Systemic Risk in the EU
Contrasting "inter-sector" and "intra-sector" spillover risk

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Abstract

We analyse extreme return spillovers between banks, sovereign debt and real estate as well as with other EU industry sectors ("systemic risk"). We also quantify to what extent the magnitude of these spillovers increased during the current crisis. Statistical extreme value analysis is put at work in order to identify these spillover risks (as expressed by joint likelihoods of sharp drops in asset prices). The paper starts with a univariate part to evaluate the tail risk (or "extreme" Value-at-Risk) for each bank, real estate and government bond index separately. The estimation of tail-VaR exploits the empirical stylized fact that financial returns are fat tailed. Nonsurprisingly, the extreme VaR significantly increased during the crisis. The paper's bivariate part identifies the likelihood of extreme sectoral spillovers by means of Huang's (1992) non-parametric estimator for the tail copula. Intra-sector linkages are found to dominate inter-sector linkages and domestic linkages generally exceed cross-border linkages. In line with the univariate downside risk results, systemic risk seems to have increased for nearly all considered pairs. Finally, there is some evidence of a flight to quality effect into government bonds.

Keywords: banking system risk; financial crisis; extreme value theory; Hill-estimator; stable tail dependence function

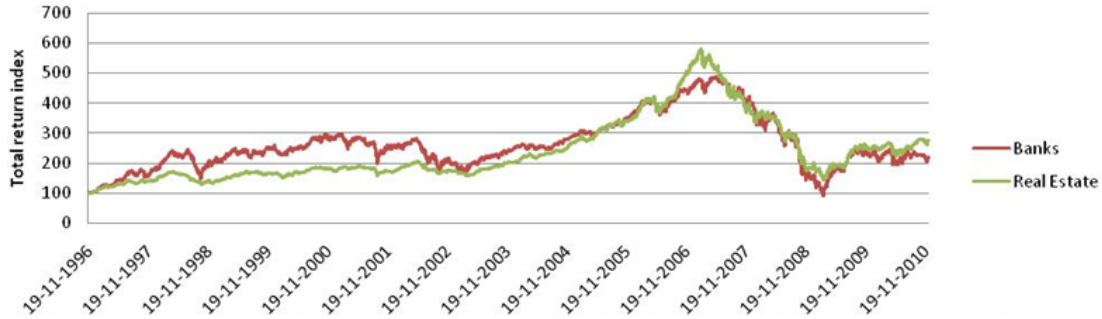
JEL codes: G21, G28, G29, G12, C49

1 Introduction

The ongoing financial and economic crisis seems characterized by systemic risk spillovers - as reflected by joint changes in asset market values - across different economic sectors (i.e. real estate, banks, and, more recently, also sovereign debt). The narrative of the roots of the 2007 crisis is by now well known. The contamination of the Western banking system by securitized subprime mortgage loans led to the systemically most important banking crisis in the Western world since the Great Depression. Consensus in the academic world seems to exist on the main triggers of the 07-09 "twin" crisis, see e.g. Goodhart (2008). First, collateralized debt and obligations (CDOs, CMOs) were (too) favourably rated by rating agencies upon receiving large fees by the emitting financial institutions, i.e. a textbook case of a conflict of interest situation. This combined with an excessive optimism in the future evolvement of the housing prices and the gradual loosening of financial regulation (e.g. the 1999 abolishment of Glass Steagal) led to increasingly excessive risk taking by financial institutions and the perfect storm of 2007-2009. The resulting lack of liquidity and the enormous depreciation of assets on the balance sheet of financial institutions together with the uncertainty and confusion amongst investors and consumers, turned this financial crisis into an economic crisis.

European banks were not only triggered into distress because of erroneous investments into US subprime loans: just like their US counterparts, they contributed to the emergence of real estate bubbles by providing easy and cheap credit in massive amounts although the impact was stronger in some countries than in others (Ireland, Spain and the UK stand out upon comparing with other EU countries). As can be seen in figure 1, the EU banking sector and real estate sector follow the same return pattern indeed (return series exhibit a stunning 91% correlation!).

Figure 1: Total return index for banking and real estate sector



Correlation Table	Banking sector	Real estate sector
Banking sector	1	0.913
Real estate sector	0.913	1

Note: For this figure the total return index of the super sectors indices of the EU are used. Data are from November 19th, 1996 to December 10th,2010, containing 3669 data points. The source of raw data is Datastream.

Undoubtedly, spillover risk between the banking sector and sovereign debt also increased since the start of the crisis in 2007 due to the massive increase in Western country debt. Especially the PIIGS countries and their potential impact on eurozone banks are at the heart of attention nowadays.

This paper's main objective is to quantify the linkages between market value changes of banks, real estate and government bonds during periods of stress and see whether these linkages themselves have a propensity to change over time. For sake of convenience we will use the term "spillover risk" and "systemic risk" interchangeably although some people would probably argue that systemic risk should only be used to refer to interbank linkages. We define systemic risk as the potential for global (system-wide) financial instability. This may both be caused by distressed banks triggering other banks into distress; but other shocks like sharp falls in the values of certain assets (subprimes, government bonds) may also trigger global financial instability. We therefore also dub linkages between banks, real estate and sovereign debt as "systemic risk" linkages.

Whereas variance-covariance analysis has been by far the most popular approach to identify financial return linkages, we focus on probabilistic measures of volatility and systemic spillover risk based on the market returns of risky securities. The proposed market-based measures for downside risk and systemic risk within and across banks, real estate, government bonds and other industry sectors are conditioned on the most extreme security returns. In order to condition on the univariate and multivariate tails of the return distribution we apply statistical extreme value analysis. We estimate downside risk by means of unconditional

extreme quantiles that are situated much further in the distributional tail than the conventional 5 or 1% Value-at-Risk (VaR) quantiles. We believe that the incidence of these conventional VaR events does not fully capture the rarity of the systemic events recently observed and therefore we look a lot further into the tails. The bivariate spillover risk is defined as the conditional probability of a sharp drop in the price of a risky security conditional on a sharp fall in the price of another security. This reflects the tail dependence between the two securities.

Variances and correlations have been previously criticized because they can be deceptive as devices to measure volatility and comovements and more specifically if one focuses on quantifying the risk of extreme events and extreme co-movements during crisis periods. First, variances are central and symmetric whereas we are mainly interested in the downside of the return distribution. Also, correlations capture linear dependence in the centre of a return distribution whereas crisis spillovers are by definition located in the distributional tail. Some observers have also claimed that (extreme) shock propagation from one asset or market to another may be essentially nonlinear in nature. If so, this nonlinear spillover will not be captured by linear correlation whereas the semi-parametric estimation technique that we employ for co-crash probabilities allows for capturing nonlinear forms of dependence – if present in the data. For a more elaborate discussion on the pitfalls of correlation see e.g. Embrechts et al. (1997) or de Vries (2005). A limitation of this market-based approach is the implicit assumption that market values accurately discount the near and distant future. However, financial markets did not foresee the current financial crisis to say it mildly. On the other hand, our goal is not to predict downside risk and systemic risk. Neither do we claim that these measures can act as early warning indicators: we rather use it as a descriptive tool for assessing the downside risk and the systemic risk over a specified sample period.

Statistical extreme value analysis has been previously employed as an approach to measure extreme security linkages (or "risk" spillovers). Hartmann et al. (2004) identified extreme linkages between G-5 stock and sovereign bond indices. They find, inter alia, that stock-bond co-crashes are equally likely than flight to quality from stocks into bonds. The same authors apply this methodology in order to assess banking system stability between the US and Europe, see Hartmann et al. (2006). They define two measures of systemic risk, dubbed contagion risk and extreme systematic risk. The "contagion" risk is the joint probability that different banks' market value of equity capital is jointly crushed (a domino effect) whereas extreme systematic risk is the co-crash probability that a bank's equity capital is triggered

down conditional on an adverse macroshock (i.e. a negative shock in a bank stock index, yield spread etc.). Whereas the contagion risk is found to be much higher for the US than for Europe, extreme systematic risk is of comparable magnitude for both continents. However, both proxies of systemic risk are rising over time.

Straetmans et al. (2008) test whether the 9/11 terrorist attacks had an impact on extreme downside risk as well as extreme comovements of US sectoral stock indices with the market as a whole. They find that both have significantly increased. The increase of extreme systematic risk after 9/11 can be interpreted as a terrorism risk premium priced in the market.

Pais et al. (2010) quantify spillover risk between the Australian banking and real estate sector. Nonsurprisingly, they find that real estate-banking spillover risk has increased since the 2007 crisis. Our study can be seen as an extension of the Pais et al. study to the eurozone area.

Anticipating on our results, we find that downside risk (tail risk) is quite heterogenous across asset classes and strongly increased during the crisis. The magnitude of intrasector asset linkages is found to dominate inter-sector asset linkages. As for domestic vs. cross border spillovers, the latter were found to be generally quit low. Also, inter-sector spillover risk between banking and real estate as well as banking and government debt (systemic risk) significantly increased due to the crisis. We observe this increase in the real estate-banks linkage despite the fact that their spillover risk was already quite high prior to the crisis; stated otherwise, financial markets already discounted the system-wide spread of mortgage backed securities. On the other hand, pre-crisis linkages between banking and sovereign debt are found to be very low. Financial markets could have hardly foreseen that the 07-09 banking crisis could turn out into a system-wide EURO crisis characterized by disrupted eurozone debt markets. For the crisis period, we also find some evidence for flight to quality effects from sectoral stock indices into government bonds.

The rest of the paper proceeds as follows. Section 2 shortly reviews statistical extreme value theory and accompanying semi-parametric estimation procedures. Section 3 discusses the empirical results. Section 4 provides summary and conclusions.

2. Theory

The empirical risk analysis of extreme events consists of a univariate part and a bivariate part.

2.1. Univariate analysis

In the univariate step we calculate measures of tail risk for individual banks, and indices of the real estate sector and sovereign debt. The tail risk of every bank and country index is calculated by means of a tail version of the Value-at-risk (VaR). Assume that $X > 0$ stands for the left tail losses in the return series of financial assets (for sake of convenience we map these negative returns to the right tail by putting a minus sign). We first exploit the empirical stylized fact that financial returns follow a Pareto-type tail decline, i.e.

(1) $$P\{X > x\} \approx ax^{-\alpha} \ ,$$

where the tail index α governs the rate of tail decay and *a* stands for a scaling constant.

Let $X_{i,n}$ represent the i-th ascending order statistic of X with $X_{1,n} \leq \cdots \leq X_{i,n} \leq \cdots \leq X_{n,n}$.To calculate the individual tail index, we use the Hill (1975) estimator:

(2) $$\hat{\gamma}_{HILL} = \frac{1}{\hat{\alpha}} = \frac{1}{m}\sum_{j=0}^{m-1} \ln\left(\frac{X_{n-j,n}}{X_{n-m,n}}\right)$$

Where the tail cut off point $X_{n-m,n}$ is the m-th ascending order statistic form the (minus of) the return series. This order statistic determines the start of the empirical tail (the lowest of the extreme returns that is used in estimation). The parameter *m* which reflects the number of extremes is determined by means of so-called Hill plots.[1]

The tail index can be used as an input to calculate the exceedance probability governed by the Pareto-type tail decline in (1):

(3) $$\hat{P}\{X > x\} = \frac{m}{n}\left(X_{n-m,n}\right)^{\hat{\alpha}} x^{-\hat{\alpha}} ,$$

[1] More complex algorithms based on minimizing an empirical equivalent of the Hill statistic's Asymptotic Mean Squared Error are also widely used but heuristic Hill plots are simple and intuitively appealing. The plots are omitted for sake of space considerations but are available upon request from the authors.

Or, alternatively, the p% daily quantile $\hat{x}_p$ of the loss distribution is obtained by inverting the above estimator for x and setting P=p:

$$\hat{x}_p = X_{n-m,n}\left(\frac{m}{pn}\right)^{1/\hat{\alpha}} \tag{4}$$

See e.g. de Haan et al. (1994) for an intuitive derivation of the twin pair of estimators (3)-(4). The latter authors also derived asymptotic normality of the estimator.

What does this VaR estimator add to the already abundant toolkit of VaR estimation techniques available to risk managers? The difference with risk managers' daily practice lies in the extremity of quantiles to be calculated with (4). Indeed, whereas regulators typically require disclosure of VaR numbers at the 5 and 1 percent significance level, the recent systemic events observed in the banking sector, the real estate and the sovereign bond sector seem much less frequent, i.e. corresponding with lower significance levels. We will therefore set the marginal significance level p both at 1% and at 0,1%. Quantiles that correspond with a 0,1% significance level are expected to happen once in 1,000 trading days or once in 1,000/260 ≈ 4 years.[2] One can even question whether that is sufficiently extreme to capture the low frequency character of the recent systemic events. But even lower values for p are perfectly implementable in the EVT setup.

To determine the statistical and economic significance of the crisis impact on the tail index (2) and the tail-VaR (4), we perform a pair of structural change t-tests:

$$T_\gamma = \frac{\hat{\gamma}_1 - \hat{\gamma}_2}{s.e.[\hat{\gamma}_1 - \hat{\gamma}_2]} \tag{5}$$

$$T_{VaR} = \frac{VaR_1 - VaR_2}{s.e.[VaR_1 - VaR_2]} \tag{6}$$

June 1st 2007 is taken as candidate-breakpoint. The asymptotic normality of the Hill statistic and the accompanying quantile estimator ensures that the test statistics should also converge to a standard normal distribution in sufficiently large samples.[3] The standard deviations in the denominators of both tests are estimated by using a bootstrap procedure (see, for example, Straetmans et al., 2008, for more details). The number of bootstrap replications is set at 600[4].

[2] We use the number of trading days in one single year and not the number of calendar days.
[3] This can be easily shown by simulating small sample critical values for a number of data generating processes. The details of this Monte Carlo study are omitted for sake of space considerations but available upon request.
[4] Higher values of bootstrap replications do not alter the outcomes.

The bootstrapped values for γ and VaR are also used to calculate 95% confidence intervals by means of the 15th and 585th ascending order statistic of the bootstrapped sample.

3.2. Bivariate part

To measure the spillover risk between assets or countries, we calculate the probability that one risky security return sharply drops given that the same happens to another risky security return. For sake of convenience, a "sharp" drop in asset value is defined as a threshold or Value-at-Risk (VaR) exceedance that occurs with probability *p*. For sake of convenience we choose a common *p* for all assets. Notice this still allows for differing corresponding quantiles or VaR levels because the marginal return distributions will in general be nonequal. Thus, if one considers S risky securities, the VaR_i are set such that all corresponding exceedance probabilities are the same:

(7) $$P\{X_1 > VaR_1\} = \ldots = P\{X_i > VaR_i\} = \ldots = P\{X_S > VaR_S\} = p,$$

From elementary probability calculus the conditional co-crash probability of a sharp drop in i conditional on z boils down to:

(8) $$CP_i \equiv P\{X_i > VaR_i(p) | X_z > VaR_z(p)\}$$

$$= \frac{P\{X_i > VaR_i \text{ and } X_z > VaR_z\}}{P\{X_z > VaR_z\}}$$

$$= \frac{P\{X_i > VaR_i\} + P(X_z > VaR_z) - P\{X_i > VaR_i \text{ or } X_z > VaR_z\}}{P\{X_z > VaR_z\}}$$

$$= \frac{2p - P\{X_i > VaR_i \text{ or } X_z > VaR_z\}}{p}$$

$$= 2 - \frac{P\{X_i > VaR_i(p) \text{or } X_z > VaR_z(p)\}}{p}$$

After defining the CP measure, we use statistical Multivariate Extreme Value Theory (MEVT) to estimate CP by means of the so-called "tail dependence function" or "tail copula", see Huang (1992) for the theory and Hartmann et al. (2004) for an earlier application.

Let $X_{i,n-k}$ and $X_{z,n-k}$ stand for the kth highest order statistics of returns of entity i and z respectively. An empirical counterpart for (6) boils down to:

(9) $$CP_{iz} = 2 - \frac{1}{k}\sum_{t=1}^{n} I\{X_i > X_{i,n-k} \; or \; X_z > X_{z,n-k}\}$$

An intuitive derivation of this semi-parametric estimator is provided in Huang (1992) and Hartmann et al. (2004). Eq. (9) counts the relative frequency that either one (entity i or entity z) or both entities experience a joint extreme loss. Notice that *k* determines the number of extremes used in estimating the tail copula; as such it plays the same role as the parameter m in estimating the Hill estimator. Just as the parameter *m*, a popular procedure to determine *k* is to plot CD over a sufficiently long grid and to select *k* in a horizontal stable range where the estimator's bias and variance somewhat offset each other.

The main advantage of the statistical MEVT methodology is that it enables one to tackle the very low frequency nature of systemic events. Previous empirical approaches to modeling systemic events including the use of multinomial logit models (see e.g. Gropp et al. (2009)) or quantile regression methodology (see e.g. Adrian and Brunnermeier (2008)) typically analyze collapses in bank stocks corresponding with marginal exceedance probabilities that do not fall below the 1 percent level. This does not really correspond with very infrequent tail events. Upon assuming the use of daily return data, a 1 percent marginal exceedance probability corresponds with a quantile or crisis level that is expected to be exceeded once every 100 days. Of course, the true frequency of systemic events remains a subjective matter but most people would probably agree that joint stock price comovements that are expected to happen more than once a year can hardly be dubbed "extreme" or "systemic".

Another appealing feature of the MEVT approach constitutes the fact that SR measures can be estimated without knowing the marginal distributions, i.e. one does not need to estimate the Value-at-Risk levels VaR_1 and VaR_2 that characterize the asset pairs' tail risk in order to calculate (9). Thus, the considered SR indicators purely reflect information on the dependence between extreme bank stock returns and are not "contaminated" by e.g. asymmetries or inequalities in the marginal distributions.

Yet another advantage is that the MEVT methodology takes account of "nonlinear dependence" and "tail dependence" – provided these empirical stylized facts are present. It is

often suggested that contagion phenomena or systemic risk spillovers may be nonlinear dependence phenomena that cannot be captured by simple linear approaches like e.g. regression/correlation analysis. Also, it is by now generally accepted that financial returns exhibit "tail dependence", see e.g. de Vries (2005) for the case of bank stock returns. Capturing the tail dependence feature is essential for accurately assessing SR. Pairs of random variables are tail dependent if the joint conditional exceedance probability $P\{X > s | Y > s\}$ does not vanish when the exceedance level s grows large, i.e. $\lim_{s\to\infty} P\{X > s | Y > s\} > 0$.

The MEVT approach is also characterized by certain limitations. First of all, an empirical approach that uses bank stock returns to evaluate SR is by definition unable to evaluate the potential systemic impact of large nonquoted banks. Also, the market efficiency assumption that bank stocks fully reflect a bank's liquidity and solvency situation at each time instance may be considered by some as too restrictive. Moreover, the fact that MEVT estimation techniques only use tail observations implies that one needs sufficiently large samples to start with as one typically uses only 1 to 5 percent of the full sample for estimating the tail features.[5] Finally, the tail copula methodology as employed in this paper does not allow SR indicators to be truly time varying but reflects the SR over a given sample period (typically several years). This problem is partly remedied in the paper by estimating the SR indicators over a rolling window size.

4 Empirical results

We retrieve Datastream daily total return indices for banks, real estate indices, government bonds and other sector indices. We consider individual banks, government bond and country real estate indices as well as EMU-wide industry indices. The top 40 EU banks (by asset size) are taken from Harrison (2010).[6] To maximize the number of banks as well as the length of the time series, we compromise on a time series length starting from November 19th, 1996 until December 10th, 2010 (n=3,669 daily returns). The remaining 30 largest EU banks (commercial banks, investment banks, retail banks) are located in 13 EU countries; the geographic spread enables us to compare domestic with cross-border bank spillover risk

[5] Experience learns that full samples of 500 return observations may already be sufficient in order to obtain reasonably accurate estimates of the tail features. The samples in this paper – even the subsamples - are much larger such that we do not have to worry about small sample problems.

[6] This list includes all banks and diversified financial institutions that are not exclusively owned by the state. This implies that it excludes e.g. the German Landesbanks and the Spanish Cajas but it includes the likes of RBS and Lloyds (Harrison, 2010).

(insurance companies and pension funds are excluded). Stock price data of individual real estate companies will not be used due to their large number and size differences across EU companies; instead 13 EU country indices are used. These so-called "super" indices encompass real estate investment and services and real estate investment trusts. 10-year government bond "benchmark" total return indices are downloaded for the same 13 EU countries. Finally, total returns of 12 EU sectoral indices will also be downloaded in order to assess the changed sensitivity to shocks from banking, real estate and sovereign debt to the rest of the economy.

As outlined previously, the empirical outcomes will be grouped into a set of univariate results and a set of bivariate results. Moreover, the full sample is split in a pre-crisis period and a crisis period to investigate the extent to which the financial crisis altered the level of univariate downside risk and bivariate systemic risk. In line with many other empirical studies on the credit crunch, we let the crisis start June 1st, 2007. In late June 2007, Bear Stearns hedge funds were the first victims of the devaluation of the CDOs and CMOs.

5.1. Univariate results: tail estimation and VaR results

Estimating downside risk by means of quantile estimator (4) first of all requires estimating the tail index $\gamma = 1/\alpha$. The calculation of the Hill statistic (2) requires the selection of a threshold parameter *m* which reflects the number of extremes used in estimation. We used Hill plots to trade off the empirical bias and variance of $\hat{\gamma}_{HILL}$.[7] Based on these plots we decided to calibrate *m* at 50 for the whole time span, at 40 for the pre-crisis period and at 30 for the crisis period.

Table 1 summarizes full sample and subsample (pre-crisis and crisis) Hill estimates $\hat{\gamma}_{HILL}$ together with 95 percent confidence intervals and the two-sided structural change t-test (5) that compares pre-crisis with crisis tail indices. Conform with the t-test, the 95% confidence interval has been determined by using a bootstrap.

Higher estimates of γ indicate fatter tails (a thin tail like the normal df would imply that γ=0). Upon comparing the full sample estimates across different types of risky assets, one sees that on average real estate sector returns exhibit fatter tails than bank stocks whereas government

[7] Hill plots were omitted for sake of space considerations but available upon request from the authors.

bonds exhibit the thinnest tails.[8] The latter feature is in line with the generally observed lower market risk for bonds as compared to equity. As concerns temporal stability of the tail index, a majority of crisis tail index estimates exceeds their pre-crisis levels but the differences are only statistically significant in a minority of cases. This apparent stability of the tail behaviour – as reflected by the tail index – is consistent with earlier work on the stability of the tail index, see e.g. Koedijk et al. (1992) on exchange rates, or Janssen and de Vries (1989) on US stock markets.

[8] Average tail indices for real estate, banks and government bonds equal 0.345, 0.301 and 0.262, respectively.

Table 1: Hill estimates for the tail index: full sample, pre-crisis and crisis results

		Full Sample Period	Pre-crisis Period	Crisis Period	T-test
Banking Sector	DEUTSCHE BANK	0.311 (0.237; 0.380)	0.209 (0.151; 0.312)	0.355 (0.246; 0.457)	-2.203***
	Landesbank Berlin Holding	0.321 (0.223; 0.403)	0.310 (0.227; 0.423)	0.306 (0.214; 0.425)	0.067
	COMMERZBANK	0.306 (0.228; 0.375)	0.280 (0.211; 0.365)	0.353 (0.235; 0.458)	-1.070
	BNP PARIBAS	0.273 (0.208; 0.335)	0.279 (0.190; 0.340)	0.355 (0.188; 0.440)	-1.044
	SOCIETE GENERALE	0.251 (0.195; 0.313)	0.221 (0.152; 0.305)	0.304 (0.205; 0.407)	-1.344
	NATIXIS	0.423 (0.339; 0.515)	0.219 (0.148; 0.307)	0.396 (0.245; 0.499)	-2.370**
	ROYAL BANK OF SCTL.GP.	0.441 (0.306; 0.543)	0.198 (0.149; 0.289)	0.436 (0.290; 0.631)	-2.529**
	HSBC HDG.	0.262 (0.182; 0.337)	0.219 (0.160; 0.290)	0.338 (0.221; 0.457)	-1.684*
	BARCLAYS	0.382 (0.270; 0.462)	0.273 (0.213; 0.346)	0.367 (0.268; 0.531)	-1.294
	LLOYDS BANKING GROUP	0.415 (0.290; 0.530)	0.218 (0.156; 0.277)	0.443 (0.296; 0.599)	-2.803***
	STANDARD CHARTERED	0.285 (0.224; 0.374)	0.267 (0.197; 0.362)	0.316 (0.224; 0.457)	-0.709
	ING GROUP	0.315 (0.237; 0.383)	0.222 (0.147; 0.328)	0.341 (0.244; 0.493)	-1.480
	DEXIA	0.349 (0.270; 0.462)	0.333 (0.231; 0.421)	0.375 (0.259; 0.508)	-0.528
	BANQUE NALE.DE BELGIQUE	0.275 (0.217; 0.362)	0.283 (0.201; 0.371)	0.370 (0.252; 0.482)	-1.166
	KBC GROUP	0.275 (0.218; 0.382)	0.283 (0.200; 0.377)	0.370 (0.255; 0.479)	-1.192
	BANCO SANTANDER	0.302 (0.201; 0.349)	0.247 (0.165; 0.335)	0.300 (0.218; 0.408)	-0.842
	BANCO BILBAO VIZCAYA ARGENTARIA	0.246 (0.191; 0.318)	0.286 (0.198; 0.364)	0.308 (0.190; 0.412)	-0.312
	BANCO POPULAR ESPANOL	0.244 (0.186; 0.290)	0.268 (0.199; 0.345)	0.271 (0.161; 0.326)	-0.065
	UNICREDIT	0.244 (0.194; 0.339)	0.312 (0.219; 0.353)	0.310 (0.213; 0.400)	0.047
	INTESA SANPAOLO	0.283 (0.217; 0.353)	0.245 (0.176; 0.334)	0.411 (0.300; 0.521)	-2.412**
	NORDEA BANK	0.247 (0.189; 0.311)	0.233 (0.180; 0.320)	0.263 (0.180; 0.342)	-0.561
	SEB	0.297 (0.229; 0.381)	0.234 (0.175; 0.302)	0.347 (0.248; 0.449)	-1.871*
	SVENSKA HANDELSBANKEN	0.258 (0.194; 0.329)	0.192 (0.142; 0.277)	0.308 (0.213; 0.395)	-1.990**
	SWEDBANK	0.301 (0.221; 0.375)	0.236 (0.175; 0.295)	0.304 (0.201; 0.379)	-1.221
	DANSKE BANK	0.316 (0.231; 0.371)	0.261 (0.184; 0.354)	0.310 (0.210; 0.402)	-0.768
	NATIONAL BK.OF GREECE	0.232 (0.173; 0.293)	0.213 (0.158; 0.269)	0.264 (0.178; 0.342)	-1.027
	EFG EUROBANK ERGASIAS	0.098 (0.057; 0.130)	0.081 (0.041; 0.186)	0.161 (0.106; 0.218)	-1.907*
	BANK OF IRELAND	0.438 (0.346; 0.555)	0.283 (0.200; 0.363)	0.340 (0.230; 0.476)	-0.767
	ALLIED IRISH BANKS	0.389 (0.296; 0.496)	0.303 (0.212; 0.401)	0.351 (0.239; 0.482)	-0.595
	BCP	0.253 (0.190; 0.326)	0.299 (0.224; 0.397)	0.231 (0.159; 0.329)	1.107
Country Real estate Indices	Germany	0.212 (0.159; 0.286)	0.225 (0.162; 0.294)	0.291 (0.197; 0.396)	-1.093
	France	0.310 (0.236; 0.369)	0.267 (0.190; 0.353)	0.274 (0.154; 0.362)	-0.104
	UK	0.289 (0.227; 0.370)	0.254 (0.187; 0.323)	0.268 (0.179; 0.350)	-0.238
	Netherlands	0.403 (0.306; 0.478)	0.234 (0.156; 0.342)	0.266 (0.189; 0.430)	-0.400
	Italy	0.281 (0.214; 0.366)	0.303 (0.202; 0.384)	0.263 (0.191; 0.412)	0.538
	Spain	0.314 (0.228; 0.372)	0.348 (0.261; 0.436)	0.304 (0.199; 0.380)	0.681
	Sweden	0.222 (0.176; 0.297)	0.320 (0.242; 0.407)	0.223 (0.146; 0.300)	1.691*
	Ireland Δ	0.360 (0.267; 0.457)	0.000 (0.000; 0.000)	0.000 (0.000; 0.000)	0.000
	Belgium	0.280 (0.202; 0.388)	0.220 (0.147; 0.313)	0.315 (0.196; 0.457)	-1.220
	Austria	0.515 (0.364; 0.639)	0.698 (0.468; 0.905)	0.359 (0.244; 0.492)	2.630***
	Denmark	0.345 (0.261; 0.430)	0.349 (0.260; 0.505)	0.346 (0.225; 0.466)	0.031
	Portugal Δ	0.811 (0.649; 1.381)	1.331 (0.570; 1.777)	2.182 (0.783; 9.102)	-0.369
	Greece	0.142 (0.091; 0.214)	0.090 (0.057; 0.128)	0.496 (0.303; 0.668)	-4.170***
10y gov. bond indices	Germany	0.202 (0.150; 0.263)	0.218 (0.156; 0.319)	0.245 (0.175; 0.338)	-0.448
	France	0.233 (0.167; 0.307)	0.249 (0.177; 0.321)	0.198 (0.130; 0.289)	0.918
	UK	0.221 (0.154; 0.274)	0.249 (0.183; 0.305)	0.263 (0.177; 0.361)	-0.251
	Netherlands	0.198 (0.152; 0.251)	0.214 (0.152; 0.296)	0.204 (0.149; 0.295)	0.190
	Italy	0.225 (0.177; 0.294)	0.231 (0.157; 0.325)	0.266 (0.172; 0.361)	-0.537
	Spain	0.191 (0.149; 0.247)	0.216 (0.151; 0.289)	0.218 (0.133; 0.288)	-0.035
	Sweden	0.316 (0.239; 0.387)	0.308 (0.212; 0.403)	0.301 (0.208; 0.403)	0.102
	Ireland	0.327 (0.239; 0.414)	0.235 (0.177; 0.323)	0.379 (0.242; 0.469)	-2.174**
	Belgium	0.186 (0.143; 0.261)	0.209 (0.136; 0.298)	0.198 (0.138; 0.288)	0.201
	Austria	0.223 (0.168; 0.283)	0.251 (0.183; 0.317)	0.230 (0.157; 0.314)	0.398
	Denmark	0.220 (0.161; 0.308)	0.271 (0.158; 0.349)	0.294 (0.219; 0.428)	-0.332
	Portugal	0.318 (0.243; 0.428)	0.344 (0.234; 0.445)	0.339 (0.239; 0.463)	0.053
	Greece Δ	0.539 (0.379; 0.675)	0.253 (0.151; 0.300)	0.501 (0.323; 0.696)	-2.410**

Note: The Hill estimates are based on eq. (2). A two sided t-test from eq. (5) is used to compare the pre-crisis with the crisis period. The full sample period runs from November 19, 1996 until December 10, 2010; the pre-crisis period runs from November 19, 1996 until June 1, 2007 and the crisis period runs from June 1, 2007 until December 10, 2010. The superscripts *,**,*** denote significance at the 10%, 5% and 1% level respectively. The countries with a triangle (Δ) have an incomplete data set.

At best, however, the tail index of risky security returns is an imperfect measure of tail risk; We use it as an input to calculate extreme measures of market risk like the extreme VaR measure in (4). Analogous to the previous table, table 2 contains full sample and subsample estimates of the extreme quantile measure (4) and for a corresponding marginal exceedance probability p=99,9%. This implies that the calculated quantiles can be seen as return barriers that are expected to be exceeded once every 1,000 days (or once every 3.8 years). The two-sided t-test from eq. (6), for the difference between pre-crisis and the crisis period, is shown in the last column. Upon comparing full sample downside risk estimates across different types of risky assets, banks, real estate indices and government bonds exhibit average VaR estimates equal to 6.93%, 6.30% and 1.04%, respectively. However, there is quite some heterogeneity in the outcomes. Nonsurprisingly, bank VaR's are highest for two Irish banks (10.98% VaR for Bank of Ireland and 10.9% for Allied Irish Banks). For real estate, Ireland exhibits the highest VaR as well. This already provides some casual evidence of a spillover effect between Irish real estate and the Irish banking sector. Comparable "co-spikes" seem to occur for other banks and corresponding real estate indices but in a less pronounced fashion and we will have to resort to more advanced measures to explicitly measure the spillover risk (see next section). As for government bond tail risk, we identified the highest downside risk somewhat surprisingly in the UK long term bond market, followed by Greece and Ireland.

Upon comparing pre-crisis with crisis VaR's we observe a clear increase for nearly all considered risky assets. Moreover, and contrary to the tail index results, the structural shifts in tail risk seem more often statistically significant (see right column with t-tests). This can be understood by the fact that VaR estimates summarize information on the tail index as well as the scaling constant, as reflected by parameter a in (1) and its estimation equivalent $\hat{a} = \frac{m}{n}\left(X_{m,n}\right)$ in (3). Indeed, even if the tail index is not changing in a significant way, the scaling constant can which may in turn induce a shift in tail risk.

Table 2: 99.9%VaR estimates: full sample, pre-crisis, crisis outcomes and structural change

		Full Sample Period	Pre-crisis Period	Crisis Period	T-test
Banking Sector	DEUTSCHE BANK	13.57%	9.16%	21.13%	-3.02***
	Landesbank Berlin Holding	14.46%	13.96%	14.97%	-0.30
	COMMERZBANK	15.18%	11.09%	23.95%	-2.79***
	BNP PARIBAS	12.65%	10.87%	19.88%	-2.80***
	SOCIETE GENERALE	12.85%	10.27%	19.01%	-2.83***
	NATIXIS	18.25%	6.42%	29.93%	-4.79***
	ROYAL BANK OF SCTL.GP.	22.28%	9.13%	39.12%	-2.38**
	HSBC HDG.	10.29%	8.51%	15.27%	-2.02**
	BARCLAYS	19.08%	10.15%	30.33%	-3.52***
	LLOYDS BANKING GROUP	20.97%	8.80%	39.26%	-2.98***
	STANDARD CHARTERED	14.34%	11.33%	20.45%	-2.20**
	ING GROUP	17.88%	11.72%	27.61%	-2.68***
	DEXIA	16.72%	10.17%	27.55%	-2.45**
	BANQUE NALE.DE BELGIQUE	7.99%	7.94%	10.09%	-0.97
	KBC GROUP	7.99%	7.94%	10.09%	-0.90
	BANCO SANTANDER	12.35%	10.12%	15.20%	-2.05**
	BANCO BILBAO VIZCAYA ARGENTARIA	10.74%	10.46%	14.61%	-1.65*
	BANCO POPULAR ESPANOL	8.93%	7.31%	12.51%	-3.26***
	UNICREDIT	12.05%	10.05%	19.13%	-2.87***
	INTESA SANPAOLO	12.77%	10.52%	21.58%	-2.44**
	NORDEA BANK	10.99%	9.59%	13.70%	-1.75*
	SEB	14.82%	9.68%	24.36%	-3.25***
	SVENSKA HANDELSBANKEN	9.83%	6.83%	15.28%	-3.66***
	SWEDBANK	14.43%	8.32%	21.53%	-3.67***
	DANSKE BANK	11.22%	8.03%	15.21%	-2.68***
	NATIONAL BK.OF GREECE	11.91%	8.98%	16.96%	-3.09***
	EFG EUROBANK ERGASIAS	9.56%	9.12%	11.35%	-1.97**
	BANK OF IRELAND	30.12%	9.15%	42.23%	-3.64***
	ALLIED IRISH BANKS	26.68%	9.10%	40.81%	-3.37***
	BCP	9.06%	8.53%	10.30%	-0.85
Country Real estate Indices	Germany	8.11%	8.63%	7.53%	0.71
	France	5.84%	3.53%	7.68%	-3.66***
	UK	8.74%	4.53%	12.17%	-4.84***
	Netherlands	8.65%	4.03%	9.97%	-3.71***
	Italy	9.42%	7.80%	11.87%	-1.79**
	Spain	7.92%	6.77%	10.15%	-1.92*
	Sweden	8.08%	8.35%	9.54%	-0.88
	Ireland Δ	52.21%			
	Belgium	3.97%	2.70%	6.06%	-2.42**
	Austria	11.68%	2.89%	14.68%	-3.66***
	Denmark	8.03%	6.77%	10.64%	-1.38
	Portugal Δ	78.54%	115.55%	4574.09%	0.00
	Greece	11.56%	10.17%	19.64%	-1.26
10y gov. bond Indices	Germany	1.42%	1.41%	1.69%	-1.15
	France	1.57%	1.66%	1.34%	1.42
	UK	2.57%	2.47%	3.31%	-1.57
	Netherlands	1.32%	1.32%	1.43%	-0.52
	Italy	1.41%	1.41%	1.59%	-0.67
	Spain	1.34%	1.32%	1.60%	-1.18
	Sweden	2.68%	2.47%	3.01%	-0.92
	Ireland	2.52%	1.47%	4.42%	-3.74***
	Belgium	1.30%	1.31%	1.40%	-0.40
	Austria	1.42%	1.45%	1.54%	-0.40
	Denmark	1.39%	1.42%	1.84%	-1.15
	Portugal	2.35%	1.94%	3.36%	-1.86*
	Greece Δ	5.22%	1.43%	8.94%	-2.27**

Note: The 99.9% VaRs are based on eq. (4). A two sided t-test from eq. (6) is used to compare the pre-crisis with the crisis period. The full sample period runs from November 19, 1996 until December 10, 2010; the pre-crisis period runs from November 19, 1996 until June 1, 2007 and the crisis period runs from June 1, 2007 until December 10, 2010. The superscripts *,**,*** denote significance at the 10%, 5% and 1% level respectively. The countries with a triangle (Δ) have an incomplete data set.

5.2 Spillover risk

Although the marginal probabilities of extreme events may be relatively small, conditional spillover probabilities may be much higher due to the dependence that exists between extreme returns. Reconsider again the conditional co-crash probability in (8). If the two risky assets (denoted i and z) evolve in a fully independent way, it follows from elementary probability calculus that the conditional crash probability reduces to the marginal probability of experiencing financial distress in one institution:

$$
\begin{aligned}
CP_i &\equiv P\{X_i > VaR_i(p) \mid X_z > VaR_z(p)\} \\
&= \frac{P\{X_i > VaR_i(p) \text{ and } X_Z > VaR_z(p)\}}{P\{X_z > VaR_z(p)\}} \\
&= \frac{P\{X_i > VaR_i(p)\} \times P\{X_z > VaR_z(p)\}}{P\{X_z > VaR_z(p)\}} \\
&= p
\end{aligned}
$$

Stated otherwise, knowing that one institution is triggered into distress does not make the likelihood of such an event happening elsewhere higher in case of full independence. The conditioning does not add any information. The conditional probability will exceed the marginal probability provided events are tail dependent. In the case of e.g. banks, this may require interconnectedness via the interbank market. We fill focus on three main types of tail dependence in this paper. First, traditional systemic risk is identified as return spillover risk form one bank to another. Although healthy banks' solvency risk– as proxied by the probability that equity capital drops below a certain threshold - may be relatively small, the mere fact that an interconnected bank is triggered into distress makes insolvency of other banks connected to the sick one more likely. Also, the same tail dependence may occur between extreme spikes in bank capital and asset investments that were supposed to be relatively riskfree (e.g. securitized subprime loans and sovereign bonds). We will therefore also identify the extent of tail dependence – as measured by the co-crash probability (8) – between bank stocks and fluctuations in market value of sovereign bonds and real estate indices. De Vries (2005) provided a theoretical justification for tail dependence between bank stocks and the components at the asset side of a bank's balance sheet. Indeed, he showed that heavy tailed bank asset risks obeying Pareto-type tail declines like in (1) automatically imply nonzero tail dependence between bank stocks and those underlying risk factors as well as tail

dependence across banks that invested in those common risk exposures. In practice banks are indeed exposed to similar risks because their investments are partly overlapping: they all invested into high-yield sovereign bonds as well as high-yield subprime products.

In total our dataset consists of 30 banks, 13 real estate indices and 13 government bond indices which imply a total of $\binom{56}{2} = 1{,}540$ possible bilateral spillovers to be assessed. We distinguish between intra-sector spillovers (between banks, between real estate indices and between government bonds) and inter-sector spillover risk (banks-real estate, banks-government bonds, real-estate-government bonds). Notice that intra-sector and inter-sector spillovers are not the same as "domestic" vs. "cross-border" spillovers. For example, bank spillovers as well as spillovers between banks, real estate and government bonds can both be domestic in nature (i.e. for banks and other assets within the same country) but can also be of a cross-border nature. For sake of presentational convenience we will not report all these estimates but only certain aggregated averages. The number of extreme losses (k) used in eq. (9) is set at the values that were used for estimating the tail indices. A sample of the data is checked for relative stability of CP values by changing k (see appendix A). CP values are found to be reasonable stable around the k values that were also used for the tail indices.

Table 3 contains aggregated (averages) CP values between every bank or country index and the 3 sectors (banks, real estate, government bonds) and for the full sample period. For example, if Deutsche Bank crashes, the average likelihood that another bank in the 32 bank sample is also triggered into distress equals 28.21%. That is remarkably high because it implies that this will happen nearly once out of three times. As a second example, the 11.93% crash chance of the German real estate index w.r.t. EU banks reflect the average CP value between the real estate index and the 32 EU banks in the sample.

The 1,540 disaggregated results (available upon request) as well as the averaged results in Table 3 revealed some interesting stylized facts. First, intra-sector CP values (banks vs. banks, real estate vs. real estate, bonds vs. bonds) dominate inter-sector CP values (banks vs. real estate, banks vs. bonds, real estate vs. bonds) most of the time. The disaggregated outcomes also show that the highest CP values occur for banks located in the same country. For example Commerzbank and Deutsche Bank have a CCP of 50% and Bank of Ireland and Allied Irish Banks have a CCP of 56%, i.e. the chance of joint financial distress is more than 50%! Inter-sector CP values are found to be higher for banks vs. real estate than for banks vs.

Table 3: Average conditional crash probabilities of banks, real estate indices and sovereign debt conditional on banks, real estate indices and sovereign debt (full sample)

		Banking Sector	Country Real estate Indices	10y gov. bond Indices
Banking Sector	DEUTSCHE BANK	28.21%	16.92%	2.46%
	Landesbank Berlin Holding	10.69%	10.15%	3.54%
	COMMERZBANK	29.45%	18.15%	2.31%
	BNP PARIBAS	28.00%	16.00%	4.00%
	SOCIETE GENERALE	28.83%	16.62%	6.00%
	NATIXIS	25.52%	20.77%	2.31%
	ROYAL BANK OF SCTL.GP.	28.34%	17.08%	4.31%
	HSBC HDG.	21.93%	14.46%	2.77%
	BARCLAYS	30.14%	19.85%	7.08%
	LLOYDS BANKING GROUP	27.93%	15.08%	4.77%
	STANDARD CHARTERED	27.17%	18.92%	2.00%
	ING GROUP	36.62%	22.77%	2.77%
	DEXIA	22.69%	13.69%	1.54%
	BANQUE NALE.DE BELGIQUE	7.17%	8.00%	2.31%
	KBC GROUP	29.17%	21.69%	4.31%
	BANCO SANTANDER	30.28%	19.23%	2.92%
	BANCO BILBAO VIZCAYA ARGENTARIA	26.83%	15.69%	3.23%
	BANCO POPULAR ESPANOL	25.59%	16.31%	4.46%
	UNICREDIT	33.24%	20.77%	4.00%
	INTESA SANPAOLO	25.24%	14.15%	1.85%
	NORDEA BANK	26.21%	15.54%	4.00%
	SEB	33.31%	20.92%	3.85%
	SVENSKA HANDELSBANKEN	28.55%	19.23%	4.15%
	SWEDBANK	28.21%	18.92%	3.69%
	DANSKE BANK	26.07%	20.00%	4.46%
	NATIONAL BK.OF GREECE	23.79%	16.77%	5.69%
	EFG EUROBANK ERGASIAS	6.62%	6.15%	1.69%
	BANK OF IRELAND	19.52%	13.23%	4.77%
	ALLIED IRISH BANKS	22.97%	15.85%	4.62%
	BCP	15.79%	9.85%	2.31%
Country Real estate Indices	Germany	11.93%	9.50%	2.15%
	France	28.47%	29.67%	2.92%
	UK	26.80%	24.83%	4.15%
	Netherlands	29.80%	29.67%	3.69%
	Italy	19.13%	20.17%	3.23%
	Spain	6.87%	6.83%	4.00%
	Sweden	25.07%	23.67%	6.15%
	Ireland Δ	6.13%	6.83%	5.08%
	Belgium	21.60%	21.33%	3.23%
	Austria	25.47%	20.33%	3.08%
	Denmark	5.33%	10.67%	0.46%
	Portugal Δ	2.40%	3.50%	1.08%
	Greece	4.53%	3.00%	2.15%
10y gov. bond Indices	Germany	1.47%	1.23%	39.83%
	France	1.20%	0.77%	34.50%
	UK	7.40%	6.77%	9.17%
	Netherlands	2.40%	1.69%	37.17%
	Italy	1.40%	0.77%	33.00%
	Spain	2.67%	2.77%	35.33%
	Sweden	9.07%	6.15%	8.33%
	Ireland	4.73%	4.46%	21.50%
	Belgium	1.07%	1.54%	39.00%
	Austria	1.60%	1.23%	39.17%
	Denmark	4.33%	3.69%	20.50%
	Portugal	4.20%	4.15%	23.50%
	Greece Δ	5.33%	6.15%	9.67%

Note: conditional probabilities are calculated using eq. (9). The countries with a triangle (Δ) have an incomplete data set.

government bonds and are negligibly low for real estate-government bond pairs. As concerns domestic CP values, domestic bank linkages dominate cross border bank linkages. Finally, domestic inter-sector linkages are also found to exceed cross-border inter-sector linkages (the latter two observations can be seen from the disaggregated data not included in the paper). Maybe somewhat surprising is the fact that the highest intra-sector CP do not seem to occur between bank pairs but between government bond pairs. This somewhat contradicts the general notion that the banking sector is most prone to financial instability and that banks are "special" in that sense.

Let us now turn to a subsample analysis of CP values to check for crisis robustness of CP. 77.5% of estimated (intra-sector and inter-sector) CP values have increased in the crisis period. The highest number of increased CP values (88.0%) can be found for pairs that involve banks; 71.1% of the pairs that involve real estate indices have increased; finally, only 24% of the pairs that involve government bonds have increased. This may be due to the fact that the sovereign bond crisis only broke out at the end of the sample which implies it is not fully discounted yet into the estimates and one would need longer samples.

Using the disaggregated CP estimates for all possible pairs, the intra- and inter-sector average CP is calculated for the full period, the pre-crisis period and the crisis period. The results are provided in table 4. The Mann-Whitney U test (two sided) is used to test if there is a significant difference between the pre-crisis and the crisis period averages.[9] The averages in the table again confirm earlier findings but then for the pre-crisis and crisis periods. Intra-sector spillovers dominate inter-sector spillovers and government bonds seem more aligned with each other than banks. Upon comparing subsample averages, CP estimates all significantly increase except for intra-sector government bond linkages that decrease. The latter fact may be understood by a flight to quality effect from PIIGS debt into German debt during the crisis period. Clearly if the joint likelihood of crashing PIIGS debt and booming German debt increases, it automatically follows that the likelihood of co-crashes between German debt and PIIGS debt should fall.[10]

[9] The same conclusions hold upon comparing the averages with a t-test that is approximately normally distributed.

[10] Flight to quality probabilities (crashing PIIGS bonds vs. booming German bonds) are indeed found to be much higher for the crisis period as compared to their pre-crisis counterparts. Moroever, they exceed co-crash probabilities between PIIGS debt and German debt.

Table 4: Intra-sector and inter-sector CP averages: full sample, pre-crisis and crisis

		Full period	Pre-crisis period	Crisis period	MW U test
Intra-sector	Banks	25.1	18.6	32.2	N1=N2=435 U= 41138.5***
	Real estate	16.2	10.9	21.6	N1=N2=78 U= 1987.5***
	Govr. Bond	27.0	41.8	26.9	N1=N2=78 U= 1989.0***
Inter-sector	Banks - Real estate	16.4	9.0	22.3	N1=N2=390 U= 34492.0***
	Banks - Govr. Bond	3.6	2.1	6.4	N1=N2=390 U= 33438.0***
	govr. Bond - Real estate	3.2	1.7	4.8	N1=N2=169 U= 7745.5***

Note: The average intra-sector and inter-sector CP values are calculated for different samples. CP is calculated using eq. (9)).The full sample period runs from November 19, 1996 until December 10, 2010; the pre-crisis period runs from November 19, 1996 until June 1, 2007 and the crisis period runs from June 1, 2007 until December 10, 2010. A Mann-Whitney U (MW U) test (two-sided) is used to compare the pre-crisis with the crisis period. The superscripts *,**,*** denote significance at the 10%, 5% and 1% level respectively.

5.3 Other sector dependence

As a complement to the three-sector linkage analysis, we also consider extreme financial market linkages with other economic sectors. To that purpose stock market indices (total returns) of the twelve main EU economic sectors are considered (including the three we considered previously). Table 5 reports average CP estimates for these 12 sectors w.r.t. a EMU-wide bank index, real estate index and government bond index.

Table 5: Conditional co-crash probabilities between 12 EU economic sectors vs. banking, real estate and sovereign debt: full sample, pre-crisis and crisis

	Full Sample Period			Pre-crisis Period			Crisis Period		
	EMU Govr. bonds	Real Estate	Banking	EMU Govr. bonds	Real Estate	Banking	EMU Govr. bonds	Real Estate	Banking
Oil & Gas	4,00%	56,00%	80,00%	5,00%	42,50%	62,50%	6,67%	76,67%	90,00%
Basic Materials	2,00%	76,00%	86,00%	2,50%	82,50%	90,00%	3,33%	83,33%	90,00%
Industrials	2,00%	72,00%	96,00%	2,50%	70,00%	92,50%	3,33%	93,33%	96,67%
Consumer Goods	2,00%	50,00%	78,00%	0,00%	62,50%	95,00%	3,33%	90,00%	83,33%
Health Care	6,00%	44,00%	66,00%	2,50%	60,00%	75,00%	10,00%	60,00%	63,33%
Consumer Service	2,00%	58,00%	82,00%	2,50%	60,00%	75,00%	3,33%	86,67%	93,33%
Telecommunication	4,00%	30,00%	58,00%	5,00%	45,00%	62,50%	3,33%	76,67%	76,67%
Utilities	8,00%	62,00%	78,00%	7,50%	70,00%	72,50%	6,67%	66,67%	76,67%
Banking	4,00%	72,00%	100,00%	2,50%	65,00%	100,00%	3,33%	90,00%	100,00%
Real Estate	2,00%	100,00%	78,00%	2,50%	100,00%	60,00%	3,33%	100,00%	83,33%
Technology	4,00%	20,00%	50,00%	2,50%	25,00%	50,00%	3,33%	70,00%	80,00%
EMU Govr. bonds	100,00%	0,00%	2,00%	100,00%	2,50%	2,50%	100,00%	0,00%	0,00%

Note: Conditional probabilities are calculated using eq. (9). The full sample period runs from November 19, 1996 until December 10, 2010; the pre-crisis period runs from November 19, 1996 until June 1, 2007 and the crisis period runs from June 1, 2007 until December 10, 2010. The EMU govr. bond index starts only from January 1, 1999 onwards.

On average, co-crash probabilities (CP) between sectoral stock indices and government debt are weakest whereas CPs with banks are found to be highest; sectoral linkages with real estate take on an intermediate position. The strong extreme linkages with the banking sector are due to the financial intermediation role of the banks vis-à-vis the rest of the economy. Nonsurprisingly, the subsample results show that co-crash probabilities between economic sectors and banks have increased during the crisis because bank industry loans sharply decreased during the credit crunch. the crisis. General sector-real estate linkages also increased although this can be a side-effect of the increase in industry-bank relations. As for the sectoral indices-government bond linkages, being small for the full sample, they also hardly change across subsamples. In the next subsection we investigate the hypothesis whether a flight to quality effect occurred from sectoral stock indices into government bonds before and during the crisis. If present it will be interesting to see how the magnitudes of these flight to quality joint probabilities compare to the sector-bond co-crash probabilities in the table above.

5.4. Flight to quality from sectors into government bonds?

The flight to quality probabilities (FTQ) between common stock of the 12 main economic sector indices and EMU government bonds are summarized in Table 6. We calculate the probability of a sharp rise in EMU government bond prices given a sharp decline in the market values of the 12 main EU sectoral indices. The table further distinguishes between full sample, pre-crisis and crisis values.

Table 6: Flight to quality from 12 main EU economic sectors into EMU government bonds

	Full Sample Period	Pre-crisis Period	Crisis Period
	EMU Govr. Bonds*	EMU Govr. Bonds*	EMU Govr. Bonds*
Oil & Gas	32,00%	15,00%	50,00%
Basic Materials	40,00%	17,50%	50,00%
Industrials	38,00%	22,50%	53,33%
Consumer Goods	24,00%	17,50%	50,00%
Health Care	20,00%	15,00%	40,00%
Consumer Service	28,00%	15,00%	46,67%
Telecommunication	18,00%	12,50%	46,67%
Utilities	28,00%	12,50%	43,33%
Banking	40,00%	15,00%	53,33%
Real Estate	36,00%	12,50%	46,67%
Technology	12,00%	10,00%	36,67%
EMU Govr. Bonds*	100,00%	100,00%	100,00%

Note: FTQ between common stock of 12 main economic sectors and an EMU government bond index is calculates using eq. (9). The full sample period runs from November 19, 1996 until December 10, 2010; the pre-crisis period runs from November 19, 1996 until June 1, 2007 and the crisis period runs from June 1, 2007 until December 10, 2010. The EMU Govr. bond index runs from January 1, 1999 until December 10, 2010.

Upon comparing Table 6 with Table 5, one can immediately see that flight to quality into government bonds seems the dominant feature of the sectoral stock index-government relation regardless whether one considers crisis periods or not. Upon replacing the EMU government bond index with the German long term government bond index, the results above become even more pronounced. This is to be expected because the EMU government bond index also reflects the PIIGS country debt problem which somewhat mitigates the flight to quality outcomes.

6. Conclusion

This paper quantified pre-crisis vs. crisis EU tail risk and systemic risk within and across economic sectors. We therefore use total return indices of bank stocks, government bonds, real estate indices and other industry stock indices. The paper consists of a univariate and a bivariate part to identify univariate tail risk and bivariate systemic risk, respectively.

We identified univariate downside risk (or "tail" risk) by means of techniques from univariate extreme value analysis. Upon assuming that financial returns exhibit a Pareto-type heavy tail decay, the tail index and accompanying 99.9% extreme VaR quantile were estimated for every bank and country index. On average the banking sector exhibits the highest downside risk, followed by real estate and government bonds. Also, downside risk significantly increased for almost all banks and country indices during the recent crisis.

In the bivariate part we calculated co-crash probabilities (CP) for all possible combinations of EU banks (30 banks), real estate indices (12) and government bond indices (12). This led to 1,540 co-crash probability estimates. We further distinguished between intra-sector (bank-bank, real estate-real estate and bond-bond) spillovers and inter-sector (bank-real estate, bank-bond, real estate-bond) spillovers. Moreover, intra-sector or inter-sector spillovers can be situated in the same country (domestic) or can exhibit a cross-border character. First, we found that intra-sector spillover risk usually dominates inter-sector spillover risk. Second, domestic spillovers dominate cross-border spillovers and this does not only hold for bank pairs but also mixed asset pairs (banks-real estate, banks-bonds, real estate-bonds). Also, the latest financial crisis significantly increased both the inter-sector and intra-sector spillover risk.

As a benchmark for comparison, we also considered extreme co-crash probabilities between stock indices for the 10 remaining EU economic sectors and EMU-wide indices for banks, real estate and sovereign debt. The market value of sectoral common stock is most exposed to extreme shocks in bank equity capital followed by sharp drops in real estate. Extreme shocks in the market value of sovereign debt have the smallest impact on the rest of the economy although this result may also be due to the lack of crisis data at the end of the sample. Upon comparing pre-crisis with crisis spillovers, the general economic exposure to banking, real estate and sovereign bond shocks have all increased although the co-crash potential between sectoral stock indices and sovereign debt remains limited. This seems due to flight to quality

spillovers into sovereign debt, especially during the crisis sample. The calculation of flight to quality probabilities seems to confirm this.

References

-Adrian, T., & Brunnermeier, M. (2008), "CoVaR." *Federal Reserve Bank of New York Staff Report*, 348.

- de Haan, L., Jansen, D.W., Koedijk, K., & de Vries, C.G. (1994), "Safety First Portfolio Selection, Extreme Value Theory and Long Run Asset Risks", in J. Galambos (Ed.), *Proceedings from a Conference on Extreme Value Theory and Applications,* Kluwer Press.

-De Vries, C.G. (2005), "The simple economics of bank fragility", *Journal of Banking and Finance*, 29, pp. 803-825.

- Embrechts, P. Kluppelberg, C., & Mikosch, T. (1997), *Modelling Extremal Events*, Berlin, Springer-Verlag.

- Goodhart, C. (2008), "The background to the 2007 financial crisis", *International Economics and Economic Policy,* 4 (4), pp. 331-346.

- Gropp, R.E., Lo Duca, M. & Vesala, J. (2009), "Cross-Border Bank Contagion in Europe." *International Journal of Central Banking* 5(1): 97-140.

- Harrison, E. (2010), *The largest European banks by assets*. Credit Writedowns and Global Macro Advisors. Retrieved June 2, 2011, from the World Wide Web: http://www.creditwritedowns.com/2010/06/the-largest-european-banks-by-assets.html

- Hartmann, P., Straetmans, S. , & de Vries, C.G. (2004), "Asset market linkages in crisis periods", *The Review of Economics and Statistics*, 86, pp. 313-326.

- Hartmann, P., Straetmans, S. , & de Vries, C.G. (2006), "Banking system stability: A cross-Atlantic perspective", in R. Stulz and M. Carey (eds.), *The Risks of Financial Institutions*, pp. 133-188, The University of Chicago Press, Chicago.

- Huang, X. (1992). *Statistics of bivariate extreme values.* Tinbergen Institute Research Series Ph.D. thesis no 22, Erasmus University Rotterdam.

- Hill, B.M. (1975), "A simple general approach to inference about the tail of a distribution", *The Annals of Statistics*, 3, pp. 1163-1173.

- Janssen, D.W. & de Vries, C.G. (1991), "On the frequency of large stock returns: putting booms and busts into perspective", *Review of Economics and Statistics*, 73, pp. 19-24.

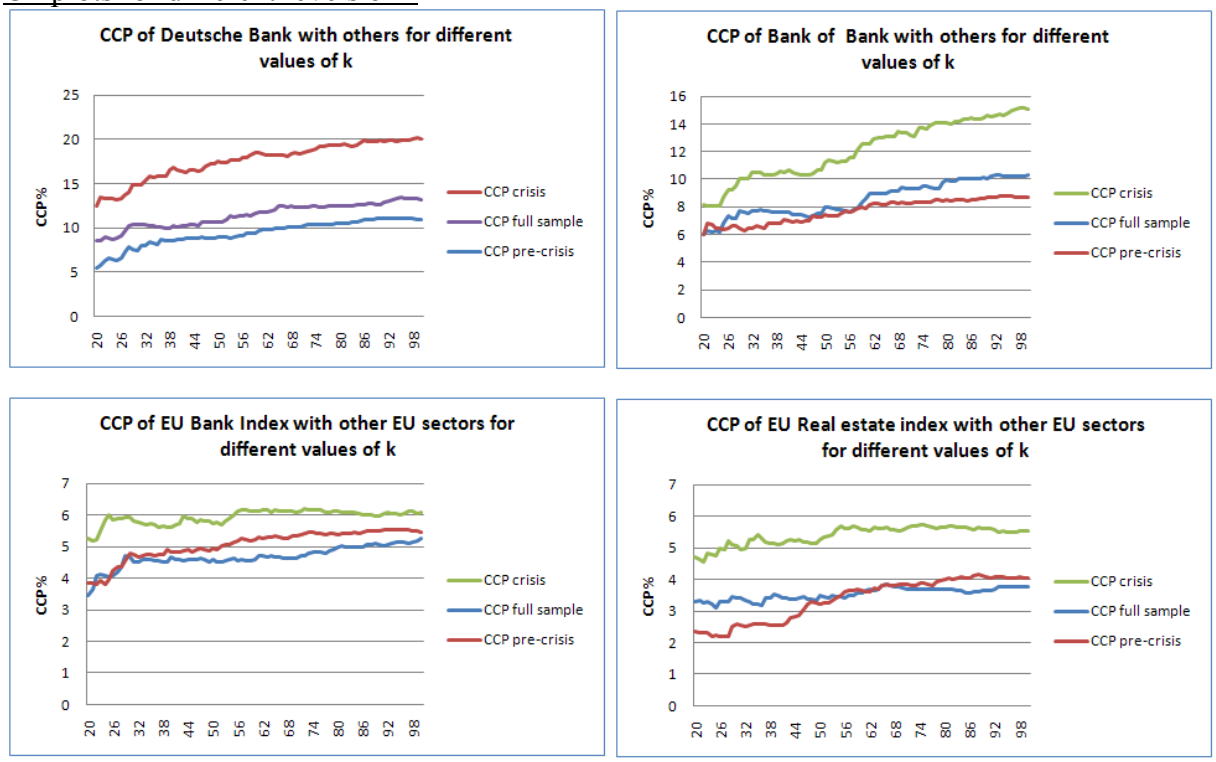
- Koedijk, K., Stork, P.A., & de Vries, C.G. (1992), "Foreign exchange rate regime differences viewed form the tails", *Journal of International Money and Finance*, 11, pp. 462-473.

- Pais, A., & Stork, P. (2010), "Contagion risk in the Australian banking and property sector", *Journal of Banking and Finance*, 35 (3), pp. 681-697.

- Straetmans, S., Verschoor, W., & Wolff, C. (2008), "Extreme U.S. stock market fluctuations in the wake of 9/11", *Journal of Applied Econometrics,* 23, pp. 17-42.

Appendix A

CP plots for different levels of k



Note: The CP plots for Deutsche Bank, Bank of Ireland, Bank index (from the main EU sectors) and Real estate index (from the main EU sectors). With the average CCP on the vertical axis and the k on the horizontal axis. The full sample period runs from November 19, 1996 until December 10, 2010; the pre-crisis period runs from November 19, 1996 until June 1, 2007 and the crisis period runs from June 1, 2007 until December 10, 2010. The source of raw data is Datastream.