The Information in Systemic Risk Rankings☆

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Abstract

We propose to pool alternative systemic risk rankings for financial institutions using the method of principal components. The resulting overall ranking is less affected by estimation uncertainty and model risk. We apply our methodology to disentangle the common signal and the idiosyncratic components from a selection of key systemic risk rankings that are recently proposed. We use a sample of 113 listed financial sector firms in the European Union over the period 2002-2013. The implied ranking from the principal components is less volatile than most individual risk rankings and leads to less turnover among the top ranked institutions. We also find that price-based rankings and fundamentals based rankings deviated substantially and for a prolonged time in the period leading up to the financial crisis. We test the adequacy of our newly pooled systemic risk ranking by relating it to credit default swap premia.

Keywords: systemic risk contribution, risk rankings, forecast combination, financial regulation, banking supervision.

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1. Introduction

Since the 2008–2009 global financial crisis, many new approaches have been developed to quantify and rank 'systemic risk' contributions of firms in the financial sector. However, few of these approaches are currently actively used at public policy institutions such as central banks or supervising authorities. Possible reasons for this lack of adoption include a weak theoretical foundation for a number of these measures, as well as their frequent reliance on financial market data, which renders the rankings inherently volatile. We argue that the presence of multiple alternative and arguably noisy measures of financial sector firms' systemic risk contributions raises two important questions. First, is there a straightforward way to combine currently available systemic risk rankings to amplify the signal and reduce the noise due to model risk and estimation uncertainty? Is a combined ranking sufficiently robust for policy purposes and targeted banking supervision? Second, does a robust measure of systemic importance correlate with financial institutions' cost of debt finance? Is it in line with the public sector guarantee for the most systemically important institutions? Similar questions are raised in, for instance, Kelly, Lustig, and Van Nieuwerburgh (2011).

In our study we argue that the first questions can be addressed in an affirmative way while responses to the last questions depend mostly on the financial health of the sovereign. Specifically, we provide a principal components based methodology to combine systemic risk rankings of financial institutions with the aim of achieving a robust combined ranking. The combined ranking is based on six risk ranking methodologies and disentangles their common (signal) and idiosyncratic (noise) parts. Our approach reflects the notion that risk averse policy makers only pay attention to systemic risk rankings when other complementary approaches point in the same direction. Indeed, when different measures of systemic risk point in the same direction, it may be branded as irresponsible to pay no attention to the common signal, given the stakes at hand. In our study we find that if systemic risk rankings do not point in the same direction, policy makers interpret this situation as a warning signal that prices in markets may be dislocated from their fundamentals. Of course, some rankings and systemic risk measures may be more useful than others. Information about a possible dislocation between prices and fundamentals may be distilled from our methodology. Since our principal components are obtained from a cross-sectional dataset, the analysis can be performed and repeated in any time period.

In order to extract the common information content of different input rankings, we perform an iterated cross-sectional aggregation of rankings based on a fairly straightforward factor model. The combined ranking is constructed from the eigenvalue that explains most of the variance of the observed data subject to a normalization. The usual optimality properties of the principal component hold in our modeling approach as well; see Lawley and Maxwell (1971). In our study, the method of principal components is used in the cross-section direction only. We do not obtain estimates of factors in a time series context. For a time series approach to 'systemic risk' we refer to Moreno and Pena (2013) and Giglio, Kelly, and Pruitt (2015).

We apply our general framework to the European Union financial sector, studying $N = 113$ firms during $T = 139$ months from March 2002 to September 2013. As a result, our sample contains most of the build-up phase of financial instability in Europe during the expansion years of 2003-07, the materialization of systemic risks during the global financial crisis between 2008-09, and the most acute phase of the euro area sovereign debt crisis from 2010-12. Our sample of listed financial sector firms contains commercial banks, insurers, asset managers, and broker/dealers. In terms of ranking methodologies, we consider risk rankings based on criteria such as SRISK (Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2015), MES (Acharya, Pedersen, Philippon, and Richardson, 2010), the leverage ratio (Fostel and Geanakoplos, 2008; IMF, 2009; Geanakoplos and Pedersen, 2014), systematic risk defined as the so-called CAPM beta times market capitalization (Benoit, Colliard, Hurlin, and Pérignon, 2015), ΔCoVaR (Adrian and Brunnermeier, 2014; Castro and Ferrari, 2014), and firm's Value-at-Risk (Adams, Füss, and Gropp, 2014; White, Kim, and Manganelli, 2015).

We focus on three main empirical findings. First, we demonstrate that the cross-sectional consistency between the different rankings is far from perfect. The respective mean rank correlations are positive, but routinely fall below 0.5. The poor association is not due to a few outliers, but is symptomatic of the fact that different ranking methodologies actually order financial firms differently in the cross-section. Of course, this is problematic for supervisory purposes. In addition, standard unit root tests suggest that a substantial fraction (up to 66%) of ranks tend to be non-stationary in the time dimension. Given the possibly non-stationarity properties of many of the rankings, we focus mainly on the cross-sectional dimension of the principal components analysis and discuss how these properties vary over the course of the two financial crises embedded in our sample. We clearly find that our combined ranking is substantially less volatile over time than most rankings taken in isolation. Crucially, our pooled risk ranking leads to relatively little variation (turnover) among firms at the top of the ranking. This feature is important for targeted banking supervision, as re-deploying on-site supervisory teams is costly and requires months of lead time in practice.

Second, when studying the time series of the results from our cross-sectional principal components analysis, we find a rising discrepancy during 2006–2007 between the loadings of price-based systemic risk rankings (such as VaR, ΔCoVaR, and MES) versus systemic risk rankings that also incorporate book values (such as Leverage and SRisk). This appears to signal a dislocation between market prices and fundamentals already in the onset to the 2008 financial crisis. Hence different systemic risk measures signal different messages at a time when they are, arguably, the most important. Similar (smaller sized) changes in loadings emerge several times during the subsequent European sovereign debt crisis. Substantial deviations between the information embedded in different systemic risk rankings as evidenced by the principal component loadings may be used by policy makers as possible "red flags" to signal that imbalances in markets are building up, and that closer inspection of such potential imbalances is warranted.

Third, when we investigate the relationship between systemic importance and credit default swap (CDS) prices, we show that the systemic importance of financial firms tends to vary negatively with their CDS premia, provided that the sovereign is financially healthy. The extent of systemic importance of banks appears to correlate with a benefit from a funding perspective in the market for unsecured funds for some firms, most likely due to an implicit public sector guarantee; see also Kelly et al. (2011). For banks located in certain stressed euro area countries we obtain the opposite result, particularly during the most acute phase of the euro area sovereign debt crisis from 2010–2012. In this case the sovereign cannot provide a credible guarantee, and, if anything, appears to have become a liability to its more systemically important firms. To summarize, less implicit government support appears to be available for European financial firms that are 'too-systemically-safe-to-bother', and for firms that are backed by a financially weak sovereign.

Many contributions are made to formalize the notion of systemic risk and to investigate systemic risk contribution of individual financial firms. Acharya et al. (2010) are amongst the first to develop a model in which the capital shortfall experienced by a financial firm at a time when the financial system is undercapitalized generates negative externalities to the entire economy. He and Krishnamurthy (2014), Brunnermeier and Sannikov (2015), and Boissay et al. (2015) study economies with financial frictions that are, due to highly nonlinear amplification mechanisms, prone to instability and can occasionally enter volatile crisis periods. In all these models, financial firms do not take account of the possible costs of their risk taking during a crisis. It is important that empirical measures of systemic risk contribution – once further progress is made towards reliable measurement – provide a way to 'internalize' systemic risk externalities, for example via additional capital and liquidity requirements, as well as targeted banking supervision. The latter entails deploying on- and off-site teams to those banks where the expected loss from a bankruptcy would be the most devastating to the macroeconomy.

ECB (2009, 2010, 2011) and Bisias et al. (2012) provide comprehensive surveys of the empirical literature on systemic risk measurement. Our study may also relate to two other strands of literature. First, the optimal combination of alternative forecasts is often taken as a simple and effective way to improve and robustify the forecasting performance of individual models; see, for example, the seminal contribution of Bates and Granger (1969). As a result, forecast combinations are now in widespread use in central banks, among private sector forecasters, and in academic studies; see Aiolfi et al. (2010) for a comprehensive survey on forecast and nowcast combination. Second, the analysis of factor models by the method of principal components is widely understood and frequently applied in the social sciences.

Recent applications of principal component methods to systemic risk include Billio et al. (2012), Moreno and Pena (2013), and Giglio et al. (2015).

Two recent studies are closely related to ours. Giglio et al. (2015) evaluate a sizeable collection of systemic risk measures and rank them in their ability to forecast macroeconomic downturns in the U.S. and Europe. They adopt a dynamic factor analysis to obtain systemic risk indexes in the time dimension, and then demonstrate that such a systemic risk index provides significant predictive information out-of-sample for the lower tail of macroeconomic outcomes. Our paper is related to theirs in that we both evaluate a compendium of systemic risk measures, not in isolation, but as a group. Our analysis is different, however, in that we apply factor analysis *across rankings* in the cross-section dimension, at each point in time, to form optimal combinations of rankings. Giglio et al. (2015) instead follow Moreno and Pena (2013) and apply factor analysis *across firms* to obtain a systemic risk index in the time dimension. Benoit et al. (2015) provide a theoretical and empirical survey of systemic risk measures. They demonstrate that, given a certain set of assumptions, several popular systemic risk measures can be formulated as (non-linear) functions of market risk measures such as the CAPM beta. In an earlier empirical investigation of U.S. financial firms (Benoit et al. (2013)), they note that a one-factor linear model appears to explain most of the variability across four systemic risk measures (MES, SES, SRISK, and ΔCoVaR). Our paper is different in that they stop short of pursuing that intuition further by extracting the common variation across systemic risk measures to obtain a combined ranking that is less affected by model risk and estimation uncertainty (see also Danielson et al., 2015). Moreover, once we obtain our combined ranking, we investigate how systemic importance co-varies with CDS data at the firm level.

The remainder of this paper is set up as follows. Section 2 discusses our input measures and corresponding ranks. Section 3 introduces our basic methods of pooling risk ranks. Our main empirical results are discussed in Section 4. Section 5 investigates the relationship between a firm's systemic importance and its CDS spread. Section 6 concludes.

2. Data

2.1. Data sources

We consider monthly observations of six systemic risk rankings for $N = 113$ financial sector firms located in the European Union. The sample period is March 2002 to September 2013, comprising $T = 139$ months. We obtain our data from two sources. For risk measures 1–4 below, our data comes from the vLab website.[4] For risk measures 5–6, we have been granted access to the confidential Bundesbank submissions to the European Systemic Risk Board (ESRB). The ESRB publishes aggregate statistics of ΔCoVaR in their quarterly updates of their risk dashboard.[5] While many other systemic risk measures exist, our sample of risk measures 1–6 is a reasonably complete set of market based measures that regulators may look at in practice. The set nests the measures investigated by Benoit et al. (2013). All risk rankings are at a monthly frequency.

For our later empirical analysis, we also consider CDS data at the firm level. All CDS are obtained from Bloomberg, and are end-of-month values.

2.2. Ranking criteria

We rank-order our sample of financial firms according to the following risk measures.

2.2.1. SRisk

SRisk is an estimate of the capital shortfall a given financial firm i is expected to experience conditional on a severe market decline, see Brownlees and Engle (2015). It operationalizes the theoretical framework of Acharya et al. (2010) and can be interpreted as the systemic risk contribution of a given financial firm. SRisk is a function of a firm's size, leverage, and its expected equity loss given a market downturn. As a result, it combines balance sheet data (on liabilities) with market data (on equity market volatility, systematic risk, and market capitalization).

[4] See `http://vlab.stern.nyu.edu`.
[5] See `http://www.esrb.europa.eu/pub/rd/html/index.en.html`.

2.2.2. Marginal expected shortfall (MES)

MES is introduced as a risk measure in Acharya et al. (2010). We use the version of MES as discussed in Brownlees and Engle (2015). MES is the expected return of a financial firm's stock conditional on a market return being in its lower tail. Brownlees and Engle (2015) computes MES based on a TGARCH-DCC specification (see Engle (2002)), thus using a dynamic volatility model and correlation model to estimate MES.

2.2.3. Leverage ratio (LVG)

We consider the "quasi-market value of leverage" as defined in Engle et al. (2014). Accordingly, leverage is A/W, where A is the market value of equity plus the book value of debt, and W is the market value of equity. Research undertaken relatively early after the onset of the global financial crisis by the IMF (2009) argued that it was not necessarily weakly capitalized financial firms that tended to do badly during the crisis, as could perhaps have been expected, but that instead failed banks tended to be characterized by high leverage ratios and funding illiquidity; see also Fostel and Geanakoplos (2008) and Geanakoplos and Pedersen (2014). As a result, leverage is a key variable for supervisors.

2.2.4. Dollar systematic risk ($\beta\times MV$)

$\beta\times$MV combines two ingredients of separate interest: a time-varying beta estimate times a firm's market capitalization. In this way, we obtain an estimate of the nominal (absolute) risk of the firm's market capitalization to systematic (market) shocks. The time-varying beta coefficient is estimated based on Engle (2012). We interact the beta coefficient with a measure of total size for two reasons. First, it can be shown that MES (our second measure) is an affine function of the CAPM beta (see Section 5 in Benoit et al. (2015)) if a single factor model describes asset returns. By interacting a beta coefficient with size we break this (trivial) link. Second, size is an important determinant of systemic importance in its own right; see Völz and Wedow (2011).

2.2.5. $\Delta CoVaR$

CoVaR is defined as the value-at-risk (VaR) of the financial system as a whole, usually approximated by a market index, conditional on a certain institution i being in distress. The distress of institution i, in turn, is captured by that institution being at its own individual VaR. ΔCoVaR_i is defined as the VaR of the financial system when institution i is in distress, minus the VaR of the system when institution i is at its median value. In Adrian and Brunnermeier (2014), the relationship between the VaR of the system and the equity return of a given institution is allowed to depend on additional covariates, as in Hautsch et al. (2014).

2.2.6. Value-at-Risk (VaR)

The value-at-risk of institution i is an intermediate output of the calculation of ΔCoVaR, see Adrian and Brunnermeier (2014). We include it as a measure of market perceptions regarding a firm's business risk. For an application of VaR and volatility spillovers in a systemic risk context, see Adams et al. (2014) and Diebold and Yilmaz (2014). VaR is increasing in equity price volatility, which in turn reflects the volatility of a firm's assets and associated future dividends.

2.3. Rankings

To make the data as comparable across months and across rankings as possible, we compute the ranks as follows. Let $Y_{i,j,t}$ denote the original observed data (such as SRisk) for firm $i = 1, \ldots, N_{j,t}$ for ranking $j = 1, \ldots, 6$ at time t, where $N_{j,t}$ denotes the number of firms for ranking j at time t. Our data for our subsequent analysis of risk rankings is

$$X_{i,j,t} = 1 - \operatorname*{rank}_{N_{j,t}}(Y_{i,j,t})/(N_{j,t} + 1), \tag{1}$$

i.e., all ranks $X_{i,j,t}$ are unit free, and lie inside the unit interval by design. Ranks $X_{i,j,t}$ are comparable across rankings, while the original quantities $Y_{i,j,t}$ are not. A higher $X_{i,j,t}$ is associated with a higher systemic importance.

3. Basic methodology

3.1. Factor model

To investigate the joint information content of the different systemic risk rankings, we use a factor model structure of the form

$$X_{i,t} = \Lambda_t f_{i,t} + \varepsilon_{i,t}, \quad i = 1, \dots, N, \quad t = 1, \dots, T, \tag{2}$$

where $X_{i,t} = (X_{i,1,t}, \dots, X_{i,J,t})' \in \mathbb{R}^{J\times 1}$, $\Lambda_t \in \mathbb{R}^{J\times R}$, $f_{i,t} \in \mathbb{R}^{R\times 1}$, $\varepsilon_{i,t} \in \mathbb{R}^{J\times 1}$, T is the number of months, N denotes the number of financial institutions, and R and J denote the number of factors and systemic risk rankings, respectively. Based on the risk rankings discussed in Section 2, $J = 6$, while we have $N = 113$ firms observed over $T = 139$ months.

If there are no missing values, parameter and factor estimation are straightforward. All required estimators are available in closed form. In particular, we have

$$\hat{\Lambda}_t = U_t = [U_{1,t}, ..., U_{R,t}], \qquad \hat{f}_{i,t} = \hat{\Lambda}_t' X_{i,t}, \qquad \hat{F}_t = (\hat{F}_{1,t}, \dots, \hat{F}_{R,t}) = X_t \hat{\Lambda}_t,$$

$$\hat{S}_t = \frac{1}{N}\sum_{i=1}^{N} X_{i,t} X_{i,t}' = \hat{\Lambda}_t \Sigma_t^f \hat{\Lambda}_t' + \Sigma_t^\epsilon,$$

where Σ_t^f is the variance-covariance matrix of the common factors, Σ_t^ϵ is the variance-covariance matrix of the error terms, U_t collects the eigenvectors of $\hat{S}_t$ corresponding to its R largest eigenvalues and $\hat{F}_t \in \mathbb{R}^{N\times R}$ with columns $\hat{F}_{r,t}$ for $r = 1, \dots, R$. The first column $\hat{F}_{1,t}$ of $\hat{F}_t$ is associated to the eigenvalue which explains most the variance of $\hat{S}$ and is therefore our main object of interest.

We note that factors (principal components) are only identified up to a sign convention. In principle, loadings can flip signs over adjacent time periods t just because of this feature. To prevent this from happening in our empirical study below we require the loadings on LVG to be positive.

3.2. An EM algorithm for missing values

In the presence of missing values, the estimation algorithm needs to be slightly extended. We adopt the Expectation-Maximization (EM) iterative procedure as described in Stock and

Watson (2002). The procedure is designed for the setting $X_{i,j,t} \sim \text{NID}(\Lambda_{j,t} f_{i,t}, 1-\Lambda_{j,t}\Sigma_t^f \Lambda'_{j,t})$, where $\Lambda_{j,t}$ is the jth row of Λ, and, as above, $\Sigma_t^f \in \mathbb{R}^{R\times R}$ is the covariance matrix of the common factors. The algorithm works in the following basic steps. Starting from a set of estimates $\hat{\Lambda}_t$, we first construct pseudo observations $X^*_{i,j,t}$, with $X^*_{i,j,t} = X_{i,j,t}$ if $X_{i,j,t}$ is observed, and $X^*_{i,j,t} = \hat{\Lambda}_j \hat{f}_{i,t}$ otherwise. Next, we re-standardize the $X^*_{i,j,t}$s and apply a principal components analysis to obtain our next estimates of $\hat{\Lambda}_t$ and $\hat{F}_t$. These steps are repeated until convergence. In our empirical application, we typically obtain convergence of the EM algorithm in less than five iterations.

4. Empirical results

4.1. The case for combing systemic risk rankings

This section argues that it is sensible from a supervisory perspective to combine different systemic risk rankings. We show that different rankings give vastly different systemic risk indications during certain periods. Moreover, the individual systemic risk rankings can be quite volatile in the time dimension. By contrast, even a "naive" combined ranking that takes an unweighted average of all available rankings at the firm level already exhibits considerably less time series variability than most individual rankings.

As a motivating example, Figure 1 plots the systemic risk rank of Deutsche Bank using all six methodologies. We observe two general features that apply to many financial sector firms in our sample. First, the measures can give quite different signals about how systemically important a specific firm is in relative terms. For example, Deutsche Bank is among the top three systemically important firms according to SRisk. It is substantially less risky when systemic risk is measured in terms of MES, $\beta\times$MV, or VaR. This suggests that the leverage of Deutsche Bank drives its high rank in SRisk, even though Leverage (LVG) on its own also results in a less dominant systemic risk rank except during 2007–2008. Second, we see that the different ranks may be quite volatile over time. VaR and ΔCoVaR show clear peaks in the rankings during 2006–2007, whereas both ΔCoVaR and MES appear very volatile during the European sovereign debt crisis period 2011–2012. This is a clear impediment for the use of these measures in the day-to-day supervisory practice.

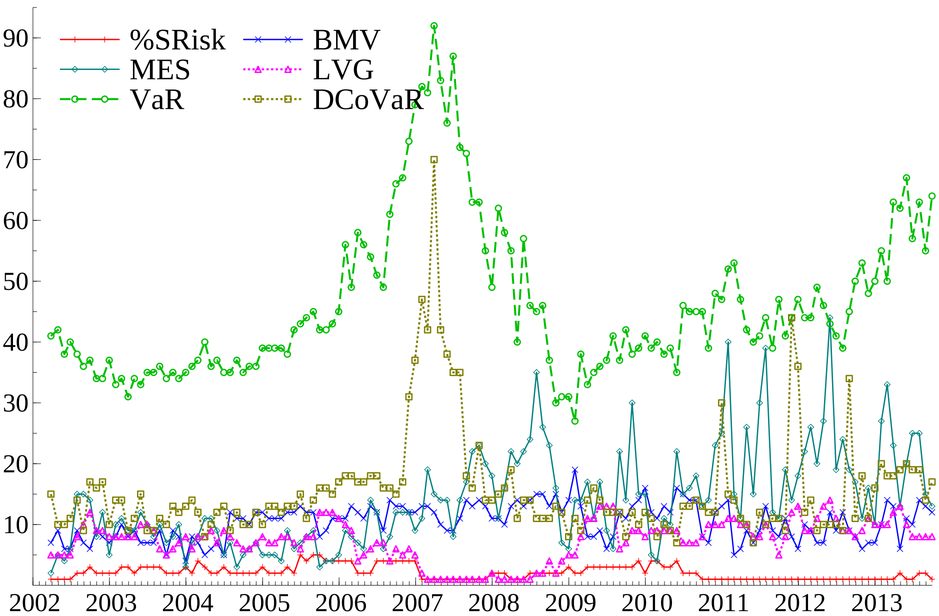

Figure 1: Rank instability: the case of Deutsche Bank
The figure shows the time series plots of the rankings associated to Deutsche Bank over the sample 2002/3-2013/9. The raw input ranks vary from $i = 1, \ldots, 113$ on the vertical axis, where 1 denotes the most systemically risky financial firm.

A more complete picture is presented in Figure 2 where we present the cross-sectional scatter diagrams between SRisk and the other systemic risk rankings on one specific date. First we notice that the cross-sectional association between the different rankings is far from perfect. We find, as expected, substantial correlation between SRisk and Leverage, though even there the R^2 of a linear regression of one on the other does not exceed 0.66. The situation for the other rankings is worse: the correlation between the different measures is poor, with R^2s typically not exceeding 0.23. Also the scatter diagrams clearly indicate that the poor fit is not due to a few outliers, but is symptomatic of the different rankings ordering the financial firms in the sample differently. This may be problematic for supervisory purposes.

In Table 1 we provide descriptive statistics of the volatility of our six input rankings. The table reports the cross-sectional average of the firm-level time series standard deviation of each rank. The time series standard deviation is computed over different periods and indicates how (un)stable a specific rank is over time. We compare the volatilities for

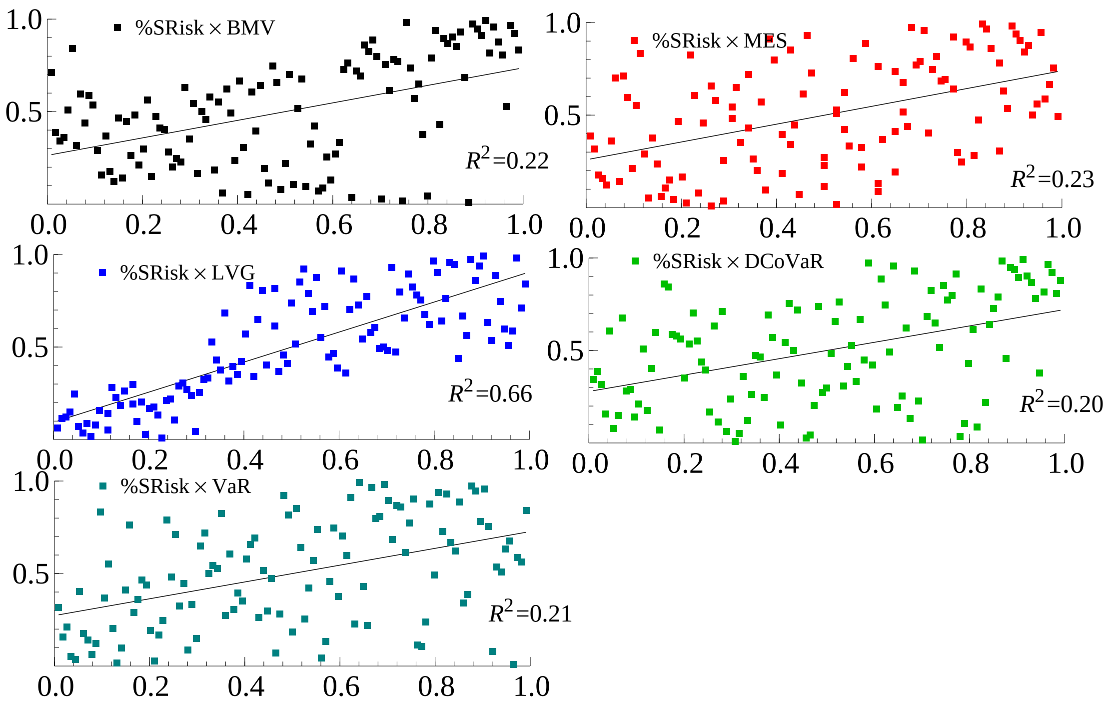

Figure 2: SRisk rank vs other risk ranks
The figure shows the scatter plots of SRisk ranks versus other ranks at 29/6/2012. Symbols refer to $i = 1, \ldots, 113$ firms. Ranks are calculated as in (1).

Table 1: Descriptive statistics: rank volatility
For each ranking, the table reports 100 × the cross-sectional average of the time series standard deviations of the ranks. We report results for the period 2006-2013 (column two), and distinguish four different sub-samples (columns three to six).

	2006-2013	pre-crisis	fin. crisis	debt crisis	post OMT
Start	Jan 2006	Jan 2006	Aug 2007	Oct 2009	Sep 2012
End	Sep 2013	Jul 2007	Sep 2009	Aug 2012	Sep 2013
%SRisk	12.6	5.3	9.1	3.9	2.6
$\beta\times$MV	7.5	3.5	5.1	5.5	4.3
MES	18.3	11.4	13.3	15.1	13.5
LVG	9.8	3.0	4.8	4.8	3.7
ΔCoVaR	13.8	10.0	9.4	13.5	4.5
VaR	15.6	11.6	12.3	11.2	5.5
Naive 1/6	9.1	5.3	6.0	5.4	3.5

the individual rankings with a "naive" combined ranking (bottom row), which equals the unweighted average over the six ranks included in our study. For the period 2006-2013, the $\beta\times$MV and LVG based rankings tend to be the least volatile. This is intuitive, as they are in part based on the book value of assets (LVG). For $\beta\times$MV, the estimate of market β typically increases for sharp falls in market value, leaving the relative position of $\beta\times$MV rather stable. Rankings that are exclusively or primarily based on financial market data inputs are more volatile (MES, VaR, ΔCoVaR, SRisk, in that order). Over the full sample, the time series variation in our naive unweighted average of all rankings is higher than that of $\beta\times$MV, but lower than that of all the other rankings.

Table 1 reports the results for different sub-samples. We distinguish a pre-crisis period (January 2006–July 2007), a period of financial crisis (August 2007–September 2009), the most acute phase of euro area sovereign debt crisis (October 2009–August 2012), and a key period following the announcement of the Outright Monetary Transaction (OMT) programme by the European Central Bank (September 2012–September 2013). The OMT programme is widely credited for ending the most acute phase of the euro area sovereign debt crisis; see, for example, Lucas et al. (2014).

Overall, the rank volatility is higher during the financial and the euro area sovereign debt crisis than in the pre-crisis and post-OMT periods. Put differently, risk rankings may be particularly volatile in exactly those periods where they are (arguably) of the most immediate interest to policy makers. Reassuringly, the unweighted average (naive combined ranking) is among the least volatile ranking methods in each of the subsamples. This again suggests that combining rankings may result in substantial benefits.[6]

From a supervisory perspective, high "turnover at the top" of any ranking creates difficulties in formulating a supervisory strategy. Table 2 studies this issue by reporting the number of top 25 most systemically important financial institutions that were also in top 25 one year earlier. The closer the number is to 25, the more stable is the top of that ranking. Again, rankings that are based (in part) on balance sheet items tend to do better in terms of stability than rankings mainly based on market prices. Among the six input rankings, $\beta\times$MV is the most stable, followed by %SRisk, LVG, VaR, MES, and ΔCovar. A

[6]The ranking volatility is substantially lower over sub-periods than it is for the full sample. This is largely due to a number of institutions changing their rank gradually over the sample period, which results in a substantial (unconditional) rank volatility over the full sample.

Table 2: Descriptive statistics: rank stability
The table reports the number of top 25 firms in December of any year which are also in top 25 one year earlier. The closer the table entry is to 25, the less turnover occurred. CR_1 is a combined ranking based on the first principal component.

	%SRisk	$\beta\times$MV	MES	LVG	ΔCoVaR	VaR	Naive 1/6	CR_1
2007	20	23	15	20	14	18	17	18
2008	18	23	13	17	19	16	22	23
2009	24	22	14	20	14	15	22	23
2010	23	23	14	19	6	12	17	17
2011	23	23	17	18	22	23	20	20
2012	23	24	15	23	11	15	19	18
Average	21.8	23	14.6	19.8	14.3	16.5	19.5	19.8

Table 3: Descriptive statistics: rank stationarity
The table reports the rejection rates of the null hypothesis of a unit root based on Augmented Dickey-Fuller (ADF) univariate tests. Lag length selection is automatic and based on the Schwarz' Bayesian information criterion (BIC). CR_1 is the ranking based on the first principal component.

	%SRISK	$\beta\times$MV	MES	LVG	ΔCoVaR	VAR	Naive 1/6	CR_1
Rejection %	0.36	0.69	0.85	0.34	0.56	0.36	0.51	0.75

naive/unweighted combination is stable at the top, with on average approximately 20 firms in the top-25 that were also at the top one year earlier. The principal components based ranking behaves slightly better than the naive average rank, in the sense of having even less turnover at the top.

To investigate the persistence in systemic risk rankings, Table 3 reports the results of univariate Dickey-Fuller tests for the time series of rankings for a specific metric and firm. For each metric, the table reports the frequency (across firms) of rejections of the unit root hypothesis. For %SRisk, LVG, and VaR, the unit root hypothesis is not rejected for about 2/3 of the firms considered, indicating that these ranks are persistent and slowly moving. ΔCoVaR appears slightly less persistent, with the unit root hypothesis being rejected for slightly more than half of the firms. The MES and $\beta\times$MV measures appear to be least persistent in a time series sense. Given the possibly non-stationarity properties of many of the rankings, we focus in our subsequent analysis mainly on the cross-sectional dimension of the principal components analysis and discuss how these properties vary over the course of the two financial crises embedded in our sample period.

Table 4: Descriptive statistics: Correlation among risk ranks

The table reports the time series medians of the cross-sectional linear (Spearman) correlations, as well as their time series inter-quartile ranges in brackets below. See Figure 2 as an example of cross-sectional correlation at a single point in time.

	%SRisk	$\beta\times$MV	MES	LVG	VaR
$\beta\times$MV	0.36				
	[0.22, 0.53]				
MES	0.43	0.52			
	[0.38, 0.49]	[0.44, 0.63]			
LVG	0.81	0.36	0.32		
	[0.78, 0.84]	[0.23, 0.47]	[0.23, 0.40]		
VaR	0.37	0.27	0.48	0.44	
	[0.31, 0.47]	[0.10, 0.39]	[0.40, 0.55]	[0.31, 0.52]	
ΔCoVaR	0.29	0.62	0.51	0.20	0.20
	[0.21, 0.38]	[0.54, 0.67]	[0.37, 0.62]	[0.11, 0.29]	[0.12, 0.28]

Table 4 presents pairwise (Spearman) cross-sectional correlations for different systemic risk rankings. This allows us to see whether there is much overlap between the information contained in the different rankings, or not. If the overlap is limited, different measures may accentuate different facettes of systemic importance (unlikely in our assessment), or may be subject to substantial estimation uncertainty and model risk (as argued in Danielson et al., 2015). The cross-sectional correlations are in general rather stable over time and positive. The highest median correlation (0.81) is between SRisk and LVG. The cross-sectional correlation between ΔCoVaR and $\beta\times$MV (0.62) is quite high as well.

4.2. Principal components analysis and combined ranking

We now turn to our principal components analysis of the systemic risk rankings. Figure 3 presents the distribution of the $J = 6$ ordered and sum-normalized eigenvalues $\delta_1, \dots, \delta_J$. The histograms provide the time series frequencies of the cross-sectional (sum normalized) eigenvalues.

The factor corresponding to the first eigenvalue explains approximately 50% of the total variation. There is quite some time series variation in the percentage of variance explained by the first principal component given that it ranges from 30%-70% over time. We can conclude that there are times at which the information contained in the six systemic risk rankings is quite dispersed, while at other times the information content is fairly concentrated. The first

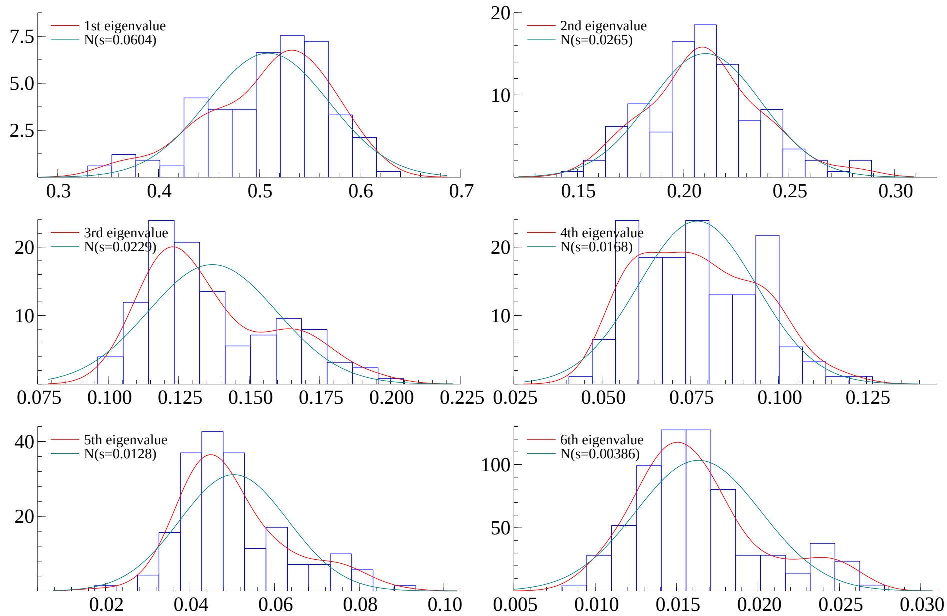

Figure 3: How many risk factors? Distribution of six ordered eigenvalues
Each principal components analysis is performed over the cross-section of firms, with time t held fixed. The figure shows the time series histograms of the $J = 6$ ordered and sum normalized eigenvalues.

two eigenvalues together explain more than 70% of the total data variance. As a result, it is unlikely that more than two factors are required to summarize the information contained in the six systemic risk rankings at any time.

Figure 4 gives some more insight by providing the time series plot of the different eigenvalues. Interestingly, the first factor bottoms out near a value of 30% at the beginning of 2007, a few months before the onset of the financial crisis. By contrast, the second eigenvalue appears to peak during the same period. We interpret this as a signal that different systemic risk measures signal different messages precisely when they are the most important. Our six risk measures are most similar at the absolute height of the global financial crisis, a few months after the collapse of Lehman brothers. This is a humbling finding, providing a dual conclusion. First, a simple combined robust ranking may be preferable to a single individual risk measure from a supervisory perspective. Second, a useful additional signal for supervisory purposes may be obtained by keeping track of the times when the different rankings appear less in agreement. It is precisely during such periods that more scrutiny

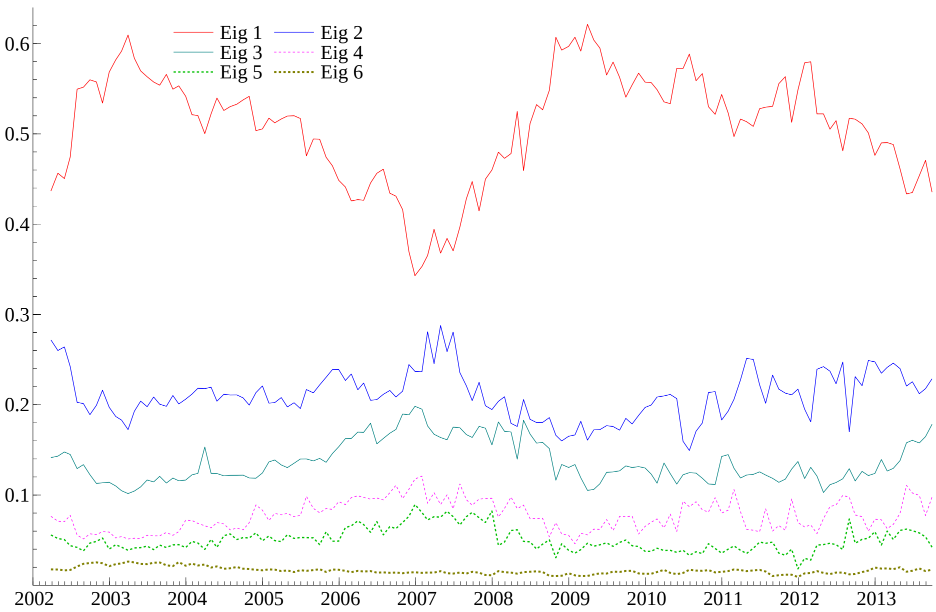

Figure 4: Time series plot of ordered eigenvalues
The figure shows the time series plots of six ordered eigenvalues from the most important in terms of explained variance (top) to the least important (bottom). The sample is from 2002M3-2013M9.

may be warranted from the side of the supervisor.

To investigate which rankings are most informative for the first principal component, the top 6 panels in Figure 5 present the distribution of factor loadings for the first principal component. The distributions of the loadings appear similar for all six systemic risk rankings. Only the time series dispersion of the loading on VaR is somewhat higher, followed by ΔCoVaR. All loadings have a positive and similarly sized mean. We may conclude that the first factor has the interpretation of a "level" component, where each ranking contribute approximately equally to the first factor's composition.

The bottom 6 panels in Figure 5 provide a complementary message by showing the frequencies of loadings for the second principal component. There is a clear difference between the loadings for %SRisk and LVG on the one hand, and $\beta\times$MV, MES, and ΔCoVaR on the other hand, with VaR striking the middle ground. The second component thus appears to pick up a difference between rankings that are more based on the book (such as LVG, %SRisk) versus the other rankings.

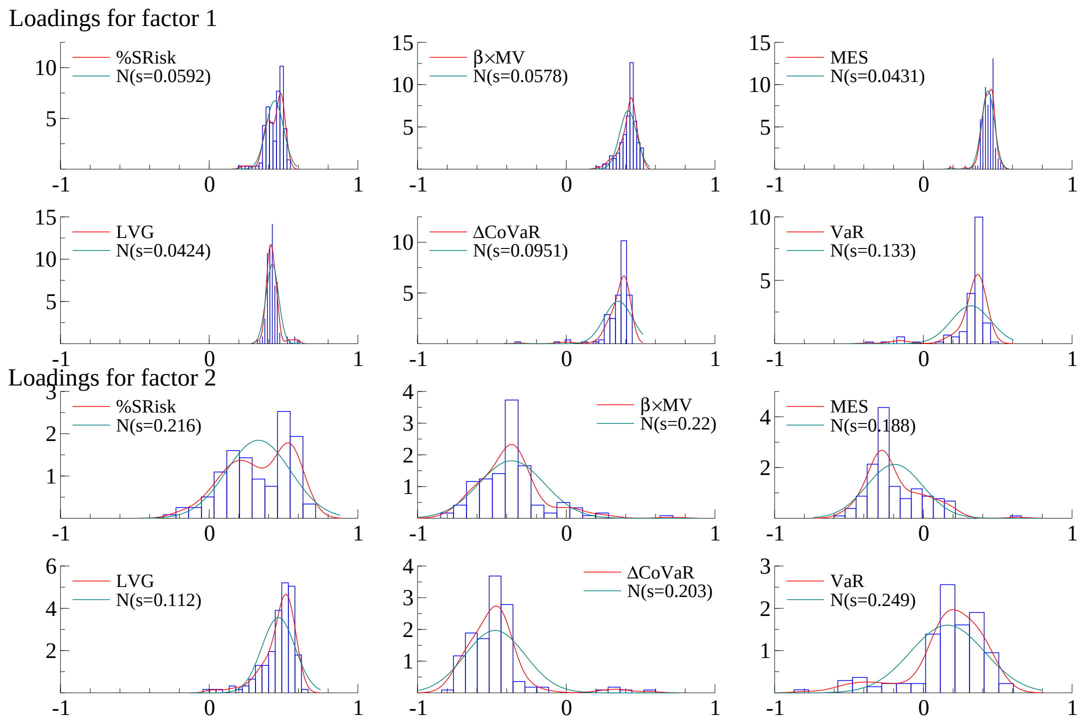

Figure 5: Factor loadings for the first and second factor: distributions
The distribution (over time) of loading parameters $\hat{\Lambda}_t$ associated with the first factor (top six panels) and second factor (bottom six panels), see (2).

If we consider the time series plots of the loadings in Figure 6, we confirm the roughly equal weights for each of the 6 rankings during most of the sample period. At the same time, we see a clear change in behavior before the inception of the sub-prime crisis in August 2007, particularly for VaR and ΔCoVaR, and to a lesser extent also for $\beta\times$MV. In a strikingly non-volatile market environment, just before the burst of the lending bubble, market based risk indicators (such as VaR and ΔCoVaR) can suggest a substantially different ordering of the systemic risk of financial sector firms than measures that are at least partly based on book values (such as LVG and %SRisk). This finding is in line with the "volatility paradox" as described in Brunnermeier and Sannikov (2015) and Boissay et al. (2015). It is also in line with impressions from policy circles such as Borio (2010)'s "financial stability paradox", according to which *systemic* risks are highest when *measured* risks (such as, for example, the U.S. VIX) are particularly low. It is encouraging that a combined ranking based on the

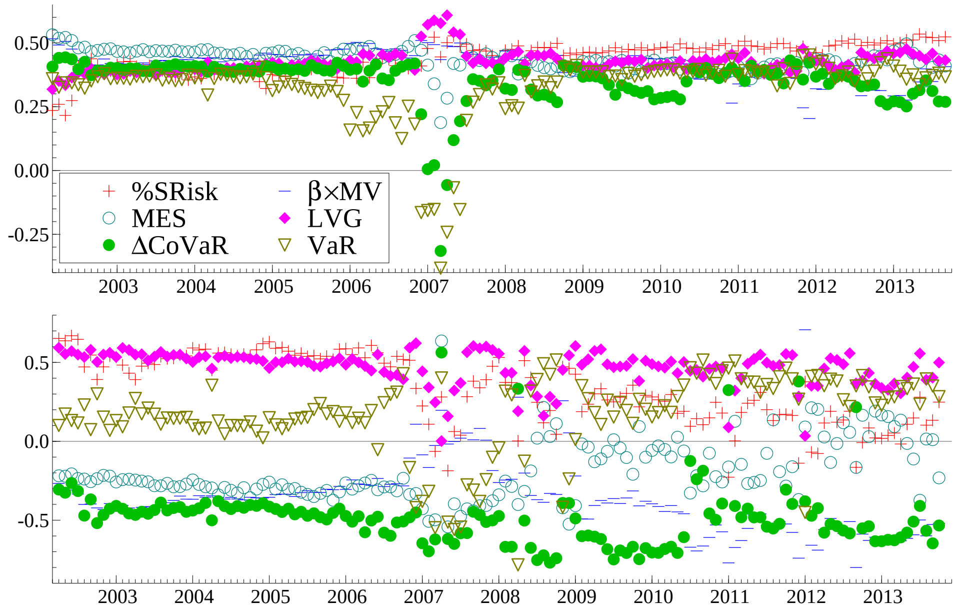

Figure 6: Time series frequencies of factor loadings for the first and the second factor
The figure shows the time series frequencies (as histograms) of the cross-sectional loading parameters associated with the first and second principal components. The top and bottom 6 panels correspond to the loadings for the first and second component, respectively.

first principal component goes "short" the more market based measures at such times to match the information content in the other rankings.[7]

The second panel in Figure 6 shows the time series pattern for the loadings of the second principal component. During the first half of the sample, the factor clearly takes a difference between LVG and %SRisk on one side, and MES, $\beta\times$MV, and ΔCoVaR on the other, with relatively little weight for VaR. In the onset of the financial crisis, however, when the dominance of the first principal component diminishes, the weights for the second component start shifting considerably. Late 2006 and most of 2007, VaR starts to combine strongly with MES and ΔCoVaR to form a separate signal. In Spring 2007, these three rankings roughly make up all of the second factor, with the remaining loadings being near 0. For the rest of 2007, these price-based measures are offset against LVG, and to some extent %SRisk. VaR thus appears to have taken over the position of $\beta\times$MV in the onset of the

[7]Principal components are determined only up to a sign convention. In principle, loadings could "flip" just because of this feature. This is not the case here, as we required the loading on LVG to be positive.

Table 5: Top 25 systemically important firms: September 2013

The table presents the *top* 25 (alphabetic order, first column) systemically risky financial firms at September 2013 for our sample of $N = 113$ listed firms headquartered in the European Union according to a rank CR_t based on $\hat{F_{1,t}}$. X and o indicate whether these systemically risky financial firms were in the top 25 also at four different time periods, or not. The four time periods are the midpoints of the subsamples in Table 1.

Top 25 at Sep 2013	Oct 2006	Sep 2008	Mar 2011	Mar 2013
Aegon NV	X	X	X	X
Allianz SE	X	X	X	X
Aviva PLC	X	X	X	X
AXA SA	X	X	X	X
Banco Bilbao Vizcaya Argentaria	*o*	*o*	X	X
Banco Popolare SC	*o*	*o*	*o*	X
Banco Santander SA	*o*	X	X	X
Barclays PLC	X	X	X	X
BNP Paribas	X	X	X	X
CNP Assurances	X	*o*	*o*	*o*
Commerzbank AG	X	X	X	X
Credit Agricole SA	X	X	X	X
Credit Suisse Group AG	X	X	*o*	X
Deutsche Bank AG	X	X	X	X
Erste Group Bank AG	X	X	*o*	X
ING Groep NV	X	X	X	X
Intesa Sanpaolo SpA	*o*	*o*	X	X
Legal & General Group PLC	X	X	X	*o*
Lloyds Banking Group PLC	*o*	*o*	X	*o*
Natixis	X	X	X	*o*
Nordea Bank AB	*o*	*o*	X	*o*
Royal Bank of Scotland Group PLC	X	X	X	X
Societe Generale	X	X	X	X
UniCredit SpA	*o*	X	X	X
Unione di Banche Italiane SCPA	*o*	*o*	X	X

2008 financial crisis.

Also during the subsequent sovereign debt crisis, loadings for the second factor are substantially different than in the pre-2007 era. In particular, the second factor now mainly picks up the discrepancy between VaR and LVG on the one hand, and $\beta\times$MV and ΔCoVaR on the other hand. This factor becomes increasingly important as the European sovereign debt crisis unravels, as can be seen from the relative magnitude of the first eigenvalue in Figure 4.

Table 5 presents the top 25 systemically important financial institutions in our sample at September 2013, in alphabetical order. In addition, the table checks whether these top-25 firms were also classified as such at the end of four specific months: before the crisis (Oct

2006), after the fall of Lehman (Sep 2008), during the sovereign debt crisis (Mar 2011), and after the OMT implementation (Mar 2013). Both banks and other (non-bank) financial institutions can be found at the top of the list. This holds for all periods considered. It is clear that there is much persistence in the composition of the list: several financial institutions that were the most systemically important in or before 2008 still are systemically important in 2011 and even 2013. This suggests that regulations regarding SIFIs adopted between 2009-2012 may not have had sufficient 'bite' to substantially alter the composition of what are the systemically important financial firms in Europe.

5. Systemic importance and market prices

This section focuses on the relationship between systemic risk rankings and the CDS spreads of commercial banks. We measure the systemic risk ranking by the first principal component CR_1 from Section 4 based on all six systemic risk rankings considered. CDS data are only available for a subset of our financial firms. We focus on banks, as implicit public sector guarantees are discussed mostly in the context of banks. Our data consist of CDS spreads for a sub-group of 35 banks from December 2005 to September 2013. The group of banks consists of the intersection between the banks in our original data set and the European banks that participated in the EBA 2014 stress test and for which liquid CDS data is available.

In the first part of this section we use correlation analysis to establish whether there exists a negative relationship between systemic importance and the level of CDS spreads. One of the arguments raised in the literature is that systemically important banks might benefit from an implicit public sector guarantee; see Völz and Wedow (2011) and Kelly et al. (2011). Conversely, it may also be the case that governments in distress are incapable of bailing out their systemically important banks, which might lead to a positive relation between systemic importance and the CDS spread. We compute the linear cross-sectional correlations between the combined ranking CR_1 and the CDS premium level. Table 6 shows the results.

The cross-sectional correlations reveal that the combined systemic risk ranking covaries

Table 6: Linear correlation: systemic importance and CDS premia

This table includes selected time series quantiles (quantile 5%(Q05), quantile 25%(Q25), quantile 50% (Q50), quantile 75%(Q75), quantile 95%(Q95)) of the linear cross-sectional correlations between the combined ranking and the CDS premia. The cross-sectional correlations are also reported separately for the sub-sample of banks from stressed versus non-stressed countries.

	Cross-sectional		
	All countries	Stressed countries	Non-stressed countries
Q05	−0.15	−0.21	−0.57
Q25	0.05	−0.04	−0.40
Q50	0.15	0.10	−0.17
Q75	0.28	0.26	−0.01
Q95	0.44	0.43	0.14

positively with the CDS spread approximately 80% of the observed months. If we divide our banks into two groups according to whether the bank is headquartered in a stressed or non-stressed country, the pattern is markedly different for banks from stressed versus non-stressed countries. Stressed countries in our classification are Greece, Italy, Ireland, Portugal, Portugal and Spain, while non-stressed countries are Austria, Denmark, France, Germany, Netherlands, UK and Sweden.[8] Systemic risk rankings and CDS spreads covary positively most of the time for stressed countries, whereas they covary negatively most of the time for non-stressed countries. A negative covariation relates to the claim of a systemic risk discount for financial institutions that profit from implicit government guarantees; compare the arguments in Kelly et al. (2011). Banks from stressed countries are less likely to benefit from such guarantees as their sovereign is already stressed. This may cause a higher, positive correlation between systemic risk ranking and CDS spread in those countries, quite opposite to the situation for banks under non-stressed sovereigns.

Table 7 further scrutinizes the above patterns by means of panel regressions. We regress the CDS spread levels on lagged rankings in the following way. Using the original CR_1 values from the previous month, we construct half-samples, terciles, and quartiles using the natural breaks for the ranks. For example, for terciles we group firms with CR_1 in the ranges T1= $[1.00, 0.67]$, T2= $[0.67, 0.33]$, and T3= $[0.33, 0.00]$, respectively, with T1 being

[8] For similar groupings of countries, see e.g. Acharya and Steffen (2015) and Eser and Schwaab (2015).

the most systemically important. For each group, we construct a dummy variable that we include in the regression. In addition, we try to account for part of the credit risk of each bank by including lagged log leverage and the lagged log market value of the bank. From a credit risk perspective, leverage may result in a higher credit risk as it is a prime ingredient of the distance to default (see e.g. Geanakoplos and Pedersen, 2014; Duffie et al., 2009), whereas size typically results in lower credit risk due to diversification arguments (see e.g. Wheelock and Wilson, 2012). We also include a dummy variable for the group of distressed countries.

Regressions (1)–(3) present the results for halves, terciles, and quartiles, respectively. We treat the least systemically important group as our benchmark in each case. For all three regressions, we note that the most systemically important firms (H1, T1, Q1) correlate with higher CDS spread levels. Only if we go to quartiles, the CDS spread level for Q1 is slightly below that of Q2, but the difference is far from significant. It appears that systematic risk correlates with a positive rather than a negative CDS premium. This contrasts with the systemic risk discount for such firms claimed elsewhere in the literature, for other settings.

The Distress dummy is positive, which matches the positive spread for stressed countries. Note that time dummies are included, such that any trends have been removed and the results mainly refer to the cross-sectional patterns. Also leverage (LVG) and size (MV) have there expected positive and negative sign, respectively. In our context, however, these variables may also correlate with our combined systemic risk ranking, such that the effect of H1, T1 (and T2), and Q1 (and Q2, Q3) is over and above that of the controls MV and LVG.

Table 6 was suggestive of a different relation between CDS spreads and systemic risk rankings for distressed (D) and non-distressed (ND) firms. Regressions (4)–(6) present the results where we interact the groups with the Distress dummy variable. Interestingly, for non-distressed countries, the relation between systemic risk and CDS spreads is negative for all subgroups of systemic risk rankings, although they are not statistically significant. By contrast, for distressed countries the relation is positive and significant at the 5% or 10% level. The premia are highest for the most systemically risky firms. The coefficients for

Table 7: CDS panel regressions

Regression results for panel regressions for CDS spread levels. Reported standard errors are based on clustering at the bank level, and all regressors are lagged compared to the CDS spread level. The data consist of CDS spread series over Dec 2005 till Sep 2013 for 35 banks. Most regressors are dummies indicating whether the firm in a specific month has systemic risk ranking CR_1 in the top 50% (H1), top 33% (T1) or middle 33% (T2), or top 25% (Q1), 25%–50% (Q2), or 50%–75% (Q3). We also include a dummy Distress to indicate whether the bank originates in Greece, Italy, Ireland, Portugal, Portugal or Spain. Quantile indicators may be preceded by ND or D, indicating the quantile indicator interacted with the Non-distress and Distress regional dummy, respectively. Regressions control for month dummies, as well as for log market value (MV), and log leverage (LVG). Significance is denoted by $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$. Regressions (1)–(6) contain all data, while (7), (8), and (9) contain the periods January2006−Aug2008, Sep2008−Feb2011, Mar2011−September2013, respectively.

	(1)	(2)	(3)		(4)	(5)	(6)	(7)	(8)	(9)
H1	107.79*			ND-H1	-77.66					
	(61.07)				(74.98)					
T1		143.76**		ND-T1		-62.30				
		(69.77)				(133.37)				
T2		127.45*		ND-T2		-59.71				
		(63.05)				(86.71)				
Q1			139.80*	ND-Q1			-68.83	4.01	98.70	-91.24
			(77.35)				(85.22)	(7.01)	(84.11)	(115.59)
Q2			152.38**	ND-Q2			-88.99	-7.19	58.68	-104.12*
			(73.32)				(61.06)	(8.43)	(63.89)	(59.47)
Q3			54.70							
			(48.45)							
				D-H1	150.75**					
					(68.27)					
				D-T1		155.79**				
						(71.13)				
				D-T2		123.69*				
						(65.19)				
				D-Q1			144.54**	-1.04	44.95	155.90
							(67.35)	(10.31)	(41.94)	(141.20)
				D-Q2			180.08**	-3.97	69.31	227.81
							(84.21)	(10.77)	(66.19)	(152.43)
				D-Q3			23.85	-7.91	-56.29	131.72
							(40.45)	(9.14)	(34.53)	(97.48)
Distress	180.56***	177.92***	181.51***		-31.35	-31.13	-41.32	13.64	123.65	47.41
	(37.65)	(36.51)	(38.33)		(91.92)	(134.96)	(87.62)	(9.78)	(83.34)	(133.20)
LVG	63.20*	65.25*	65.92*		62.06*	65.10*	61.00*	9.39	12.49	48.24
	(31.72)	(34.58)	(36.93)		(31.99)	(34.78)	(35.82)	(6.38)	(23.10)	(70.92)
MV	-88.17***	-87.31***	-86.52***		-93.16***	-89.24***	-91.08***	-2.09	-66.35***	-124.52***
	(28.51)	(27.77)	(28.24)		(28.42)	(27.10)	(26.42)	(3.00)	(16.21)	(45.46)
Const	709.68**	656.36**	646.97**		943.01**	879.46**	922.12***	25.11	667.01***	1,362.94**
	(293.66)	(281.77)	(289.57)		(355.63)	(338.71)	(328.64)	(36.82)	(202.24)	(600.93)
Month dummies	YES	YES	YES		YES	YES	YES	YES	YES	YES
Observations	3,069	3,069	3,069		3,069	3,069	3,069	985	1,026	1,058
R^2	0.58	0.58	0.58		0.59	0.58	0.59	0.65	0.46	0.57

the other control variables are very stable, with the exception of the Distress dummy. This dummy picks up the effect of the least systemically risky firms in distressed countries. As the coefficient is negative, it confirms our earlier results that dominant effect in our sample is that of a high CDS spread for firms that have a harder time benefiting from implicit guarantees by their governments.

As the strength of government guarantees varied over the course of our sample period, we perform a sample split analysis in models (7)–(9) using the quartile groups. We distinguish the pre-crisis period (7), the period of the financial crisis (8), and the subsequent period of the sovereign debt crisis (9). This considerably reduces our sample size, such that most results become insignificant. Still, it is interesting to look at the patterns we obtain from the data. The most systemically relevant firms from non-distressed countries (ND-Q1 and ND-Q2) have higher spreads during the financial crisis, but lower spreads cross-sectionally during the subsequent European sovereign dept crisis. Again, we stress that time effects have already been accounted for by the month dummies. The negative coefficients are in line with the argument of implicit government guarantees in a situation where the government appears solvent. For the stressed countries, we confirm the findings that systemically important firms had higher CDS spreads in the cross-section during the financial crises than in the pre-crisis period. However, during the sovereign debt crisis, the cross-sectional difference in spreads for systemically important banks further increases, in line with a lack of credible government guarantees for these firms during most of this period.

We conclude that the relation between CDS spreads and systemic risk rankings is subtle and changes over the course and the nature of a crisis. In line with earlier work, we find weak signals that systemically risky firms may benefit from implicit government guarantees, but only to the extent that these guarantees are issued (implicitly) by a credibly solvent sovereign. If the sovereign itself is under stress, systemically risky firms typically have higher CDS spread levels compared to their non-systemic counterparts.

6. Conclusions

We have presented a principal components methodology for the pooling of systemic risk rankings of financial institutions to obtain a combined ranking that is less affected by estimation uncertainty and model risk. In an application to 113 E.U. financial sector firms from 2002-2013 we find that the combined ranking is more stable at the top and is less volatile than individual input rankings. Hence our pooled rank is potentially suitable for policy purposes and it can be a guidance to target banking supervision within the ECB. We further assess the relationship between systemic importance and financial market outcomes, such as firms' CDS premia. In particular, we find weak evidence of implicit government guarantees in cases where the sovereign is strongly solvent. In cases of a distressed government, we find opposing evidence that systemically risky financial institutions correlate with higher CDS spread levels.

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