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The determinants of extreme dependence in financial markets

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The determinants of extreme dependence in financial markets

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Abstract:

This paper examines the determinants of large comovements in financial markets. More specifically, we analyze the relationship between a dependence indicator drawn from multivariate extreme value theory and a set of economic and financials factors. Applications are realized for pairs relating G5 countries with 14 mature and 25 emerging countries, both for equity and bond markets. Our results show that trade linkage variables (i.e. import demand and trade competition) appear as the most important determinants and, to a lesser extent, the distance between countries. Results are robust to changes in the extreme dependence measure and econometric specification of the model. We also identify some significant differences between mature and emerging countries.

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Keywords: extreme-value theory, contagion, gravity models, cross-market linkages

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1. Introduction

Asset prices comovements are the subject of an extensive literature, which brings important insights for market practioners and regulators. In particular, the reaction of a country's financial markets to fluctuations of their counterparts in other countries is key for building efficient portfolios or the transmission of economic policy. While early attempts were limited to the measure of the intensity of the relationship between markets[1], notably aiming at capturing possible increased integration during the globalization and capital controls alleviating processes, some researchers have tried to identify its fundamental origins.

In a recent paper, Forbes and Chinn (2004) proceed to an extensive study of the determinants across countries and across time of the international linkages between stock and bond markets. They show that direct trade flows appear to be the strongest and most important determinant of cross-country linkages while foreign direct investment does not appear significant. The effect of bank lending and trade competition is unstable and fluctuates across specifications. They also show that the effect of these fundamental determinants has increased through time and their results are robust to the incorporation of additional determinants or exclusion of potential outliers. In their paper, international linkages are measured through the beta of non-core countries returns to the one of core countries (conditionally on global, sectoral and cross-country market factors).

This paper provides a direct extension of Forbes and Chinn's article. While the authors are studying the full distribution of returns, we concentrate on its left tail, that is on negative extreme movements. In financial markets, such events are characteristic of crises which have themselves been the subject of a very large academic literature. The vast majority of this literature has concentrated on the debate concerning whether the violent widespread of financial shocks all over the world, like observed repeatedly (e.g., the 1987 stock market crash, the Asian flu, the Russian crisis, the September 2001 terrorist attacks), is a pure contagion effect or the simple expression of interdependence between markets. While early works were advocating the contagion mechanism as the interpretation of the significant increase in correlation between markets observed during sharp downturns[2], this interpretation has been strongly challenged by Boyer et al. (1999) and Forbes and Rigobon (2002) who showed that the apparent increased in correlation might simply reflect the mechanical bias induced by the increase in the volatility of underlying markets. On the basis of this result, Forbes and Rigobon (2002) suggest a heteroskedasticity-adjusted correlation measure to identify contagion episodes. This latter measure has itself been strongly critized, due to an oversimplistic latent factor model structure (Dungey et al., 2004; Corsetti et al., 2005) but also due to its linearity.

It is in this last perspective that Straetmans (1997), Bae et al. (2003), Longin and Solnik (2001) and Hartmann et al. (2004) have proposed models of extreme comovements. It is precisally the purpose of extreme-value theory to provide statistical analysis of these joint co-crashes episodes (tail dependence). It thus offers renewed and more robust approaches to the modeling of extreme contagion in extreme markets (Costinot et al., 2000; Chan-Lau et al.; 2004). In particular, it allows one to cope with the limitations of traditional tools like Pearson correlation[3]. Extreme-value theory can be replaced in the context of the copula concept, which is encountering increasing interest in various domains of economics and finance[4]. Every joint distribution function can be split into its univariate marginal distribution functions and a copula function. Copulas are free of the properties of marginal distributions and present a desirable

[1] See Karolyi and Stultz (2003) for a survey.
[2] See, among many others, King and Wadhwani (1990) or Baig and Goldfajn (1999).
[3] Among exemples of pitfalls of correlation, we can cite: (i) a zero correlation of risks does not imply independence of risks, (ii) possible values of the correlation coefficient depend on the marginal distributions. Indeed, the edge values 1 and –1 are not always attainable, (iii) correlation is not invariant under simple transformations of variables. See for instance, Embrechts et al. (1999).
[4] For introductory applications in finance, see Bouyé et al. (2000) or Cherubini et al. (2004). For the specific analysis of contagion, see Patton (2006a, 2006b), Rodriguez (2007), Manner and Candelon (2008), Applications in economics are more sparse. See however Granger et al. (2006) or Bonhomme et Robin (2004) for pionnering approaches.

invariance property which allows them to remain the same irrespectively of any strictly increasing transformation of the marginals.

In this paper, we rely on a bivariate measure of extreme dependence, which involve the empirical copula, following Coles et al. (1999) and Poon et al. (2004). In the case of a bivariate normal distribution, this measure is equivalent to the correlation coefficient, but might differ significantly for more general joint distributions. We then estimate regression models relating these measures to a set of determinants. That way, we investigate the impact of economic and financial linkages between countries on a tail dependence measure drawn from extreme-value theory.

The set of fundamental determinants is composed of international bank lending, foreign direct investments, direct trade flows, trade competition in third markets and several measures typical of a gravity model of trade. Gravity models are explaining international trade flows with variables like economic size and, more characteriscitally, geographical distance and cultural similarities. While their theoretical foundations are still subject to debate, gravity models seem to encounter large empirical support[5]. Our application is made for a large sample of country pairs, while the majority of studies of contagion are generally limited to a small set of countries. Following Forbes and Chinn (2004), we decompose the world into five core countries (in practice, the G5 countries: US, Japan, Germany, UK and France) and a set of 39 other countries, 14 being classified as mature and 25 as emerging. From this spectrum, we are able to collect complete data for a set of near 150 bilateral pairs.

One can find in the literature other attempts to investigate determinants of joint crisis. However, the vast majority of such approaches are only directed at studying currency crises, castigating the role of trade (Eichengreen, Rose and Wyplosz, 1996; Glick and Rose, 1999), competition in third markets (Forbes, 2002) or bank lending (Van Rijckeghem and Weder, 2001).

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[5] See, for example, Feenstra et al. (2000) or Rose (2004).

Bae et al. (2003) also proposes an analysis of the determinants of contagion but they limit themselves to market determinants (regional conditional volatility, level of interest rate, exchange rate changes) leaving aside the question of fundamental linkages and they use a multinomial logit regression of joint large returns which leads to an oversimplification of the distribution tail structure.The current paper is clearly extending the literature as we offer a generalization of previous results in studying a large panel of countries, both for stock and bond markets, during longer periods of time, with a set of general market cross-dependence factors and a robust methodology for estimating extreme dependence.

Our results show that trade linkage variables (i.e. import demand and trade competition) appear as the most important determinants and, to a lesser extent, the distance between countries. For other determinants, relationships are not significant or at least unstable across specifications. We also show that the explanatory power of the determinants is higher for bond markets than for stocks, and when non-core countries are mature, and thus of similar level of development than core countries, rather than emerging. Finally, sensitivity analysis clearly illustrate that major results are robust to changes in the measurement of extreme dependence and to the econometric specification of the model.

The rest of the paper is as follows. In Section 2, we present the methodology for measuring extreme dependence. In Section 3, we describe the dataset. Empirical results are collected in Section 4. We begin with the basic results concerning the determinants of extreme dependence and then investigate various sensitivity analysis (tests of robustness of the econometric specification, distinction between type of countries, use of alternative measure of extreme dependence). Section 5 concludes.

2. Measuring and modelling extreme dependence

If one is interested in studying the extreme dependence between two random variables X and Y, this might involve quantities like the joint probability:

$$\lim_{x,y\to\infty} \Pr(X > x, Y > y), \tag{1}$$

or the conditional probability:

$$\lim_{x,y\to\infty} \Pr(X > x | Y > y). \tag{2}$$

In financial applications, X and Y stand for asset returns. For multivariate analysis, it is often useful to remove the influence of marginal distributions by transforming the original variables using their empirical distribution function. More specifically, let us introduce $(U_X, U_Y) = (F_X(X), F_Y(Y))$ where $F_X(X)$ and $F_Y(Y)$ are the marginal distribution functions for X and Y, respectively. The conditional probability (2) can then be replaced by the corresponding one:

$$\lim_{u\to 1^-} \Pr(U_X > u | U_Y > u). \tag{3}$$

Notice that (U_X, U_Y) possess the same dependence structure as (X, Y). In simple words, we have replaced the analysis of the conditional probability that, say, $X > 20\%$ given that $Y > 30\%$, by the probability that both financial variables are in the top centile of their distribution, i.e. $u = 99\%$ [6]. The advantage of the uniform transformation is to facilitate comparisons among variables which are otherwise dependent on scale and location parameters. Furthermore, once the parameters are estimated, it is always possible to reverse the problem and estimate empirically quantities like (2).

Probabilities alike (1), (2) or (3) concentrate on the joint distribution of extremes. More generally, the global relationship between X and Y is characterized by the joint distribution

$F(x,y)=\Pr(X \le x, Y \le y)$ with $F(x,\infty)=F_X(X)$ and $F(\infty,y)=F_Y(Y)$. In recent years, emphasis have been put in the literature on copulas. Copulas are mathematical functions which relate multivariate distribution to marginal (univariate) ones. Formally, the copula $\mathbf{C}$ is defined as the function such that $F(x,y)=\mathbf{C}(F_x(x),F_Y(y))$. Moreover, copulas have various attractive properties[7]. First, if marginal distributions are continuous, the copula function is unique. Second, copulas are invariant to strictly increasing transformations. Having introduced the copula, it is straigthforward, using standard probability theory[8], to show that the limit probability (3) can be restated as:

$$\lim_{u\to 1^-}\frac{\overline{\mathbf{C}}(u,u)}{1-u}=\lim_{u\to 1^-}\frac{1\text{-}2u+\mathbf{C}(u,u)}{1-u}=\chi\,, \tag{4}$$

where $\overline{\mathbf{C}}(u,u)=\Pr(U_X>u,U_Y>u)$. $\chi\in[0,1]$ measures upper tail dependence. If $\chi=0$, X and Y are not dependent in the tails. If $\chi=1$, we have $\Pr(U_X>u|U_Y>u)=1$, which means that the probability that an extreme return is observed for X conditional on the fact that an extreme return is observed for Y is equal to one.

There exists numerous copulas which are characterized by different tail dependence. Famous examples are: (i) the Gumbel copula $\mathbf{C}(u_1,u_2;\theta)=\exp\left(-\left[(-\ln u_1)^\theta+(-\ln u_2)^\theta\right]^{-1/\theta}\right)$ for which $\chi=2-2^{1/\theta}$; (ii) the Student copula

$\mathbf{C}(u_1,u_2;v)=\int_0^{u_1}\mathbf{t}_{v+1}\left(\sqrt{(v+1)/\left(v+\left[\mathbf{t}_v^{-1}(u_1)\right]^2\right)}\right)\times\left(\mathbf{t}_v^{-1}(u_2)-\rho\mathbf{t}_v^{-1}(u_1)/\sqrt{1-\rho^2}\right)du$ where $\mathbf{t}_v(.)$ is the Student distribution with v degrees of freedom and ρ is the correlation coefficient and for which $\chi=2-2\mathbf{t}_{v+1}\sqrt{(v+1)(1-\rho)/(1+\rho)}$; (iii) the Normal copula

[6] We assume that the threshold *u* is the same for both uniform transformations, solely for ease of presentation. The framework perfectly accomodates the possibility of different thresholds for each variable.
[7] For a detailed treatment of copulas, see Joe (1997) or Nelsen (1999).
[8] In particular, we use the result that $\Pr(U_X>u|U_Y>u)=\Pr(U_X>u,U_Y>u)/\Pr(U_Y>u)$.

$\mathbf{C}(u_1,u_2;v)=\int_0^{u_1}\Phi\left(\left(\Phi^{-1}(u_2)-\rho\Phi^{-1}(u_1)\right)/\sqrt{1-\rho^2}\right)du$ for which $\chi=1$ if $\rho=1$ and zero for any other value of ρ. This last result is particularly interesting since it shows that except in the case of two perfectly correlated variables, there is no tail dependence for the Normal multivariate distribution even for $\rho\neq 0$. Note that the extreme-value measures recently sudied by Hartmann et al. (2004) are directly related to χ. More specifically, these authors study the probability of a co-crash given that one is observed in a market, $E[\kappa|\kappa\geq 1]$ where κ counts the number of crashes among the two markets. It is straightforward to show that this probability is equivalent to $\chi+1$.

Tail dependence is a very special form of extreme dependence. It means that tail realizations of both variables always occur together. For random variables which are asymptotically independent, different degrees of dependence are attainable for large but finite realizations of random variables, that is for $u\to 1$ but $u<<1$. In the other way round, estimates of χ overestimate the degree of dependence when the two series are asymptotically independent. This makes extreme-value theory tools largely inappropriate. In practical applications, like analyzing a portfolio risk, this will lead to significant bias, as illustrated by Poon et al. (2004) for international stocks indices. To cope with these issues, one can rely on the alternative measure which was proposed in Coles et al. (1999):

$$\overline{\chi}=\lim_{u\to 1^-}2\frac{\log(1-u)}{\log\overline{\mathbf{C}}(u,u)}-1, \tag{5}$$

It is a sensible measure of extreme dependence as it gives the rate at which $\Pr(U_X>u|U_Y>u)$ converges to zero. One can show that the bias of overestimation of extreme value is directly depending on this rate. $\overline{\chi}\in[-1,+1]$ with $\overline{\chi}<0$, $\overline{\chi}=0$ and $\overline{\chi}>0$ describes negative dependence, exact independence and positive dependence, respectively. In the case of the

Normal distribution, $\bar{\chi}$ is the correlation coefficient. In our empirical analysis, we use $\bar{\chi}$ as our extreme dependence measure.

To compute empirically $\bar{\chi}$, Poon et al. (2004) suggest to apply a tail index estimator (Hill, 1980) to the modified values of X and Y. More specifically, they first transform the bivariate returns (X,Y) to unit Fréchet marginals (S,T) using the transformations $S=-1/\log F_X(X)$ and $T=-1/\log F_Y(Y)$, from which we define a new variable $Z=\min(S,T)$. Based on the assumption of independent observations on Z, the estimators for $\bar{\chi}$ and its variance are as follows:

$$\hat{\bar{\chi}}=\frac{2}{n_u}\left(\sum_{j=1}^{n_u}\log\left(\frac{z_{(j)}}{u}\right)\right)-1, \tag{6}$$

$$\mathrm{var}\left(\hat{\bar{\chi}}\right)=\left(\hat{\bar{\chi}}+1\right)^2/n_u, \tag{7}$$

with asymptotic normality of $\hat{\bar{\chi}}$ ensured by results in Smith (1987). $z_{(1)},\ldots,z_{(n_u)}$ are the n_u observations of the variable Z that exceed u. Notice that all the description of the methodology has been made on the analysis of the largest realizations of (X,Y) while our study concentrates on the smallest realizations of it, that is most negative realizations. However, it is easy to reformulate the problem this way since $\min\left(z_{(1)},\ldots,z_{(n)}\right)=-\max\left(-z_{(1)},\ldots,-z_{(n)}\right)$.

The estimators critically depend on the choice of the threshold u or, equivantly, of the number n_u. Basically, the choice involves a trade-off between the bias of the estimator, which gets large when n_u increase as we head towards the center of the distribution, and its variance, which is large when a limited number of observations is chosen. Some authors use ad-hoc values like, say, 5% of the observations (Chan-Lau et al., 2004), or advocate the use of graphical methods (Hartmann et al., 2004). More efficient methodologies exist but most of them necessitate a very large number of observations (Danielsson and de Vries, 1997) or need to postulate assumptions on the underlying distribution (Longin and Solnik, 2001). In this paper, we use the threshold selection technique which was developed by Huisman et al. (2001) as it is data-driven and particularly adapted to small-sample (in the time series dimension) like ours. It is based on a weighted least-square model of the bias of the estimator. In practice, it turns out that the procedure leads on average to select 7% of observations for our sample (roughly 45 observations).

The estimation of $\hat{\bar{\chi}}$ is repeatedly done for every pair of countries (a core country selected among the G-5 and a non-core country selected among the 14 mature countries or among the 25 emerging countries), leading to N pairs. The analysis is then based on simple cross-section regressions of the individual $\hat{\bar{\chi}}_i$'s, $i = 1,..., N$, on the relevant economic and financial determinants:

$$\hat{\bar{\chi}}_i = \alpha_i + \sum_{k=1}^{K} \beta_i F_{ik} + \varepsilon_i , \qquad (8)$$

where F_{ik} stands for the k^{th} determinant as observed for the i^{th} pair of country (e.g., bilateral trade flows between Japan and Peru). To estimate equation (8), we first use OLS, and then proceed to some sensitivity analysis where we use outliers-robust regressions methods of estimating β_i parameters and their variance. With the same objective of limiting risks of spurious results due to some outliers, we also estimate Probit models where the binary dependent variable is based on the test of perfect extreme dependence, i.e. $H_0 : \bar{\chi} = 1$.

3. Data

The dataset is drawn from various sources and is mainly composed of two blocks. The first block is made of financial time-series on which measures of extreme dependence are empirically fit. Equity indices are the ones computed by MSCI (Morgan Stanley Capital Indices), with the exception of Russia where, due to unavailability, it is replaced by the Ros index. Bond indices are EFFA-Datastream for the set of core and mature countries[9] while we use JP Morgan EMBI bond indices for emerging countries[10]. Following market practices[11], equity returns are changed in USD while bond returns are left in their denomination currency.

The sample spans the period from September 9, 1994, to September 21, 2007 (681 observations) for equities and from June 6, 1997 to September 21, 2007 (538 observations) for bonds. In both cases, it covers well-known episodes of global financial crises and contagion episodes like the Asian flu of late 1997, the Russian crisis of 1998, the September 2001 attacks or the Summer 2007 subprime crisis. Returns are computed as the log difference between two consecutive observations of indices. We have chosen a weekly frequency rather than daily since daily returns series makes inference on linkages difficult due to differences in time zones and might thus require intra-daily data[12]. Moreover, working with weekly data allows one to concentrate on more sustained crash phenomena which are assumed to have stronger effects on the real economy and financial institutions.

Extreme value methods, and notably the extreme dependence estimator here adopted, are based on the assumption that the variables are independent. Financial returns are known to exhibit time-series dependence, mostly in terms of heteroskedasticity. Moreover, it has been repeatedly shown that changes in volatility across time might lead to spurious evidence of contagion effects or extreme dependence linkages[13]. In order to remove these effects, we apply GARCH(1,1) filters on raw returns before applying extreme dependence estimators. Models are

[9] EFFA-Datastream indices cover all bonds issued by governement authorities for all maturities.
[10] EMBI covers US dollar denominated Brady Bonds, Eurobonds, and local market debt instruments issued by sovereign and quasi-sovereign entities.
[11] This practice reflects the fact that while the exchange rate volatility is quite negligible when compared with the one of equity returns, this is the contrary concerning bond returns, at least for mature countries. See for instance Xin (2004). Moreover, one should observe that emerging bonds are labelled in USD which is their (*hard*) currency denomination.
[12] See, for early contributions, King and Wadhwani (1990) or Lin, Engle and Ito (1994).
[13] See among others, Forbes and Rigobon (2002) or Poon et al. (2004).

estimated over the full period, assuming a t-Student conditional distribution in order to take into account the skewness and kurtosis of the innovations.

The second block of data is made of the set of determinants. It is based on the mixing of the real and financial factors which are used by Forbes and Chinn (2004) and gravity model variables[14]. Forbes and Chinn (2004) select four key variables for global linkages in financial markets: bank lending, foreign direct investments, direct trade flows and trade competition in third markets. We follow these authors and construct variables in a similar fashion to them. All data used for computations are labelled in US dollars. All GDP data are extracted from the Chelem database of the CEPII research center[15].

Bank lending is based on lending data compiled by the Bank of International Settlements on the basis of consolidated foreign claims of reporting banks (Table 9B of BIS Quarterly Review). Bank lending is computed as total consolidated international claims of a core-country banks in direction of a given non-core country divided by the non-core country's GDP. Foreign direct investments are computed as the ratio between foreign direct investments of the core-country in the non-core country and the non-core country's GDP. For foreign direct investments, we use national sources of official statistics organizations[16]. Direct trade flows are measured as the ratio between the sum of all imports from the non-core country coming from the core country and non-core country's GDP. Data source is the Chelem database. Trade competition is measured with information at the industry level. More precisely, for a given pair of countries and a given industry, trade competition is based on the product of two terms. The first one, aiming at capturing the importance of a core-country for a given industry sector, is given by the share of the exports of this core-country in the world total exports for that industry. The second one,

[14] One might observe that gravity-equation models variables are also incorporated in the sensivity analysis section of the published version of Forbes and Chinn (2004). The authors show that gravity variables are highly significant and reduces the effect of direct trade, which is an additional indication of their importance.
[15] See http://www.cepii.fr/anglaisgraph/bdd/chelem.htm.
[16] These statistics organizations are the US Bureau of Economic Analyis, the UK Office for National statistics, the Banque de France, the Bundesbank and the Japanese Ministry of Finance.

aiming at capturing the importance of the industry for the non-core country, is obtained as the ratio of exports of a given industry for this country with GDP of this country. Those product terms are then summed up across all industries and finally scaled by the maximum value observed across all pairs of countries, so that it fluctuates between 0% and 100% where 100% is attained by the pair of countries with the largest trade competition[17]. In this paper, we use the 11 sectors nomenclature offered by the Chelem database.

Gravity variables are based on original data drawn from the International Trade Data website of Jon Haveman[18]. *Distance* provides (the natural logarithm of) the Great Circle distance in kilometers between capital cities. *Contiguity* is a binary variable which takes the value 1 if both countries have a common land border or a small body of water border and zero elsewhere. *Common language* is a binary variable which takes the value 1 if both countries share the same primary language and zero elsewhere. Finally, *ProdGDP* stands for the natural log of the product of the two countries' GDP.

In Table 1, we give the list of all countries for which we were able to recover data. Apart from the five core countries, we have gathered information for 14 other mature countries, both for equity and bonds markets, and for 25 emerging countries, of which 23 have data for stocks and 17 have data for bonds.

In Table 2 and Table 3, we report descriptive statistics on stock and bond returns, respectively. In both cases, we distinguish between raw returns and returns filtered for GARCH dynamics. Equity returns present a positive average in almost all countries, with the exception of a basket of Asian countries (Japan, China, Philippines, Taïwan and Thailand), partly due to exchange rate depreciation against USD. Volatility is comprised between 15.2% and 54.3% annually with an average of 27.9%. The dispersion in volatility is particularly large between mature (20.6% on average) and emerging (35.1% on average) countries. All countries are

[17] For exemple, it turns out that in 1994 the pair of countries with the highest score for trade competition in third markets were Japan and Singapore and the pair of countrries with the lowest score were Japan and Argentina.

characterized by a rejection of the normality at the 1% level. This is due to a significant excess kurtosis for all countries and a significant negative skewness for almost all countries (exceptions are France, Italy, Sweden, Peru, Taïwan, Thailand). To some extent, this negative skewness can be related to extreme returns since in general the minimum return is larger (in absolute terms) than the maximum return. After being GARCH-filtered, the returns are still exhibiting non-Gaussian characteristics despite a large reduction in excess kurtosis. This supports the choice of a t-Student conditional distribution during the GARCH estimation. The Ljung-Box statistics applied to returns show that some emerging countries display significant autocorrelation, which is typical of illiquid investments (Getmanski, Lo and Makarov, 2005). Finally, the Ljung-Box statistics applied to squared returns show that raw returns display significant heteroskedasticity for almost all countries, which can be efficiently modeled through a GARCH(1,1) as filtered returns as the null of homoskedasticity cannot be rejected for almost all countries (the sole exception being Italy).

Bonds have trended downwards for most mature and core countries (price return only) while they have trended upwards for emerging markets (including coupon returns). Here also, we observe a large heterogeneity in volatility across countries. While the volatility for mature countries stay limited between 3% and 4% (annualized figures), the average volatility is more than 15% for emerging countries and is even more than 35% for Russia. Bond returns also exhibit non-Gaussian behavior due to both significant negative skewness and excess kurtosis but one can observe a huge difference between emerging countries where the rejection of normality is very large. The difference between both type of countries also express itself in the dependence structure with significant joint autocorrelation for numerous emerging countries – which can probably again be linked to some stale pricing. Finally, the GARCH filtering seems efficient to

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[18] http://www.macalester.edu/research/economics/page/haveman/trade.resources/tradedata.html#Gravity.

model the heteroskedasticity and helps achieving a reasonable reduction in the non-normality of the distribution but not sufficiently.

In Table 4, we report summary statistics for the set of determinants. Notice that due to unavailability of data on some couples, the full list of 195 bivariate pairs of countries cannot be used, the sample being limited to slightly less than 150 pairs. As can be seen in Table 4, this loss of data is coming exclusively from a lack of enough detailed information on bilateral foreign direct investments. In terms of correlation, we observe that the vast majority of correlations are positive, with the exception of correlations involving the Distance measure. Generally speaking, correlations remain fairly limited, notably the ones who involve traditional determinants and gravity-model variables. The highest correlation is attached to the two traditional trade variables (Import demand and Trade Competition), with a correlation of 58% over the period 1994-2005.

4. Empirical results

In this section, we summarize our main empirical results. We start by presenting the aggregated results for the whole set of countries when the model (8) is estimated through OLS. Then, we introduce various sensitivity analysis of the previous general results. First, we compare the results obtained for the sample of mature countries vs emerging ones. Second, we check the robustness of the regression through the implementation of binary model and non-OLS regressions. Third, we analyze an alternative measure of extreme dependence.

4.1. What determines extreme dependence?

Empirical results for the OLS estimation of equation (8) are detailed in Table 5. Before commenting these results in details, let us first mention a few words about the expected signs. If one starts from the assumption that the higher the relationship between two countries, the higher the dependence, we might expect a positive sign for all fundamental variables (Bank lending, FDI, Import Demand, Trade Competition) and the gravity-model variables with the exception of the Distance measure where a negative sign is naturally expected. However, as put forward by Forbes and Chinn (2004), the sign attached to all these variables can be deemed unpredictable. For instance, tariff reductions in core countries can trigger a deterioration of the situation of the domestic countries while improving the one of countries abroad, and thus a drop in core country stock market and a boom in competing countries' ones, suggesting a negative correlation between trade and dependence.

Results for the global set of countries are contained in the first two columns of Table 5 (results for subset of countries are discussed in the next section). Five variables appear as significant determinants of the extreme dependence between core and non-core countries, both for stocks and bonds: Import Demand, Trade Competition, Bank Lending, Distance and Contiguity. The first two variables were already identified by Forbes and Chinn (2004) as significant, castigating the conclusion that trade variables are of primary importance for explaining cross-country linkages. One key difference, thought, is the fact that signs are inverted with the ones posted by those authors. While this can be linked to methodological issues and, notably, the fact that we here analyze extreme dependence while the authors analyze standard correlation statistics (through betas), the fairly high correlation between both measures (see Table 4) can also generate some form of instability in the result.

For other variables, signs are typically in line with simple expectations as the returns of core and non-core countries are all the more related that the underlying countries are geographically close and even have a common frontier and that the core country banks are significant lenders for non-core country's economy. Some other variables seem to act as significant, but with a different impact for bond and stock markets, with a common language favoring extreme dependence in bond markets while a large aggregate economic size (as shown by the product of individual GDPs) seems to encourage extreme dependence in stock markets.

All in all, one can notice that the regression seems to indicate that the set of variables are achieving a fairly good job at explaining the extreme dependence indicator, as shown by R^2 statistics and F-tests. These statistics are clearly larger than the ones posted by Forbes and Chinn (2004). One possible explanation stems from the fact that we cover a more recent period than these authors (1986-2000 in their paper versus 1994-2005 here) while they have identified that the determinants have become more significant in the recent period.

4.2. Sensitivity analysis

Mature vs emerging countries

In Table 5, we present a subsample analysis where we separate the sample of non-core countries into mature and emerging ones[19]. Three striking results emerge:

- First, the explanatory power is much larger for mature countries than for emerging ones. This means that the set of variables we identify are mainly able to explain extreme dependence between countries of similiar economic development. Pure unexplained contagion effects are probably much more effective to explain joint crisis in emerging markets.
- Second, the explanatory power seems much more important for bond than for stock markets, as stated by the proportion of explained variance and the lack of global

[19] Another subsample analysis could be to distinguish between subperiods. The difficulty is that the sample will become too much limited to estimate in a robust way the extreme dependence indicator which necessitates fairly large samples in the time-series dimension.

significance (F-test) even at the 10% level in the case of stocks for emerging countries. This difference between bond and stock markets was also clear for the whole panel of countries but the additional issue here is that few variables remain significant in the bond markets equation.

- Third, and as a corollary, the set of significantly robust determinants for all markets and asset classes is reducing to a large extent and we can principally put in this category Import Demand and Trade Competition. Bank lending and three gravity-model variables (Distance, Contiguity and the economic size) can also deemed important for some asset classes and geographical zones but their effect is much more unstable.

Robustness of the regression

The results presented in Table 5 are based on simple OLS regressions. There are various reasons why we can doubt about its robustness: limited sample, unknown distribution, estimated endogeneous regressors… Here, we try to assess whether the results are robust to alternative econometric specifications of the model.

First, we implement a binary version of the model and estimated it through a Probit model. More specifically, we construct an extreme dependence binary indicator where we use the asymptotic normality of $\hat{\bar{\chi}}$. Given the expression for its variance (see equation (7)), we construct the binary indicator which equals 1 if we cannot reject the hypothesis (at the 10% level) that $\hat{\bar{\chi}}$ is equal to 1 and zero in the contrary case. This indicator serves as the endogeneous variable in the Probit model while we left the explanatory variables unchanged. A positive (negative) coefficient is thus interpreted as increasing (decreasing) the probability of being dependent in the extremes. The Probit model is expected to be more robust as the binary transformation dampens the impact of very large observations.

In a second attempt to assess the robustness of the results, we use a Least Absolute Deviation model where one minimizes the sum of the absolute values of the residuals, which makes it more resistant to outliers than OLS which are based on a minizimization of squared residuals and thus give greater weight to large realizations. To find out the solution, we here adopt an iterative weighted least-squares approach where the weights are based on the absolute value of residuals. To evaluate the significance of the estimated coefficients, we furthermore adopt a bootstrap methodology, where we draw randomly with replacement from the original sample of observations. For each of the 10 000 bootstrap replications, we search the Least-Absolute Deviations solution. We then use the bootstrapped distribution of estimated coefficients to estimate their standard error and their p-values.

Results for both robustness approaches are summarized in Table 6. The most important variable seems to be Import Demand and followed by Distance and, to a lesser extent, Trade Competition. Bank lending is confirmed as a key variable in explaining extreme dependence in bond markets. Some significant explanatory power can also be conceeded to Contiguity and the Product of GDP, albeit in less systematic way. All in all, the econometric robustness analysis seems to confirm what was learnt from simple OLS regressions.

An alternative measure of extreme dependence

As a final sensitivity analysis, we compare the results of the base model (8) for alternative definitions of extreme dependence. We here use the Multivariate Conditional Spearman's Rho (MCSR) which was introduced by Schmid and Schmidt (2006). The bivariate Spearman Rho has a longstanding use in statistics. In heuristic terms, it is based on the correlation of ranks of each variable and is thus robust to outliers, contrary to the traditional (Spearman) correlation is based on realized values and thus depend on their amplitude. The objective of the MCSR is to generalize it in a multivariate setting while authorizing to limit itself to specific part of the distribution (hence, the term *Conditional*). The MCSR is defined as:

$$\rho(p)=\frac{\int_{[0,p]^d}\mathbf{C}(\mathbf{u})d\mathbf{u}-\int_{[0,p]^d}\Pi(\mathbf{u})d\mathbf{u}}{\int_{[0,p]^d}\mathbf{M}(\mathbf{u})d\mathbf{u}-\int_{[0,p]^d}\Pi(\mathbf{u})d\mathbf{u}}, \tag{9}$$

where $\mathbf{u}$ stands for a d-dimension vector with $\mathbf{u}\in[0,1]^d$, $\mathbf{C}(\mathbf{u})$ is the copula associated with the random vector, $\mathbf{M}(\mathbf{u})=\min(u_1,...,u_d)$ is the Fréchet-Hoeffding copula and $\Pi(\mathbf{u})=\prod_{i=1}^d u_i$ is the independence copula. p, $p=0,...,1$, stands for the probability which defines in which part of the distribution the calculations are done. Schmid and Schmidt (2006) suggest the following empirical estimator of (9):

$$\hat{\rho}_n(p)=\left\{\frac{1}{n}\sum_{j=1}^{n}\prod_{i=1}^{d}\left(p-\hat{u}_{ij,n}\right)^{+}-\left(\frac{p^2}{2}\right)^d\right\}\Bigg/\left\{\frac{p^{d+1}}{d+1}-\left(\frac{p^2}{2}\right)^d\right\}, \tag{10}$$

where $\hat{u}_{ij,n}=F_{X_i}\left(X_{ij}\right)$ and n is the number of observations. In this paper, we voluntary restrict ourself to bivariate calculations of the MCSR ($d=2$) in order to reproduce the regression on the pairs previously defined. Notice that this estimator is different from the traditional Spearman rho, unless in the special case where $p=100\%$. The choice of p is not trivial and might influence the final results. In order to remain general, we compute the results for various values of it and more specifically $p=5\%$, $p=7\%$ and $p=10\%$.

The results are displayed in Table 7. Some differences with the EVT extreme dependence indicator can be observed. For stocks, Bank lending and economic size are not significant anymore while they were in previous results, at the 5% and 10% levels respectively. In the other way round, significance of the contiguity and direct investments factors is increasing. For bonds, the major difference comes from the lack of significance of the contiguity variable and, in the other way round, the significance at the 5% level of the economic size. Another noteworthy global difference is that the explanatory power of the set of variables seems higher for the MCSR indicator than the EVT one, as shown by higher R^2 and F-statistic.

All in all, though, the differences between EVT and MSCR estimators are minor. In particular, we observe that trade variables (Import demand and trade competition) are the most important ones, followed by Distance, and that bonds extreme dependence is better explained than stocks one.

5. Conclusions

This paper has proposed an analysis of the determinants of extreme dependence in financial markets. More specifically, we relate a measure drawn from multivariate extreme value theory to a set of variables characteristic of the fundamental economic, financial and gravity-model linkages between countries. Application are realized for pairs relating G5 countries with 14 mature and 25 emerging countries, both for equity and bond markets, and the tail of netagive returns (losses).

Our results show that trade linkage variables (i.e. import demand and trade competition) appear as the most important determinants and, to a lesser extent, the distance between countries. For other determinants, relationships are not significant or at least unstable across specifications. Those results seem thus to parallel the ones obtained by Forbes and Rigobon (2004), albeit their analysis was not concentrated on the tail of the distribution, or the ones obtained by various authors on the determinants of currency crises, albeit our analysis is not restricted to such specific events and is simultaneously analyzing bond and stock markets. We also show that the explanatory power of the determinants is higher for bond than for stocks markets, and when non-core countries are mature, and thus of similar level of development than core countries, rather than emerging. Finally, sensitivity analysis clearly illustrate that major results are robust to changes in the measurement of extreme dependence, where we substitute the EVT estimator with the Multivariate Conditional Spearman Rho recently introduced by Schmid and Schmidt (2006), and to the econometric specification of the model, where we substitute OLS estimator with a Least-Absolute deviation estimator and a binary Probit model.

Various avenues for additional research might be explored in the future. Firstly, the set of determinants might be expanded. Among candidates, we can think about industrial structure (Roll, 1992), mutual fund (Kaminski et al., 2001) or cross-listing (Karolyi, 2003). However, one can imagine that it might be difficult to collect the relevant data for a large spectrum of countries like the one we have gathered in this paper. Second, we have here resorted to a direct analysis of extreme dependence. A large part of the literature has put emphasis on the necessity of distinguishing between contagion and interdependence, without drawing clear conclusions. Due to the fact that contagion is generally understood as any linkage which does not have fundamental grounds, one might consider that pure contagion can be infered as the residual and the intercept of our model (that is everything which is not related to the fundamental determinants). For instance, we have interpreted the fact that the explanatory power of the regression was lower for emerging countries as an indication that these countries are more prone to pure contagion.

Still, we could go some steps further. For instance, we could try to build a taxonomy of the difference between contagion and interdependence that would be based on the comparison of the relative determinants of extreme indicators and standard correlation measures. Another road would consist in studying the evolution across time of the fundamental parameters, for instance along the lines drawn by Bayoumi et al. (2003), although this exercice would be limited by the necessity of large samples to get robust estimates of extreme indicators.

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Table 1. List of countries covered in this study

Group	Name	Acronym	Equities	Bonds
Core countries				
	France	FR	√	√
	Germany	GE	√	√
	Japan	JP	√	√
	United States	US	√	√
	United Kindgom	UK	√	√
Other mature markets				
	Austria	AS	√	√
	Australia	AU	√	√
	Canada	CN	√	√
	Denmark	DN	√	√
	Ireland	EI	√	√
	Finland	FI	√	√
	Italy	IT	√	√
	Netherlands	NL	√	√
	Norway	NW	√	√
	New Zealand	NZ	√	√
	Portugal	PO	√	√
	Sweden	SD	√	√
	Spain	SP	√	√
	Switzerland	SW	√	√
Emerging countries				
	Argentina	ARG	√	√
	Brazil	BR	√	√
	Bulgaria	BU		√
	China	CH	√	√
	Chile	CL	√	
	Colombia	CO	√	√
	Ecuador	EC		√
	Hong Kong	HK	√	
	Indonesia	ID	√	
	India	IN	√	
	Israel	IS	√	
	Korea	KO	√	√
	Malaysia	MLS	√	√
	Mexico	MX	√	√
	Peru	PE	√	√
	Philippines	PH	√	√
	Pakistan	PK	√	
	Poland	PL	√	√
	Russia	RS	√	√
	South Africa	SA	√	√
	Singapore	SI	√	
	Taiwan	TA	√	
	Thailand	TH	√	√
	Turkey	TU	√	√
	Venezuela	VE	√	√

Table 2. Descriptive statistics on equity returns

(09/09/94 to 09/21/2007, weekly data)

	Raw returns											Filtered returns				
	N	**Avg**	**Std**	**Min**	**Max**	**VaR 1%**	**SK**	**KU**	**JB**	**Q(5)**	**Q²(5)**	**SK**	**KU**	**JB**	**Q(5)**	**Q²(5)**
FR	681	0.182	2.620	-9.828	10.867	-6.766	-0.109	1.25	45.4	4.72	61.84	-0.095	0.736	16.4	5.66	13.71
GE	681	0.170	2.996	-12.499	12.675	-7.708	-0.258	2.10	132.7	2.67	125.90	-0.367	0.985	42.8	1.20	10.38
JP	681	-0.019	2.986	-9.605	11.016	-6.796	0.253	0.90	30.1	16.90	21.73	0.074	1.013	29.8	10.52	3.52
US	681	0.174	2.206	-12.308	7.574	-5.480	-0.500	2.91	268.0	11.93	52.17	-0.428	1.021	50.4	10.64	5.81
UK	681	0.138	2.107	-8.145	10.617	-5.526	-0.244	1.60	79.3	3.76	51.51	-0.451	1.001	51.5	3.44	2.28
AS	681	0.172	2.616	-11.182	7.181	-6.951	-0.503	1.07	61.2	3.62	48.87	-0.434	0.764	37.9	3.85	5.09
AU	681	0.179	2.411	-11.230	11.571	-6.517	-0.394	2.15	148.8	5.33	63.64	-0.478	0.882	48.0	2.65	7.93
CN	681	0.244	2.658	-14.063	11.457	-6.558	-0.645	3.01	304.9	9.92	31.38	-0.510	1.263	74.8	5.28	1.96
DN	681	0.263	2.435	-12.930	7.375	-6.286	-0.668	2.55	234.5	5.04	8.84	-0.534	1.826	127.1	5.16	2.07
EI	681	0.140	2.673	-13.941	13.080	-8.331	-0.719	3.41	387.8	4.60	22.10	-0.733	2.241	203.4	4.70	5.91
FI	681	0.311	4.825	-25.174	20.541	-15.096	-0.600	3.06	307.1	9.59	38.88	-0.271	1.075	41.1	5.44	2.64
IT	681	0.150	2.854	-13.517	17.872	-7.363	0.075	3.83	417.9	4.03	99.16	-0.169	1.010	32.2	7.09	25.49
NL	681	0.164	2.686	-10.999	14.810	-8.178	-0.458	2.94	268.7	8.70	188.03	-0.494	0.904	50.9	3.39	10.11
NW	681	0.224	3.076	-16.965	13.208	-10.080	-0.758	3.37	386.8	1.21	39.05	-1.038	3.592	488.4	2.54	2.22
NZ	681	0.060	2.864	-14.568	12.022	-8.046	-0.284	2.06	129.4	15.73	48.32	-0.423	1.460	80.7	7.44	5.00
PO	681	0.166	2.547	-10.492	12.641	-6.947	-0.226	1.84	101.8	16.67	47.69	-0.149	0.979	29.7	18.84	2.96
SD	681	0.257	3.526	-20.936	20.331	-8.408	-0.395	4.06	485.9	2.40	26.12	-0.212	1.120	40.7	1.80	3.76
SP	681	0.256	2.781	-11.408	14.252	-7.323	-0.201	1.52	70.5	1.22	68.27	-0.254	0.369	11.2	1.95	2.17
SW	681	0.196	2.395	-11.491	12.977	-5.596	-0.007	2.89	236.4	3.69	52.90	-0.217	1.251	49.7	2.50	6.49
ARG	681	0.110	5.083	-33.647	25.349	-12.880	-0.327	4.94	705.3	14.72	193.44	-0.041	1.324	50.0	12.10	6.13
BR	681	0.201	5.241	-22.879	19.257	-15.092	-0.633	1.68	125.3	4.85	45.55	-0.786	1.698	151.9	7.87	3.17
CH	681	-0.026	4.833	-24.336	22.536	-14.006	-0.209	2.78	224.9	12.54	72.67	-0.166	1.224	45.6	7.11	5.03
CL	681	0.109	2.951	-15.091	11.018	-8.373	-0.396	2.19	154.0	31.33	77.35	-0.345	1.471	74.9	30.85	1.44
CO	681	0.177	3.968	-21.268	15.038	-11.531	-0.390	3.17	303.3	39.96	37.01	0.189	1.573	74.3	37.02	0.84
HK	681	0.087	3.437	-21.056	13.654	-8.813	-0.531	3.75	431.5	6.91	30.73	-0.437	1.635	97.6	6.39	4.71
ID	681	0.001	7.236	-64.504	45.602	-20.178	-0.870	16.39	7711.8	33.86	277.17	-0.452	2.510	201.9	21.97	5.87
IN	681	0.165	3.656	-15.358	13.367	-10.826	-0.373	1.63	91.1	10.98	27.99	-0.385	0.967	43.4	12.35	1.06
IS	681	0.158	3.479	-16.119	16.442	-9.313	-0.213	2.68	208.7	3.02	17.45	-0.456	1.677	103.4	3.33	0.81
KO	681	0.136	5.707	-52.713	28.586	-15.156	-1.115	13.29	5156.4	28.00	84.45	-0.621	2.083	166.9	11.36	7.61
MLS	681	-0.017	4.663	-42.796	34.164	-13.690	-0.949	21.04	12663.0	13.66	158.11	-0.477	2.852	256.7	18.35	8.64
MX	681	0.179	4.340	-31.676	20.631	-11.483	-0.802	5.60	961.4	13.39	49.13	-1.144	6.794	1458.1	6.27	0.25
PE	681	0.311	3.681	-14.114	20.527	-9.237	0.090	2.93	244.6	10.82	78.76	-0.179	1.617	77.8	9.51	0.86
PH	681	-0.102	4.218	-27.884	16.193	-12.348	-0.614	5.27	830.0	22.48	61.36	-0.438	2.327	175.4	15.68	1.19
PK	681	0.013	4.529	-19.861	18.794	-13.300	-0.458	2.30	173.9	22.61	111.74	-0.453	0.966	49.7	27.29	2.71
PL	681	0.141	4.695	-21.871	14.899	-12.099	-0.265	1.67	86.9	7.05	29.52	-0.222	0.922	29.8	6.25	2.22
RS	681	0.491	7.019	-35.372	43.079	-21.598	-0.320	6.57	1237.3	11.75	66.48	-0.484	6.247	1133.9	8.52	0.57
SA	681	0.136	3.518	-15.168	13.077	-10.983	-0.580	2.16	170.7	12.40	49.06	-0.604	1.967	151.2	8.24	2.43
SI	681	0.071	3.306	-25.795	18.506	-9.135	-0.607	8.28	1987.5	7.10	89.38	-1.015	5.352	929.5	6.89	6.59
TA	681	-0.004	3.892	-14.403	19.363	-9.935	0.096	2.27	147.1	7.66	26.77	-0.223	1.221	48.0	7.99	5.81
TH	681	-0.135	5.547	-25.714	27.725	-15.667	0.136	3.16	286.3	17.96	216.20	-0.250	0.965	33.5	10.78	1.29
TU	681	0.265	7.535	-73.767	38.611	-20.606	-1.267	15.53	7029.5	6.83	34.13	-1.010	9.320	2580.3	6.77	0.91
VE	681	0.057	6.567	-69.462	45.542	-13.527	-1.811	26.00	19552.8	6.94	0.56	-2.517	27.537	22235.5	5.82	0.30

Notes. Acronyms for various countries are given in the first column (see Table 1 for correspondence). Returns are multiplied by 100. Filtered returns are obtained through GARCH(1,1) filters applied on raw returns. GARCH models are estimated assuming a t-Student conditional distribution. N is the number of observations. Avg is the mean, Std the standard deviation, Min the minimum weekly return, Max the maximum weekly return. VaR 1% is the empirical Value-at-Risk at the 1% risk level, SK is the skewness, KU the excess kurtosis. JB the Jarque-Bera normality-test statistics. Under the null of normality, it is asymptotically distributed according to a χ^2 distribution with two degrees of freedom with critical value equal to 9.21 at the 99% level. Q(5) is the Ljung-Box statistic with five lags applied to returns. Under the null of no autocorrelation for orders 1 to 5, it is asymptotically distributed according to a χ^2 distribution with five degrees of freedom with critical value equal to 15.09 at the 99% level. $Q^2(5)$ is the equivalent statistics but applied to squared returns.

Table 3. Descriptive statistics on bond returns

(06/06/97 to 09/21/2007, weekly data)

					Raw returns							Filtered returns				
	N	**Avg**	**Std**	**Min**	**Max**	**VaR 1%**	**SK**	**KU**	**JB**	**Q(5)**	**$Q^2(5)$**	**SK**	**KU**	**JB**	**Q(5)**	**$Q^2(5)$**
FR	538	-0.002	0.487	-2.364	1.369	-1.272	-0.531	1.15	54.8	6.64	10.31	-0.488	1.035	45.4	5.54	4.74
GE	538	-0.001	0.475	-2.003	1.236	-1.274	-0.483	0.74	33.0	6.46	6.51	-0.419	0.647	25.1	5.40	2.99
JP	538	-0.001	0.367	-2.472	1.810	-0.959	-0.509	6.33	921.7	20.68	91.46	-0.334	2.278	126.4	7.36	5.11
US	538	0.010	0.633	-3.149	1.695	-1.730	-0.612	1.34	73.7	6.40	24.33	-0.453	0.791	32.5	3.69	3.69
UK	538	0.002	0.690	-3.713	2.530	-1.761	-0.234	1.72	70.9	9.59	37.77	-0.053	0.599	8.3	5.78	13.57
AS	538	-0.002	0.454	-1.731	1.128	-1.197	-0.508	0.58	30.7	6.52	6.27	-0.454	0.604	26.7	6.18	5.24
AU	538	-0.023	0.582	-2.617	2.125	-1.444	-0.024	1.70	65.1	10.30	25.44	-0.072	0.673	10.6	9.96	6.08
CN	538	0.005	0.592	-2.927	1.496	-1.507	-0.427	0.89	34.1	9.76	28.66	-0.391	0.461	18.4	6.33	0.92
DN	538	-0.007	0.424	-1.545	1.447	-1.100	-0.327	0.83	24.9	6.90	10.85	-0.256	0.517	11.9	8.02	2.51
EI	538	0.023	0.552	-2.399	1.419	-1.545	-0.568	1.03	52.8	4.96	15.33	-0.477	0.960	41.1	5.32	7.05
FI	538	-0.011	0.401	-1.555	1.084	-1.194	-0.495	1.03	45.7	7.80	13.14	-0.459	1.059	44.1	6.62	3.65
IT	538	0.010	0.474	-1.639	1.245	-1.245	-0.399	0.43	18.4	5.38	4.28	-0.362	0.553	18.6	5.55	2.12
NL	538	-0.004	0.465	-2.018	1.142	-1.268	-0.494	0.78	35.4	4.56	10.47	-0.429	0.793	30.6	4.16	5.11
NW	538	-0.013	0.484	-2.302	1.976	-1.564	-0.467	2.99	220.2	5.66	43.32	-0.440	1.741	85.3	6.34	3.77
NZ	538	-0.002	0.479	-1.646	1.915	-1.168	-0.004	1.13	28.6	4.79	18.21	-0.122	0.828	16.7	5.82	2.90
PO	538	-0.003	0.419	-1.476	1.207	-1.177	-0.432	0.60	24.8	11.77	14.08	-0.268	0.824	21.7	11.20	5.76
SD	538	-0.006	0.475	-1.789	1.688	-1.355	-0.396	0.99	36.1	9.50	30.92	-0.279	0.526	13.2	10.25	1.39
SP	538	0.002	0.467	-1.749	1.175	-1.275	-0.473	0.44	24.4	5.11	8.97	-0.405	0.306	16.8	5.74	4.71
SW	538	-0.008	0.468	-2.079	1.379	-1.118	-0.394	1.06	39.1	17.10	5.79	-0.276	0.683	17.3	17.13	1.91
ARG	538	-0.049	3.276	-25.637	9.221	-11.591	-2.097	12.27	3770.9	13.96	74.22	-1.567	8.773	1945.3	6.89	0.31
BR	538	0.249	2.780	-17.502	12.671	-9.602	-1.109	7.80	1472.8	12.39	163.00	-1.913	11.121	3100.7	11.35	0.53
BU	538	0.200	2.330	-29.598	13.638	-7.062	-4.131	57.35	75252.8	19.61	36.90	-2.015	13.459	4424.9	15.29	0.92
CH	538	0.138	0.678	-2.635	3.561	-1.767	-0.007	2.37	126.4	9.31	149.83	-0.093	1.240	35.2	2.72	10.48
CO	538	0.204	1.834	-12.433	10.862	-6.389	-0.815	11.18	2863.4	36.14	267.43	-1.003	3.768	408.5	23.45	12.36
EC	538	0.252	4.237	-26.861	20.261	-13.498	-0.647	6.38	949.6	10.81	19.24	-0.996	6.116	927.5	11.88	1.95
KO	538	0.108	1.035	-11.525	6.861	-2.139	-3.226	45.23	46791.5	57.65	57.86	-1.962	16.380	6359.3	13.27	0.47
MLS	538	0.152	1.309	-12.937	7.904	-3.622	-1.644	25.61	14944.2	97.46	211.39	-0.614	1.032	57.7	21.70	9.40
MX	538	0.198	1.275	-11.338	6.001	-3.328	-1.559	15.14	5357.3	13.87	90.33	-1.141	6.160	967.4	8.78	5.48
PE	538	0.218	2.319	-15.252	11.600	-6.241	-0.772	8.31	1603.2	10.60	106.24	-1.274	5.318	779.3	8.84	9.53
PH	538	0.203	1.429	-7.595	8.181	-5.555	-0.766	7.89	1446.6	21.05	73.62	-1.109	5.028	677.0	11.21	2.80
PL	538	0.149	0.950	-7.450	4.800	-2.621	-1.280	12.14	3452.7	1.92	81.65	-1.387	10.057	2439.9	3.09	0.51
RS	538	0.225	4.923	-54.040	37.255	-16.889	-2.772	38.70	34256.2	61.24	94.05	-2.310	17.167	7084.4	24.37	0.23
SA	538	0.185	1.432	-10.503	14.216	-4.271	0.030	30.20	20448.7	37.49	320.22	-0.598	5.743	771.3	11.02	1.28
TH	538	0.123	1.561	-13.663	8.305	-6.540	-2.453	26.20	15927.3	87.37	216.08	-1.623	28.065	17892.8	5.78	0.33
TU	538	0.230	2.118	-18.501	15.922	-7.304	-1.549	21.97	11038.4	10.80	115.77	-3.054	23.500	13216.2	13.76	0.26
VE	538	0.230	2.602	-30.103	13.557	-6.472	-2.754	36.93	31255.8	42.85	39.85	-0.803	5.063	632.5	9.99	15.48

Notes. See Table 2.

Table 4. Summary statistics for fundamental determinants

	Bank_lending	**FDI**	**ImportDemand**	**Trade_Competition**	**Common_Lang**	**Log_Distance**	**Contigu**	**ProdGDP**
Period of observation	1994-2006	Various	1994-2005	1994-2005	Fixed	Fixed	Fixed	1994-2006
N	195	148	195	195	195	195	195	195
Mean	5.30%	2.95%	2.49%	17.88%	0.08	8.57	0.05	13.32
Median	2.34%	1.46%	1.25%	13.28%	0.00	8.98	0.00	13.30
Standard deviation	8.90%	4.20%	3.38%	15.28%	0.28	0.98	0.22	1.19
Minimum	0.18%	0.10%	0.14%	2.23%	0.00	5.46	0.00	10.16
Maximum	73.68%	27.33%	19.08%	95.80%	1.00	9.85	1.00	16.40
Correlation matrix	Bank_lending	FDI	ImportDemand	Trade_Competition	Common_Lang	Log_Distance	Contigu	ProdGDP
Bank_lending	1.00							
FDI	0.45	1.00						
ImportDemand	0.48	0.43	1.00					
Trade_Competition	0.32	0.37	0.58	1.00				
Common_Lang	0.34	0.33	0.28	0.05	1.00			
Log_Distance	-0.23	-0.23	-0.38	-0.04	0.00	1.00		
Contigu	0.28	0.22	0.51	0.09	0.27	-0.48	1.00	
ProdGDP	-0.09	0.02	0.12	0.10	0.08	0.04	0.11	1.00

Sources. See body text.
Notes. Bank lending, FDI, ImportDemand and Trade_Competition and ProdGDP are computed as averages over the specified period. Contigu and Common_Lang are binary variables.

Table 5. Regressions analysis of the determinants of extreme dependence

	All countries		Mature countries		Emerging countries	
	Stocks	**Bonds**	**Stocks**	**Bonds**	**Stocks**	**Bonds**
Intercept	0.857***	1.439***	0.671**	2.046***	0.490	0.390
	(0.244)	(0.292)	(0.343)	(0.314)	(0.409)	(0.541)
Bank_lending	0.408**	0.943**	0.192	0.505	0.670**	-0.718
	(0.199)	(0.410)	(0.374)	(0.343)	(0.267)	(1.678)
FDI	0.798*	0.106	0.392	-0.197	-0.271	1.186
	(0.462)	(0.550)	(0.531)	(0.486)	(1.244)	(2.306)
ImportDemand	-2.143***	-5.889***	-0.992	-2.341**	-1.458	-5.620***
	(0.671)	(0.889)	(1.246)	(1.141)	(1.123)	(1.195)
Trade_Competition	0.324**	0.592***	0.186	0.447**	0.198	0.694**
	(0.129)	(0.170)	(0.240)	(0.219)	(0.184)	(0.274)
Common_Lang	-0.019	0.227***	0.065	0.101	-0.148	0.099
	(0.060)	(0.083)	(0.088)	(0.081)	(0.095)	(0.245)
Log_Distance	-0.094***	-0.151***	-0.131***	-0.128***	-0.009	-0.054
	(0.019)	(0.024)	(0.029)	(0.027)	(0.040)	(0.056)
Contigu	0.17**	0.202**	-0.027	0.019	0.424**	0.413
	(0.082)	(0.101)	(0.102)	(0.094)	(0.210)	(0.288)
ProdGDP	0.028*	0.019	0.068***	-0.034	-0.001	0.030
	(0.016)	(0.018)	(0.026)	(0.024)	(0.020)	(0.026)
N	144	121	62	62	82	59
Adjusted R^2	0.296	0.436	0.356	0.495	0.067	0.123
F-test	8.534	12.493	5.215	8.467	1.732	2.018
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.105)	(0.063)

Notes. OLS estimations of the regressions (8). Standard errors in parentheses below coefficients. *, **, *** denotes significance of the coefficients at the 10%, 5% and 1% significance levels, respectively.

Table 6. Regressions robustness analysis

	Probit models		LAD with bootstrap	
	Stocks	**Bonds**	**Stocks**	**Bonds**
Intercept	1.280	7.549 ***	1.043 ***	1.686 ***
	(1.923)	(2.442)	(0.267)	(0.451)
Bank_lending	2.036	14.771 **	0.670 **	1.579 **
	(1.721)	(7.088)	(0.369)	(0.645)
FDI	12.243 *	3.935	1.244 *	0.729
	(7.069)	(5.771)	(0.721)	(0.518)
ImportDemand	-18.413 ***	-50.518 ***	-4.862 ***	-6.173 ***
	(5.830)	(13.513)	(0.977)	(1.175)
Trade_Competition	3.461 ***	3.342 **	0.583 **	0.422 ***
	(1.120)	(1.553)	(0.164)	(0.182)
Common_Lang	-0.361	1.403 *	-0.001	0.152 **
	(0.583)	(0.808)	(0.103)	(0.104)
Log_Distance	-0.748 ***	-1.176 ***	-0.105 ***	-0.175 ***
	(0.175)	(0.238)	(0.024)	(0.029)
Contigu	0.832	1.912	0.194	0.018
	(0.662)	(3.155)	(0.120)	(0.103)
ProdGDP	0.276 **	0.131	0.021	0.018
	(0.138)	(0.141)	(0.016)	(0.026)
N	144	121	144	121
# (%) Dep = 1	44 (30.6%)	51 (42.1%)		
R^2 Mc Fadden	0.305	0.438		
Wald test	49.105	37.103		
(p-value)	(0.000)	(0.000)		
LR	54.020	72.183		
(p-value)	(0.000)	(0.000)		

Notes. In this Table, we report the results of robustness analysis of the regressions (8) where the coefficients and their significance are not estimated through OLS. Probit models are based on the transformation of the extreme dependence indicator into a binary variable which takes value 1 if the indicator is not significantly different from 1 and zero in the contrary case. LAD regressions are aiming at minimizing the absolute value of the residuals. Standard errors are in parentheses below coefficients. *, **, *** denotes significance of the coefficient at the 10%, 5% and 1%, respectively. For determining the significance levels and the standard errors in the case of the Probit model, we use the asymptotic normality of the coefficients. In the case of the LAD regressions, we use the bootstrap distribution of coefficients. The number of bootstrap replications is fixed to 10,000.

Table 7. Senstivity test with an alternative extreme dependence measure

	p=5%		*p*=7%		*p*=10%	
	Stocks	**Bonds**	**Stocks**	**Bonds**	**Stocks**	**Bonds**
Intercept	0.854 ***	1.444 ***	0.852 ***	1.445 ***	0.813 ***	1.431 ***
Bank_lending	0.200	0.933 ***	0.216 *	0.877 **	0.171	0.821 **
FDI	0.626 **	-0.001	0.612 **	-0.056	0.627 **	0.039
ImportDemand	-1.829 ***	-4.384 ****	-1.657 ***	-4.461 ***	-1.504 ***	-4.517 ***
Trade_Competition	0.207 **	0.574 ***	0.179 **	0.634 **	0.153 **	0.649 ***
Common_Lang	0.030	0.176 **	0.01	0.174 **	0	0.179 **
Log_Distance	-0.089 ***	-0.213 ***	-0.088 ***	-0.208 ***	-0.084 ***	-0.201 ***
Contigu	0.147 ***	0.089	0.140 ***	0.111	0.149 ***	0.126
ProdGDP	0.009	0.043 **	0.01	0.041 **	0.012	0.039 **
N	144	121	144	121	144	121
Adjusted R^2	0.458	0.584	0.466	0.561	0.485	0.543
F-test	16.09	22.03	16.6	20.19	17.84	18.8
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes. Equations are similar to regressions (8) but where the endogeneous variable is replaced by the MCSR estimator given in (10). Equations are estimated by OLS. *, **, *** denotes significance of the coefficient at the 10%, 5% and 1%, respectively.