EXTREMAL DEPENDENCE IN INTERNATIONAL OUTPUT GROWTH: TALES FROM THE TAILS

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Abstract

The statistical modelling of extreme values has recently received substantial attention in a broad spectrum of sciences. Given that in a wide variety of scenarios, one is mostly concerned with explaining tail events (say, an economic recession) than central ones, the need to rely on statistical methods well qualified for modelling extremes arises. Unfortunately, several classical tools regularly applied in the analysis of central events, are simply innapropriate for the analysis of extreme values. In particular, Pearson correlation is *not* a proper measure for assessing the level of agreement of two variables when one is concerned with tail events.

This paper explores the comovement of the economic activity of several OECD countries during periods of large positive and negative growth (right and left tails, respectively). Extremal measures are here applied as means to assess the degree of cross-country tail dependence of output growth rates. Our main empirical findings are: (I) the comovement is much stronger in left tails than in right tails; (II) asymptotic independence is claimed by the data; (III) the dependence in the tails is considerably stronger than the one arising from a Gaussian dependence model. In addition, our results suggest that, among the typical determinants for explaining international output growth synchronization, only economic specialization similarity seems to play a role at extreme events.

KEYWORDS: Extreme value dependence; Output growth synchronization; Pearson correlation; Statistics of extremes.

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1. INTRODUCTION

The increasing need for modelling tail events has heavily contributed to the growing attention which has been recently devoted to the statistical analysis of extremes. In effect, in a multiplicity of situations, one may be particularly interested in focusing on rare tail events (say, a financial crisis), rather than on regular central events. The class of methods pertaining to the tribe of tail event modelling is frequently known in statistical parlance under the names of statistics of extremes (Beirlant *et al.*, 2004) or as extreme value theory (De Haan and Ferreira, 2006). A cornerstone result in extreme value modelling is the extremal types theorem (see, for instance, Coles, 2001). Just as the central limit theorem plays a leading role in the large sample modelling of means, the extremal types theorem is a key result which describes in general terms the asymptotic behavior of the maxima of a sequence of random variables. Roughly speaking, this result establishes that the limit distribution of properly standartized maxima converges to the Generalized Extreme Value (GEV) distribution which is fully characterized by location, scale and shape parameters. An introduction to the statistical modelling of extreme values can be found, for instance, in Coles (2001). For a comprehensive overview see, for example, De Haan and Ferreira (2006). Applications are thriving in many areas with modern methods of extreme value statistics being illustrated by questions which arise in the fields of Environmetrics (Sang and Gelfand, 2009), Ecology (Mendes *et al.*, 2010), Climatology (Ramos and Ledford, 2009), Hidrology (Cooley *et al.*, 2007), Quality Control (Fougères *et al.*, 2009), Terrorism Risk Analysis (Mohtadi and Murshid, 2009), as well as in many other contexts wherein there is the need to model consequences of far from average rare events. Although applications of extreme value statistics are also known in Finance (Longin and Solnik, 2001; Poon *et al.*, 2003, 2004; Straetmans *et al.*, 2008; Embrechts, 2009a), the number of applications in Economics is still scarce.

Unfortunately, several classical tools recurrently applied in the analysis of central events, are simply innapropriate for the analysis of extreme values. In particular, Pearson correlation, which is certainly the most widely used measure for assessing the degree of association between two variables of interest, is *not* proper for assessing the level of agreement of two variables at extreme levels. Applications of Pearson correlation are manifold. For example, in the growth cycle literature, Pearson correlation coefficient is the most extensively used measure of synchronization of economic activity. Despite of its broad use in applications, the price of its simplicity comes at the cost of some important limitations. These are particularly notorious when one intends to evaluate the comovement of two variables in the tails. Firstly, Pearson correlation makes no distinction between large positive and negative values. Specifically, in the context of the growth cycle literature, this implies that this measure places the same weight on positive and negative growth rates. Secondly, Pearson correlation is defined through an average of departures from the mean, so that its unsuitableness for quantifying dependence at tail events is self evident. Hence, in particular this measure becomes inappropriate for evaluating the strength of the comovement of output growth rates for periods which are far from average levels, such as during moments for which there is an extremely sharp decline in economic activity.

Notwithstanding, Coles *et al.* (1999) and Poon *et al.* (2003, 2004) have recently developed two theoretically rooted extremal dependence measures, along with a set of inference and estimation methods which can be very handy for practical applications. As it will be discussed below, these joint tail dependence measures arise thus as natural candidates for assessing the level of agreement of two variables at extreme levels, and in particular for modelling synchronization of economic activity at extreme events. A noteworthy feature is that if the dependence structure is Gaussian, one of the above mentioned extremal measures (namely $\overline{\chi}$) coincides with Pearson correlation ρ. This benchmark case is remarkably useful for guiding how does the dependence in the tails (as measured by $\overline{\chi}$) compares with the one arising from fitting a Gaussian dependence model.

This paper explores the comovement of the economic activity of several OECD countries during periods of large positive and negative growth. Extremal measures are here employed, as a means to evaluate the degree of cross-country tail dependence of output growth rates, over the past 50 years. Our analysis allow us to gaze at the comovements of international output growth from a completely novel standpoint. In consequence, this endows us with the means to collect some new stylized facts for cross-country output dynamics. *Firstly*, the application of extremal dependence measures, allow us to observe that the comovement of output growth rates is much stronger in left tails than in right tails. In particular, this implies that during acute recession periods the economic magnetism synchronizing growth cycles is much stronger than during the utmost expansionary periods. *Secondly*, asymptotic independence is claimed by the data. This is in line with Poon *et al.* (2003, 2004), who also find evidence of asymptotic independence in stock markets returns, and who note that this characterization is not only important for a more comprehensive understanding of the comovement of the variables during extreme events as it also brings deep implications for modelling the data. *Thirdly*, dependence in the tails is shown to be much stronger than the one arising from a Gaussian dependence model. In particular this implies that if we intend to use Pearson correlation for measuring synchronization of output growth rates during extreme scenarios, we will tend to underestimate the dependence in the tails.

The aforementioned caveats of the most predominantly employed measure of synchronization of economic activity motivates a further point of discussion. Are the factors driving the mechanics of propagation of shocks the same over junctures of sharp variations in output? Put differently, are the typical determinants of synchronization tenable throughout moments of exceptional positive and negative growth? As a byproduct of our analysis puts forward, among some of the most standard determinants for explaining international output synchronization (see, among others, Baxter and Kouparitsas, 2005; Inklaar *et al.*, 2008), only economic specialization similarity seems to play a role at extreme events.

The plan of this paper is as follows. The next section introduces measures of extreme value dependence along with guidelines for estimation and inference. In Section 3 we put at work these extremal dependence measures in order to explore the comovement of the economic activity of several OECD countries during periods of extreme positive and negative growth. Here we also assess if the determinants typically found as relevant for explaining international output growth sychronization also hold when the focus relies on extreme events. Concluding remarks are given in Section 4.

2. MEASURING DEPENDENCE IN THE TAILS

2.1 Dual Measures of Joint Tail Dependence

The link between the joint distribution function and its corresponding marginals can provide helpful information regarding the dependence of two random variables. In statistical parlance, the function C establishing such connection is defined as a copula (Nelsen, 2006). A key result in copula modelling is Sklar's theorem which, in its simplest form, establishes the existence and unicity of *a* copula C, for any given set of continuous marginals assigned to a certain joint distribution (see, for instance, Theorem 1 in Embrechts, 2009b). The most straightforward example of copula arises when the variables of interest are independent, so that the joint distribution function can be written as the product of the marginals, and so the corresponding copula is simply given by $\mathrm{C}(u,v) = uv$, for $(u,v) \in [0,1]^2$. Other examples of copulas can be found, for instance, in Granger *et al.* (2006), and references therein. As we shall see below, copulas also have a word to say regarding joint tail dependence modelling. In the sequel we collect a simple inequality from copula literature to be used below, namely

$$(2u-1)_+ \ \leq \ \mathrm{C}(u,u) \ \leq \ u, \quad \text{for } 0 < u < 1, \tag{1}$$

where $(.)_+$ denotes the positive part function.[1]

Before we are able to measure dependence in the extreme levels of the variables G_1 and G_2, here representing the output growth rates of two countries of interest, we first need to convert the data into an appropriate common scale. Only if the data are transformed into a unified scale fair comparisons can be made. Output growth rates are known to possess fat tails (Fagiolo *et al.*, 2008), so that transforming the data into the unit Fréchet scale becomes the natural choice.[2] This can be accomplished by turning the original pair (G_1, G_2) into

$$(Z_1, Z_2) = \left(-(\log F_{G_1})^{-1}, -(\log F_{G_2})^{-1}\right). \tag{2}$$

The marginal distribution functions G_1 and G_2 are typically unknown so that in practice the empirical distribution functions $\widehat{F}_{G_1}$ and $\widehat{F}_{G_2}$ are plugged in (2). After such relocation has been performed, the order of magnitude of the high quantiles of G_1 becomes comparable with those of G_2, so that all differences in the distributions that may persist are simply due to the dependence between the variables. A natural measure for assessing the degree of

[1] Inequality (1) is a ramification of a more general result known as Fréchet-Hoeffding bounds (see, for example, Nelsen 2006, pg. 11) which states that for any copula C

$$(u+v-1)_+ \ \leq \ \mathrm{C}(u,v) \leq \min\{u,v\}, \quad \text{for } (u,v) \in (0,1)^2.$$

[2] Although, we are restricting the exposition to the unit Fréchet scale, it should be pointed out that the conceptual framework underlying all measures presented here remains unchanged for cases wherein the variables are transformed into unit Pareto margins as, for instance, in Straetmans *et al.* (2008). In such case, in lieu of making use of (2), we would convert the pair (G_1, G_2) into $(\tilde{Z}_1, \tilde{Z}_2) = \left((1-F_{G_1})^{-1}, (1-F_{G_2})^{-1}\right)$.

dependence at an arbitrary high level z, is given by the bivariate tail dependence index χ (Coles *et al.*, 1999; Poon *et al.*, 2003, 2004), defined as

$$\chi = \lim_{z\to\infty} \Pr\{Z_1 > z \mid Z_2 > z\}. \tag{3}$$

Roughly speaking, χ measures the degree of dependence which may eventually prevail in the limit. Observe that, as it is clear from (3), χ is constrained to live in the interval $[0, 1]$. If dependence persists as $z \to \infty$, so that $0 < \chi \leq 1$, then we say that G_1 and G_2 are *asymptotically dependent.* If the degree of dependence vanishes in the limit, then $\chi = 0$, and in this case we say that the variables are *asymptotically independent.*

As discussed by Poon *et al.* (2003, 2004), this extremal dependence characterization is not only consequential for a more fine understanding of the comovement of the variables during extreme events as it also brings deep implications for statistically modelling the data. In particular, it is important to observe that if the variables are asymptotically independent then any naive application of multivariate extreme value distributions will lead to an overrepresentation of the occurrence of simultaneous extreme events.

Interestingly, it can be shown (Coles *et al.*, 1999), that χ can also be recasted in terms of a limit of a function of the copula C. More concretely, it holds that

$$\chi = \lim_{u\to 1} \chi(u), \tag{4}$$

where

$$\chi(u) = 2 - \log \mathrm{C}(u, u)/\log u, \qquad \text{for } 0 < u < 1. \tag{5}$$

Hence, the function C not only "couples" the joint distribution function and its corresponding marginals, as it also provides helpful information for modelling joint tail dependence. It is also worth mentioning that although we focused the discussion above around the measure χ, the function $\chi(u)$ is also important on its own right. In fact, $\chi(u)$ can be understood as a quantile dependent measure of dependence. Specifically, the sign of $\chi(u)$ can be used to ascertain if the variables are positively or negatively associated at the quantiles u, and as a consequence of (1), the level of dependence is known to be bounded as follows[3]

$$2 - \log(2u-1)_+/\log u \;\leq\; \chi(u) \;\leq\; 1, \qquad \text{for } 0 < u < 1. \tag{6}$$

It is worth noting that extremal dependence should be measured according to the dependence structure underlying the variables under analysis. In effect, if the variables are asymptotically dependent, the measure χ is appropriate for assessing what is the strength of dependence which links the variables at the extremes. If the variables are asymptotically independent then $\chi = 0$, so that χ unfairly pools in tandem cases wherein although dependence may not prevail in the limit, it may persist for relatively large levels of the variables. In order to measure extremal dependence under asymptotic independence, Coles *et al.* (1999) introduced the following measure

$$\overline{\chi} = \lim_{z\to\infty} \frac{2\log \Pr\{Z_1 > z\}}{\log \Pr\{Z_1 > z, Z_2 > z\}} - 1, \tag{7}$$

which takes values on the interval $(-1; 1]$. The interpretation of $\overline{\chi}$ is to a certain extent analogous to Pearson correlation, namely: values of $\overline{\chi} > 0$, $\overline{\chi} = 0$ and $\overline{\chi} < 0$, respectively correspond positive association, exact independence and negative association in the extremes. In effect it follows that if the dependence structure is Gaussian then $\overline{\chi} = \rho$ (Poon *et al.*, 2003, 2004). This benchmark case is particularly helpful for guiding how does the dependence in the tails, as measured by $\overline{\chi}$, compares with the one arising from fitting a Gaussian dependence model. For a comprehensive inventory for the functional forms of the extremal measure(s) $\overline{\chi}$ (and χ), over a broad variety of dependence models, see Heffernan (2000).

[3] As usual, for $(2u-1)_+ = 0$, the lower bound of (6) should be interpreted by taking the limit $(2u-1)_+ \to 0^+$.

The concepts of asymptotic dependence and asymptotic independence can also be characterized through $\overline{\chi}$. More specifically, for asymptotically dependent variables, it holds that $\overline{\chi} = 1$, while for asymptotically independent variables $\overline{\chi}$ takes values in $(-1, 1)$. Hence χ and $\overline{\chi}$ can be seen as dual measures of joint tail dependence: if $\overline{\chi} = 1$ and $0 < \chi \leq 1$, the variables are asymptotically dependent, and χ assesses the size of dependence within the class of asymptotically dependent distributions; if $-1 \leq \overline{\chi} < 1$ and $\chi = 0$, the variables are asymptotically independent, and $\overline{\chi}$ evaluates the extent of dependence within the class of asymptotically independent distributions.

In a similar way to (4), the extremal measure $\overline{\chi}$ can also be written using copulas, viz.

$$\overline{\chi} = \lim_{u \to 1} \overline{\chi}(u), \tag{8}$$

with

$$\overline{\chi}(u) = \frac{2 \log(1-u)}{\log(1 - 2u + \mathrm{C}(u,u))}. \tag{9}$$

Hence, the function C can provide helpful information for assessing dependence in extremes both under asymptotic dependence and asymptotic independence. In addition, the function $\overline{\chi}(u)$ plays an analogous role to $\chi(u)$, in the context of asymptotic independence. Thus it can also be used as quantile dependent measure of dependence, which, as a result of (1), is known to be bounded by

$$2\log(1-u)/\log(1-2u)_{+} - 1 \ \leq \ \overline{\chi}(u) \ \leq \ 1, \qquad \text{for } 0 < u < 1. \tag{10}$$

In the next subsection we direct our attention into estimation features of the dual measures of joint tail dependence χ and $\overline{\chi}$ introduced above.

2.2 Nonparametric Estimation of Extremal Dependence

Although the representations provided above are enlightening from the conceptual stance, they are not directly well-suited for estimation purposes. Nevertheless, these can be suitably reparametrized relying on a result due to Ledford and Tawn (1996, 1998), which establishes that, under fairly mild assumptions, the univariate variable $\mathcal{Z} = \min\{Z_1, Z_2\}$ has a regularly varying tail with index $-1/\eta$. Formally

$$\Pr\{\mathcal{Z} > z\} \sim \frac{\mathcal{L}(z)}{z^{1/\eta}} \quad \text{as } z \to \infty, \tag{11}$$

where $\mathcal{L}(z)$ is used to denote a slowly varying function, i.e., $\lim_{x\to\infty} \mathcal{L}(xz)/\mathcal{L}(x) = 1$, for every $z > 0$. The constant η, which is constrained to the interval (0,1], is the so-called coefficient of tail dependence. Trivially, the result reported in (11) can be restated as

$$\Pr\{Z_1 > z, Z_2 > z\} \sim \frac{\mathcal{L}(z)}{z^{1/\eta}} \quad \text{as } z \to \infty. \tag{12}$$

Hence, if we plug (12) in (7), the following notable reparametrization (Coles *et al.*, 1999) of $\overline{\chi}$, in terms of the coefficient of tail dependence η, arises

$$\overline{\chi} = 2\eta - 1. \tag{13}$$

From the practical stance this representation is quite appealing since it only depends on η, which can be estimated nonparametrically. This can be performed through the well known Hill tail index estimator (Hill, 1975) defined as

$$\widehat{\eta}_H = \frac{1}{k} \sum_{i=1}^{k} \left\{ \log \mathcal{Z}_{(n-k+i)} - \log \mathcal{Z}_{(n-k)} \right\}, \tag{14}$$

and which in this case is also the maximum likelihood estimator of η. Here and below, we use $\mathcal{Z}_{(1)} \leq \ldots \leq \mathcal{Z}_{(n)}$, to denote the order statistics of a random sample $\{\mathcal{Z}_i\}_{i=1}^{n}$ from $\mathcal{Z} = \min\{Z_1, Z_2\}$. Hence, from the discussion given above, the nonparametric estimation of $\overline{\chi}$ (Poon *et al.*, 2003, 2004) follows naturally as

$$\widehat{\overline{\chi}} = 2\widehat{\eta}_H - 1, \tag{15}$$

with corresponding variance

$$\text{var}\{\widehat{\overline{\chi}}\} = \frac{(\widehat{\overline{\chi}} + 1)^2}{\mathcal{Z}_{(n-k)}}. \tag{16}$$

A remark regarding practicalities. The value of the estimate produced according to (14) appreciably depends on k, which represents the number of observations used to conduct the tail index estimation. There is a clear bias-variance tradeoff playing a role here. If too few observations are elected then the produced estimate is subject to a large variance. On the other hand, if too many observations are plugged in into the estimation a bias will arise. In order to select the optimal $k^\star$, one can make use of a well known iterative subsample bootstrap procedure proposed by Daníelsson and De Vries (1997). A brief description of this method is based on a recursive application of the following stages. In a *first step* a Hall subsample bootstrap (Hall, 1990) is employed to subsamples of size n_1 to yield a starting value for $k^\star$ (*say* $k_1^\star$). In a *second step*, the Hill estimator (14) is routinely applied to the subsamples using the starting value $k_1^\star$ in order to consistently estimate a first order parameter α. Lastly, in a *third step* the estimation of a second order parameter β is conducted through an estimator proposed in Daníelsson and De Vries (1997). The optimal value for $k^\star$ is then given by properly combining k_1 and the first and second order parameters, viz.: $k^\star = k_1^\star(n/n_1)^{2\beta/(2\beta+\alpha)}$.

In what concerns inference, we can take full advantage of the asymptotic normality of the Hill estimator (De Haan and Ferreira, 2006, Chapter 3). Hence, if $\widehat{\overline{\chi}}$ is significantly less than 1, at the α-level, so that

$$\widehat{\overline{\chi}} < 1 - z_\alpha \sqrt{\text{var}\{\widehat{\overline{\chi}}\}}\ ,$$

then we infer that the variables are asymptotically independent and take $\chi = 0$. It is important to underscore that only if there is no significant evidence to reject $\overline{\chi} = 1$, we prosecute with χ estimation, which is done under the assumption $\overline{\chi} = \eta = 1$.

Similarly to what was done above, wherein we evidenced how the Hill estimate of η could be used to estimate $\overline{\chi}$, here we use the maximum likelihood estimator of the slowly varying function

$$\widehat{\mathcal{L}(z)} = (1 - k/n)(\mathcal{Z}_{(n-k)})^{1/\eta}, \tag{17}$$

in order proficiently estimate χ (Poon *et al.*, 2003, 2004). Thus, if we introduce (17) in (12), under the constraint $\widehat{\overline{\chi}} = 1$, and make use of the definition of the extremal measure χ, the following estimator arises

$$\widehat{\chi} = (k/n)\mathcal{Z}_{(n-k)}$$

$$\text{var}\{\widehat{\chi}\} = k(n-k)/n^3(\mathcal{Z}_{(n-k)})^2.$$

The next section puts at work the dual measures of joint tail dependence described above as well as their corresponding estimation methods .

3. SYNCHRONIZATION AT EXTREMES

3.1 Extremal Dependence in International Output Growth

Our empirical analysis entails 15 OECD countries: Austria, Belgium, Canada, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, UK and US. The main criteria for selecting the aforementioned catalog of nations was the period for which the first observation was available. In fact, since the methods introduced in the foregoing section are based on large sample results, there is the need to confine the breadth of the study to countries for which a longer span of data is at one's disposal. We use the first differences of the logarithm of the (seasonally adjusted) Industrial Production (IP) index, with the time horizon ranging from January 1960 to December 2009, gathered from Thompson Financial Datastream.[4] As mentioned above the presented measures are based

[4] There are two exceptions to be noted. Namely for Canada and Spain, the data was only available starting from January 1961 and 1964, respectively.

on asymptotic theory, so that other economic activity measures such as the GDP, which is only available on a quarterly basis and, for most countries, over shorter periods of time, are not considered. Although we are aware that the index used here is a proxy for measuring economic activity evolution, it is widely known that the IP is strongly correlated with the aggregate activity as measured by GDP (see, for instance Fagiolo *et al.*, 2008).

[Insert Table 1 about here]

We start the analysis with Pearson correlation ρ which is reported in Table 1. This table summarizes correlation between all possible pairs of economies and thus supplies an important benchmark for comparison with extremal dependence measures in the following sense. If we believed that a Gaussian dependence model was ruling the mechanics of the comovement of international output growth then dependence in the left and right tails should coincide with Pearson correlation coefficient.[5] In particular, this would imply that the degree of association should be alike in periods of extreme declines and increases in economic activity. As we shall see below this happens not to be the case, as there is an overall proclivity towards a larger international comovement throughout periods of sharp declines than during acute increases in output growth. In addition, as it will be discussed in the sequel any naive estimation based on ρ tends to underestimate the strength of extremal dependence in output growth comovements.

A short comment regarding notation. In order to draw a distinction between left and right tails dependence, as measured by $\overline{\chi}$, we make use of the shorthand notations $\overline{\chi}_{\mathrm{L}}$ and $\overline{\chi}_{\mathrm{R}}$, respectively.

[Insert Table 2 about here]

[5] As discussed above, in a Gaussian dependence model it holds that $\overline{\chi} = \rho$.

In Table 2 we outline the results from the examination of joint left-tail dependence in the comovement of economic output. Some brief remarks regarding the construction of this table are in order. Firstly, the optimal $k^\star$ was estimated by dint of the iterative subsample bootstrap procedure of Daníelsson and De Vries (1997), for each possible pair of countries. Secondly, the corresponding estimates of the coefficient of tail dependence η are obtained through (14). Finally, in order to work out the estimates of $\overline{\chi}_{\mathrm{L}}$, the Hill estimates obtained in the latter step are introduced in (15).[6]

From the inspection of Table 2 we can ascertain that in the overall, the reported results are considerably higher than the corresponding counterparts reported in Table 1. To be more precise, in 90.48% of the cases it is verified that the estimated value of $\overline{\chi}_{\mathrm{L}}$ lies above ρ. The lesson here is the following: the strength of economic activity comovement is much stronger during sharp declines than a Pearson correlation would foretell. Additionally, there is strong evidence to support the hypothesis of asymptotic independence in left tails. In fact, in 96 pairs, out of a total of $105 = \binom{15}{2}$, we are not able to reject the null of asymptotic independence at the α-level of 5%. Moreover, the percentage of non-rejections increases into 97.1%, with only 3 pairs suggesting asymptotic dependence, if we consider an α-level of 10%. Such pairs are (Japan, Germany), (Canada, Spain) and (UK, Canada), with corresponding χ values given by 0.3090, 0.3160 and 0.3173, respectively.

[**Insert Table 3 about here**]

Table 3 sums up an analogous exercise to the one reported in Table 2, but now focusing on right tails. Likewise, there is also a general evidence for the estimated values of $\overline{\chi}_{\mathrm{R}}$ to be larger than their corresponding correlations, as measured by ρ, although the strength of the

[6] All the R (R Development Core Team, 2007) codes developed to implement these procedures are available from the authors upon request.

dominance is here markedly lower. More specifically, in 71.90% of the cases the computed values of $\overline{\chi}_{\mathrm{R}}$ remain above Pearson correlation. Particularly, this implies that the extent of the synchronization is manifestly larger during periods of sharp increases in the economic activity growth than a naive estimate of ρ would predict. Furthermore, the statistical evidence in favor of the hypothesis of asymptotic independence is also here remarkably clear with all pairs supporting the null at the α-level of 10%. The comparison of Tables 2 and 3 also brings an enlightening point into the discussion: in the overall left-tail dependence is markedly stronger than right-tail dependence. To be more specific, in 78.57% of the cases the estimated value of $\overline{\chi}_{\mathrm{L}}$ dominates $\overline{\chi}_{\mathrm{R}}$. The message here is the following: dependence is more pronounced in periods of sharp declines than during epochs of steep increases in economic activity growth.

[Insert Figure 1 about here]

To make a long story short, we depict in Figure 1 the average values per country for $\overline{\chi}_{\mathrm{L}}$, $\overline{\chi}_{\mathrm{R}}$ and for ρ. This figure wraps up the discussion given above concerning the relative ordering between these measures. On one hand, Figure 1 highlights that in average $\overline{\chi}_{\mathrm{L}}$ dominates $\overline{\chi}_{\mathrm{R}}$, which is consistent with the observations made above vis-à-vis the dominance of left tails over right tails. On the other hand, it is also clear from the inspection of this figure that, in average, $\overline{\chi}_{\mathrm{L}}$ and $\overline{\chi}_{\mathrm{R}}$ lie above ρ. This complies with the aforementioned discussion regarding the supremacy of the dependence in the tails in comparison with the one which would arise from a Gaussian dependence model.

3.2 Do Typical Determinants of Comovement Hold in the Tails?

In this section, we assess if the determinants typically found as important in explaining international output synchronization are tenable when one focus on extremal dependence.

Among the several variables deemed to influence output synchronization, the foremost candidates are trade variables. Although it has long been acknowledged that trade is an important linkage between economies, theory is ambiguous whether intensified trade relations result in more or in less output comovement. From one point of view, comparative advantage trade theories postulate that increasing trade leads to a higher degree of production specialization and consequently to a lower comovement (see, for example, Krugman 1992). From another point of view, according to a wide range of theoretical models of international trade, with either technology or monetary shocks, increasing trade often results in higher comovement. For instance, Frankel and Rose (1998) assert that closer trade links lead to higher output synchronization as an outcome. The underlying issue is whether bilateral trade is mainly intra-industry or inter-industry driven. In the former case one would expect higher comovement whereas in the latter lower comovement would be predicted. Hence, along with the role of bilateral trade, one should also take into account the relative trade specialization.

Another potential determinant often considered in the literature is the similarity of the production composition. The intuition here is that countries with similar economic structure should be in like manner affected by sector-specific shocks which may induce an higher output comovement (see, for example, Imbs 2004). The existence of other similarity mechanisms paralleling in the economies is also reckoned among the conceivable determinants of synchronization. For example, the implementation of coordinated policies may also have an effect in synchronization. If two countries adopt similar policies, either monetary or fiscal, an higher synchronization may be induced (see, for example, Inklaar *et al.* 2008).

As in theory, many factors may potentially underlie output synchronization, identifying the determinants of comovement becomes an empirical matter. Among the variables that have been pointed out in the literature as possible explanatory determinants of international output comovement (for a comprehensive overview see, for example, Inklaar *et al.* 2008, and references therein), we concern ourselves with the variables that have been found robust in related work.[7] Two influential papers in this respect are Baxter and Kouparitsas (2005) and Inklaar *et al.* (2008). On one hand, Baxter and Kouparitsas (2005) consider over one hundred countries and the variables under analysis are: bilateral trade between countries; total trade in each country; sectoral structure; similarity in export and import baskets; factor endowments; and gravity variables. On the other hand, Inklaar *et al.* (2008) considered an even larger assortment of potential variables for 21 OECD countries. The results of the latter suggest that besides bilateral trade between countries (as in Baxter and Kouparitsas 2005), variables capturing similarity of monetary and fiscal policies, as well as specialization measures are robust determinants of international output comovement.

As Inklaar *et al.* (2008) also consider the monthly IP as a measure of economic activity and the set of countries is closer to our case, we will draw heavily on their findings vis-à-vis the selection of the variables to be examined in the remaining analysis. Thus, we consider as possible determinants of output comovement the following variables: (i) the bilateral trade between countries; (ii) three specialization indicators; (iii) a similarity measure of monetary policy stance; and (iv) a similarity measure of fiscal policy stance. Some specific comments, about the meaning and computation of each of these yardsticks, will be provided in the sequel. For the ease of exposition in the following we make use of some simplifying conventions regarding notation. The indices i and j are reserved to represent countries, whereas t is taken to denote time. Hence in cases where the respective meaning of these indices is clear from the context they may be ommited. In addition, capital letters are intended to

[7] Recent work makes use of extreme bounds analysis, suggested by Leamer (1983) and developed by Levine and Renelt (1992) and Sala-i-Martin (1997), to ascertain the 'robustness' of the determinants. Here the word 'robust' should be understood in Leamer's terminology, and hence it applies to variables whose statistical significance does not depend on the information set.

represent 'totals' of the corresponding indices (for instance, T should be understood as the total number of time t periods).

Starting with the first variable mentioned above, here we make use of *bilateral trade intensity*, for the pair of countries (i, j), which is given by

$$\frac{1}{T}\sum_{t=1}^{T}\frac{x_{ijt}+m_{ijt}+x_{jit}+m_{jit}}{x_{it}+m_{it}+x_{jt}+m_{jt}}. \tag{18}$$

Here x_{ijt} and m_{ijt} respectively denote exports and imports from country i to country j, while x_{it} and m_{it} respectively represent total exports and imports of country i. This basically corresponds to the preferred measure of Baxter and Kouparitsas (2005). All data regarding trade flows is taken from the CHELEM International Trade Database and covers the period from 1967 up to 2008.

As mentioned earlier three indicators of specialization measure are here calculated. More specifically the computed indicators are: industrial similarity; export similarity; and intra-industry trade. The *industrial similarity*, proposed by Imbs (2004), can be written as

$$\frac{1}{T}\sum_{t=1}^{T}\left(1-\frac{1}{L}\sum_{l=1}^{L}|s_{ilt}-s_{jlt}|\right), \tag{19}$$

where s_{ilt} denotes the production share of industry l in country i. As in Inklaar *et al.* (2008), we resort to the 60-Industry Database of the Groningen Growth and Development Centre, which has data mainly at the 2-digit ISIC detail level and the sample period ranges from 1979 up to 2003. By its turn, *export similarity*, suggested by Baxter and Kouparitsas (2005), is computed as

$$\frac{1}{T}\sum_{t=1}^{T}\left(1-\frac{1}{P}\sum_{p=1}^{P}|s_{ipt}-s_{jpt}|\right), \tag{20}$$

where s_{ipt} is product p's share of country i's total exports. Likewise Baxter and Kouparitsas (2005), export shares are obtained using trade data by commodity at the 2-digit ISIC detail level for all country pairs. Finally, the measure of *intra-industry trade* is given by

$$\frac{1}{T}\sum_{t=1}^{T}\left(1-\frac{\sum_p |x_{ijpt}-m_{ijpt}|}{\sum_p (x_{ijpt}+m_{ijpt})}\right), \tag{21}$$

where x_{ijpt} and m_{ijpt} respectively denote the exports and imports of product p from country i to country j. Again, trade data by commodity at the 2-digit ISIC detail level is used.

Concerning the similarity measure of monetary policy stance, we follow Inklaar *et al.* (2008) and compute the correlation for all country pairs of the monthly short-term interest rates taken from the OECD Main Economic Indicators database, using the available data up to December 2009. Regarding the measure of fiscal policy stance, we compute the correlation for all country pairs of the cyclically adjusted government primary balance, as a percentage of potential GDP, available at the OECD Economic Outlook Database, with the sample period ranging in most cases from 1970 up to 2009.

[**Insert Table 4 about here**]

In Table 4, we set forth the regression results using as dependent variable a measure of the degree of association (namely, the Pearson correlation coefficient, the left and right joint tail dependence, respectively measured by $\overline{\chi}_{\mathrm{L}}$ and $\overline{\chi}_{\mathrm{R}}$) and as covariates the above described factors, to wit: bilateral trade intensity; a specialization measure; and two policy stance similarity indicators. For the Pearson correlation coefficient, the results are broadly similar to those obtained by Inklaar *et al.* (2008). We also find evidence supporting the importance of bilateral trade intensity, specialization measure and monetary policy stance similarity for explaining comovement. In contrast, the fiscal policy stance indicator is not statistically significant in our case. One should note that besides the fact that both the set of countries and the sample period are not the same, we use the cyclically adjusted government primary balance whereas Inklaar *et al.* (2008) use the cyclically adjusted government total balance. As it is widely acknowledged, the government primary balance is a more adequate measure of the current fiscal policy stance since it is not affected by interest rate payments on the government debt which reflects an accumulated governmental deficit over previous years.

The question that now arises is the following. Are the standard determinants of synchronization tenable over periods of exceptional positive and negative growth? An answer to this question is given by examining in Table 4 the regression outputs for the cases wherein $\overline{\chi}_{\mathrm{L}}$ and $\overline{\chi}_{\mathrm{R}}$ are taken as dependent variables. From this exercise, a major conclusion can be readily gathered. With the exception of the specialization measure, all the above determinants are not statistically significant. This means that for the comovement in extreme events what really seems to matter is the specialization similarity between economies. On the face of it, the vehicle of propagation of shocks over scenarios of sharp variations in output appears to be the specialization similarity across economies. Among the specialization indicators considered, the evidence for the export similarity measure, proposed by Baxter and Kouparitsas (2005), is the strongest as it is statistically significant in the regression for both tails. By its turn, the industrial similarity measure, as suggested by Imbs (2004), is clearly important for explaining left-tail dependence whereas the intra-industry trade, used by Inklaar *et al.* (2008), seems to be more relevant for right-tail dependence.

4. FINAL REMARKS

Extreme value theory methods are at the crux of the statistical modelling of tail events. The theory and methods at discussion have received a pronounced recognition in applications over several fields of research. In fact, given that in a broad variety of situations, one is chiefly interested in learning from costly tail events, the need to be equipped with statistical methods accredited for extreme value modelling arises. Yet, several statistical tools oftentimes employed in the analysis of central events are simply improper for tail event modelling. Particularly, Pearson correlation is *not* a suitable measure for evaluating the strength of joint tail dependence.

This paper examines the synchronization of several OECD countries during periods of abrupt declines and sudden increases in international economic activity, over the last 50 years. From the conducted analysis some noteworthy empirical findings are here collected. The first to be stressed is the asymmetric tail behavior of extremal dependence. In fact, our results point towards a remarkable dominance of left tails over right tails. Particularly, this implies that sychronization is more intense during periods of sharp declines than during scenarios of large positive growth. A second result to be mentioned is that our results pinpoint statistical evidence in favor of asymptotic independence. Another point to be noted is that dependence in the tails is appreciably stronger than the one suggested by a Gaussian dependence model. Thus, in particular, this implies that Pearson correlation considerably underestimates the level of synchronization in periods large positive and negative growth. Lastly, our results put forward that, among the standard determinants used for explaining international output growth synchronization, only specialization similarity seems to play a role during extreme events.

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Table 1: Pearson correlation of the output growth rates for OECD countries.

	Pearson correlation ρ														
	AUS	BEL	CN	FIN	FR	GER	IT	JP	NL	NOR	POR	SP	SWE	UK	US
AUS		0.3073	0.0820	0.0743	0.0515	0.1449	0.2760	-0.0489	0.1767	0.0181	-0.0325	-0.0018	0.0467	0.1881	0.0206
BEL	0.3073		0.0133	0.0414	0.0463	0.1603	0.2736	-0.0425	0.0382	0.0190	-0.0291	0.0400	0.0788	0.2181	0.0470
CN	0.0820	0.0133		0.1664	0.0939	0.0848	0.0737	0.1749	0.0693	0.0690	-0.0030	0.1162	0.0506	0.1569	0.3715
FIN	0.0743	0.0414	0.1664		0.0726	0.1285	0.0828	0.0673	0.0488	-0.0362	0.1048	0.0195	0.2594	0.0368	0.0704
FR	0.0515	0.0463	0.0939	0.0726		0.1093	0.0536	0.1110	0.0898	-0.0375	0.0178	0.0823	0.1213	0.0215	0.0443
GER	0.1449	0.1603	0.0848	0.1285	0.1093		0.0684	0.2262	0.1136	-0.0157	0.0969	0.0922	0.0350	0.1527	0.1430
IT	0.2760	0.2736	0.0737	0.0828	0.0536	0.0684		0.0511	0.1678	0.0829	0.0576	0.1196	0.1088	0.1715	0.1180
JP	-0.0489	-0.0425	0.1749	0.0673	0.1110	0.2262	0.0511		0.0237	0.0073	0.1232	0.1434	0.0401	0.0831	0.2068
NL	0.1767	0.0382	0.0693	0.0488	0.0898	0.1136	0.1678	0.0237		-0.1022	0.0541	0.1139	0.0376	0.1817	0.0545
NOR	0.0181	0.0190	0.0690	-0.0362	-0.0375	-0.0157	0.0829	0.0073	-0.1022		0.0288	0.0352	0.0266	-0.0423	0.0270
POR	-0.0325	-0.0291	-0.0030	0.1048	0.0178	0.0969	0.0576	0.1232	0.0541	0.0288		0.1793	-0.0832	0.0426	-0.0391
SP	-0.0018	0.0400	0.1162	0.0195	0.0823	0.0922	0.1196	0.1434	0.1139	0.0352	0.1793		0.1336	0.0208	0.0776
SWE	0.0467	0.0788	0.0506	0.2594	0.1213	0.0350	0.1088	0.0401	0.0376	0.0266	-0.0832	0.1336		0.1265	0.0936
UK	0.1881	0.2181	0.1569	0.0368	0.0215	0.1527	0.1715	0.0831	0.1817	-0.0423	0.0426	0.0208	0.1265		0.1493
US	0.0206	0.0470	0.3715	0.0704	0.0443	0.1430	0.1180	0.2068	0.0545	0.0270	-0.0391	0.0776	0.0936	0.1493	

NOTES: AUS = Austria ; BEL = Belgium ; CN = Canada ; DK = Denmark ; FIN = Finland ; FR = France ; GER = Germany ; IT = Italy ; JP = Japan ; NL = Netherlands ; NOR = Norway ; POR = Portugal ; SP = Spain ; SWE = Sweden ; UK = United Kingdom ; US = United States of America.

Table 2: Left-tail dependence of the output growth rates for OECD countries.

	$\overline{\chi}_L$ (Left-tail dependence as measured by $\overline{\chi}$)														
	AUS	BEL	CN	FIN	FR	GER	IT	JP	NL	NOR	POR	SP	SWE	UK	US
AUS		0.3306	0.2233	0.2082	0.3355	0.3089	0.2815	0.4649	0.1783	0.2174	-0.0602	0.1045	0.2144	0.4512	0.1616
BEL	0.3306		0.1193	-0.0221	0.2472	0.2042	0.4695	0.2222	0.1455	0.2685	-0.0286	0.4878	0.2374	0.6945	0.0304
CN	0.2233	0.1193		0.6593	0.5195	0.3835	0.3426	0.7964	0.4253	0.1821	0.1495	0.8673	0.1820	0.5378	0.7113
FIN	0.2082	-0.0221	0.6593		0.4634	0.7133	0.3876	0.5085	0.1248	0.2421	0.3009	0.2620	0.4097	0.2709	0.3070
FR	0.3355	0.2472	0.5195	0.4634		0.3134	0.2743	0.4468	0.2970	0.1311	0.1985	0.3537	0.4243	0.4265	0.1549
GER	0.3089	0.2042	0.3835	0.7133	0.3134		0.4390	0.6803	0.2650	-0.0718	-0.0177	0.0292	0.5709	0.5559	0.5489
IT	0.2815	0.4695	0.3426	0.3876	0.2743	0.4390		0.2807	0.1579	0.0760	0.4741	0.2466	0.6350	0.6165	0.3513
JP	0.4649	0.2222	0.7964	0.5085	0.4468	0.6803	0.2807		-0.0920	0.3153	0.0926	0.1648	0.3136	0.4895	0.3582
NL	0.1783	0.1455	0.4253	0.1248	0.2970	0.2650	0.1579	-0.0920		-0.1104	0.2051	0.2198	0.2431	0.2890	0.3893
NOR	0.2174	0.2685	0.1821	0.2421	0.1311	-0.0718	0.0760	0.3153	-0.1104		0.2435	0.5762	0.3724	0.0752	0.2126
POR	-0.0602	-0.0286	0.1495	0.3009	0.1985	-0.0177	0.4741	0.0926	0.2051	0.2435		0.1882	0.0904	0.1701	0.2392
SP	0.1045	0.4878	0.8673	0.2620	0.3537	0.0292	0.2466	0.1648	0.2198	0.5762	0.1882		0.1485	0.3036	0.6660
SWE	0.2144	0.2374	0.1820	0.4097	0.4243	0.5709	0.6350	0.3136	0.2431	0.3724	0.0904	0.1485		0.4895	0.5396
UK	0.4512	0.6945	0.5378	0.2709	0.4265	0.5559	0.6165	0.4895	0.2890	0.0752	0.1701	0.3036	0.4895		0.5002
US	0.1616	0.0304	0.7113	0.3070	0.1549	0.5489	0.3513	0.3582	0.3893	0.2126	0.2392	0.6660	0.5396	0.5002	

NOTES: AUS = Austria ; BEL = Belgium ; CN = Canada ; DK = Denmark ; FIN = Finland ; FR = France ; GER = Germany ; IT = Italy ; JP = Japan NL = Netherlands ; NOR = Norway ; POR = Portugal ; SP = Spain ; SWE = Sweden ; UK = United Kingdom ; US = United States of America.

Table 3: Right-tail dependence of the output growth rates for OECD countries.

	$\overline{\chi}_{\mathrm{R}}$ (Right-tail dependence as measured by $\overline{\chi}$)														
	AUS	BEL	CN	FIN	FR	GER	IT	JP	NL	NOR	POR	SP	SWE	UK	US
AUS		0.6020	-0.1907	0.1072	0.2875	0.0959	0.4584	-0.0053	0.1407	0.2027	0.1304	-0.0555	-0.0856	0.3831	0.0998
BEL	0.6020		-0.1243	0.1239	0.1812	0.4930	0.2857	-0.0490	0.1587	-0.0184	0.0108	0.2388	0.1102	0.3831	-0.1974
CN	-0.1907	-0.1243		0.0735	-0.0836	0.1854	0.3215	0.1592	-0.2801	0.3181	0.0693	0.0359	0.0835	0.1513	0.0721
FIN	0.1072	0.1239	0.0735		0.1750	0.2358	0.0839	0.0895	0.1574	0.1701	0.0198	-0.1508	0.5396	0.1720	0.1569
FR	0.2875	0.1812	-0.0836	0.1750		0.1403	0.1693	0.3287	0.3095	0.2648	0.0644	0.2075	0.3047	0.1609	0.3225
GER	0.0959	0.4930	0.1854	0.2358	0.1403		0.1651	0.2693	0.1188	0.0198	0.2646	0.4709	0.1236	0.2091	0.0873
IT	0.4584	0.2857	0.3215	0.0839	0.1693	0.1651		0.0043	0.0708	0.0794	0.4226	0.0937	0.1480	0.5779	0.4077
JP	-0.0053	-0.0490	0.1592	0.0895	0.3287	0.2693	0.0043		-0.0782	0.1348	0.4659	0.0242	0.0529	0.2261	0.2324
NL	0.1407	0.1587	-0.2801	0.1574	0.3095	0.1188	0.0708	-0.0782		0.1875	0.0252	0.1197	-0.0721	0.3355	0.1409
NOR	0.2027	-0.0184	0.3181	0.1701	0.2648	0.0198	0.0794	0.1348	0.1875		0.0292	0.3102	0.2181	0.1926	0.0765
POR	0.1304	0.0108	0.0693	0.0198	0.0644	0.2646	0.4226	0.4659	0.0252	0.0292		0.0945	-0.1106	0.1111	0.1880
SP	-0.0555	0.2388	0.0359	-0.1508	0.2075	0.4709	0.0937	0.0242	0.1197	0.3102	0.0945		0.2879	0.2222	0.0695
SWE	-0.0856	0.1102	0.0835	0.5396	0.3047	0.1236	0.1480	0.0529	-0.0721	0.2181	-0.1106	0.2879		0.0968	-0.0010
UK	0.3831	0.3831	0.1513	0.1720	0.1609	0.2091	0.5779	0.2261	0.3355	0.1926	0.1111	0.2222	0.0968		0.2691
US	0.0998	-0.1974	0.0721	0.1569	0.3225	0.0873	0.4077	0.2324	0.1409	0.0765	0.1880	0.0695	-0.0010	0.2691	

NOTES: AUS = Austria ; BEL = Belgium ; CN = Canada ; DK = Denmark ; FIN = Finland ; FR = France ; GER = Germany ; IT = Italy ; JP = Japan NL = Netherlands ; NOR = Norway ; POR = Portugal ; SP = Spain ; SWE = Sweden ; UK = United Kingdom ; US = United States of America.

Table 4: Comovement Determinants over Pearson Correlation and Extremal Dependence Measures.

	Specialization Measure					
	Industrial similarity		Export similarity		Intra industry trade	
Pearson Correlation						
	Coefficient	t-HCSE	Coefficient	t-HCSE	Coefficient	t-HCSE
Bilateral trade	0.571	2.89	0.533	2.20	0.526	2.07
Specialization measure	0.146	3.50	0.087	2.79	0.102	1.58
Short-term interest rate	0.091	2.06	0.102	2.31	0.107	2.34
Cyclically adjusted government primary balance	0.008	0.34	0.002	0.09	-0.005	-0.19
Left-tail Extremal Dependence						
	Coefficient	t-HCSE	Coefficient	t-HCSE	Coefficient	t-HCSE
Bilateral trade	0.528	1.25	0.385	0.71	0.578	1.22
Specialization measure	0.344	3.12	0.233	3.02	0.149	0.93
Short-term interest rate	-0.074	-0.57	-0.052	-0.41	-0.028	-0.21
Cyclically adjusted government primary balance	0.030	0.41	0.013	0.18	0.011	0.14
Right-tail Extremal Dependence						
	Coefficient	t-HCSE	Coefficient	t-HCSE	Coefficient	t-HCSE
Bilateral trade	0.439	1.02	0.293	0.77	0.059	0.14
Specialization measure	0.111	1.33	0.127	2.08	0.279	1.75
Short-term interest rate	-0.009	-0.08	-0.011	-0.10	-0.016	-0.15
Cyclically adjusted government primary balance	0.068	1.41	0.059	1.20	0.031	0.55

NOTES: constant is included ; t-HCSE (Heteroscedasticity Consistent Standard Errors).

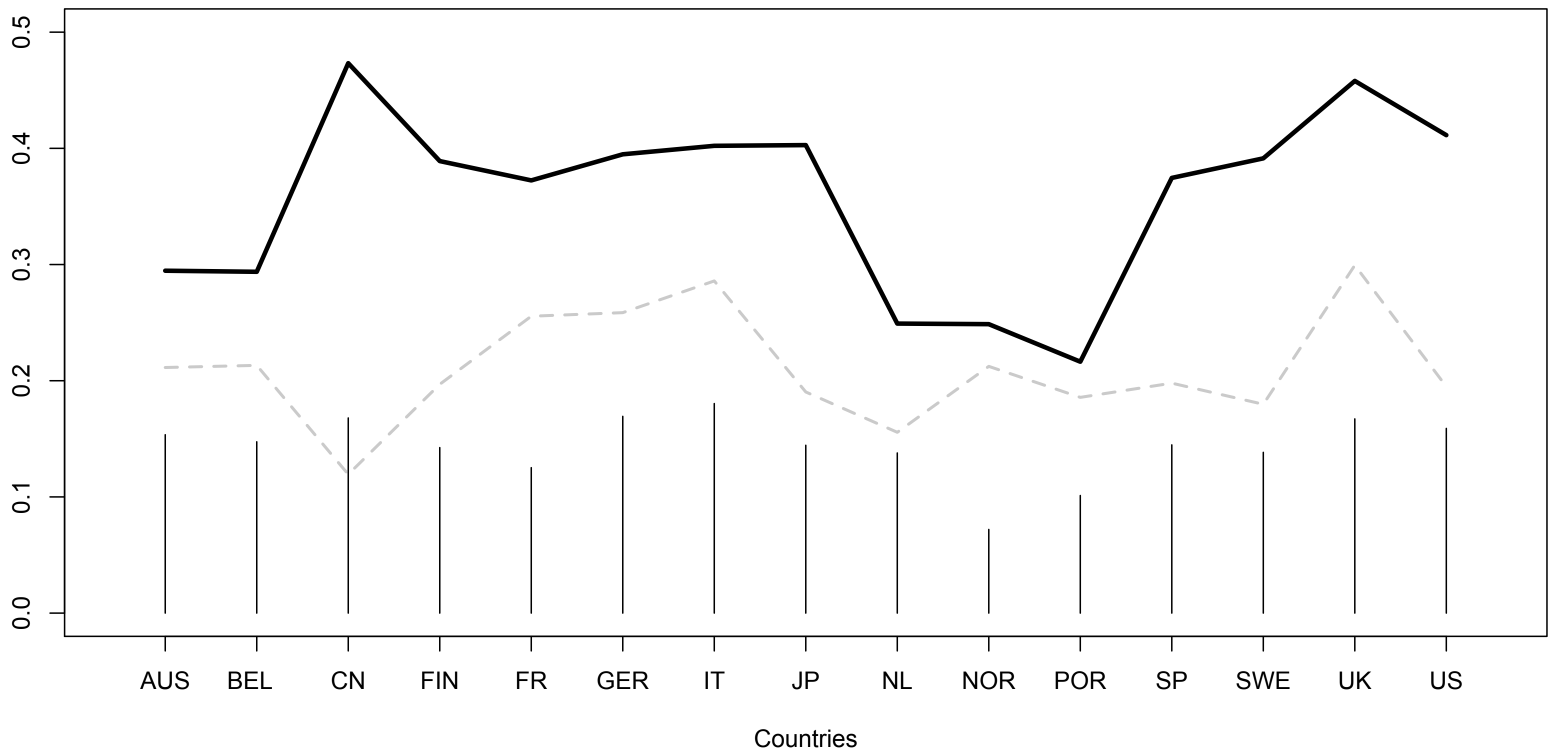

Figure 1: Average values per country for each of the dependence measures considered. The vertical bars correspond to Pearson correlation ρ, while the solid and the dashed lines respectively correspond to the left-tail and right-tail extremal dependence as measured by $\overline{\chi}_{\mathrm{L}}$ and $\overline{\chi}_{\mathrm{R}}$.