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Abstract in English

This research compares systemic risk in the banking sector, the insurance sector, the construction sector, and the food sector. To measure systemic risk, we use extreme negative returns in stock market data for a time-varying panel of the 20 largest U.S. firms in each sector. We find that systemic risk is significantly larger in the banking sector relative to the other three sectors. This result is robust to separating out correlations with an economy-wide stock market index. For the non-banking sectors, the ordering from high to low systemic risk is: insurance sector, construction sector, and food sector. The difference between the insurance sector and the construction sector is no longer significant after correcting for correlations with the economy as a whole. The correction has a large effect for the banking sector and the insurance sector, and a smaller effect for the other two sectors.

Key words: Systemic risk, financial markets, banking, extreme value theory

JEL code: G01, G11, G21

Abstract in Dutch

Dit onderzoek vergelijkt systeemrisico in de bancaire sector, de verzekeringssector, de bouwsector en de voedingssector. Om systeemrisico te meten, gebruiken we voor elke sector de extreme waarden van de fluctuaties in aandelenkoersen voor een tijdsvariërend panel van de 20 grootste bedrijven in de VS. We vinden dat systeemrisico significant groter is in de bancaire sector vergeleken met de andere drie sectoren. Dit resultaat blijft overeind als we corrigeren voor correlaties met algemene aandelenindex. Voor de niet-bancaire sector is de volgorde van hoog naar laag systeemrisico: verzekeringssector, bouwsector, en de voedingssector. De verschillen tussen de verzekeringssector en de bouwsector zijn niet meer significant na correctie voor correlaties met de aandelenindex. De correctie heeft een groter effect voor de bancaire sector en de verzekeringssector in vergelijking met de andere twee sectoren.

Steekwoorden: Systeemrisico, financiële markten, banken, extreme waarde theorie

Systemic risk across sectors: Are banks different?*

Sander Muns[†] and Michiel Bijlsma[‡]

March 31, 2011

Abstract

This research compares systemic risk in the banking sector, the insurance sector, the construction sector, and the food sector. To measure systemic risk, we use extreme negative returns in stock market data for a time-varying panel of the 20 largest U.S. firms in each sector. We find that systemic risk is significantly larger in the banking sector relative to the other three sectors. This result is robust to separating out correlations with an economy-wide stock market index. For the non-banking sectors, the ordering from high to low systemic risk is: insurance sector, construction sector, and food sector. The difference between the insurance sector and the construction sector is no longer significant after correcting for correlations with the economy as a whole. The correction has a large effect for the banking sector and the insurance sector, and a smaller effect for the other two sectors.

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1 Introduction

The 2007-08 crisis has forcefully shown the impact on the real economy and the cost to society of a systemic banking crisis. This has triggered renewed efforts to measure the risk of such a crisis occurring. Measurement of systemic risk would help regulators in their risk assessments. In addition, it is a necessary first step in the analysis of the drivers of systemic risk.

It is generally accepted that the banking sector is more fragile than other sectors. Banks are more fragile than nonfinancial firms because of the inherent maturity mismatch on their balance sheet, which makes them vulnerable to bank runs. Furthermore, contagion within the financial sector can amplify and spread initially localized problems to other banks. Finally, the banking sector interacts with the real economy, resulting in an additional mechanism that can amplify and propagate shocks hitting the financial sector.

We use an indicator for systemic risk first proposed by Huang (1992) and further developed in Hartmann et al. (2004), which measures the expected number of institutions that experiences an extreme event given that at least one institution experiences such an extreme event. In accordance with this literature, we use stock prices to define an extreme event as an extreme negative return. As our focus is on extreme events which are by definition very scarce, our research is in the field of extreme value theory (EVT). A parametric estimation of the tail behavior enables us to make out-of-sample estimates of the systemic risk indicator.

The stock price based approach constrains our results to listed firms, but stock data is available for most of the largest banks. A side benefit of the stock price based approach is that our risk measure is also of interest for investors considering the downside risk of a diversified asset allocation within a specific sector, especially the banking sector. Although extreme negative returns generally do not correspond to a bank failure, we will refer to them as such. To the extent that stock prices are forward-looking, the indicator may act as an early warning system for systemic crises. The underlying assumption is that stock market data reflects all publicly available information about (*i*) individual asset and liability side risks and (*ii*) dependencies between different banks' risks. This means that stocks are assumed to be sufficiently liquid.

Using the systemic risk indicator, we do two things. First, we examine if systemic risk is actually higher in the banking sector than in other sectors. We compare the risk measure for the banking sector with the insurance sector and two non-financial sectors, the food sector and the construction sector. We expect systemic risk to be larger in the banking sector than in the other sectors.

Second, we try to separate out extreme events that are driven by the correlation with the economy as a whole. To this end, we use returns conditional on the market return, besides the unconditional returns, such that the effect of the market return is eliminated. The remaining dependencies in the conditional returns describe systemic risk in the financial sector that is uncorrelated to the market portfolio, which we interpret as uncorrelated to the economy as a whole. Thus, they describe shocks and common exposures to other factors than the market return, possibly amplified by the effect of contagion.

Our paper is related to several strands of literature. Basically, systemic risk can be defined based on different types of data, e.g., balance sheet data, CDS-spreads, or stock return data.[1] Some papers estimate the probability of a failure for a specific bank from its so-called distance to default (see, e.g., Crosbie and Bohn (2003), Gropp et al. (2009), and Segoviano and Goodhart (2009)). This distance equals the number of standard deviations by which the expected asset value exceeds the default point. It requires balance sheet data to determine the default point, and stock market data to determine the standard deviation and the expected asset value. However, balance sheet data are only available at a yearly or quarterly frequency and are vulnerable to so-called window dressing. Moreover, some important balance sheet items may be represented by unavailable off-balance sheet data.

Other papers use credit default swap (CDS) rates to estimate the probability of a failure (see, e.g., Huang et al. (2009) and Giglio (2010)). A CDS provides insurance on the payments of a bond in case of a credit event, where the underlying bond may also be issued by a non-listed firm. A disadvantage is that most CDS spreads are only available since a few years. Furthermore, CDS spreads are sensitive to changes in perceived counterparty risk, and the liquidity of CDS markets may be limited. This means that movements in CDS spreads are not necessarily associated with changes in the size of capital buffers.

Our paper is also related to several other works that use stock prices. Adrian and Brunnermeier (2010) define the firm-specific CoVaR for banks as the difference in value-at-risk (VaR) for the financial system when a particular bank comes into distress. The CoVaR measure is estimated by employing quantile regressions on weekly return data. Each CoVaR corresponds to the banks' contribution to the aggregate systemic risk.

Papers that apply EVT and focus on extreme returns in stock market data are more directly related to our work. Indeed, using EVT Longin (2001) shows that the correlation of large negative returns is much larger than the correlation of positive returns. Bae et al. (2003) evaluate contagion in financial markets based on the co-incidence of extreme return shocks across countries within a region and across regions. Contagion is predictable at a short horizon and depends on regional interest rates, exchange rate changes, and conditional stock return volatility. Slijkerman et al. (2005) find with a bivariate EVT approach that the ten largest European insurers share more interdependencies than the ten largest European banks. Hartmann et al. (2007) assess bank contagion risk in Europe and the United States by adopting multivariate EVT to estimate the simultaneous crash probabilities of stock returns. A structural increase in bank contagion risk has taken place over the second half of the 1990s, both in Europe and the U.S. The exposure of banks to extreme systematic shocks is estimated by the likelihood of a co-crash of a stock return and the market return. This exposure is roughly comparable for Europe and the U.S.

Zhou (2010) employs EVT to compare three related bank-specific measures of systemic risk. The Pearson correlation coefficient of any of the measures and the size of the bank turn out to be insignificant. Bühler and Prokopczuk (2010) estimate dependencies within several sectors by conducting a multivariate EVT approach. A parametric copula is estimated with stock prices of the five most important firms in each sector. They find that systemic risk in the banking sector is indeed significantly larger than in all other sectors of the economy. In particular, it differs from the systemic risk in the insurance sector. To our knowledge, Bühler and Prokopczuk (2010) is the only study which has thus far compared the dependencies in the banking sector with other sectors empirically.

[1] Extensive overviews of the literature on systemic risk are in De Bandt and Hartmann (2000), and Allen et al. (2010).

We add to this literature in the following ways. First, we compare systemic risk in different sectors. We find that systemic risk is significantly larger in the banking sector compared to other sectors. This is in line with the results of Bühler and Prokopczuk (2010), but we assess a considerably larger sample of firms. Our result is robust to separating out correlations with the economy as a whole by determining returns relative to an economy-wide stock market index. For the non-banking sectors, the ordering from high to low systemic risk is: insurance sector, construction sector, food sector. The differences between the sectors are all significant. Using returns conditional on the market return, the difference between the banking sector and the insurance sector is no longer significant. The correction has a large effect for the banking sector and the insurance sector, and a small effect for the other two sectors.

Second, we compare the systemic risk measure as determined by using a recently developed parametric estimation method with nonparametric estimation. We find that the difference is limited for our risk measure.

The paper is structured as follows. Section 2 introduces the employed dependence measure. The empirical implementation of the dependence measure is considered in section 3. Section 4 contains our empirical results. Robustness issues are addressed in section 5. Section 6 concludes.

2 Systemic risk measure

Our starting point to assess systemic risk for a particular sector is the fragility index which was first proposed in Huang (1992), and applied in Hartmann et al. (2004), Poon et al. (2004), De Vries (2005) and Segoviano and Goodhart (2009). It is defined as the expected number of failing firms given that at least one firm is failing:

$$FI := E[\kappa \,|\, \kappa \geq 1] \tag{2.1}$$

where κ represents the number of failing firms. By conditioning on the event of at least one failure, FI measures the cross-sectional *dependencies* between failures. The measure FI is always between zero and the number of considered firms (N), and tends to increase in the number of considered firms. We therefore select a time-varying subsample of a fixed number n_0 of the largest firms.[2] Let the dummy variable $S_i^{(n_0)}$ indicate if firm i is among the selected n_0 firms. The dummy variable C_i indicates if firm i fails. The random variable describing the number of selected failures is thus given by the random variable $\kappa^{(n_0)} = \sum_{i=1}^{N} S_i^{(n_0)} C_i$, which makes the following dependence measure natural:

$$\begin{aligned} FI^{(n_0)} &:= E\left[\kappa^{(n_0)} \,\middle|\, \kappa^{(n_0)} \geq 1\right] \\ &= \frac{\sum_{i=1}^{N} E\left[C_i S_i^{(n_0)}\right]}{P\left(\kappa^{(n_0)} \geq 1\right)} \\ &= \frac{\sum_{i=1}^{N} P\left(\{C_i = 1\} \cap \left\{S_i^{(n_0)} = 1\right\}\right)}{P\left(\kappa^{(n_0)} \geq 1\right)} \end{aligned} \tag{2.2}$$

[2] This improves upon the common approach in the literature where a *fixed* set of firms is considered, since our approach handles a potential survivorship bias. Nevertheless, we show in section 5 that our results are qualitatively the same for both approaches.

To improve interpretability, we consider the *expected fraction of additional failing firms* (EAF) given that at least one firm is failing:

$$EAF^{(n_0)} := E\left[\frac{\kappa^{(n_0)}-1}{n_0-1}\,\middle|\,\kappa^{(n_0)}\geq 1\right] = \frac{FI^{(n_0)}-1}{n_0-1} \tag{2.3}$$

The measure $EAF^{(n_0)}$ is a simple linear transformation of $FI^{(n_0)}$ such that $EAF^{(n_0)}$ is between zero and one.[3] We multiply $EAF^{(n_0)}$ by 100 to express this dependence measure as a percentage instead of a fraction.

3 Implementation

This section discusses how the sectoral dependence measure $EAF^{(n_0)}$ is determined from the empirical data.

3.1 Data

We employ U.S. equity data and a value-weighted market index from the Center for Research for Security Prices (CRSP) for the period 1993-2009. Commercial banks, insurance companies, the construction sector and the food sector are identified by Standard Industrial Codes (SIC) 6000-6199, 6300-6499, 1500-1799 and 2000-2099, respectively. We will simply use the term banking sector to refer to the commercial banking sector. We use daily returns as is standard in the EVT literature in finance. This assures a large number of observations.[4] A potential drawback is that extreme events might not be identified in a series of daily returns if the corresponding information is gradually revealed on different days.

Table 1 shows that for all sectors the total number of firms in our sample varies considerably over time. Table 2 contains descriptive statistics for the daily log returns of the considered sectors. On average, the daily log returns are highest for banks. This is attributable to a larger fraction of very high positive returns, since the skewness is also higher on average. Compared to the banking sector, the average return in the insurance sector is smaller, more volatile, and admits less skewness but more kurtosis. Further, insurance companies are on average larger than banks. The normal distribution is inappropriate to model the returns since excess kurtosis is detected in all considered sectors.

Banks and insurance companies are less sensitive to the market return than the cyclical construction sector, whilst they are about as sensitive to the market as the non-cyclical food sector. This market sensitivity captures the direct exposure to macro-economic shocks as well as the indirect exposure that arises from contagion as well as feedback effects with the real economy.

We use a time-varying sample of the 20 largest firms for each day. Due to the larger number of firms, the size of the largest twenty banks exceeds the sector average by a larger multiple than observed in the other sectors. Table 2 further shows that the largest twenty banks are more sensitive to the market return

[3] Appendix A briefly discusses how $EAF^{(n_0)}$ is related to copula functions.

[4] We are constrained by the fact that intra-day prices are unavailable.

Table 1: Number of firms by year for each sector

Firms are only counted if at least 245 stock returns for the corresponding year are available.

	Banking sector	Insurance sector	Construction sector	Food sector
1993	477	185	59	99
1994	551	201	69	110
1995	583	198	72	114
1996	636	199	75	120
1997	724	188	78	121
1998	746	185	73	118
1999	781	166	69	118
2000	742	152	61	109
2001	692	141	56	93
2002	673	135	48	95
2003	659	136	45	91
2004	614	138	44	87
2005	597	142	45	82
2006	581	140	44	83
2007	563	133	46	80
2008	541	120	41	81
2009	506	116	40	79

Table 2: Descriptive statistics for daily log returns for the period 1993-2009.

The sensitivity to the market, β, is based on monthly returns relative to the value weighted index from CRSP. The mean size is the cross-sectional mean of the mean market capitalizations for each firm. The twenty firms constituting the top 20 have the largest maximal market capitalization. The firms constituting the time-varying top 20 are for at least one day among the twenty firms with the largest market capitalization. The sample period is 1993-2009.

	Banking sector	Insurance sector	Construction sector	Food sector
SIC	60-61	63-64	15-17	20
Total number of firms	1,523	347	132	218
Mean daily log return ($\cdot 10^{-4}$)	1.56	0.773	-3.42	-0.61
Mean st.dev.($\cdot 10^{-2}$)	3.47	3.52	5.71	4.45
Median st.dev.($\cdot 10^{-2}$)	2.72	2.85	4.36	3.30
Mean skewness	0.30	-0.37	-0.32	0.20
Median skewness	0.20	0.08	0.18	0.15
Mean kurtosis	29.62	41.71	28.66	22.68
Median kurtosis	12.82	16.89	11.52	12.10
Mean size (mln $)	0.88	2.27	0.43	2.24
Mean size (top 20, mln $)	35.31	23.53	1.88	20.25
Mean β (all firms)	0.56	0.77	1.09	0.65
Mean β (top 20)	1.15	0.94	1.33	0.56
Number of firms (time-varying top 20)	51	49	59	40

than the industrial average. This may reflect the fact that small banks have a more regional scope such that the sensitivity to the country-wide market index is smaller. The largest twenty banks have a larger market sensitivity than the largest twenty insurance firms, but this sensitivity is smaller than the largest twenty firms in the construction sector.[5] Under the assumption that failures of larger firms have a larger impact on the real economy, it is thus worthwhile to focus on the large firms. Otherwise, results may be biased towards the characteristics of the smaller firms.

The time-varying sample of the largest twenty firms appears to be more stable over time for sectors where the largest firms are less sensitive to the market return. For instance, only 40 different firms in the non-cyclical food sector are at least for one day in the top 20 of largest firms, while this number is 59 for the cyclical construction sector.

From time series to probabilities

A failure of firm i is defined as the event that the daily log stock return R_i is below some negative threshold return q_i:

$$\{C_i = 1\} = \{R_i \leq q_i\} = \left\{\tilde{R}_i \geq 1\right\}$$

where $\tilde{R}_i = R_i/q_i$ is the scaled daily log return. We define $\tilde{R}_{\max}$ as the cross-sectional maximum of scaled returns of the selected firms:

$$\tilde{R}_{\max} = \max_{\left\{i:S_i^{(n_0)}=1\right\}} \tilde{R}_i \tag{3.1}$$

The event of at least one failure among the n_0 selected firms, $\left\{\kappa^{(n_0)} \geq 1\right\}$, then corresponds to the event $\left\{\tilde{R}_{\max} \geq 1\right\}$.

Some simultaneous failures are at least partly attributable to simultaneous increases in the volatility of stock returns due to the presence of heteroskedasticity (see, e.g., Lamoureux and Lastrapes (1990) or Bollerslev et al. (1992)). For instance, stock volatilities were unusually high during the financial crisis triggered by a large uncertainty in future cash flows. The high stock volatilities reinforced the impact of any news event on the stock returns. As a consequence, clusters of simultaneous extreme negative returns were observed during this period. The effect of heteroskedasticity can in principle be eliminated by estimating a GARCH model for each return series to adjust the series for the time-varying volatility (see, e.g., Bae et al. (2003) or Poon et al. (2004)). Nevertheless, as argued in Hartmann et al. (2007), banking supervisors need to know the likelihood that one or several banks fail given that a bank fails, or given that there is an adverse macroeconomic shock. This pertains to simple unconditional returns. Furthermore, they argue that banking regulations are determined in advance for longer periods of time. This means that they cannot be based on the short-term volatility forecasts from a GARCH model. As a robustness check, we show in section 5 that our results are also valid for GARCH filtered returns.

A considerable part of the correlation between stock returns might be explained by the common exposure to macro-economic shocks. We filter out this effect to assess the impact of this common exposure

[5] Appendix B contains a list of the 20 largest firms in each sector.

on the dependencies. Therefore, we estimate for each firm i a simple market model

$$R_{i,t} = \alpha_i + \beta_{i,t} R_{M,t} + \varepsilon_{i,t} \tag{3.2}$$

where $R_{M,t}$ denotes the daily return of the market index. By the forward-looking nature of stock prices, the market sensitivity $\beta_{i,t}$ captures the direct exposure to macro-economic shocks as well as the indirect exposure that arises from pro-cyclical effects. Time-variation in the market sensitivity is taken into account by estimating market betas with rolling windows of five years. Each time window provides for each firm i the beta for the last year in the time window. In this way, we are able to estimate the market sensitivities for the full sample in a similar way.[6] It is tacitly assumed here that the linear dependence relation between the stock prices and the market return is valid for all market returns.

The daily residuals from the market model (3.2), i.e., the abnormal returns $e_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_{i,t} R_{M,t}$, are measures for the stock return conditional on the market return.[7] A failure conditional on the market return corresponds to a low realization of $e_{i,t}$. Therefore, the dependence measure for the *conditional* returns employs for the scaled conditional returns the scaled series $\tilde{R}_{i,t} = e_{i,t}/q_i$, where q_i is the negative failure level for the conditional returns $e_{i,t}$.

Regardless if the scaled returns are based on raw returns or conditional returns, the dependence measure from (2.3) is given by

$$EAF^{(n_0)} = \frac{\sum_{i=1}^{N} P\Big(\Big\{\tilde{R}_i \geq 1\Big\} \cap \Big\{S_i^{(n_0)} = 1\Big\}\Big)}{(n_0 - 1) P\Big(\tilde{R}_{\max} \geq 1\Big)} - \frac{1}{n_0 - 1} \tag{3.3}$$

The constant n_0 is a positive integer number which we set at 20. We obtain as follows a time series for each of the random variables $S_i^{(n_0)}$ from empirical data: A firm's size is defined as its market capitalization, which is measured by the product of the closing price and the number of shares outstanding. This means that the *instantaneous* market capitalization is affected by extreme negative returns. Hence, selecting returns of the n_0 largest firms based on the instantaneous market capitalization would tend to exclude some extreme negative returns. We omit this potential selection bias by selecting the largest n_0 firms by the one day *lagged* market capitalizations. This provides us the time series for each selection variable $S_i^{(n_0)}$ in (3.3).

The time series of scaled daily returns $\tilde{R}_i$ of firm i is based on the time series of the firm's daily stock return R_i and the failure level q_i. These series are in turn used for the cross-sectional maximum of selected scaled returns, $\tilde{R}_{\max}$. The daily stock returns are directly obtained from the data. For the failure level q_i, we use the Value-at-Risk (VaR) of a firm which is the convenient approach in risk management.[8]

[6] We added returns for the period 1989-1992 to obtain estimates for the first years of the sample 1993-2009. Monthly returns are used to mitigate the impact of outliers in the series of daily stock returns on the OLS regression. Regressing average monthly returns in the financial sector on (the change of) the federal funds rate or the 10 year U.S. treasury rate did not yield any significant result in an OLS setup. Further, the term spread was insignificant. The same holds true when one considers one year lagged interest rates. This has led us to restrict the model to the market model. We show in section 5 that our results are robust under including a quadratic market return variable in 3.2.

[7] If the true model for firm i is given by $R_{i,t} = \alpha + \beta R_{M,t} + \gamma Z_{i,t} + \eta_{i,t}$, then the estimated parameter $\hat{\beta}_i$ in the restricted model $R_{i,t} = \alpha_i + \beta_i R_{M,t} + \eta_{i,t}$ captures the total effect of $R_{M,t}$ on $R_{i,t}$, as desired. This consists of the direct effect β_i and the indirect effect $\gamma \partial Z_{i,t} / \partial R_{M,t}$ that runs via the omitted variable $Z_{i,t}$.

[8] The capital requirements for market risk in Basel II and in the proposed Basel III are based on the Value-at-Risk concept.

The complete sample of available returns for the corresponding firm is employed for the VaR regardless if the firm is always included in the set of n_0 largest firms. For a given probability p_A, we set the failure level equal to the p_A%-VaR. This means that q_i equals the p_A% lower quantile of daily stock returns of firm i. More formally, $p_A = P(R_i \leq q_i \,|\, A_i = 1)$, where A_i is a dummy variable indicating if the daily stock return is available. Intuitively, the daily stock return is below the failure level once in $1/p_A$ days. If we choose $p_A = 2\%$, a firm is below the failure level for approximately 5 times per year, provided that daily returns are available for the complete year. Notice that more volatile firms face a higher failure level, but fail as frequently as stable firms.

Probability estimators

It follows from (3.3) that the measure $EAF^{(n_0)}$ requires estimates of

(P1) the p_A% Value-at-Risk quantiles q_1, ..., q_N to obtain the series $\tilde{R}_1, \ldots, \tilde{R}_N$.

(P2) the exceeding probabilities beyond one for the series $\tilde{R}_{\max}$, $P\Big(\tilde{R}_{\max} \geq 1\Big)$.

(P3) the expected number of selected failures for each period, $\sum_{i=1}^{N} P\Big(\Big\{\tilde{R}_i \geq 1\Big\} \cap \Big\{S_i^{(n_0)} = 1\Big\}\Big)$.

Estimates are based on either a nonparametric (NP) estimator or a parametric (Par) estimator. The NP estimator is only feasible for a given failure probability p_A that is sufficiently large. For small values of p_A, the variance in the NP estimator may be relatively large. Therefore, the Par estimator is especially appropriate for small p_A. On the other hand, the Par estimator requires a larger dataset, because the variance of the parametric estimate of the probabilities in (3.3) is larger for a small dataset.[9]

We choose both the NP estimator and the Par estimator for (P1) and (P2). To be consistent, we use the same estimator for (P1) and (P2). We use, however, always the NP estimator to estimate (P3). Because we consider the size of a firm as given, i.e. it is given which firms are selected, the estimation only employs the limited number of observations where the event $\Big\{S_i^{(n_0)} = 1\Big\}$ is true. This means that unless a firm is very frequently selected into the sample, we can only use the nonparametric estimator to estimate (P3).

NP estimator

The nonparametric estimator $\hat{P}_{NP}$ simply estimates the probability of an arbitrary event A by the observed fraction:

$$\hat{P}_{NP}(A) = \frac{\#A}{\text{total number of events}}$$

The quantiles q_i in (P1) are such that $\hat{P}_{NP}(R_i \leq q_i) = p_A$, where p_A is the given failure probability for an available stock return. It follows that q_i is equal to the $\lfloor p_A\,(T+1)\rfloor$-th smallest return for a time series of length T of the daily stock returns R_i of firm i.[10] The nonparametric estimator is, therefore, only defined for $p_A \geq 1/(T+1)$. Given an appropriate p_A and some n_0, we can estimate $EAF^{(n_0)}$ directly

[9] $EAF^{(n_0)}$ can even be negative for a small dataset. This follows from the estimation procedure of the Par estimator, which is discussed below. The point is that we separately estimate (P2) from (P3), which results in a separate estimation bias for the numerator terms and the denominator.

[10] $\lfloor x \rfloor$ denotes the largest integer not larger than x.

from its definition by computing the mean additional fraction of selected firms that fail for the periods where at least one firm is failing:

$$EAF^{(n_0)} = \frac{1}{(n_0 - 1) |T_1|} \sum_{t \in T_1} ([\#\text{selected firms that fail in period } t] - 1) \tag{3.4}$$

where a failure is, as before, a return below the failure level, T_1 is the set of periods where at least one selected firm fails, and $|T_1|$ is the number of periods in this set. Exactly the same result is obtained when we estimate (P2) and (P3) with the nonparametric estimator and substitute the estimates in (3.3).

Par estimator

Extreme events are by definition rare. The method with the nonparametric estimator may be inappropriate for small p_A since the dependence measure depends on a small number of observations such that it admits a large variance. In that case, we can make a parametric estimate of the tail behavior to determine $EAF^{(n_0)}$ (see e.g. Hartmann et al. (2004), Poon et al. (2004) and Straetmans et al. (2008)). More specifically, we adopt the procedure proposed in Gomes et al. (2009) to obtain tail quantile estimators. This novel bootstrap procedure uses besides the usual Hill tail estimator (see Hill (1975)), two second-order parameters to arrive at a minimum variance reduced bias (MVRB) quantile estimator. The interested reader is referred to Gomes et al. (2009) for the technical details. We address the following sequential steps to estimate $EAF^{(n_0)}$ in (3.3):

(P1) *the quantiles* $q_1, ..., q_N$
The estimation algorithm is applied on each return series R_i in order to obtain q_i and the series of scaled returns $\tilde{R}_i = R_i / q_i$.

(P2) *the failure probability* $P\left(\tilde{R}_{\max} \geq 1\right)$
Following (3.1), we calculate the time series of the cross-sectional maximum of selected scaled returns, $\tilde{R}_{\max}$, from the series of scaled returns $\tilde{R}_i$. We make a separate parametric estimation for the tail of this series to estimate $P\left(\tilde{R}_{\max} \geq 1\right)$. Namely, the estimator $\hat{P}_{Par}\left(\tilde{R}_{\max} \geq q\right)$ for the quantile $q = 1$ in the denominator of equation (2.1) is obtained by implementing the following bisection method on the employed quantile estimator: We vary the estimate $\widehat{p_A}$ for the probability $P\left(\tilde{R}_{\max} \geq 1\right)$ until the corresponding quantile estimate $\hat{q}_{Par} = q_{Par}\left(\widehat{p_A}\right)$ is sufficiently close to one. More specifically, we get for $\hat{P}_{Par}\left(\tilde{R}_{\max} \geq 1\right)$ a sequence of intervals $\left[p_l^{(i)}, p_u^{(i)}\right]$ of decreasing length, where $p_l^{(i)}$ and $p_u^{(i)}$ are the lower bound and upper bound of the i-th iteration, respectively. The convergence criterion of the bisection method is set at $\left(p_u^{(i)} - p_l^{(i)}\right) / p_l^{(i)} \leq 10^{-7}$.

(P3) We use the nonparametric estimate for (P3).

For the NP estimator as well as the Par estimator, we assign an equal probability to each time period. In fact, we implicitly assume that the realization of the time series are a random draw from some underlying random variable, which is a common approach for forecasting on a long time horizon.

Inference

To test whether differences in the dependence measure $EAF^{(n_0)}$ are statistically significant, we apply a bootstrap procedure. This re-sampling procedure is as follows. Let $EAF_X^{(n_0)}$ and $EAF_Y^{(n_0)}$ denote the dependence measures for X and Y, which are two different sets of (possibly conditional) return series defined over the *same* period. Suppose we observe that $EAF_X^{(n_0)} > EAF_Y^{(n_0)}$, and we want to test if the difference is significant.

The following moving block bootstrap method is employed to test the null hypothesis $EAF_X^{(n_0)} = EAF_Y^{(n_0)}$ against the one-sided alternative $EAF_X^{(n_0)} > EAF_Y^{(n_0)}$. For each bootstrap b, two sets $X(b)$ and $Y(b)$ of artificial time series of length nl are constructed by pairwise sampling n possibly overlapping blocks of l subsequent periods from the sets X and Y.[11] The blocks capture possible inter-temporal dependencies in the series, such as volatility clustering. We bootstrap pairwise by selecting each pair of blocks over the same period from X and Y. As a consequence, the constructed series of each bootstrap face an equal market volatility. The bootstrapped measures $EAF_{X(b)}^{(n_0)}$ and $EAF_{Y(b)}^{(n_0)}$ are based on the artificial time series $X(b)$ and $Y(b)$, respectively. Repeating this exercise a large number of times, B, we get B samples $EAF_{X(b)}^{(n_0)} - EAF_{Y(b)}^{(n_0)}$ from the distribution of $EAF_X^{(n_0)} - EAF_Y^{(n_0)}$. The P-value for the null hypothesis $EAF_X^{(n_0)} = EAF_Y^{(n_0)}$ equals the fraction of non-positive bootstrap samples $EAF_{X(b)}^{(n_0)} - EAF_{Y(b)}^{(n_0)}$.

4 Results

We determine the systemic risk indicator for a time-varying sample of the largest 20 firms using both unconditional returns and conditional returns, defined as the residuals from the market model (3.2). For each of the four sectors, Figure 1 shows the expected additional fraction of extreme negative returns given that at least one firm incurs an extreme negative return as a function of the firm-specific probability on an extreme negative return, p_A. We consider values of p_A below one percent. The solid lines are the values determined using the NP estimator, the dashed lines those using the Par estimator.

The overall picture is that the ranking of the sectoral $EAF^{(20)}$ from high to low is as follows; first the banking sector, second the insurance sector, third the construction sector, and fourth the food sector.[12] Notably, the banking sector exhibits far more systemic risk for very small p_A than the other three sectors. For instance, if a failure corresponds with an unconditional daily stock return below the 0.5% VaR level, Figure 1 indicates that *given* that at least one large bank is failing, on average 8.1% of the other 19 large banks fails on that particular day. This number is only 5.0% for the insurance sector, 3.4% for the construction sector, and about 2.5% for the food sector. If a failure is defined as a conditional return below the 0.5% VaR level. about 4.0% of the other 19 large banks is expected to face a failure given that at least one large bank is incurring a failure, This number is about 3.0% for the insurance sector, about 2.4% for the construction sector, and about 1.7% for the food sector. Notice that the latter number is

[11]As in Hartmann et al. (2007) we follow Hall et al. (1995) by setting the block length equal to $l = T^{1/3}$. The number of blocks, n, for each bootstrap is the nearest integer to $T/l = T^{2/3}$.

[12]This contrasts with the result of Slijkerman et al. (2005) who obtain the puzzling result that systemic risk is slightly larger for the insurance sector than the banking sector. A possible explanation for this ambiguity involves that their analysis is restricted to a cross-sectional average of bivariate risk measures, whereas our risk measure directly considers twenty firms for each period. Further, they consider ten large European banks and ten large European insurers, while we consider the twenty instantaneously largest U.S. firms in each sector.

Figure 1: $EAF^{(20)}$ based on raw returns.

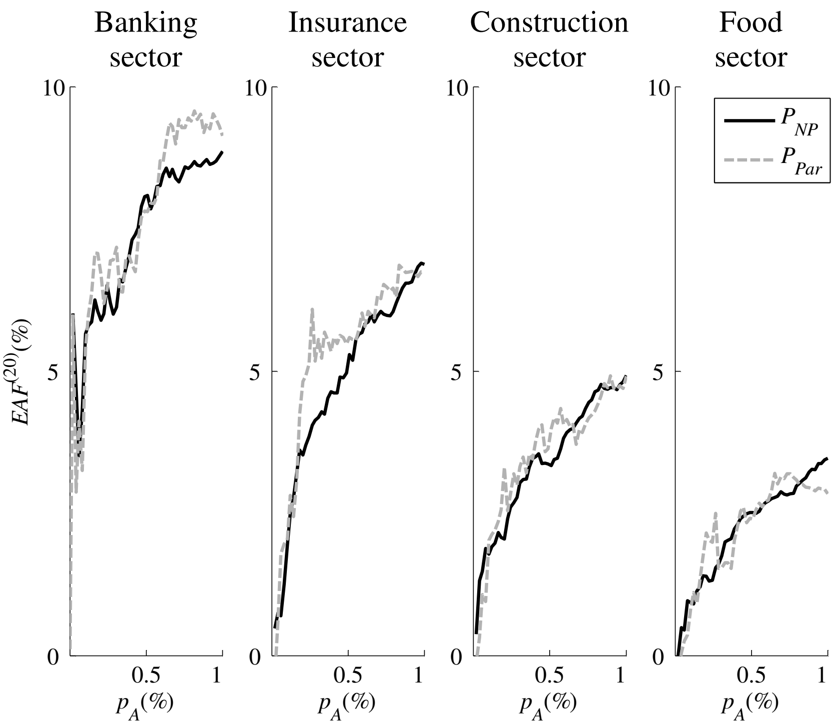
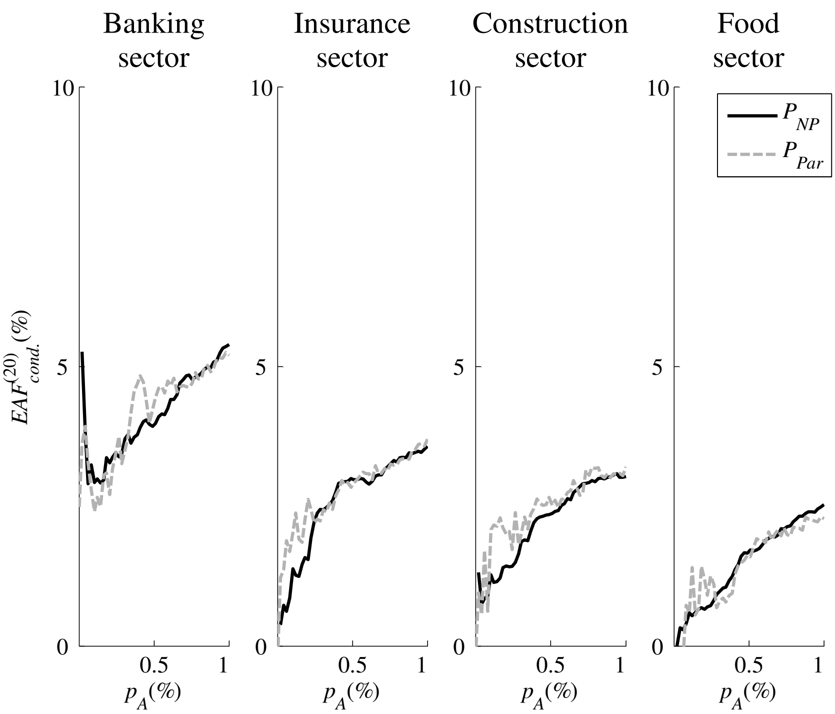


Figure 2: $EAF^{(20)}$ based on the abnormal returns from the market model (3.2).



quite small because it implies for the food sector that on average only 1.32 of the twenty largest firms fails *given* that at least one firm in the food sector fails.

Figure 2 shows the results for the case where a failure is defined as a *conditional* return below its VaR level. The decline in the dependence measures indicates that the market return explains some part of the sectoral variation in $EAF^{(20)}$. Still, the order of the sectors is unchanged and the banking sector is relatively more systemic for very small failure probabilities.

For any p_A, $EAF^{(20)}$ determined by the nonparametric estimator is hardly more than 1.5% point from $EAF^{(20)}$ determined by employing the Par estimator. Hence, we focus on the results of the nonparametric estimator.

To assess whether the differences between the sectors and the decline in the measure when using unconditional results are significant, we perform 5,000 bootstrap replications of the returns of the time-varying sample of the largest 20 firms in each sector. Table 3 contains the P-values for the differences in $EAF^{(20)}$ between the sectors. In each cell, the upper P-value pertains to a 0.5% probability on a firm-specific failure, whereas this probability p_A equals 1% for the lower P-value. The linearity of $EAF^{(20)}$ in $FI^{(20)}$ implies the same P-values for the null hypothesis of equality of $FI^{(20)}$. The upper triangle refers to $EAF^{(20)}$ based on raw returns, the lower triangle to conditional returns from the market model. The main diagonal compares $EAF^{(20)}$ based on raw returns with $EAF^{(20)}$ based on residuals. More specifically, it contains the P-values for the null hypothesis that $EAF^{(20)}$ is equal for the raw returns and the conditional returns.

Table 3: Bootstrapped P-values for null hypothesis of $EAF^{(20,X)} = EAF^{(20,Y)}$ against the one-sided alternative $EAF^{(20,X)} > EAF^{(20,Y)}$, where for the full sample $EAF^{(20)}$ is larger for sector X than for sector Y.

The upper triangle refers to $EAF^{(20)}$ based on raw returns, the lower triangle to conditional returns from the market model. The main diagonal compares $EAF^{(20)}$ based on raw returns with $EAF^{(20)}$ based on residuals. In each cell, the upper P-value pertains to a 0.5% probability on a firm-specific failure, whereas this probability is 1% for the lower P-value. All results are based on 5,000 bootstrap replications of the (conditional) returns of the time-varying sample of the largest 20 firms in each sector.
* indicates significant at the 5% level of confidence.

	Banking sector	Insurance sector	Construction sector	Food sector
Banking sector	0.000* 0.000*	0.000* 0.003*	0.000* 0.000*	0.000* 0.000*
Insurance sector	0.021* 0.000*	0.000* 0.000*	0.004* 0.000*	0.000* 0.000*
Construction sector	0.003* 0.000*	0.115 0.067	0.013* 0.003*	0.019* 0.002*
Food sector	0.000* 0.000*	0.002* 0.001*	0.020* 0.038*	0.018* 0.003*

The upper triangle shows that for both failure probabilities, the banking sector admits significantly more simultaneous failures, i.e., more systemic risk, than the other three sectors.[13] This difference is also

[13]Unless stated otherwise, we use a significance level of 5%.

significant for the other sectors. We thus find in the case of unconditional returns

$$EAF^{(20,\text{banks})}_{\text{returns}} > EAF^{(20,\text{insurance})}_{\text{returns}} > EAF^{(20,\text{construction})}_{\text{returns}} > EAF^{(20,\text{food})}_{\text{returns}} \tag{4.1}$$

The larger tail dependencies in the banking sector imply that tail risk of common risk factors, such as market risk or interest rate risk, plays a relatively large role in this sector. This may stem from a larger exposure to common factors as well as a fatter tail for common factors. Explanations for the larger dependencies in the conditional returns of the construction sector than of the food sector include a larger common exposure to factors that are not captured by the simple market model such as housing prices, interest rates, etc, or fatter tails for the common factors.

In the limit $p_A \to 0$, the risk is only determined by the factor with the fattest tail. Figure 1 suggests that a common factor is dominant for the banking sector, whereas idiosyncratic risk is dominant for the other three sectors.[14] As was shown in Table 2, the exposure to the market return is not larger in the banking sector than in the construction sector. Further, Figure 2 shows that after eliminating the impact of the market return, systemic risk is about the same for the limiting case $p_A \to 0$. Both facts suggest that another common factor than the market return is the driving force behind the systemic risk in extreme negative returns of the banking sector. We will show in section 5 that common heteroskedasticity explains the sectoral differences in the limiting case. It is left for future research to find out which factors drive the common volatilities of the extreme returns in the limiting case.

The cells in the lower triangle in Table 3 indicate that for the conditional returns:

$$EAF^{(20,\text{banks})}_{\text{cond.ret}} > EAF^{(20,\text{insurance})}_{\text{cond.ret}} \approx EAF^{(20,\text{construction})}_{\text{cond.ret}} > EAF^{(20,\text{food})}_{\text{cond.ret}} \tag{4.2}$$

Besides a contagion effect on idiosyncratic shocks, explanations for the larger dependencies in the banking sector include common heteroskedasticity, larger common exposures to other factors such as interest rates, currencies, foreign exchanges, etc, or other mis-specifications of the simple market model (3.2).

Notice from (4.2) that the insurance sector and the construction sector, no longer differ significantly. Apparently, the larger common exposure to the market return in the insurance sector explains the difference between these two sectors in (4.1). After correcting for this effect, the possibly larger amplification mechanisms on idiosyncratic shocks in the insurance sector compensate for the possibly larger common exposures in the construction sector.

The results also show that for each sector the dependence measure $EAF^{(20)}$ is significantly lower for the conditional returns than for the raw returns. This means that a considerable proportion of each $EAF^{(20)}$ for raw returns is attributable to the possibly amplified exposure to the market return.

Table 4 shows that the decline when using conditional returns is significantly larger for the financial sector than for the non-financial sector.[15]:

$$DIF^{(20,\text{banks})} \approx DIF^{(20,\text{insurance})} > DIF^{(20,\text{construction})} \approx DIF^{(20,\text{food})} \tag{4.3}$$

[14] Notice that a contagion effect on an idiosyncratic shock transform the shock into a systematic shock.

[15] We obtain this result by taking the average of the two P-values in each cell.

Notably, the larger contagion effect on the market return in the financial sector significantly exceeds the effect of the larger average market beta in the construction sector.

Table 4: Bootstrapped P-values for the null hypothesis $DIF^{(20,X)} = DIF^{(20,Y)}$ against the one-sided alternative $DIF^{(20,X)} > DIF^{(20,Y)}$, where for the full sample $DIF^{(20)}$ is larger for sector X than for sector Y.

The upper and lower P-value in each cell pertain to $p_A = 0.5\%$ and $p_A = 1\%$, respectively. All results are based on 5,000 bootstrap replications of the (conditional) returns of a time-varying sample of the largest 20 firms for each sector. For each bootstrap, $EAF^{(20)}$, is obtained for the raw returns and the conditional returns of sectors X and Y. This gives for sectors X and Y 5,000 pairwise differences in $EAF^{(20)}$ between the raw returns and the conditional returns. * indicates significant at the 5% level of confidence.

	Banking sector	Insurance sector	Construction sector
Insurance sector	0.025* 0.179		
Construction sector	0.002* 0.002*	0.064 0.011*	
Food sector	0.000* 0.000*	0.003* 0.000*	0.192 0.061

5 Robustness issues

In this section we assess the robustness of our results by enlarging the set of failure events to less negative returns, by taking common heteroskedasticity into account, by adding a quadratic term in the market model, and by using a fixed sample of firms, and by using rolling estimation windows.

Enlarging the set of failure events to less negative returns

The plots so far only considered failure probabilities up to 1%. Figure 3 shows that the banking sector has still the most dependencies when raising p_A up to 20%.

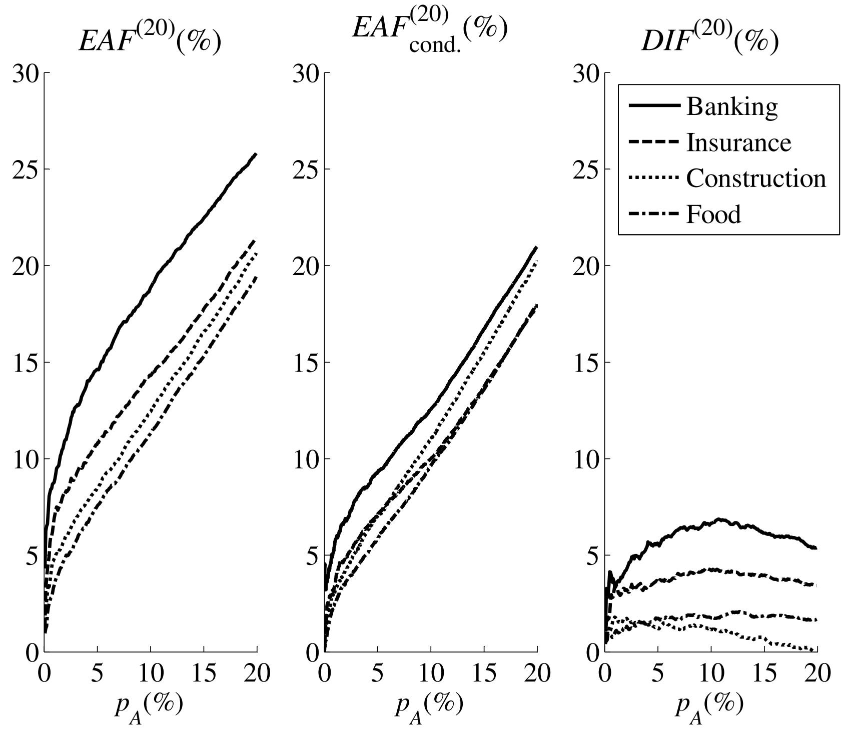
Heteroskedasticity

Some of the dependencies might be the result of common heteroskedasticity in stock returns. We check this by estimating the following ARMA(1,1)-EGARCH(1,1) model for firm i:

$$\begin{aligned} R_{i,t} &= \mu_{i,t} + \epsilon_{i,t} \\ \mu_{i,t} &= \mu_i + \phi_i R_{i,t-1} + \theta_i \epsilon_{i,t-1} \\ \epsilon_{i,t} &= \sigma_{i,t} z_{i,t} \\ \log \sigma^2_{i,t} &= \omega_i + \alpha_i z_{i,t-1} + \gamma_i \left(|z_{i,t-1}| - E|z_{i,t-1}| \right) + \beta_i \log \sigma^2_{i,t-1} \\ z_t &\sim t(\nu_i) \end{aligned}$$

The EGARCH setup which was introduced in Nelson (1991) is able to capture the well document asymmetric response in the volatility into account. In particular, a large negative shock tends to increase

Figure 3: Systemic risk measures with failure probabilities up to $p_A = 20\%$ for raw returns (left), abnormal returns from the market model (3.2) (middle), and the difference between the two measures (right). The nonparametric estimator from (3.4) is employed.



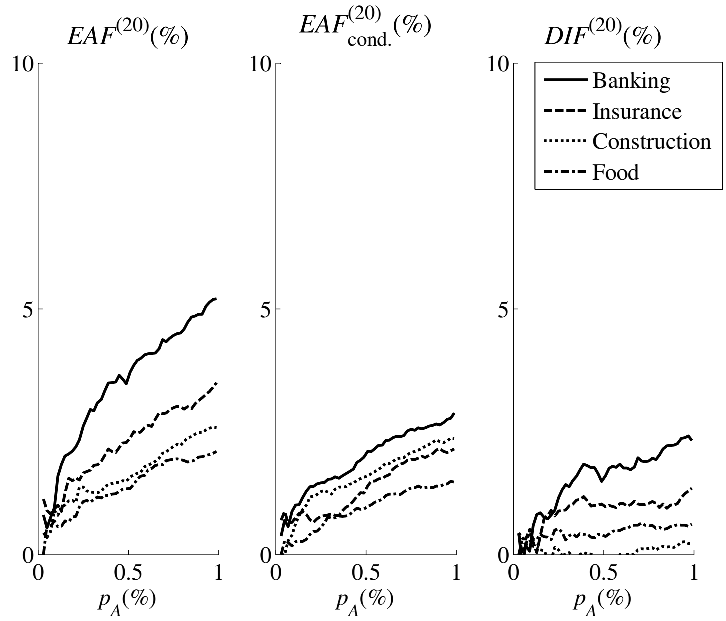
volatility much more than a large positive shock. We allow the standardized innovations $z_{i,t}$ to exhibit fat tails by imposing a student-t distribution with ν_i degrees of freedom.

The firm-specific parameters μ_i, ϕ_i, θ_i, ω_i, α_i, γ_i, β_i and ν_i are estimated by maximum likelihood. Subsequently, the dependencies in the series of standardized innovations $\{z_t\}$ is investigated with our systemic risk measure. This procedure is applied by taking the raw returns for $R_{i,t}$ as well as by taking the estimated abnormal returns $e_{i,t}$ from the market model (3.2).

Comparing Figure 4 with Figures 1 and 2 makes clear that a considerable part of the dependencies is attributable to common heteroskedasticity in stock returns. Namely, the banking sector faces the largest decline (not plotted), which indicates that the cross-sectional correlation in $\sigma_{i,t}$ is largest for the extreme losses in the banking sector. After correcting for this effect by standardizing the returns and conditional returns, the left and middle plot in Figure 4 show that the dependencies in the standardized innovations are still largest for the banking sector. The order is also unchanged when p_A is not too small. For very small p_A ($\ll 0.5\%$), we see that common heteroskedasticity is the main driver for the larger systemic risk in the banking sector. It is left for future research to determine the drivers of the common heteroskedasticity.

The same results hold for the conditional losses, except that the construction sector admits somewhat more dependencies than the insurance sector. Indeed, the difference between the dependencies of these two sectors was insignificant in the baseline model. Further, the difference between the two types of

Figure 4: Systemic risk measures for a time-varying sample of the largest 20 firms for EGARCH filtered returns (left), EGARCH filtered abnormal returns from the market model (3.2) (middle), and the difference between the two measures (right). The nonparametric estimator from (3.4) is employed.



EGARCH-filtered dependencies is largest for the banking sector (right plot), which suggests that the impact of the market return is again largest for the banking sector.

Sample selection of firms

Because firms enter and leave the set of twenty largest firms, the sample of firms varies over time in the baseline model. As a consequence, the number of firms that are for at least one day in the set of largest firms is considerably larger than twenty for all sectors (see Table 2). As a robustness check, we employ the same analysis for a constant sample of firms. More specifically, we use the twenty largest firms that are listed over the complete sample range 1993-2009.[16] The size of a firm is measured by the maximal size over the whole sample period.

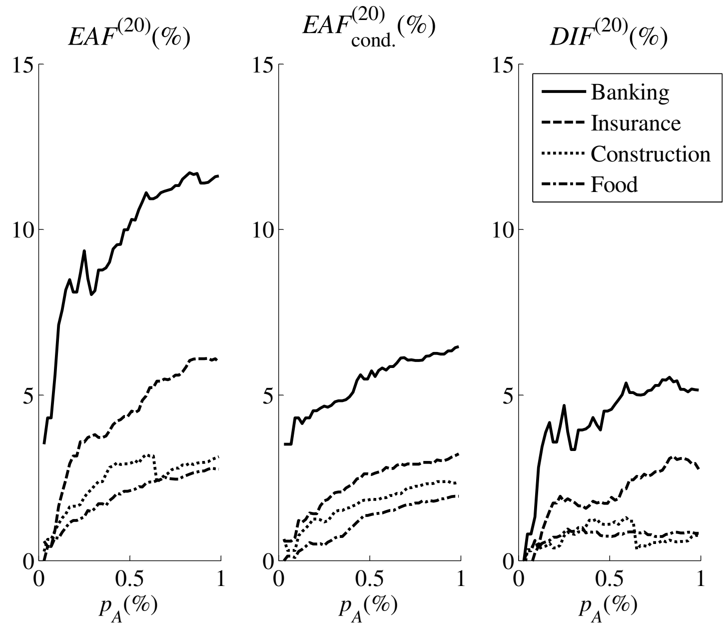
The results in Figure 5 are very similar to Figure 1 and Figure 2. Again, the banking sector is exposed to the largest systemic risk. The order of the other sectors is also unchanged. Moreover, the decline in $EAF^{(20)}$ when switching to abnormal returns of the market model is again largest for the banking sector. This indicates that our results are robust to the method of sample selection.

Quadratic market model

The market model (3.2) is very parsimonious. This single-index model follows from the CAPM model under the rather restrictive assumption that either asset returns are (jointly) normally distributed random

[16]The sample for the construction sector consists of only nineteen firms as no more firms are listed over the whole sample period.

Figure 5: Systemic risk measures for a *fixed* sample of the largest 20 firms for raw returns (left), abnormal returns from the market model (3.2) (middle), and the difference between the two measures (right). The nonparametric estimator from (3.4) is employed.



variables or that investors employ a quadratic form of utility. It is therefore very well possible that this simple model does not capture the behavior in the tails of the market return. The observed skewness in stock returns conditional on the market return has motivated some authors (e.g., Harvey and Siddique (2000) and Barone-Adesi et al. (2004)) to consider the model

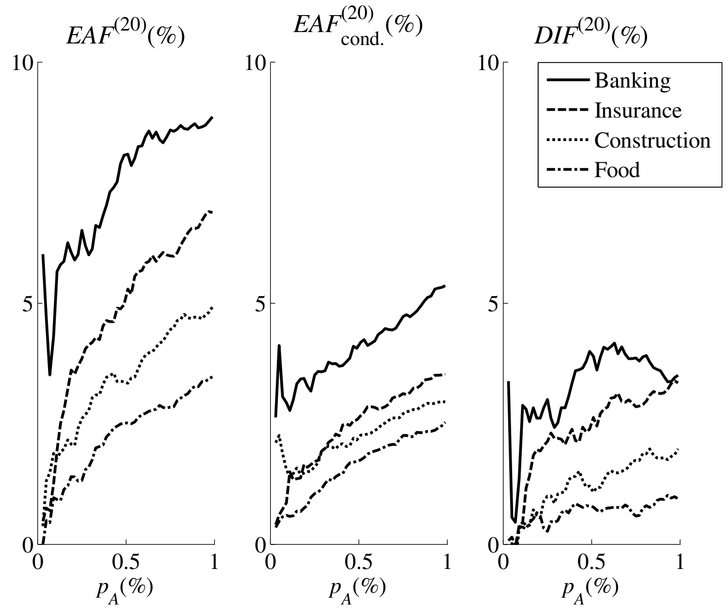
$$R_{i,t} = \alpha_i + \beta_{i,t} R_{M,t} + \gamma_{i,t} R_{M,t}^2 + \varepsilon_{i,t} \tag{5.1}$$

Employing the same analysis as before yields a new systemic risk measure for the abnormal returns $\varepsilon_{i,t}$. The variation of this measure is plotted as a function of the failure probability p_A in the middle plot of Figure 6. The measure in the left plot is the nonparametric estimate of Figure 1 as it is based on the raw returns. The right plot is the difference between the two risk measures as a function of p_A. Again, the banking sector exhibits most systemic risk, and the order of the other three sectors is unchanged.

Rolling estimation windows

The baseline model employs the full sample to determine the failure levels for the returns and the abnormal returns. This may give a distorted picture, since the increased volatility during the financial crisis has resulted in a cluster of exceedings of the failure level. As a robustness check, we take changes in the failure levels into account by using rolling estimation windows of five years. The market models are re-estimated for each estimation window, such that the failure levels in the earlier estimation windows are not affected by the extreme negative returns during the financial crisis. The failure probabilities p_A are set at the 0.5% VaR level for the returns as well as the abnormal returns from the market model. We check the

Figure 6: Systemic risk measures for a time-varying sample of the largest 20 firms for raw returns (left), abnormal returns from the *quadratic* market model (5.1) (middle), and the difference between the two measures (right). The nonparametric estimator is used.



robustness of the results in (4.1), (4.2) and (4.3).

Figure 7 suggests that the result from (4.1) that the banking sector exhibits most systemic risk and that the food sector exhibits less systemic risk are robust over time. The order of the insurance sector and the construction sector changes over time. Figure 8 shows that the same holds for the conditional

Figure 7: $EAF^{(20)}$ for rolling time windows of 5 years.

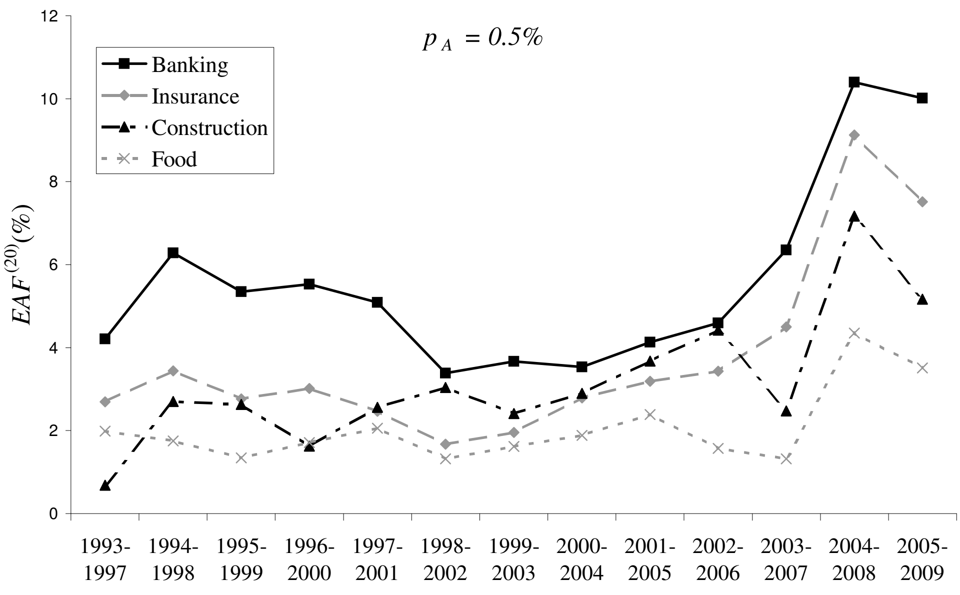


Figure 8: $EAF^{(20)}$ for abnormal returns with rolling time windows of 5 years.

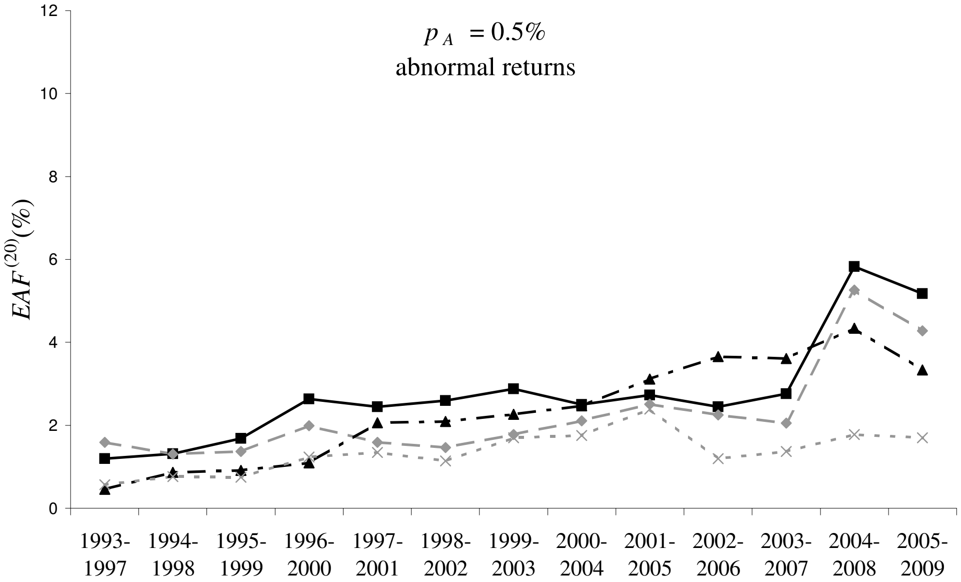
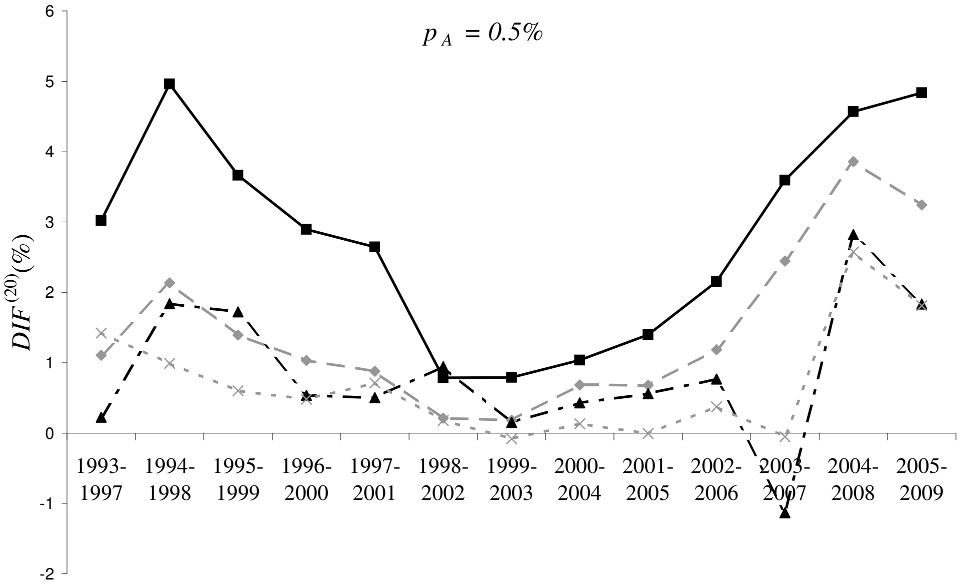


Figure 9: Difference (DIF) between EAF for returns and abnormal returns with rolling time windows of 5 years.



returns. Figure 9 indicates that the result from (4.3) that the banking sector exhibits more systemic risk than the non-financial sector by the effect of the common exposure to the market return, and the result that the food sector exhibits less systemic risk than the financial sector by the effect of the common exposure to the market return are robust over time. None of the figures enable us to distinguish the systemic risk of the insurance sector from the construction sector.

Notice that Figure 7 and 8 show that the dependencies in extreme negative returns have increased over time in all sectors, the banking sector included. However, a clear signal indicating the financial crisis can not be identified from the observations prior to the crisis. This does not necessarily imply that appropriate policy measures are infeasible.

6 Conclusions

This paper compares systemic risk in the U.S. banking sector, the insurance sector, the construction sector, and the food sector. To measure systemic risk we use extreme negative returns in stock market data for a time-varying panel of the 20 largest U.S. firms in each sector. We use an indicator for systemic risk that measures the expected number of institutions that experience an extreme event given that at least one institution experiences such an event. We determine this measure using unconditional returns as well as using returns conditional on the market return. The latter should in principle correct for correlations with the economy as a whole.

We have the following conclusions. Systemic risk is significantly larger in the banking sector relative to the insurance sector, the construction sector and the food sector. For the latter sectors, the ordering from high to low systemic risk is: insurance sector, construction sector, food sector, where the differences are again significant. This result is robust to separating out correlations with the economy as a whole by determining stock market returns relative to an economy-wide stock market index. However, using conditional returns, the difference between the insurance sector and the construction sector is no longer significant. The correction has a large effect for the banking sector and the insurance sector, and a small effect for the other two sectors. Thus, the correlation with the market return explains a relatively large part of systemic risk in the banking sector. But for very extreme negative returns, the dependencies in the banking sector are driven by common heteroskedasticity, whereas they are driven by idiosyncratic factors in the other sectors.

In addition, we find that for our sample the differences between determining systemic risk using non-parametric and parametric estimation are limited for failure probabilities above 0.1 percent. Prudential regulation considers a failure level at 1 percent or 0.1 percent in order to evaluate risk-taking behavior of an individual institution. For practical purposes, using a parametric estimator therefore seems to have additional value only for even smaller p-values or shorter sample periods.

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Appendices

A The dependency measure and copulas

We briefly discuss how the dependence measure $EAF^{(n_0)}$ in (2.3) is related to copula functions. More precisely, we argue how the probability $P\left(\kappa^{(n_0)} \geq 1\right)$ from (2.2) captures the required dependencies between the performance of firms. The sample of n_0 selected firms is given, and the firms are labeled such that only firm $1, \ldots, n_0$ is selected. All other firms are neglected for ease of exposition.

Denote the performance of firm i, e.g., the daily stock return of firm i, by the continuous random variable R_i. A failure of firm i corresponds with a performance below the firm-specific negative failure level q_i. Sklar's theorem says that any multivariate distribution can be written as a multivariate copula function, C, with as the arguments the marginal distributions transformed to the interval $[0, 1]$. The copula function solely describes the dependence structure of the marginal distributions. By applying this theory to the multivariate distribution function F of $(-R_1, ..., -R_{n_0})$, we have for the probability that none of the selected n_0 firms fails:

$$F(-q_1, \ldots, -q_{n_0}) = P(-R_1 \leq -q_1, \ldots, -R_{n_0} \leq -q_{n_0}) = C\left(P(-R_1 \leq -q_1), \ldots, P(-R_{n_0} \leq -q_{n_0})\right)$$

It follows from the negativity of the failure levels that

$$P\left(\frac{R_1}{q_1} \leq 1, \ldots, \frac{R_{n_0}}{q_{n_0}} \leq 1\right) = C\left(P\left(\frac{R_1}{q_1} \leq 1\right), \ldots, P\left(\frac{R_{n_0}}{q_{n_0}} \leq 1\right)\right)$$

which means that none of the firms fails with probability

$$P\left(\tilde{R}_{\max} \leq 1\right) = C\left(P\left(\tilde{R}_1 \leq 1\right), \ldots, P\left(\tilde{R}_{n_0} \leq 1\right)\right)$$

where $\tilde{R}_i = R_i/q_i$ and $\tilde{R}_{\max} = \max_i R_i$. The random variable $\tilde{R}_{\max}$ is continuous by the continuity of the underlying performance measures $R_1, \ldots, R_n$. Then, the probability on the complement, $P\left(\tilde{R}_{\max} \geq 1\right) = P(\kappa \geq 1)$, is evaluated by the function $g\left(r\right) := 1 - C\left(\tilde{F}_1\left(r\right), \ldots, \tilde{F}_{n_0}\left(r\right)\right)$ at $r = 1$, where C is the copula function of the scaled returns $\tilde{R}_1, \ldots, \tilde{R}_{n_0}$ with corresponding distribution functions $\tilde{F}_1, \ldots, \tilde{F}_{n_0}$.[17] The one-dimensional function $g(r)$ captures all the required dependencies for the estimation of $EAF^{(n_0)}$. It therefore suffices to parametrize the n_0-dimensional copula function C along the vector

$$\left\{\left(\tilde{F}_1\left(r\right), \ldots, \tilde{F}_{n_0}\left(r\right)\right) \middle| \, r \in \mathbb{R}\right\},$$

and to evaluate the resulting function g at $r = 1$. As a result, it is not needed to estimate the common failure probability for each of the possible $(2^{n_0} - 1)$ combinations of failing firms.

[17] C is also the copula function of $(-R_1, ..., -R_{n_0})$.

B Descriptives of largest 20 firms

Table 5: Largest 20 firms in each sector. Size refers to market capitalization in bln $ as measured by stock price times number of outstanding shares. Maximum is taken over period 1993-2009.

	Banking sector	Max size	Insurance sector	Max size
1	CITIGROUP	286.5	AMERICAN INT. GROUP INC	239.9
2	BANK OF AMERICA CORP	248.1	BERKSHIRE HATHAWAY INC DEL	162
3	WELLS FARGO & CO NEW	146.6	UNITEDHEALTH GROUP INC	85.9
4	WACHOVIA CORP 2ND NEW	115.6	METLIFE INC	52.6
5	FED. NATIONAL MORTGAGE ASSN	89.5	PRUDENTIAL FINANCIAL INC	48.3
6	BANK ONE CORP	74.3	ALLSTATE CORP	43.2
7	U S BANCORP DEL	66.2	TRAVELERS COMPANIES INC	37.8
8	BANK OF NEW YORK MELLON CORP	56.7	MARSH & MCLENNAN COS INC	36.6
9	FED. HOME LOAN MORTGAGE CORP	50.7	HARTFORD FIN. SVCS GROUP INC	33.6
10	FLEETBOSTON FINANCIAL CORP	48.8	A F L A C INC	32.4
11	WASHINGTON MUTUAL INC	44.6	AETNA INC NEW	29.9
12	VISA INC	41.8	A X A FINANCIAL INC	24.8
13	M B N A CORP	36.8	PROGRESSIVE CORP OH	24.4
14	ASSOCIATES FIRST CAPITAL CORP	35.6	AMERICAN GENERAL CORP	23.7
15	CAPITAL ONE FINANCIAL CORP	34.3	CHUBB CORP	23.3
16	WELLS FARGO & CO	33.5	C I G N A CORP	20.7
17	STATE STREET CORP	33.1	LINCOLN NATIONAL CORP IN	20.6
18	SUNTRUST BANKS INC	32.3	GENERAL RE CORP	19.9
19	HOUSEHOLD INTERNATIONAL INC	32.2	WELLPOINT HEALTH NETWRKS	19.6
20	P N C FINANCIAL SERVICES GRP INC	28.1	PRINCIPAL FINANCIAL GROUP INC	18.5

	Construction sector	Max size	Food sector	Max size
1	FLUOR CORP NEW	17.5	COCA COLA CO	217.1
2	D R HORTON INC	13.1	PEPSICO INC	128.1
3	PULTE HOMES INC	12.4	KRAFT FOODS INC	58.9
4	CENTEX CORP	10.2	ANHEUSER BUSCH COS INC	49.6
5	TOLL BROTHERS INC	9	ARCHER DANIELS MIDLAND CO	31
6	LENNAR CORP	8.4	SARA LEE CORP	29.9
7	K B HOME	8.1	CAMPBELL SOUP CO	28.5
8	K B R INC	7.4	GENERAL MILLS INC	23.5
9	QUANTA SERVICES INC	6	KELLOGG CO	22.3
10	N V R L P	6	HEINZ H J CO	22.2
11	RYLAND GROUP INC	3.9	BESTFOODS	20.2
12	M D C HOLDINGS INC	3.9	CONAGRA INC	18
13	HOVNANIAN ENTERPRISES INC	3.4	WRIGLEY WILLIAM JR CO	17.5
14	GLOBAL INDUSTRIES LTD	3.4	COCA COLA ENTERPRISES INC	16.6
15	BEAZER HOMES USA INC	3.4	QUAKER OATS CO	13.5
16	STANDARD PACIFIC CORP NEW	3.3	RALSTON PURINA CO	12.3
17	GRANITE CONSTRUCTION INC	3.1	HERSHEY CO	12.3
18	MASTEC INC	2.7	R J R NABISCO INC	12.3
19	MERITAGE HOMES CORP	2.6	MOLSON COORS BREWING CO	10.4
20	EMCOR GROUP INC	2.4	PEPSI BOTTLING GROUP INC	9.7

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