation of the probability of tail events. Using an extreme-value-based EMP crisis definition leads to a different set of crisis determinants compared to a definition based on standard errors. The probability of extreme EMP periods in our sample is affected by global risk aversion, regional contagion, the level of international reserves, foreign direct investment, history of past crises and accumulated domestic credit and real exchange rate related imbalances.

JEL classification: C10, E44, F37, F32, G01

Keywords: Currency crisis, Contagion, Exchange market pressure, Extreme value theory, Macroeconomic imbalances

Non-technical summary

Although several of the central and eastern European (CEE) countries have experienced foreign exchange crises in the 1990s, associated with substantial output and living standard costs, these episodes and their causes have rarely been studied in detail. This paper investigates extreme exchange market pressure (EMP) periods and the role played by various macroeconomic imbalances and cross-country contagion, devoting explicit attention to the tail characteristics of the exchange market pressure index when defining crisis episodes. We use an exchange market pressure index which includes the change in the nominal exchange rate, the main policy rate and the change in international reserves. This way, we are also able to capture crisis episodes that can be characterised as failed attacks against the currencies of CEE countries[1].

As crisis episodes for individual countries are rare events, their prediction is challenging, especially since standard estimation results may be biased if the series follow a distribution very different from normal. Identification of the explanatory factors can also be difficult, as some imbalances may build up for a long time, implying that in a boom period also the markets' assessment (e.g. measures of risk premia) tends to be a poor guide to the probability of emergence of a crisis.

The empirical literature has found that exchange market pressure indices, similarly to other financial time series, tend to be heavy tailed. This means that relatively large mass is concentrated in the tails of their distribution. As a result, the probability of 'extreme' currency moves is higher than under the normal distribution (Koedijk et al., 1990, Garita and Zhou 2009). Our investigation supports the finding that the Exchange Market Pressure indices of most CEE economies in the period 1995-2011 have heavy tails.

The method for analysing the extreme observations (tail events) applied in this paper is based on extreme value theory, which allows approximating the tails by a general distribution. The analysis of the tail behaviour of the series is particularly relevant for analysing extreme events, and enables aprecise determination of currency crisis episodes. In a large part of the literature on currency crises (e.g. Eichengreen et al. 1994, Girton and Roper 1977), crisis episodes are identified by selecting observations higher than a number of standard deviations. This assumes that the empirical distribution analysed is of a certain type, identical across countries, and that the observations corresponding to the top percentages of the distribution (i.e. the most extreme observations) can be conveniently derived from the distribution's standard deviation. For series with heavy tails, this approach can lead to a considerable underestimation of the probability of extreme events. By a more precise assessment of the probability of extreme events (and the magnitude of the extreme events of a certain probability), extreme value analysis contributes to designing more realistic scenarios for macro stress-testing and constructing early warning systems for currency crises.

The paper defines crisis events in the foreign exchange markets by using extreme value theory to estimate the tails of the distribution of EMP series. Overall, the results confirm that defining crisis episodes according to the true tail behaviour of the data has benefits compared to a method when crisis observations are defined with a certain standard deviation based threshold. In particular, it appears that the estimation based on standard errors fails to identify some key determinants of exchange market pressure periods that are significant with the EV-based thresholds, including the credit to GDP ratio and the deviation of the real exchange rate from its trend.

Turning to the explanatory factors of currency crises, the results suggest that a range of macroeconomic fundamentals and cross-country contagion from crisis events in other countries are relevant determinants of the probability of crisis episodes. These factors tend to influence the probability of exchange rate crises with different time lags. For instance, a sharp

[1] The CEE countries considered are Bulgaria, Croatia, the Czech Republic, Estonia (in the period before euro adoption), Latvia (in the period before euro adoption), Lithuania (in the period before euro adoption), Hungary, Poland, Romania, Russian Federation, Slovakia (in the period before euro adoption) and Turkey.

increase in global risk aversion (captured by the VIX index) and crises in other countries from the region can be predictors of an almost imminent crisis. Similarly, a decline in the international reserves may signal liquidity pressures which can result in an exchange rate crisis in a relatively short time. Other imbalances (e.g. excessive credit growth, real exchange rate overvaluation) may accumulate for prolonged periods before a crisis materializes. Identifying early such imbalances can give time to implement policies that may help their correction. Finally, countries that have experienced a currency crisis may face a higher chance of going through another shock in the near future.This isbecause they may remain vulnerable after a crisis for a while. Even if they follow the "right policies" to correct the imbalances that caused the crisis, the adjustment may take a long time.

In conclusion, this paper provides evidence that a careful analysis of the tail behavior of the empirical distributions by Extreme Value Theory (EVT) methods may improve our understanding of the foreign exchange crises, and that such technique may have a place in the toolbox of economists looking for more accurate models for designing early warning models to assess the risk of foreign exchange crises.

1. Introduction

Several of the central and eastern European (CEE) countries have experienced foreign exchange crises since the 1990s, yet these episodes and their causes have rarely been studied in detail[2]. The goal of this paper is to investigate the determinants of these crises, devoting attention to some distributional characteristics of the exchange market pressure periods in the CEE countries and to their macroeconomic determinants.

Foreign exchange crises are usually defined in a narrow sense as a sizeable, fast depreciation of the exchange rate. Alternatively, crisis episodes may mean situations when the high pressure on the exchange rate triggers a large increase in the domestic interest rate and/or a drop in international reserves. In this paper we use this broader definition which also includes crisis episodes that can be characterised as failed attacks against the currency. Therefore, the main variable of interest in our analysis is the exchange market pressure (EMP) index[3], which is a combination of the change in the nominal exchange rate, the main policy rate and the change in international reserves.

Foreign exchange crises tend to have very high output costs and significant detrimental impact on the living standards of the population. This makes it very important to analyse the factors that may lead to a currency crisis. At the same time, crisis episodes for most individual countries are rare events, and hence their analysis and prediction is very challenging. Moreover, various imbalances may build up for a long time, implying that in a boom period also the markets' assessment (e.g. measures of risk premia) tends to be a poor guide.

Recently, the literature on currency crises has addressed the distribution characteristics of exchange rate returns or exchange market pressure series. In particular, a consensus is emerging that these series follow a distribution with fat tails, similarly to other speculative time series (Garita and Zhou 2009, Pozo and Amuedo-Dorantes 2003, Koedijk and Kool 1992). Nevertheless, there are significant differences in the literature about how to identify the crisis episodes.

Most of the earlier literature on currency crises identifies crisis episodes by selecting observations for which an exchange market pressure measure exceeds a multiple of its standard deviation (e.g. Kaminsky et al. 1998, Eichengreen et al. 1994). However, a newer strand of literature is relying on extreme value theory methods that give more realistic estimates of the probability of tail events. Compared to the latter approach, the standard deviation threshold based method has serious drawbacks. In particular, it imposes certain assumptions about the distribution of the variable, such as a certain relationship between the

[2] One of the few exceptions is Van Poeck et al. (2007)

[3] Exchange market pressure indices were introduced by Girton and Roper (1977).

standard deviation and the percentiles of the distribution, as well as identical distribution across countries, if a uniform threshold is applied. In case the empirical distribution deviates substantially from the assumed one, the estimated probability of crisis episodes will be imprecise. Therefore, defining crisis events calls for a method taking into account the series' specific distribution characteristics in the tail and avoiding the imposition of an a priori assumption. Such a method is tail estimation using Extreme value theory. It has been applied to various financial series, to real output and inflation (Cechetti 2006 and Gochoco-Bautista 2008), but also to exchange rate returns and the exchange market pressure index for emerging markets (Pointines and Siregar 2004, Pozo and Amuedo-Dorantes 2003). It can substantially change the results and give a more realistic assessment of the probability and expected impact of tail events (e.g. Gochoco-Bautista, 2008). This way, extreme value analysis can also contribute to improving the scenarios for macro stress-testing and early warning systems for currency crises.

Extreme value theory has also been used for the formulation of a new class of measures for exchange pressure contagion between countries, reflecting the link between countries' exchange rates in the tails periods through estimating the probability of joint occurrence of crisis in two countries). Hartmann et al. (2010) and Garita and Zhou (2009) have introduced straightforward, count-based measures of cross-country tail dependence. The current paper follows Garita and Zhou's method for quantifying cross-country contagion.

The analysis in this paper is divided into two parts. In the first part (Section 2), we examine the distributions of the monthly exchange market pressure index of 12 CEE countries, namely Bulgaria, Croatia, the Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Russian Federation, Slovakia[4] and Turkey for the period January 1995 – June 2011. This part concentrates on determining tail distributions with tools used by extreme value theory. We also compare the tail behaviour of the empirical distribution across countries with the tail behaviour of some known distributions and construct individual country tail predictions for high-percentile EMP events.

In the second part (Section 3), we investigate the determinants of the crisis episodes (using the tail event definition from Section 2) devoting attention to the role of macroeconomic and financial vulnerabilities, but also accounting for the possibility of regional contagion defined via the estimated probabilities for joint occurrence of extreme EMP values in the pairs of countries from our sample. The paper also performs a systematic comparison of the extreme value-based and the standard error-based crisis thresholds and finds that the results are clearly different with the two methods. Finally, Section 4 summarizes the results of the empirical investigation and concludes.

2. The tail behavior of exchange market pressure (EMP) periods in the CEE countries

2.1 Extreme value theory and its tools

Extreme value theory is a powerful tool for investigating the behaviour of the high quantiles of time series by approximating the tail behaviour. The method originated in structural engineering and natural science, but has been also applied to financial (e.g. Le Baron and Samanta, 2004) and macroeconomic series, including exchange rate returns (Pozo and Amuedo-Dorantes 2003, Garita and Zhou 2009), GDP and inflation (Cechetti 2006, Gochoco and Bautista 2008). While a detailed overview of extreme value theory is beyond the scope of this paper, the general idea and some key concepts used are briefly and non-rigorously introduced here[5].

[4] For Slovakia and the Baltic countries the period covered is the period before these countries adopted the euro.

[5] Comprehensive works on the theoretical aspects of extreme value theory include De Haan and Ferreira (2006), Embrechts et al. (1997), Jansen and de Vries (1991). A practical overview of the Matlab-based toolbox for EV analysis (EVIM) is included Gencay et al. (2002) and Gencay and Selcuk (2003).

Extreme value theory has been applied in economics and finance following the evidence that the empirical distributions of financial time series (such as returns of financial assets and currencies) have fat tails. Previous methodologies attempting to circumvent the problem had disadvantages: for instances, if non-nested distributions are used as proxies, then the resulting estimates are strongly dependent on the maintained specific hypothesis (Koedijk et al., 1990). Extreme value theory offers a way around by approximating the behaviour of the high quantiles of different distributions with a limiting distribution (or rather, one of three limiting distributions) namely the generalized Pareto distribution (GPD). Extreme value theory uses the so-called peaks-over-thresholds method, i.e. investigates only the extreme observations above a high threshold instead of fitting a distribution for all observations[6]. The parameters of the GPD distribution are the shape parameter ξ, which is also a measure of tail heaviness[7], a scale parameter and the threshold itself (the cut-off point) for the tail[8]. With these parameters, the fitted GPD distribution can then be used to construct tail predictions, including also for points beyond the most extreme point empirically observed. , Beyond the simpler implementation and comparability, this is another big advantage of using extreme value methods (Koedijk and Kool, 1992).

For estimation of the key parameters of the EMP indices' distributions we opted for a maximum likelihood estimation strategy instead of merely relying on simple visual tools. For the detection of fat tails in time series, a set of visual tools is sometimes used, such as the quantile-quantile (Q-Q) plot and the mean excess plot (e.g. Gencay et al. 2003). For estimating the tail index, a frequently used tool is the so-called Hill estimator, which is a weighted statistics of the exceedances above a high threshold in the tail of the series (see Appendix A). This method however has a limitation: it is only valid if the distribution is known a priori to have a heavy tail or a positive shape parameter (de Haan and Ferreira, 2006). When it is challenging to formulate a prior regarding the sign of the tail index, maximum likelihood is the preferred method for determining the three parameters of the GPD distribution (Garita and Zhou 2009, McNeil 1997)[9]. As we first need to establish whether the EMP series have heavy tails, we use maximum likelihood estimation for simultaneous estimation of both the shape parameter and the threshold[10]. As the results for the other patrameters depend quite heavily on the choice of the threshold value, we compare our threshold value against the estimated ones for exchange rates and EMP series from the literature[11].

An important question is whether to pool countries for the estimation or to use country-by-country estimation. Data is usually pooled across countries to increase the number of observations and robustness, especially for low-frequency data like GDP. We follow both approaches: while for the probit estimation in the second part we use a panel in order to increase robustness, in the tail diagnostics we concentrate on individual countries and cross-country differences to better capture cross-country differences. The sample size per country (about 195 time observations, from January 1995 to June 2011) is comparable to that used for extreme value analysis of exchange rates in other studies (e.g. in Koedijk and Kool (1992)).

The extreme value literature has also addressed the issue of dependence of two or more series in the tails, which may be very different from their correlation around the average

[6] A limit law of the distribution of maxima (the Fischer-Tipett theorem) postulates that the observations beyond high thresholds converge asymptotically to GPD (in one of its three functional forms) as the threshold increases, provided that the probability distribution function belongs to the domain of attraction of GPD (de Haan and Ferreira 2006).

[7] Alternatively to the shape parameter, the so-called tail index $\alpha = 1/\xi$ is used as well.

[8] The threshold is crucial as the shape parameter (and hence the heaviness of the tails) strongly depends on it. Due to this strong dependence, the tail index is often estimated for a number of thresholds.

[9] An approach sometimes used in the literature is to approximate the empirical distribution of the data with a specific heavy-tailed distribution with well-known properties (usually from the class of the student's t-distributions) and use the latter for predictions in the tail (e.g. Cechetti 2006).

[10] Both for the visual tools and the parametric estimation, we use EVIM- a Matlab toolbox specially developed for implementing extreme value analysis by Gencay and Selcuk (2002)

[11] These are usually obtained by Monte-Carlo simulations. Examples are Jansen and de Vries (1991), and Koedijk et al. (1990), where the latter study considers time series with approximately the same number of observations.

values. In the context of currency crises, the dependence between countries' exchange rates during a crisis may be higher from that in "normal times". One key element of the mechanism involved may be the portfolio rebalancing by investors (Garita and Zhou 2009). Investors often form expectations about a crisis in a certain region on the basis of past and current crises in their other investment regions, and react with changing the portfolio composition, which may artificially increase the relationship between countries in crisis periods, or even create dependencies among countries/regions which are unrelated by fundamentals. For measuring tail dependence, Hartmann et al. (2010) develop a simple count-based estimator for bivariate dependence, and show that when the univariate distributions have heavy tails, a collapse in the returns of one currency may lead to a collapse of other currencies, if the given currency is highly tail-dependent with it. Garita and Zhou (2009) use a similar measure, called cumulative probability of joint failure, to determine EMP tail dependence and hence the probability of simultaneous occurrence of EMP crises in two countries of a region (or between two regions). The dependence is given by the following ratio:

$$CPJF_{i,j} = \frac{\sum_t Crisis_{it} Crisis_{jt}}{\sum_t Crisis_{it} + \sum_t Crisis_{jt} - \sum_t Crisis_{it} Crisis_{jt}}$$

This correlation measure takes values between 0 and 1, with values close to zero indicating very low probability of joint failure and those close to 1 – a high probability, i.e. signalling that crises of the two countries tend to coincide. The bilateral correlation measures for all couples of countries, i.e. the strength of their linkage in crisis times, serve as weights in the weighting matrix used in constructing the extreme value-based contagion measure (similarly to Garita and Zhou 2009). This way, the contagion measure is actually a weighted count of the countries in the region which are experiencing an EMP crisis at a given time:

$$C_{it}(Crisis) = \sum_{i \neq j} CPJF_{ij} Crisis_{jt}$$

$Crisis_{jt}$ is an indicator variable taking a value of 1 if country j is experiencing crisis in period j and 0 otherwise.

2.2. The exchange market pressure index

The main variable of interest, the EMP index, is calculated from monthly IMF IFS data on international reserves (*IR*), the money market interest rate (*R)* and the nominal exchange rate (*ER).*

$$EMP_{i,t} = \gamma_1 \left(\frac{ER_{i,t} - ER_{i,t-1}}{ER_{i,t-1}} \right) + \gamma_2 \left(\overline{IR}_{i,t} - \overline{IR}_{i,t-1} \right) - \gamma_3 \left(\frac{R_{i,t} - R_{i,t-1}}{R_{i,t-1}} \right) \quad (1)$$

The international reserve data is corrected for loans obtained by international organizations (IMF and "other international institutions" as listed in the IFS database) in order to avoid underestimating the exchange market pressure in the episodes when it is absorbed mainly by decreasing international reserves (Bussiere 2009.)[12]

An important issue is the choice of the appropriate weighting scheme for the three underlying series. We apply equal weights for the individual components of the EMP index (similarly to Aizenman 2010) which implies $\gamma_1 = \gamma_2 = \gamma_3 = 1$. In most papers, precision

[12] As the only data systematically available across countries and time with sufficient frequency is the IFS data for the IMF loans, we use these series for adjusting the international reserves data.

weights (inversely proportional to the variances of components) are used in order to prevent the more volatile components from dominating the index value (e.g. Girton and Roper 1997, Eichengreen et al. 1994). However, this approach has been criticized on several grounds, including the argument that the precision weighting scheme lacks an economic interpretation and that it can generate downward biases in the case of attacks on pegged currencies (Li et al., 2006). In addition, the precision weights tend to equalize the overall volatility of EMP index not only across components but also across countries, which eliminates the effects of cross-country differences in volatility (e.g. when estimating the effect of country-specific imbalances in a pooled sample). Aizenman (2010) and Li et al. (2006) use equal weights, which are recommended as an optimal approach reflecting our ignorance on the correct weighting scheme (Li et al. 2006). Principal components have also been suggested for the EMP index calculation (Pentecost et al. 2001), where the weights are determined endogenously to optimally summarize the information contained in the underlying variables, rather than imposing arbitrary weights. In this paper EMP series derived by principal components is used as a robustness check, and it is quite reassuring that the main results, also the country-specific ones, are very similar with the two methods.

2.3 The distributional properties of the EMP series

Simple statistical tests clearly suggest that the monthly EMP index series of most CEE countries are not normally distributed. The basic descriptive statistics and Jarque-Bera normality tests on the EMP index in Table 1 shows that the null hypothesis of normality is rejected with very high level of confidence (above 99%) in all cases. The values of the main moments of the statistical distribution are similar to those estimated by Pozo and Amuedo-Dorantes (2003) for a range of Asian and Latin American emerging economies.

Table 1. Descriptive statistics of the EMP distribution across countries

Country	St. deviation	Skewness	Kurtosis	JB normality
Bulgaria	1.06	2.67	30.80	6580 ***
Czech Republic	1.15	1.82	20.19	2534 ***
Croatia	1.15	0.28	4.61	24 ***
Estonia	1.10	0.23	14.71	1093 ***
Hungary	1.06	1.04	9.87	423 ***
Latvia	1.12	-2.37	23.85	6101 ***
Lithuania	1.12	0.80	15.28	1259 ***
Poland	1.06	-0.65	4.30	28 ***
Romania	1.13	2.99	22.05	3271 ***
Russia	1.17	6.73	74.14	41933 ***
Slovakia	1.20	-0.92	5.76	48 ***
Turkey	1.12	1.77	33.97	7979 ***

Note: Three asterisks denote the rejection of the Jarque-Bera null hypothesis at the 99% level.

The visual tools (such as the country Q-Q plots) suggest that most countries have heavy tails of various degrees. As our main interest is in the episodes with high positive values of the EMP index, the analysis only concentrates on the *right tail* of the distribution. The Q-Q plot (Chart C1 in Appendix C), is concave for Bulgaria, the Czech Republic, Romania, Russia and Turkey, signalling fat tailed distribution. For the rest of the countries, the Q-Q plots are closer to linear.

The maximum likelihood estimates, of the generalized Pareto distributions for every country point to heavy tailed distributions in most cases. To handle the problematic task of selecting the tail cut-off points, we use the procedure employed in Pozo and Amuedo-

Dorantes (2003): GPD is repeatedly fit and the shape parameter-estimated for a range of tail cut-off points, choosing the cut-off value from the stable segment of the shape parameter plot. The results (see Table 2)[13] are in line with the findings of earlier studies on EMP of emerging markets, such as Haile and Pozo (1997) or Garita and Zhou (2009). For most countries (except for Poland, Croatia and Slovakia) the positive value of the shape parameter suggests the presence of a heavy tail . The highest values of ξ are observed for Russia, Turkey, Bulgaria and the Czech Republic – countries which have experienced full-blown currency crises in the sample period. The values for Russia and Turkey exceed 0.5, suggesting a heavier tail than would be the case under the Student's t distribution with 2 degrees of freedom[14], for which the second moment of the distribution is not finite.[15] In contrast, for Poland, Slovakia and Croatia, there is no evidence for heavy tails in the EMP empirical distribution, as the estimated shape parameters are close to 0 or negative.

Table 2. Parameters of the estimated GPD distributions by country, estimated by extreme value methods

	Estimated shape parameter	Estimated tail index	Number of exceedances	Total observations	Percent in tail
Bulgaria	0.45	2.22	15	196	7.65
Czech Republic	0.49	2.06	30	197	15.23
Croatia	0.13	7.69	25	195	12.82
Estonia	-0.20	-	20	195	-
Hungary	0.32	3.13	25	160	15.63
Latvia	-0.11	-	15	195	-
Lithuania	0.46	2.17	15	195	7.69
Poland	-0.02	-	10	195	-
Romania	0.91	1.10	20	195	10.26
Russia	0.69	1.46	25	195	12.82
Slovakia	-0.02	-	15	105	-
Turkey	0.79	1.27	30	195	15.38

Note: Columns 1 and 2 present the estimated shape parameter (ξ) and the respective tail index (α), determined by the fitted GPD distribution. The third column lists the tail cut-off points, determined as described above by the stable portion of the shape parameter plot. Column 4 lists the total number of observations available for each country, and column 5 lists the percentage of the sample in the right tail. A tail index is not calculated for series where the estimated shape parameter is negative.

Based on the estimated tail distribution, Chart C3 shows plots of the estimated tails for five countries with different degrees of tail-heaviness: Turkey and Russia with very heavy tailed distributions, Romania and Latvia as intermediate cases and Poland as a case without evidence for fat tails. In the latter cases, the tail decays much faster, with fewer extreme values spreading far from the mean.

Using the estimated GPD distribution, which is closest to the empirical distribution for each country, we can predict the value which corresponds to the 95th percentile. In order to

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[13] The EVIM toolbox provides estimates for all three parameters: the threshold, the scale and shape parameters, although only two of them are reported in Table 2. All three parameters are also used for fitting the high quantiles of the distribution.

[14] Distributions of the class of the Student's t can be approximated by a GPD distribution with number of degrees of freedom *equal to 1/* ξ.

[15] In our analysis, the parametrically estimated ξ is subject to another robustness check, not reported here for brevity: the empirical distribution is plotted together with the estimated GPD distribution in a Q-Q plot, expecting that the dependence shows a straight line.

apply the binary choice framework, we assign a crisis indicator equal to 1 if the observation falls in this 5% tail, and 0 otherwise. While relying on a binary choice model strategy provides us with the benefits of a well-developed methodology and straightforward interpretation, we also recognize some shortcomings such as the loss of information when mapping continuous data into binary values.

The crisis indicator also serves as an input in constructing the extreme value-based contagion measure. The estimated matrix of bilateral tail dependence among the countries in the sample is reproduced in Table C3 (Appendix C). According to this measure, the degree of tail-dependence between most countries is generally low over the sample considered, with only a group of three countries (Hungary, the Czech Republic and Poland) characterized by bilateral tail dependencies larger than 0.2.

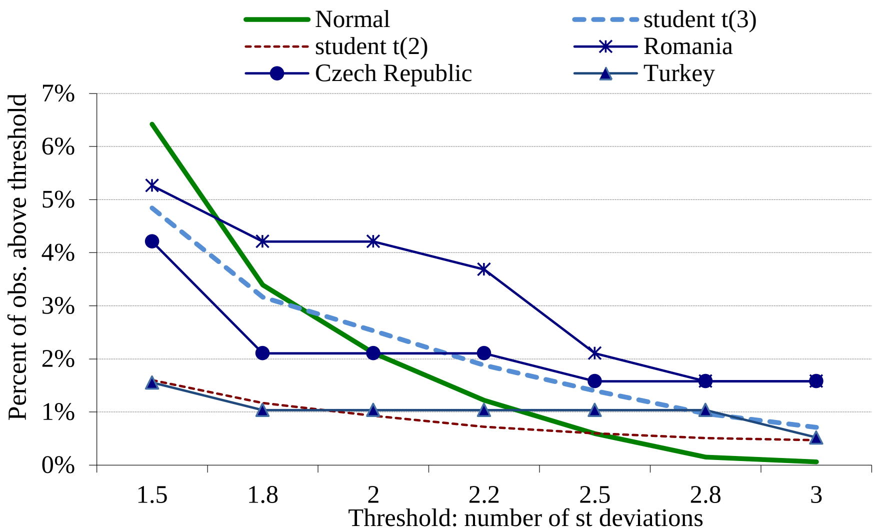
2.4 Prediction at the tails - a comparison of EVT with the standard error-based threshold

In order to illustrate the difference that extreme value-based methods make in identification of crisis periods, we perform a value-at-risk-type analysis similarly to e.g. Cechetti (2006), where he refers to the methodology as "GDP at risk" and "inflation at risk" depending on the variable analyzed. He demonstrates that imposing a standard deviation threshold on macroeconomic series like GDP or inflation would underestimate the probability of extreme events of a given magnitude, and also underestimate the expected magnitude of an event corresponding to a given tail probability. The first error is equivalent to an overly optimistic projections regarding crisis probability, the second one can lead to an underestimation of the economic consequences of a tail event. This section illustrates briefly these issues using the EMP variable; more details are provided in Appendix B.

The method of determining extreme events by using a certain number of standard deviations can be misleading if the empirical distribution is very different from the assumed one. . While in the case of normally distributed series, high percentiles can be conveniently calculated by using the known mapping between percentiles and standard deviations (e.g. the 95^{th} percentile corresponds to 1.64σ), under a different distribution, the standard error-based threshold would correspond to a different percentile of the distribution, with the size and sign of the bias depending on the actual distribution and the number of standard errors. For instance, as shown in Appendix B, a high σ-threshold applied to heavy-tailed distribution may assign more observations to the tail than applied to a thin-tailed one, as the heavy-tailed one has more data points spreading far from the mean and the tail decays slower.

The tail behavior of the empirical distributions for three of our countries indeed resembles more the theoretical heavy-tailed distributions (e.g. student's t) than the normal distribution. For instance, for Romania, even at a threshold of 3σ, about 1.8% of the observations are still larger than the threshold, which suggests quite heavy tailed distribution; and for Turkey the tail's decay is similar to a Student's t (2) distribution.

Chart 1. Percentages of tail observations under alternative thresholds – a comparison of theoretical distributions and country EMP data



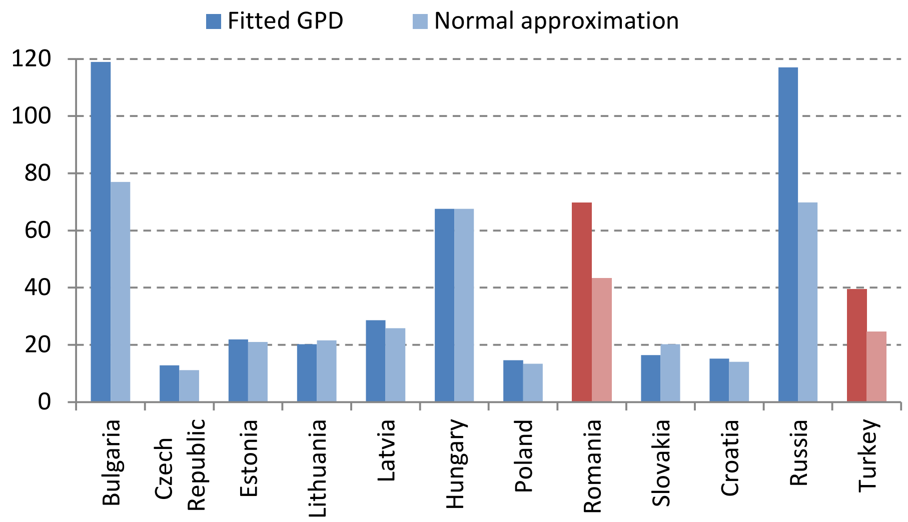
Note: The plain green line corresponds to the normal distribution, the blue and brown dotted lines to the Student's t-distribution with 3 and 2 degrees of freedom, respectively. The three lines with markers correspond to the empirical distributions for Turkey, Romania and the Czech Republic.

Another insight from Chart 1 is the difference in probability of selected tail events. A 2.3σ-event, which would occur with probability 0.06% under normal distribution, has a probability of over 1% in the empirical EMP distribution of the Czech Republic, and above 1.5% for Turkey. Moving between 1.5σ and 3σ would make the event only about 3 times less likely under the empirical distribution for Turkey (but approximately 100 times less likely were the distribution normal).

As a final illustration, Chart 2 plots 99th percentile values obtained with the fitted GPD distribution by country. For comparison, the value corresponding to 2.3 times the standard deviation is shown as well, (it would roughly correspond to the 99th percentile in the normal distribution. This comparison is similar to the illustrative comparison of GDP quantiles in Cechetti (2006). The GPD-based 99% values are higher than the twin standard deviation-based values in most cases (for Bulgaria and Romania, they differ by a factor of about 1.6 -1.7), but are rather similar for countries with estimated thin-tailed EMP distributions.

Given these differences, in section 3, where we address the determinants of exchange market crises, we also perform a comparison of the extreme value-determined thresholds with the results which would be obtained when using standard errors, both at the 95th and 99th percentile. As section 3 demonstrates, there are substantial differences in the results in terms of the significance of the explanatory factors.

Chart 2. EMP values at the 99th percentile calculated using the fitted GPD and normal approximation



Note: The dark blue bar represents the 99% “value at risk” using the fitted GPD distribution for each country, whereas the light blue bar uses normal approximation. The bars for Romania and Turkey (in red) are scaled down by a factor of 10 in order to accommodate them in the chart.

3. The determinants of exchange market turbulences

Having investigated the unconditional distribution of the EMP index variable and its tail behaviour, we continue with an enquiry into the determinants of the exchange market pressure periods. The explanatory variables under consideration are a selection of the factors identified in the large literature on foreign exchange and balance of payment crises that builds on three generations of theoretical models on exchange rate crises (see for instance Mark 2000, Bussiere 2007). These capture various measures of internal and external imbalances and financial vulnerabilities. Several studies of the determinants of currency crises have also used an extreme value-based definition of currency crises (e.g. Garita and Zhou, 2009). We follow a very similar approach, applying the methodology to the Central and Eastern European region, deepening the understanding of the time structure of the effects by including a lag structure, as well as attempting to capture imbalances which have been accumulated over time.

3.1. Methodology and explanatory variables

Similarly to earlier works in the relevant literature, the framework for investigating the influencing factors of the EMP crises is a binary choice logit model. The estimation is performed both in a pooled sample (without fixed effects) and in a fixed-effect panel framework. As also suggested by Bussiere (2007), we expect that a substantial role is played by unobservable country-specific characteristics (e.g. degree of political stability or structural differences) that are not easily measurable.

As explained in Section 2, the crisis observations are selected as exceeding the 95th or the 99th percentile of the fitted GPD distributions by country (similar to Haile and Pozo 2006).

Regarding the explanatory variables, a common approach in the earlier literature is that variables enter the equation with one lag. As shown in Bussiere (2007), this is not necessarily correct for all variables: certain variables linked to liquidity pressures (e.g. short term debt to GDP ratio) or contagion-related variables may signal a much more imminent crisis than other imbalances (e.g. currency misalignments or excessive current account deficit) that may exist for several years before a sharp correction or a crisis episode materialize in the foreign exchange market.

As most of our explanatory variables are only available at quarterly frequency, the estimation is performed with quarterly data, after converting the binary crisis indicator from monthly into quarterly frequency. This is done by propagating crisis observations, i.e. if at least one month in the quarter is a crisis observation, then the entire quarter is considered a crisis observation as well. Considering a longer time unit, which means a less precise temporal definition of currency crises, is likely to also lead to better predicting properties of the binary choice model as demonstrated by Bussiere (2007): predicting crisis episodes with a window of one year is surely somewhat easier than their prediction within a given month and is reflected in a better explanatory performance of the model.

In the literature on exchange market pressure in Central and Eastern European countries, two of the important factors affecting the occurrence of exchange market pressure episodes include **credit growth** and the **current account deficit** (Stavarek 2010; Milesi, Ferretti and Razin 1998). A significant effect of foreign capital inflow has also been identified, with volatile capital flows playing a prominent role for many emerging market crises in the past. At the same time the nature of **capital flows** matters as some types of those (e.g. FDI) may decrease the probability of foreign exchange crises, while other types (e.g. short term portfolio inflows, which are also more volatile) may have the opposite effect. For this reason, we keep account of the breakdown of these flows and test separately the impact of FDI, portfolio and "other" capital inflows.

The **external imbalance** indicators include **trade balance as a share of GDP** and the **current account balance** both as a percentage of GDP and as a deviation from its long-term trend (the latter approximated with a Hodrick-Prescott filter). The variables reflecting **foreign capital flows** (direct, portfolio and other investment) are also expressed as a share of GDP and stem from national balance of payments data.

We also include two **reserve adequacy** indicators, first of which are international reserves **as a percentage of total external debt.** Its choice is driven by data availability, although the ratio of reserves to *short-term external debt* would be more adequate as a measure of the vulnerability of the country to capital outflows[16]. A second indicator, **reserves as a share of the monetary aggregate M2** are considered as well, as too fast monetary expansion (often associated with the weakness of the domestic financial system) has been found to contribute to exchange pressure (see e.g. Stavarek 2010) in CEE countries.

The **internal imbalances** include interest rate and credit growth related variables. Our interest rate indicators are the **average lending rate of domestic financial institutions and the spread between the lending and deposit rate**, both available from the IMF IFS database[17]. In addition, in accordance with the theoretical models on balance-of-payments crises (e.g. Mark 2000), we include two domestic **credit variables**: the credit-to GDP ratio and its deviation from the long-term trend (proxied by the cyclical component extracted with a Hodrick-Prescott filter), and the credit-to-GDP ratio. These variables represent two alternatives to capture the accumulated degree of imbalance in domestic credit growth. As it is expected that excessive credit growth is a structural development with a long-term impact on EMP, long (up to 8) lags are considered in the specifications.

In line with recent models of balance of payment crises in emerging markets, which focus on the role of **contagion effects**, two measures related to international contagion and international risk aversion are included in the specification. Our first measure is the VIX index (Chicago Board Options Exchange Market Volatility Index), which reflects the risk

[16] Using the short-term debt series, which for several countries starts after 2000, would lead to omitting a number of important crisis episodes in the 1990s.

[17] Although the literature suggests that the long-term interest rate (e.g. the 10-year government bond yield) would also be informative in predicting exchange market pressure periods, unfortunately it has not been possible to find a similar measure with comprehensive coverage across countries and time.

aversion channel of global financial contagion.[18] We apply this measure based on the assumption that a crisis event in one market affects the EMP index of other markets, given their global interconnectedness, through triggering an increase in global risk aversion.

The second variable is designed to capture cross-country contagion within the CEE region. It uses the tail-dependence-based measure described in Section 2.1, which represents a weighted count of crises in the other countries in the same region, where the weights capture the strength of the bilateral relationships in crisis periods. While contagion might be due to a connection in the fundamentals between countries belonging to the same region and sharing similar institutional set-ups, it might also reflect investors' behaviour such as portfolio rebalancing across regions, which may increase the dependence between otherwise weakly connected regional markets and currencies.

It is also of interest to investigate how a history of past crisis episodes in the same country affect the probability of observing a crisis episode in the current period, as justifications can be found in the literature both for a positive and negative relationship. On the one hand, a country which has experienced recent balance of payments crisis might have weaker fundamentals, making it more susceptible to new crisis episodes. On the other hand, countries which have experienced exchange rate crises in the recent past might have an incentive to strengthen policy and take measures to reduce imbalances in order to limit probability of repeated crisis in the future (Hegerty 2009, Stavarek 2010). In order to examine this issue we also include a lagged dependent variable in the specifications[19].

3.2. Empirical results

While our main objective is to investigate the determinants of exchange rate crises using the EV method for selecting crisis episodes, we implement a range of alternative specifications in order to test the robustness of results. The variety of specifications includes crisis episodes defined at the 95th and the 99th percentile, pooled observations and fixed effect estimation.

Overall, the results appear to confirm the dependence of results on the method of selecting crisis observations, and the benefits of appropriately capturing the tail behaviour of the empirical distribution. The results are clearly different when using the extreme value-defined threshold and the standard deviation threshold. In particular, it appears that the estimation based on standard errors fails to identify some determinants of exchange market pressure periods that are significant with the EV-based thresholds, including the credit to GDP ratio, the deviation of real exchange rate from its trend and FDI flows (see Table 3).

[18] The VIX index represents a measure of the market's expectation of stock market volatility over the next 30 day period, and is often interpreted as a global indicator of risk aversion or fear factor.

[19] While the variables included are the same in the pooled and panel versions, it should be kept in mind that in the fixed effects panel the coefficient of the lagged dependent variable is likely biased due to the well-known Nickell bias.

Table 3. Results of the logit estimations with and without fixed effects at the 95th percentile

Threshold choice	EV thresholds			Standard error thresholds		
Variables		No FE	With FE		No FE	FE
	Lag	Coeff.	Coeff.	Lag	Coeff.	Coeff.
C		-3.047 ***			-3.903 ***	
		(0.447)			(0.599)	
VIX	1	0.055 ***	0.046 **	1	0.071 ***	0.061 **
		(0.015)	(0.019)		(0.019)	(0.027)
Change in int. reserves/total ext. debt	1-3	-0.092 ***	-0.138 ***	1-3	-0.161 ***	-0.092 ***
		(0.035)	(0.046)		(0.050)	(0.034)
Credit to GDP ratio	2	0.079 **	0.142	2	0.027	0.016
		(0.039)	(0.206)		(0.080)	(0.012)
Foreign direct investment	2	-0.064 *	-0.073 *	*2*	*-0.031*	-0.011
		(0.032)	(0.041)		(0.038)	(0.023)
Change in current account dev. from trend	2	-0.001 *	-0.001 *	2	-0.001	-0.001 *
		(0.001)	(0.001)		(0.001)	(0.001)
Tail contagion indicator	1	2.143 **	2.881 ***	1	1.674 **	1.329 **
		(0.945)	(1.003)		(0.786)	(0.636)
Deviation of REER from trend	5	-0.053 **	-0.057 **	5	-0.010	-0.019
		(0.029)	(0.022)		(0.044)	(0.031)
EMP tail event (-1)	1	0.979 **	0.397	1	0.898 *	
		(0.402)	(0.380)		(0.562)	
McFadden R-squared		0.17	0.26		0.19	0.28
Log likelihood		-175.66	-142.11		-110.82	-73.21
Number observations		634	634		634	562
Number crisis observations		65	65		36	39

Notes: "Int. reserves" refers to total international reserves; trend refers to the trend component of the series, extracted through a Hodrick-Prescott filter. Robust standard errors are reported in parentheses. One, two and three asterisks denote significance correspondingly at the 1, 5 and 10% level. In the indication of the lag, entries with a minus sign (e.g. "1-3") refer to the difference between the first and the third lag.

Turning to the explanatory power of the models, we find that the pseudo-R^2 values for both versions (respectively with and without fixed effects) are similar to those reported by Bussiere (2007) when a broader time definition of a crisis is applied (i.e. crisis incidence within a year). In fact, measured by the pseudo-R^2, the normal approximation provides a slightly better goodness of fit, which might be due to the fact that it selects fewer (and hence more pronounced) crisis episodes[20]. The difference in the number of crisis observations should be noted – in the adjusted regression sample, the standard-deviation-based threshold selects only 39 crisis observations compared to 65 with the EV- based methodology, which suggests that the difference from imposing standard error-thresholds is far from negligible. As shown in table 4, there is also a difference in the number of observations at the 99th percentile[21].

Regarding the fixed effects, as far as they account for unobserved, or not accounted for, country-specific factors, the results suggest that these factors may play an important role in explaining foreign exchange crises as the goodness of fit is substantially higher in the fixed effect panel setting. At the same time, in the panel setting the set of significant factors and their coefficients remain broadly unchanged, which suggests robustness of the results.

[20] The fewer observations from a heavy-tailed distribution with the standard deviation threshold as compared to the GPD-defined threshold (95th percentile) follow from the larger standard error of the heavier-tailed distribution (see the discussion in section 2 and Appendix B).

[21] This is in line with the analysis of standard deviation-based thresholds in Section 1. As explained in Appendix B, selecting observations beyond 1.64 standard deviations from a heavy-tailed distribution leaves a tail of less than 5% - as this is in the region where the normal distribution has more mass. As expected, in the 99th percentile, the opposite is the case: in the unadjusted sample the extreme value theory method selects 30 crisis observations compared with 22 with normal approximation.

Looking at the results in more detail reveals that the explanatory factors tend to influence the occurrence of crisis episodes with very different lags. Broadly as expected, the contagion indicators (the VIX and the regional contagion variable based on joint crisis incidence) are short-term predictors of the occurrence of a crisis. They enter with a lag of one quarter. Other variables enter either with longer lags or through their accumulated change over several quarters – proxied by lagged differences. This indicates that that certain imbalances and vulnerabilities may accumulate for longer periods before a crisis materializes. For instance a credit boom or exchange rate misalignment may exist for a longer period before market sentiment changes and the currency experiences a stress period. The next paragraphs will analyze in more detail the impact of the individual variables.

In the specification where crises are chosen from the 95th percentile, one of the variables with short term impact is global risk aversion (proxied by the VIX). Higher values of the VIX tend to signal a higher probability of a crisis one period later; this result is very significant and robust across all specifications. An increase in global risk aversion might trigger a sudden shift of market confidence and lead to capital withdrawals or speculative attacks on the currency even if the country's fundamentals themselves have not changed.

Another variable with a short term impact is the regional contagion indicator defined earlier (based on the probability of joint crisis of currencies). It is significant, showing that the probability of the emergence of EMP pressure in a given country is positively influenced by pressure episodes in countries, where the EMP index is tail-dependent with the index of the country considered. Recalling the discussion from Section 2, factors such as rebalancing of investors between currencies of the same region may also play a role on top of the risk aversion channel of global financial market contagion in transmitting pressure from one currency to the other. The impact of this factor is more pronounced (coefficient above 2) in the specification using extreme value-defined crises (see Table 1) as compared to the standard-error based definition.

Turning to the role of macroeconomic fundamentals, we find that unfavorable developments in reserve adequacy may also impact the chance of a currency crisis within a relatively short time frame. Our proxy for reserve adequacy (the ratio of international reserves over total external debt, or, more precisely, its change over two quarters) is significant across specifications, with 1 percentage points increase in the ratio is associated with 0.9% to 0.16% lower crisis probability. While we do not find a significant link between the level of international reserves and crisis probability, the result suggests that decreases in international reserves, particularly abrupt ones, may in principle exacerbate the chance of a crisis in the near future, which is in line with Bussiere (2007) and Aizenman et al. (2010). The alternative reserve adequacy indicator (total reserves over M2) does not turn out significant.

Current account imbalances appear to have an impact with a somewhat longer lag (2 quarters) on the EMP index, although it is only significant at the 10% level. The excessive current account is measured by the difference between the current account balance-GDP ratio and its trend. As pointed out in Bussiere (2007) and Hegerty (2009) for the general case as well as by Van Poeck et al. (2007) for the CEE countries, a progressive deterioration of the current account balance towards larger deficit compared to its trend creates upward pressure on the currency.

The credit to GDP ratio also turns out significant, with a positive sign of its second lag. Although it loses significance in the panel estimation, the variable returns to significance in the specification using 99th percentile threshold (see Table 4). The positively-signed relationship is in line with theoretical models of balance-of-payments crises (Mark, 2010) and a sizeable empirical evidence (e.g. Aizenman 2010, Tanner 2001, Van Poeck et al. 2007, to name only a few). Credit booms are in most cases a root of the imbalances leading to balance of payment and financial crises. Excessive credit growth can lead to a misallocation of resources in the economy, which increases the likelihood of a crisis event.

Increasing exchange rate overvaluation, expressed as the deviation of the real effective exchange rate from its long term trend, is also found to play a role. This indicator seems to be relevant over a longer period (5 quarters), which is in line with the common observation that exchange rate misalignments may exist or worsen for protracted periods before the occurrence of pressure periods.

Foreign direct investment as a share of GDP seems to have, at least at 10% significance, some alleviating effect on exchange market pressure, i.e. 1 percentage point higher foreign direct investment to GDP ratio reduces the probability of a currency crisis by 0.07% with two quarters time lag. In contrast, portfolio and other investment (non-FDI investment) are not found significant. The role of direct investment is broadly in line with the result of Stavarek and Aizenman (2010) and in contrasts with the finding of Hegerty (2009) suggesting that portfolio investment has the largest impact on the EMP. FDI have a more permanent character compared to portfolio investment, and are a sign of sustained business interests and general confidence of foreign investors in the economy.

Finally, it appears that past values of the EMP index are also significant with a positive sign across specifications. This indicator l seems even more significant for crisis events defined with the 99th percentile threshold. This lends support to the hypothesis of a positive state dependence of foreign exchange crises. A possible explanation is that countries that experience currency crises may remain vulnerable to another shock, since even if they follow the "right policies" to correct the imbalances that caused the crisis, the adjustment usually takes longer time. It can also be interpreted to show that once occurred, a currency crisis can take time to overcome.

Table 4. Results of the pooled and panel logit estimations at the 99th percentile

		EV thresholds		Std. dev. Threshold
Variables		No FE	FE	No FE
	Lag	Coeff	Coeff	Coeff
C		-5.82 ***		-5.434 ***
		(0.909)		(0.829)
VIX	1	0.074 **	0.055 **	0.061 **
		(0.028)	(0.023)	(0.029)
Credit to GDP (deviation from trend)	3	0.061 **	0.049 **	0.068 ***
		(0.028)	(0.023)	(0.023)
Current account deviation from trend	2-3	-0.001 *	-0.001	-0.000
		(0.001)	(0.001)	(0.001)
Lending minus deposit rate	1	0.031 **	0.032 *	0.033 ***
		(0.008)	(0.018)	(0.125)
Regional contagion variable	1	2.887 *	2.639 *	3.635 ***
		(1.571)	(1.628)	(1.216)
Reserves/debt ratio	1-3	-0.101 **	-0.091 **	-0.076
		(0.048)	(0.059)	(0.055)
Lagged dependent variable	3	2.052 **	1.816 **	-0.455
		(0.818)	(0.745)	(0.846)
McFadden R-squared		0.21	0.29	0.22
Log likelihood		-60.7	-50.3	-67.59
Number of observations		634	634	634
Number of crisis observations		17	17	22

Note: LT trend refers to the trend component of the series, extracted by Hodrick-Prescott filters. Robust standard errors are reported in parentheses. One, two and three asterisks denote significance at the 1, 5 and 10% level. Heteroskedasticity-robust standard errors are used in all estimations.

The analysis with crisis observations selected at the 99th percentile (see Table 4) also suggest that the results using extreme value are different from those with standard error-defined threshold[22]. At this point in the distribution, there are only 17 crisis observations; hence the most pronounced crisis periods are selected. The results are generally similar to those in the previous specification; another variable which appears significant in this setting is the credit spread indicator, i.e. the difference between lending and deposit interest rates of monetary financial institutions. In the literature, high values of the credit spread are associated with risk and financial distress. In addition, the credit variable significant in this specification is the deviation of the credit/GDP ratio from its trend, rather than the value of the ratio itself.

In comparison, the specification with standard error-defined crisis events has a somewhat lower R-squared and fewer variables appear to be significant. One of the largest differences is the significance of the past value of the dependent variable: while it appears to play a rather important role in the extreme value-defined crises, it is completely insignificant (and wrong-signed) in the case of the standard error-defined ones.

4. Conclusion

This paper provides evidence that a careful analysis of the tail behavior of the exchange market pressure index of CEE countries using Extreme Value Theory (EVT) is likely to contain important information about the probability of exchange market pressure periods and contributes to a more precise identification of the crises and of their determinants.

Our investigation suggests that, as established by the previous literature for other economies (e.g Asian and Latin American countries), the Exchange Market Pressure indices of most central and eastern European economies tend to be heavy-tailed. The analysis of the tail behavior of exchange market pressure series shows that while tail events are still a relatively rare event for an individual country, they tend to happen much more frequently than would be the case if these variables were normally distributed. Consequently, for many countries assuming that the series is normally distributed can lead to a strong underestimation of the risk of crises.

Overall, the results also appear to confirm the benefits of applying the extreme value analysis for more precise selection of crisis observations in fat tailed series, as opposed to applying standard error-based thresholds. The number of crisis episodes selected, the explanatory power of the model, the set of significant explanatory factors and the strength of their impact are different. In particular, it seems that the estimation based on standard errors fails to identify some important determinants of exchange market pressure periods that are clearly significant with the EVT-based thresholds.

Turning to the explanatory factors of currency crises, the results suggest that a range of macroeconomic fundamentals and cross-country contagion are relevant predictors of crisis episodes and that the time frame of the effect of the explanatory variables differs substantially. A sharp increase in global risk aversion (proxied by the VIX index), with other factors kept constant, can be an almost imminent trigger of a crisis. Similarly a drop of the reserve coverage to a lower level may signal liquidity pressures which can result in an exchange rate crisis in relatively short time.

Other imbalances help to predict the crisis with much longer lags from two to five quarters, including the indicators of current account imbalances, the deviation of domestic credit to GDP ratio and of the real effective exchange rate from their long term trends. This indicates that exchange rate overvaluation and credit booms may exist for prolonged periods before a crisis materializes. Identifying early such imbalances can give time to implement policies that help for their timely correction.

In addition, especially in the case of "severe crises", countries that have experienced a currency crisis may face a high chance of another shock in the near future, likely because they

[22] In this case, the standard-error defined threshold is 2.33σ, which would correspond to the 99th percentile in the normal distribution.

have shown vulnerability to shocks, since even if they follow the “right policies” to correct the imbalances that caused the crisis, the policy change and adjustment takes longer time.

The explanatory power of the equations seems to compare well with other studies in the field, if differences in the strictness of the crisis definitions applied are taken into account. Overall it appears that any attempt to predict the precise timing of an EMP crisis period (e.g. by determining the specific months when it happens) might be overly ambitious and the explanatory power of the macroeconomic and financial imbalances in predicting crises is very low in that case (Cuaresma and Slacik 2008). In contrast, studies that estimate the probability of crises over a longer interval, such as a year, tend to find more significant relationship between the EMP episodes and the specific imbalances, as well as a better fit. With our focus on EMP crisis events during a particular quarter, the goal has been somewhere in between.

There is clearly substantial additional work needed in the field of designing early warning systems. This paper covers only a small area of this growing field of research. Hopefully our investigations contribute to these efforts by showing that extreme value techniques may have a place in the toolbox of economists looking for more accurate models in predicting foreign exchange crises.

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Appendix A. The visual tools used by extreme value theory

The **Q-Q plot** plots the quantiles of an empirical (observed) distribution against the quantiles of a benchmark theoretical distribution (usually the exponential, which is middle-size-tailed, but other distributions like the normal one are used as benchmarks as well). It is used for diagnostics of heavy tails. For heavy-tailed distributions, a concave deviation is observed in the chart; if the empirical distribution is close to the benchmark distribution, the line is rather straight. A convex part would indicate a thin-tailed distribution.

Another visual tool is the **mean excess plot**, which shows how far extreme observations exceed a chosen high threshold, by plotting the average deviation from the threshold as a function of the threshold value. Whenever there is an upward sloping portion in the right part of the plot than it indicates a distribution with a fat tail.

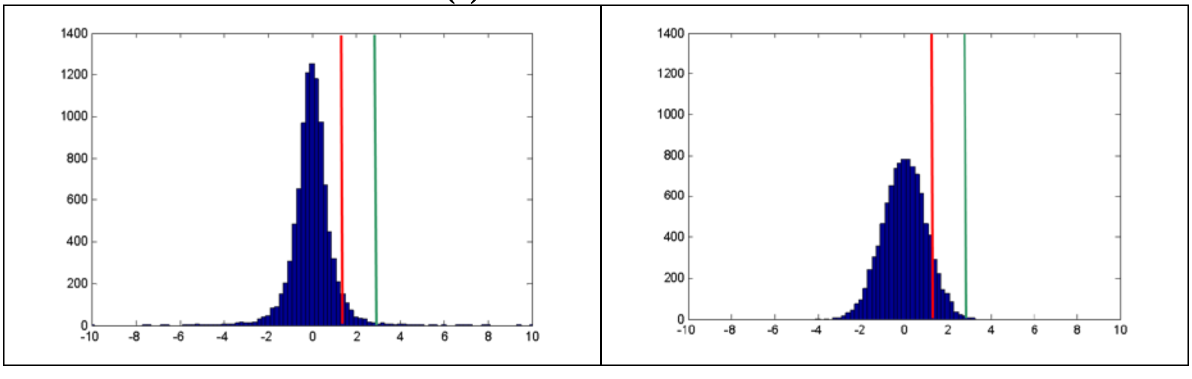
The Hill estimator estimates non-parametrically the tail fatness parameter ξ. Loosely formulated, it calculates a weighted distance between the exceedances (extreme observations) and the rest of the observations in the distribution. The Hill plot is used to determine the optimal cut-off point as the segment where the estimated ξ parameter no longer depends on marginal changes in cut-offs, i.e. the Hill plot levels out and remains stable (e.g. Gencay and Selcuk 2003). The Hill estimator has however a drawback: it is only valid if the distribution is known to be heavy-tailed. It is not informative in cases where the shape parameter is zero or negative, i.e. there is a thin tail (e.g. De Haan and Ferreira, 2006).

Appendix B. Imposing the normality assumption on a heavy-tailed distribution

This appendix gives a short graphical illustration to the bias from applying thresholds equal to a number of standard deviation to distributions whose tail behaviour is very different from normal. As an example, we consider three distributions with different tail thickness – the normal distribution and two Student's t distributions with 2 and 3 degrees of freedom. On the basis of 10000 random draws from each distribution, we construct standardized histograms and compare the values selected above with two different thresholds – one equal to 1.5σ and one in the tail of the distribution (3σ).

Chart B1 shows standardised histograms of the Student's t(3) on the left and of the normal distribution on the right. At the low threshold (1.5σ, the red vertical line) more tail observations would fall beyond the threshold under the normal distribution while with a high threshold (the red vertical line) more observations would be selected from the fat tailed Student's t. Indeed, under a normal distribution we should find only approximately 0.01% of observations beyond a threshold of 3σ.

Chart B1. Comparison of histograms with 1.5 and 3 standard deviation thresholds of Student's t(3) and the normal distribution



Note: In each case, 10000 draws from the respective distributions were performed. The histograms are standardised by dividing each observation by the respective standard deviation.

These distributional differences provide the intuition behind the observation (section 3) that the 95th percentile of the empirical distribution of the EMP series for most countries selects more observations than the threshold of 1.64σ in the same distribution.

Appendix C. Charts and tables

Chart C1. Q-Q plots against the exponential distribution for individual countries

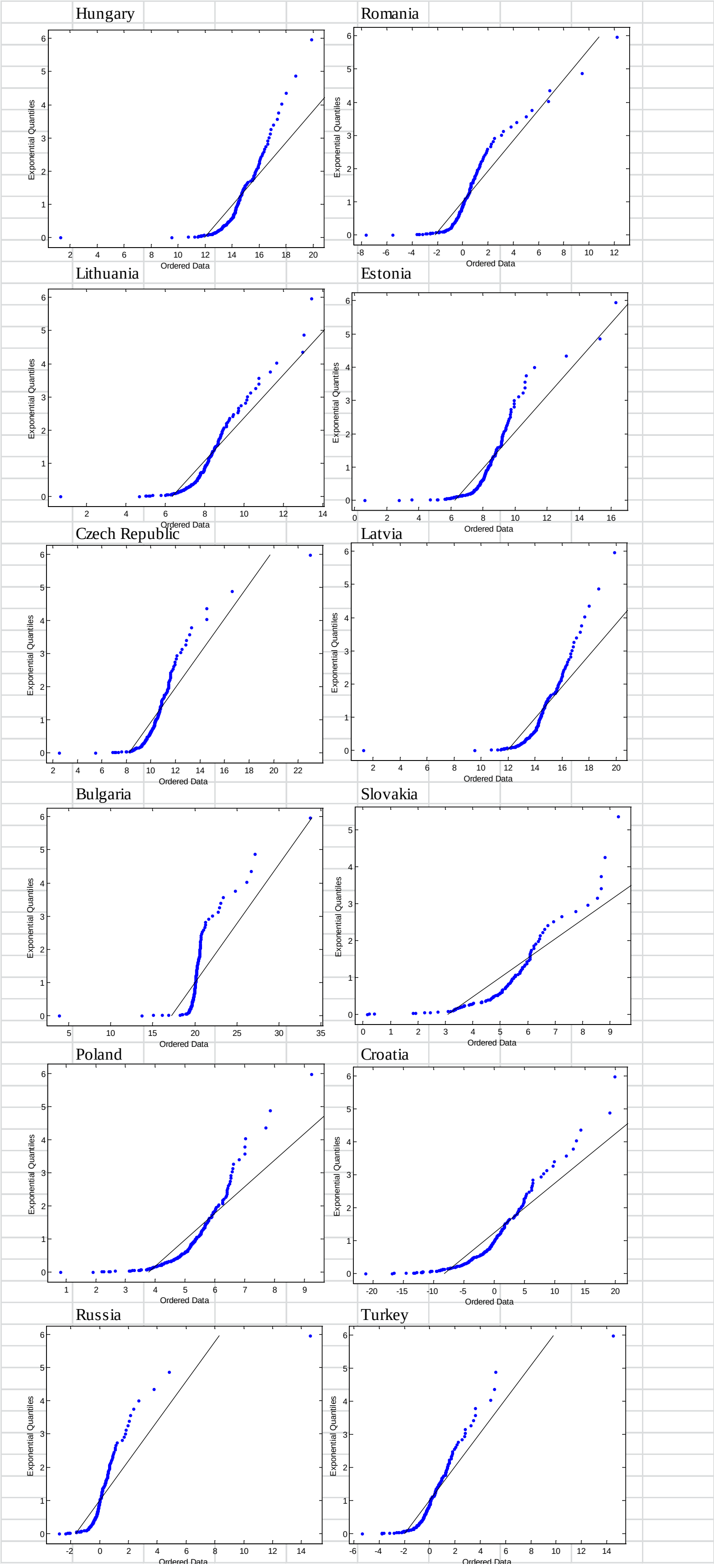


Chart C2. Fitted tails of the distribution for selected countries

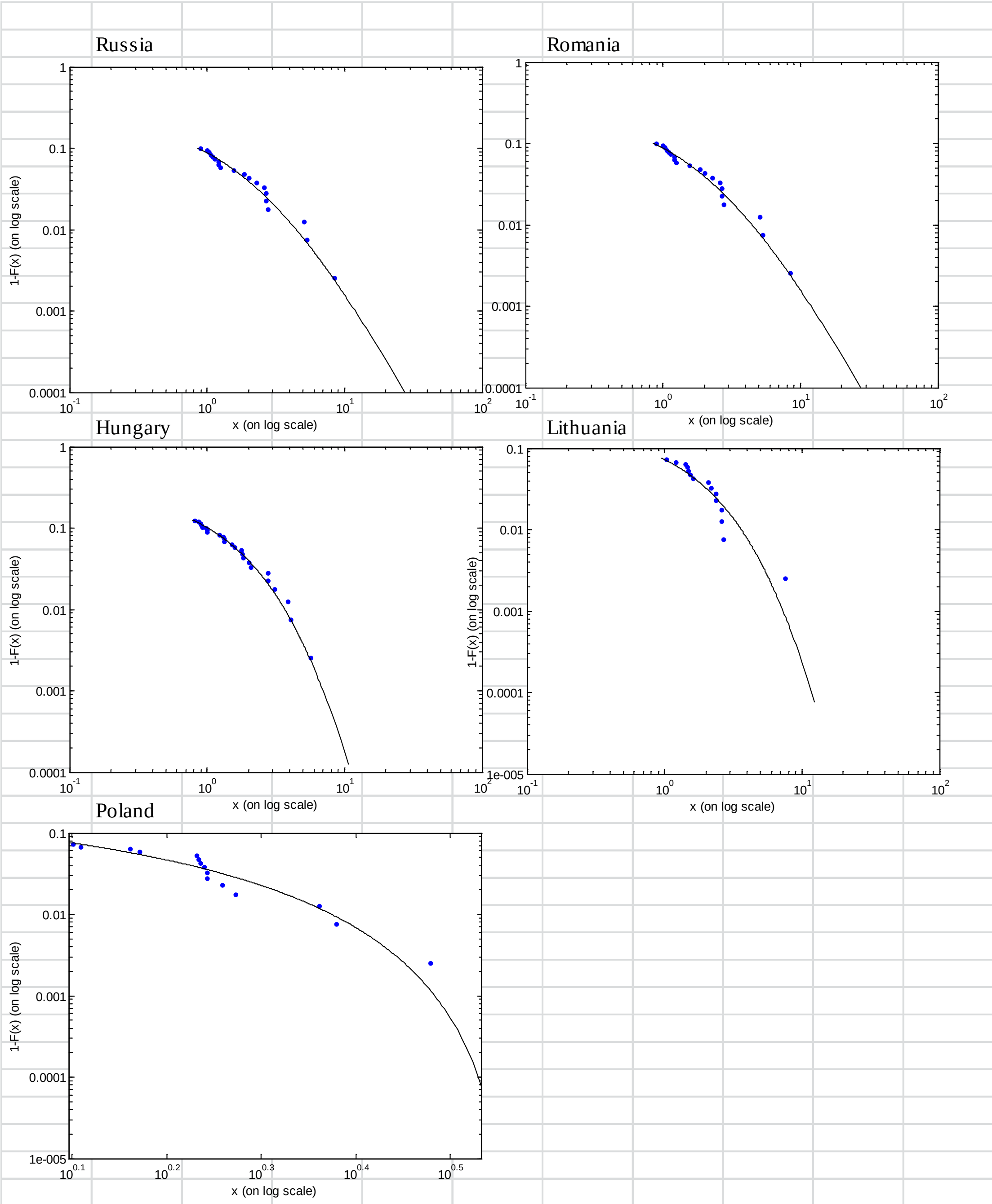


Table C1. Contagion matrix of the Central and Eastern European countries

	Bulgaria	Czech Republic	Estonia	Lithuania	Latvia	Hungary	Poland	Romania	Slovakia	Croatia	Russia	Turkey
Bulgaria	0.00	0.00	0.07	0.05	0.00	0.00	0.05	0.11	0.00	0.06	0.05	0.00
Czech Republic	0.00	0.00	0.06	0.05	0.07	0.16	0.24	0.05	0.06	0.18	0.05	0.00
Estonia	0.07	0.06	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.07	0.00	0.07
Lithuania	0.05	0.05	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.05	0.00
Latvia	0.00	0.07	0.00	0.00	0.00	0.07	0.07	0.00	0.10	0.08	0.00	0.00
Hungary	0.00	0.16	0.00	0.11	0.07	0.00	0.24	0.00	0.06	0.11	0.05	0.05
Poland	0.05	0.24	0.00	0.00	0.07	0.24	0.00	0.05	0.07	0.12	0.05	0.05
Romania	0.11	0.05	0.07	0.00	0.00	0.00	0.05	0.00	0.00	0.06	0.11	0.00
Slovakia	0.00	0.06	0.00	0.00	0.10	0.06	0.07	0.00	0.00	0.07	0.00	0.00
Croatia	0.06	0.18	0.07	0.00	0.08	0.11	0.12	0.06	0.07	0.00	0.06	0.00
Russia	0.05	0.05	0.00	0.05	0.00	0.05	0.05	0.11	0.00	0.06	0.00	0.00
Turkey	0.00	0.00	0.07	0.00	0.00	0.05	0.05	0.00	0.00	0.00	0.00	0.00

Note: The values in the cells represent the cumulative probability of joint failure (CPJF) for each pair of countries, following Garinba and Zhou (2009). The highest values of CPJF are highlighted in yellow.

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