10-2020

FRM Financial Risk Meter

Andrija MIHOCI

Michael ALTHOF

Cathy Yi-Hsuan CHEN

Wolfgang Karl HARDLE

Published in The Econometrics of Networks (Advances in Econometrics, Vol. 42), Emerald Publishing, Bingley, pp. 335-368.
DOI: 10.1108/S0731-905320200000042016

FRM Financial Risk Meter

Andrija Mihoci
Michael Althof
Cathy Yi-Hsuan Chen
Wolfgang Karl Härdle

Abstract A systemic risk measure is proposed accounting for links and mutual dependencies between financial institutions utilising tail event information. FRM (Financial Risk Meter) is based on Lasso quantile regression designed to capture tail event co-movements. The FRM focus lies on understanding active set data characteristics and the presentation of interdependencies in a network topology. The FRM indices detect systemic risk at selected areas and identifies risk factors. In practice, FRM is applied to the return time series of selected financial institutions and macroeconomic risk factors. We identify companies with extreme "co-stress", and "activators" of stress. We present $FRM@Americas$ and $FRM@Europe$ as main examples. With the $SRM@EuroArea$ and the $FRM@iTraxx$ we extend to the government bonds

Wolfgang K. Härdle thanks the supports from Deutsche Forschungsgesellschaft through the International Research Training Group 1792 High Dimensional Nonstationary Time Series, Czech Science Foundation(19-28231X) and the Taiwan YuShan Scholarship. The work of the authors is receiving support from the European Union's Horizon 2020 training and innovation programme "FIN-TECH", under the grant No. 825215 (Topic ICT-35-2018, Type of actions: CSA)

Andrija Mihoci
Brandenburg University of Technology

Michael Althof*
*Corresponding author, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany, +49 30 2093 99593, althofmi@hu-berlin.de

Cathy Yi-Hsuan Chen
University of Glasgow

Wolfgang Karl Härdle
Blockchain Research Centre, School of Business and Economics, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin,
Sim Kee Boon Institute for Financial Economics, Singapore Management University
Department of Probability and Mathematical Statistics, Faculty of Mathematics and Physics, Charles University, Prague, Czech Republic
Department of Information Management and Finance, National Chiao Tung University, Taiwan, ROC

and credit default swaps. We also show FRM-implied recession probabilities to predict recessions. Thereby, FRM indicates tail event behaviour in a network of financial risk factors.

Keywords Systemic Risk · Quantile Regression · Financial Markets · Risk Management · Network Dynamics · Recession

1 Introduction

Financial institutions and their interdependencies constitute a network that is vital for modern economies. The resulting complexity of links between these institutions which may be seen as risk factors may contribute to systemic risk. For example, a trigger event, such as an economic shock or institutional distress, may cause spillover-effects that weakens not only the network stability but also its functioning. These observations on the joint network dynamics motivated researchers and practitioners to embed tail events into risk management.

Value at Risk is describing a tail event probability hosting exclusively one single node. The CoVaR of **Adrian:2016** considers the tail event probability of node j conditional on the distress of node i, representing a bivariate tail dependence system. The TENET Tail Event NETwork risk approach by **Haerdle:2016** and **Zhu:2019** generalizes CoVaR further by involvement of a network and thus accommodates all system nodes as risk factors. TENET applies quantile regression on macroeconomic risk factors and the set of network node stock market information in a rolling window approach. The innovative idea of TENET is to apply dimensionality reduction (in a semi-parametric setting) via Lasso **Tibshirani:1996** in a quantile regression context. In further extending TENET, our paper proposes an augmented systemic risk measure that condenses the high-dimensional tail stress into a single real value indicator, FRM the Financial Risk Meter. For regulating authorities such as the Basel Committee on Banking Supervision (BCBS) this simple but augmented indicator is of great benefit. The FRM is the average over the selected penalization terms and is calculated at each time step and for each node, and its size contains essential information on the active set of influential neighboring nodes and on the contributors to systemic risk. The reason why this penalty parameter is a condensation of different risk components is explained below in section 2.1. Some of the technical implementation issues were discussed in **Yu:2017** which concern specifically the computationally intensive and thereby time-consuming L_1-norm quantile regression when done sequentially for a large number of firms. The authors consider parallel computing in R, and their, the codes are published on `www.quantlet.de` with keyword FRM.

The standard FRM is defined as the average over the series of the selected penalization terms λ for the financial institutions under consideration. The penalization parameters are based on an L_1-norm (Lasso) quantile linear regression, which are subsequently selected by the generalized approximate cross-validation criterion (GACV) **Yuan:2006** Standard FRM picks up the

$\tau = 0.05$ tail event risk level, though a $\tau = 0.1$ yields similar results. At each trading day, the returns of roughly 100 largest publicly traded financial institutions at geographic areas (Americas and Europe) as well as selected macroeconomic risk variables, ranging from 1 January 2000 until 10 July 2019, are entering the FRM technology. A 63 business days (i.e three months) rolling window yields a λ series for each firm at a given date. The average of these penalty parameters constitutes the standard FRM.

The FRM is a risk measure for joint tail events. Many other risk measures have been proposed and used in practice. For example, VIX is an implied volatility based measure not reflecting joint tail event dynamics. As mentioned above, CoVaR **Adrian:2016** concentrates on a pair of risk factors. NBER based recession indicators detect turns in economic activity examining various measures of broad activity, such as real GDP, employment, and real income. In conjunction with the NBER's recession indicator, recession probability indicators have been proposed so as to predict upcoming riskier investment environments. For example **Chauvet:2008** propose a smoothed recession probability for the United States based on four variables: non-farm payroll employment, the index of industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales. Their recession probabilities are shown on the Federal Reserve Bank of St. Louis's economic data platform, accessible here: `https://fred.stlouisfed.org/series/RECPROUSM156N`. Similarly, the Federal Reserve Bank of New York proposes a yield curve slope based predictor of future real economic activity and is based on the spread between interest rates on the ten-year US Treasury note and the three month Treasury bill as outlined in **Estrella: 1991 Estrella: 1996** More recently, communication and interaction on social media platforms as well as search queries have been included. For example, **Kristoufek:2013** examine searched items on Google Trends and their correlation with stock riskiness. These methods thus tend to look at dynamics and patterns of few data sets. The FRM framework has the advantage to address simultaneously the dynamics and co-movements of highly-dimensional networks. FRM also allows to unfold hidden dependency structures among the nodes of a financial network.

FRM may, therefore be used to quantify high/low joint tail event risks arising from single companies. Standard FRM is defined by the average of penalty parameters. Focusing on the empirical distribution in addition to average penalty parameters enables researchers and practitioners to identify companies with relatively high value of the Lasso penalty parameter λ, which, as we discussed before, is an indicator of joint tail event risk. Financial institutions with a high λ_j reading are high "co-stress" entities. Those with a larger number of marginal impact on others are "activators" of other identified "activated entities". By displaying boxplots, financial nodes with extremely high/low tail event dependencies with other companies are depicted, and the entire chain of dependencies between nodes can be unfolded.

The contribution of this paper is twofold. First the FRM is proposed: a systemic risk measure based on joint tail events. Essentially, FRM is an econometric technology for understanding tail dependence, where the penalty term from the quantile regression is taken as an indicator for tail risk. Second, FRM framework is successfully applied in empirical economic practice. Here the focus is on two selected FRM indices, namely $FRM@Americas$ and $FRM@Europe$ for the equity markets, and $SRM@EuroArea$ as an application to the asset class of government bonds. Augmenting them, for example by simultaneously checking varieties of quantiles of FRM components, one can monitor economic activity and network dynamics, and suggest further improvements in portfolio risk management.

Through the FRM dynamics, one observes several peaks which correspond to crises and other events. FRM peaks at the financial crises in 2000, 2008 and 2012. This observation motivates us viewing our FRM as a recession predictor. The FRM is shown to predict upcoming recession periods and therefore serves as an indicator for systemic risk in a variety of world regions. This result is performed by the logistic regression model with the NBER recession indicator as dependent variable and FRM as a key explanatory variable.

The research goals of this paper are correspondingly related to three aspects: (i) general risk market movement assessment, (ii) tail dependencies, spillovers identification of an active set useful for regulatory purposes and macro-prudential policy making (iii) provision of recession probabilities.

Here we summarize the major results. First, FRM correlates positively with other measures of systemic risk and peaks around crises. Second, a detailed inspection of the active set across time allows to detect the network's nodes presenting the highest risk of spillover. Regulatory entities in respective regions are therefore capable of implementing circuit breaking measures such as recapitalisations with aim to mute the emerging crisis' severity. Third, FRM is shown to predict upcoming recession periods and serves as a leading indicator for systemic risk in a variety of world regions, the US and the EU market. In fact, the financial crisis in 2008 is captured in late 2007 by FRM already, when first indicators of distress appeared in financial markets. This strongly suggests the inclusion of FRM to standard recession probability indicators in as much as they might emerge from distress in financial markets directly, and are only later captured by the more widely used macro-economic variables based models.

This paper is structured as follows: after the FRM risk measure framework is presented in Section 2, its economic and computational characteristics are discussed in Section 3. Empirical economic research results are provided in Section 4 and finally Section 5 concludes.

The underlying codes have been written in the environment of R software as developed by **R Core Team:2019** They can be downloaded at `www.quantlet.de`, indicated with in this paper for convenience.

2 FRM Systemic Risk Measure Framework

In economic tail risk management FRM offers an accessible and comprehensive measure for systemic risk measurement. In this section, the underlying methodology is presented and then FRM is defined. Since the high-dimensional financial network data exhibit non-linearities in time and space **Haerdle:2018aHaerdle:2016b** our framework utilises a moving-window based quantile regression approach.

2.1 Modelling Framework

FRM is based on financial institutions stock market returns as well as a set of macroeconomic risk factors, where the latter are conditioning variables such as volatility, credit spreads and yield curve slope inspired by the systemic risk measure CoVaR by **Adrian: 2016** which is one step further from an institution's own VaR measure. For more details on VaR see **Haerdle:2019** While the CoVaR approach yields a systemic risk measure associated with one particular financial institution relative to the financial system, thus the VaR of the financial sector conditional on this financial institution being in distress, the FRM aims to simultaneously capture all interdependencies in one single number. Consider J companies and M macroeconomic risk factors at a given trading day $t \in \{n+1, \dots, T\}$ with n denoting the estimation window size and T the number of time series observations. Linear quantile Lasso regression for return series X is given by

$$X_{j,t} = \alpha_j + A_{j,t}^\top \beta_j + \varepsilon_{j,t} \tag{1}$$

with $A_{j,t} = \begin{pmatrix} X_{-j,t} \\ M_t \end{pmatrix}$ a $p = J + M - 1$ dimensional vector of covariates, collecting the $J-1$ dimensional vector of returns of all other companies except company j and the M dimensional vector of macroeconomic risk factors the index $j \in \{1, \dots, J\}$. Correspondingly, vector β collects p underlying parameters, **Haerdle:2016**.

The regression is performed using an L_1-norm penalisation with parameter λ_j, known as the least absolute shrinkage and selection operater (Lasso) by **Tibshirani:1996**. The current company's λ_j are estimated through a modification of Lasso in a quantile regression setting **Koenker:1978** detailed further by **Li:2008** and **Belloni:2011** where the optimization is solved with

$$\min_{\alpha_j, \beta_j} \left\{ n^{-1} \sum_{t=1}^{n} \rho_\tau \left(X_{j,t} - \alpha_j - A_{j,t}^\top \beta_j \right) + \lambda_j \left\| \beta_j \right\|_1 \right\} \tag{2}$$

with check function

$$\rho_\tau(u) = \left| \tau - \mathbf{I}\{u \le 0\} \right| |u|^\gamma \tag{3}$$

given tail risk level τ, where $\gamma = 1$ corresponds to quantile regression employed here and $\gamma = 2$ to expectile regression. The linear quantile regression model

is related to residual size, the condition of the design matrix and the active set. This directly follows the work by **Osborne:2000** deriving a formula for Lasso's penalisation parameter λ in a linear regression context, and is then extended to penalised quantile regression.
Treating λ as a fixed value in the objective function of the penalized regression

$$f(\beta,\lambda) = \left\{ \frac{1}{2} \sum_{i=1}^{n} \left(Y_i - X_i^\top \beta \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}, \tag{4}$$

then the function $f(\beta,\lambda)$ is convex in parameter β. Moreover, with diverging β we observe that $f(\beta,\lambda) \to \infty$. Hence there exists at least one minimum of the function $f(\cdot,\lambda)$. According to **Osborne:1985** this minimum is attained in $\widehat{\beta}(\lambda)$ if and only if the null-vector $0 \in R^p$ is an element of the sub-differential

$$\frac{\partial f(\beta,\lambda)}{\partial \beta} = -X^\top (Y - X\beta) + \lambda u(\beta), \tag{5}$$

where $u(\beta) = (u_1(\beta), \ldots, u_p(\beta))^\top$ is defined as $u_j(\beta) = 1$ if $\beta_j > 0$, $u_j(\beta) = -1$ if $\beta_j < 0$ and $u_j(\beta) \in [-1,1]$ if $\beta_j = 0$. Then, for $\widehat{\beta}(\lambda)$ as a minimizer of $f(\beta,\lambda)$ the following has to be satisfied

$$0 = -X^\top \{Y - X\widehat{\beta}(\lambda)\} + \lambda u(\widehat{\beta}(\lambda)), \tag{6}$$

Here we denote the estimator of a parameter vector β as a function of the penalization parameter λ. This dependency follows from the formulation of the penalized regression method and its objective function (4), where we first select λ and then search for $\widehat{\beta}(\lambda)$ which minimizes (4). Using the fact that $u(\beta)^\top \beta = \sum_{j=1}^{p} |\beta_j| = ||\beta||_1$, where $||\cdot||_1$ denotes L_1-norm of a p-dimensional vector, (6) can be further rewritten in the formula

$$\lambda = \frac{\{Y - X\widehat{\beta}(\lambda)\}^\top X\widehat{\beta}(\lambda)}{||\widehat{\beta}(\lambda)||_1}. \tag{7}$$

The identity (7) leads us to consider possible constituents which influence the value of parameter λ and therein its dynamics when treated in a time-varying framework. The following three effects are then related to the size of λ:

1. size of residuals of the model;
2. absolute size of the coefficients of the model, $||\beta||_1$;
3. singularity of a matrix $X^\top X$.

The second effect can also be translated into the effect of a number of nonzero parameters the so-called active set of the model, $q = ||\beta||_0 = \sum_{j=1}^{p} \mathbf{I}(\beta_j \neq 0)$, where $||\cdot||_0$ stands for L_0-norm on R^p and $\mathbf{I}(\cdot)$ is an indicator function. As a measure of the third structure, the condition number $\kappa(X^\top X)$ defined as the ratio $\phi_{max}(X^\top X)/\phi_{min}(X^\top X)$, the maximum and the minimum eigenvalue of the matrix $X^\top X$, can be used.

Similarly, one can derive formulae for the penalization parameter λ in a quantile regression problem (2) and (3). Following **Li:2008**

$$\lambda = \frac{\theta^\top X\widehat{\beta}(\lambda)}{||\widehat{\beta}(\lambda)||_1}, \tag{8}$$

where $\theta = (\theta_1, \dots, \theta_n)^\top$ satisfies the following

$$\theta_i = \begin{cases} \tau & \text{if} \quad Y_i - X_i^\top \widehat{\beta}(\lambda) > 0; \\ -(1-\tau) & \text{if} \quad Y_i - X_i^\top \widehat{\beta}(\lambda) < 0; \\ \in (-(1-\tau), \tau) & \text{if} \quad Y_i - X_i^\top \widehat{\beta}(\lambda) = 0. \end{cases} \tag{9}$$

Hence, we observe that λ depends on cardinality of the active set q, which is again influenced by the correlation structure of the design matrix.

The optimized value of λ is found by cross-validation and will be discussed in 10 and 11. Since equation (2) has an L_1 type loss function and an L_1-norm penalty term, the estimation deals with an L_1-norm quantile optimisation. There are several options to select λ. One method is by one of the three forms of cross-validation: k-fold, leave-one-out and generalized cross-validation method, see e.g. **Tibshirani:1996** Shown by **Hastie: 2009** cross-validation is a widely used method for estimation of prediction error, but **Leng:2006** argue methods of choosing penalization parameter based on prediction accuracy are in general not consistent when variable selection is considered. Similarly **Wang:2009** arrive to the same conclusion by study of asymptotic behaviour of the generalized cross-validation to Akaike's information criterion (AIC); it is efficient if one is interested in the model error, but inconsistent in selecting the true model. The second widely used method of estimating λ is the Bayesian information criterion (BIC), and generalized approximate cross-validation criterion (GACV). For a longer discussion, see **Haerdle:2016** Modified selection criteria for penalized quantile regression which were used by **Li:2008** are BIC for quantile regression presented by **Koenker:1994**

$$BIC(\lambda) = \log\left[n^{-1}\sum_{i=1}^{n}\rho_\tau\{Y_i - X_i^\top\widehat{\beta}(\lambda)\}\right] + \frac{\log(n)}{2n}\widehat{df}(\lambda), \tag{10}$$

and GACV as introduced by **Yuan:2006**

$$GACV(\lambda) = \frac{\sum_{i=1}^{n}\rho_\tau\{Y_i - X_i^\top\widehat{\beta}(\lambda)\}}{n - \widehat{df}(\lambda)}, \tag{11}$$

where $\widehat{df}(\lambda)$ stands for the estimated effective dimension of the fitted model. **Li:2008** argued that the number of interpolated observations Y_i denoted by $\mathcal{E}$ is a plausible measure for this quantity, i.e. $\widehat{df}(\lambda) = |\mathcal{E}|$. In terms of statistical efficiency, GACV outperforms BIC, see **Yuan:2006** . In implementing the FRM model we utilise the later approach.

Finding a feasible solution of the optimization problems (2) can be computationally demanding, since one has to check all combinations of values of the tuning parameter λ and its respective model parameter estimates $\widehat{\beta}(\lambda)$. Only after all possible combinations are tracked, the particular method of choosing $\widehat{\lambda}$ can be applied. The first algorithm for finding solution of Lasso was presented by **Tibshirani:1996** in his work introducing the Lasso method itself. Then **Osborne:2000** developed an algorithm which works not only for the case where $p < n$ but also $n < p$. For the quantile regression case, solutions were proposed by **Belloni:2011** and **Li:2008** . The second is applied in this paper, since one is interested in modeling tail event dependencies when dealing with systemic risk evaluations. Formally, the optimal level λ_j for company $j \in \{1, \dots, J\}$ is selected based on the minimization

$$\min_{\lambda_j} \frac{\rho_\tau \left(X_{j,t} - \alpha_j - A_{j,t}^\top \beta_j \right)}{n - d} \tag{12}$$

where d is a measure of the effective dimensionality of the fitted model; it is the trace of the hat matrix with entries (t, q) given by $\partial \left(\alpha_j - A_{j,t}^\top \beta_j \right) / \partial X_{j,q}$, $q \in \{1, \dots, n\}$. The advantage of GACV is that it also works for the high-dimensional case, which occurs when the selected moving window size n is smaller than the number of parameters p as often encountered in risk management practice.

2.2 Financial Risk Meter (FRM)

Minimisation of (12) yields for each node a λ_j gauging dimensionality versus the size of the residuals as discussed in subsection 2.1. The distribution of the λ_j's in a moving window brings therefore important information on the network dependencies among the financial nodes. The standard FRM is simply the mean of these λ_j. The distribution of the λ_j shed light on the general market movement and provide information for macro-prudential decision makers related to the network dynamics. FRM may therefore be used to identify above average and high joint tail event risks arising from single companies. Companies with high λ_j exhibit common high stress levels as the companies at the origin of the crisis. Such a company therefore is coined as having high "co-stress". Further, the FRM's set up can always identify the respective company j in question, which is referred to as "co-stress ID" through this paper. What is more, there is information in the active set that can be used to further the understanding around likely spill-overs in the financial network. Financial institutions with high counts in active sets of other financial institutions could be "activators" of systemic stress and can be seen as major contributors of systemic risk. The first line of marginal influence are called "activated entities". We give an example in Chapter 4.3

The FRM is defined as

$$FRM = J^{-1} \sum_{j=1}^{J} \lambda_j \tag{13}$$

in each rolling window for j companies, and the distribution of individual λ_j is best shown in boxplot format, such as in Figure 1. While mean and median do not deviate much throughout the respective crisis periods, the standard distribution of λ_j increases strongly. It is seven times bigger end for $FRM@Americas$ end of 2008 compared to early 2007. It is about three times bigger early 2012 for $FRM@Europe$ compared to early 2011 and here as well mean and median of λ_j move closely together.

3 FRM Data and Computational Characteristics

The most influential economic areas globally attracting the largest financial institutions are the exchange markets of Americas and Europe. The list of selected companies are financial institutions that have at some point been an active constituent of the selected stock market indices, of which there are 612 in the Americas, and 289 in Europe. The list of macroeconomic risk factors shown are shown in Table 2 in the Appendix.

3.1 FRM Data Compilation

For both markets studied and over the horizon, all financial institution constituent of respective regions' equity market indices are compiled and prices as well as market capitalisations in USD are obtained from the Bloomberg database. For both $FRM@Americas$ and $FRM@Europe$, index constituents were available since January 2000 and form the start of the study. The macroeconomic risk factors are loaded in line with these data sets for the respective markets.

$FRM@Americas$ is composed of financial institutions from the US' S&P 1500 Composite Index, and from the Canadian TSX Toronto Composite Index, resulting in 612 financial institutions, and six macroeconomic risk factors, with daily data from 20000103 to 20190710 (4910 trading days). Estimation results are available from 20000403 (the 64th day of the series) until 20190710 (4847 trading days).

$FRM@Europe$, the financial institutions from the S&P 600 Europe have been selected, representing 289 companies from 17 European countries and are more heterogeneous compared to $FRM@Americas$. Seven macroeconomic risk factors were selected, and daily data ranges from 20000104 to 20190710 (5025 trading days). The estimation results are available from 20000331 (the 64th day of the series) until 20190710 (4962 trading days).

The conditioning macro variables are chosen in line with **Adrian:2016** so as to capture common exposure to exogenous aggregate macroeconomic risk

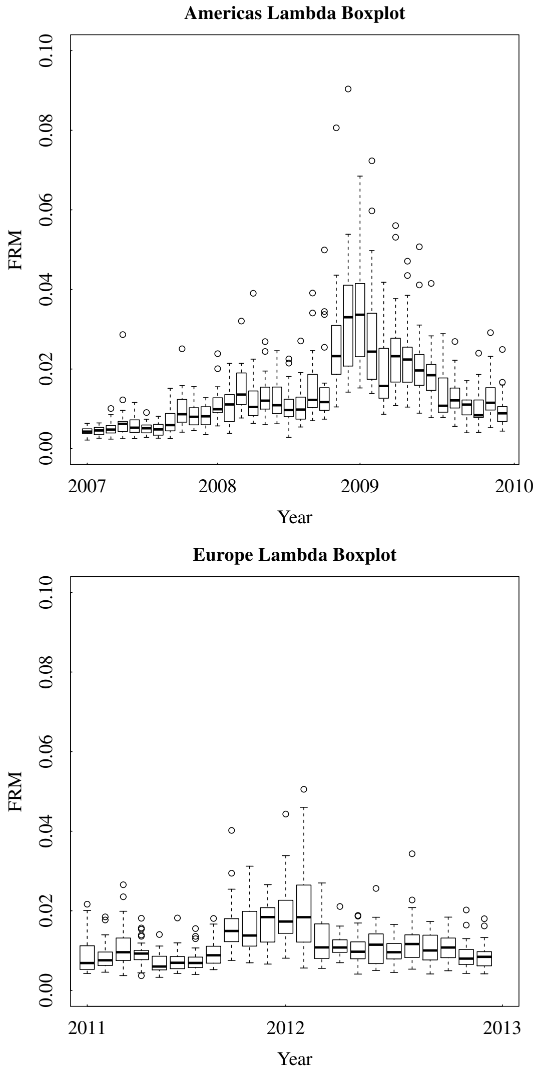

Fig. 1 Boxplot of the distribution if individual Lambdas

The top boxplot shows the $FRM@Americas$ during 2007 to 2009, the bottom one $FRM@Europe$ 2011 to 2012, both on a monthly basis.

factors. Generally those are the change in front end yield and slope of the yield curve, the change in credit spread, the equity market return, the real estate sector return and the change in equity market option implied volatility levels. In the case of $FRM@Europe$, we include the Euro Area member country specific government credit risk spread of Italian ten-year versus German ten-year government bonds. Table 2 summarizes the input variables in the Appendix.

3.2 FRM Computational Characteristics

While reporting, processing and preparing empirical results, three basic steps are identified: (a) FRM statistics and data, (b) FRM statistics and estimation and (c) FRM results and reporting. In the first part, we select the reference stock market indices for respective regions and obtain their past and present index constituents, so also include financial institutions that failed due to poor performance. This allows us to prevent survivorship bias when only studying currently existing index members, in line with **Elton:1996** analysis on mutual fund performance. We then download their closing prices, and market capitalisation at closing prices. In addition we load the macroeconomic risk factors for the respective studied period. We calculate the daily returns of these matrices of levels.
Subsequently, and on a daily basis, the stock price and macroeconomic risk factor returns are selected for the largest J companies over a moving window of s trading days for selected r days between start and end date of the study. The resulting estimates of λ_j, c_j and the active set vector β_j are stored in the estimation matrix.
Finally, these results can be studied by themselves, or applied to further studies as done here in this study for estimation of recession probabilities by economic region.
For convenience, the key ingredients of each step of the FRM algorithm are summarized in Table 3 in the appendix.

4 Economic Applications

Within this empirical study, two stock markets are focused on: *FRM@Americas* and *FRM@Europe*. While earlier versions of the FRM measure have been studied previously for the US, see for example **Haerdle:2016** this present study has four key improvements to extend and enrich the analysis. First, we improve the measure by allowing to select the biggest J financial institutions on a given day, thereby preventing a possible survivorship bias. As any potential crisis management approach necessitates the detection of the specific financial institutions at risk of influencing others, or being influenced by others to a large extend, the inclusion of failed institutions during past crises allows the detailed study of co-movements of these failed institutions at the origin of a financial crisis. Second, we apply this measure to the European stock market, specifically to the S&P 600 Europe, representing 17 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland and the United Kingdom. This results in the *FRM@Europe* and permits to capture the financial market's interconnected structure across the European economic region. In a similar fashion, the *FRM@Americas* represents the most liquid US but also Canadian financial institutions as the most liquid de-

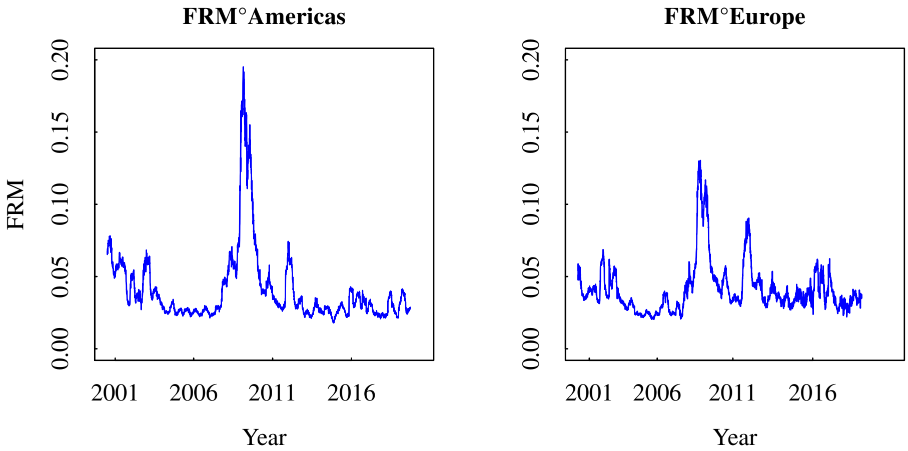

Fig. 2 FRM time series from 2000 until 2019

veloped North American markets. Both modelling and computational set-ups allow us to detect the active set, and the co-stress IDs.
Third, we apply the FRM to recession probability estimation, so as to enlarge and complement the current set of widely used recession probability estimation methods. Fourth, we apply the FRM technology to another asset class of government debt, which we name the Sovereign Risk Meter SRM. We study the tail event network dynamics of Euro Area government debt during the Eurozone debt crisis ($SRM@EuroArea$) and show how spill-over can be detected. Averaging the $SRM@EuroArea$ and the $FRM@Europe$ indicates at how a comprehensive systemic risk measure encompassing further asset classes could be constructed. Lastly, we give a brief outlook on further implications of the FRM with regards to macro-prudential policy making, and applications for portfolio risk managers.

4.1 CoStress, Activators and Network Dynamics

The first observation from Figure 2 is that the FRM peaks right when crises become systemically important. Figure 2 shows the FRM time series in both the Americas and Europe from 2000 until 2019. The peaks are, most obviously, around the 2008 financial crisis, but also around other periods of elevated systemic risk. Such periods are the US' 2001 recession around the Dot-Com bubble implosion, and in the case of Europe around the 2011 Euro Area government debt crisis. Importantly, one can observe the $FRM@Americas$ to rise synchronously in 2011, pointing out that global linkages in the financial industry are well pick up by the risk measure.

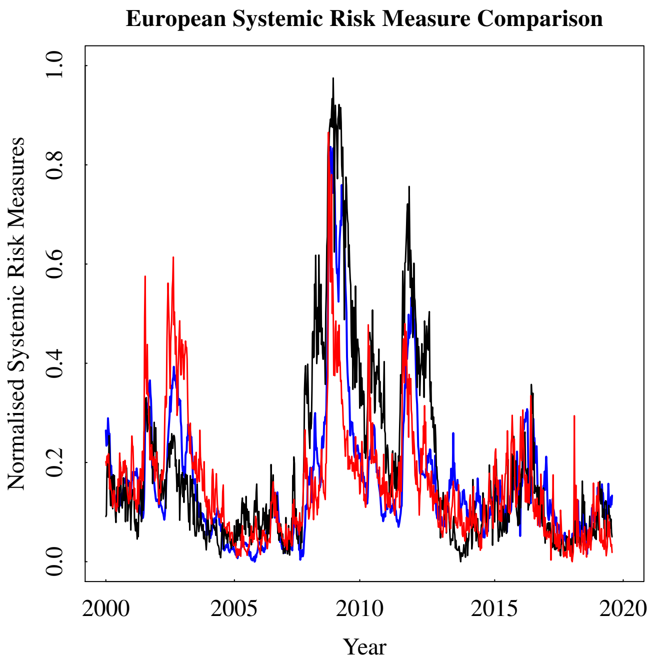

Fig. 3 Normalised risk measures for *FRM@Europe*, VSTOXX and CISS

In comparison to other risk measures, **Haerdle:2016b** and **Yu:2017** have shown co-movements for the US' version of the FRM. The *FRM@Europe* being a novelty, we show the EuroStoxx 50 Volatility Index (VSTOXX) and the ECB's CISS (**Hollo:2012** Euro Area Systemic Stress Indicator Composite Index) in comparison to the FRM measure for Europe in Figure 3. The VSTOXX is calculated by Deutsche Börse and similar to the S&P 500's VIX Index is based on implied volatility on options with a rolling 30 day expiry. The CISS is a composite indicator by the ECB's Macro-prudential Research Network MaRs, based on 15 mainly market based and equally weighted financial stress measures. Around the 2007-2009 crisis period, one can observe the CISS to move earlier. This is probably due to the fact that starting in August 2007 already, the ECB had to use emergency liquidity provision to help stabilise the system as spreads between secured and unsecured money market rates widened strongly **Quint:2017** This would likely be picked up in some of the CISS components, such as money market spread moves as well as foreign exchange moves, which are not captured by the currently calculated FRM indices.

The *FRM@Americas* and *FRM@Europe* data sets were constraint by the availability of index constituents information, going back to 2000 only. A more complete set is available back to 1990 for the S&P 500 (SPX), the

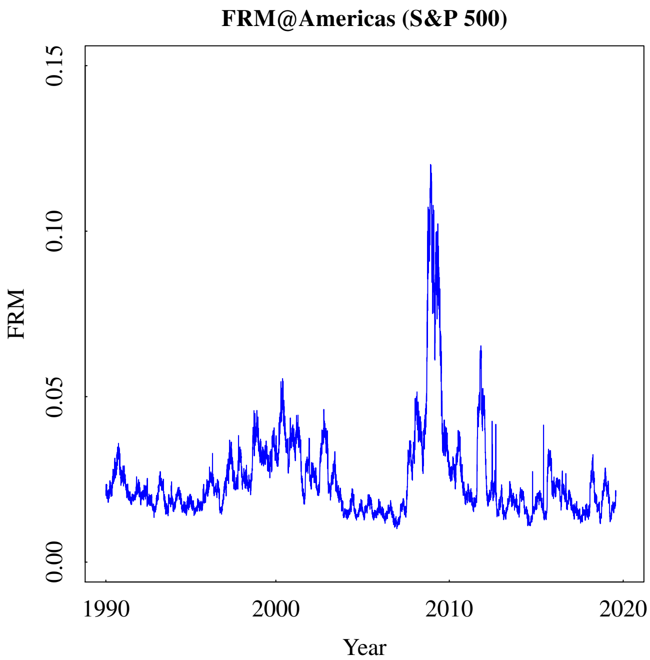

Fig. 4 FRM S&P 500 time series from 1990 to 2019, 25 largest financial institutions

result of which is shown in Figure 4. At the start of the series, only about 25 financial institutions were index constituents and we restrict this study to the largest 25. On average, those 25 make up around 74% of the overall financial institutions' market capitalisation. While the $FRM@SPX$ peaks again in 2008 as expected, previous crises were well captured as well. Most notably, there are local maxima around the early 1990s recession, the Asian crisis 1997, the Russian crisis 1998, and again a peak around the recession in 2001 and the so-called Dot-Com bubble implosion.

The FRM's key advantage however lies in its network based information, in that on the one hand, the overall FRM is a first indication of systemic risk, but on the other hand, the composition is known as well. The financial institutions with high λ_j readings are so called high co-stress entities, whose identity is known - the so called co-stress ID. There is even further information in the active set with which the identification of activators of systemic risk are known and the likely spread of contagion to the next activated entities.

To give an example in both regions, a closer look at periods of distress is undertaken, specifically the period between 2007 and 2009 in the Americas, and between 2011 and 2012 in Europe. Over both time horizons, the FRM is estimated with the same hyperparameters, only that the number of largest financial institutions is set at 25, which is shown in the top left chart in Figure

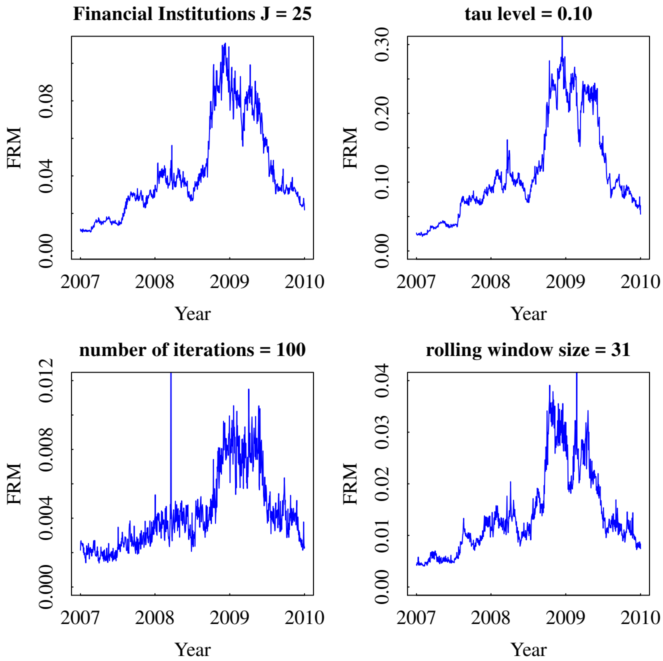

Fig. 5 FRM@Americas between 2007 and 2009 with a variety of settings and 25 financial institutions

5 and 6. Both figures also show additionally the change in hyperparameter τ, the number of iterations at 100, and shortening the moving window to 31 trading days, always on the same 25 largest financial institutions. The results are similar in shape, but the ordinates' scales differ. The FRM seems to be robust with regards to a variety of argument settings.

In order to visualise the networks connection and the strength thereof, we take the active sets of each financial institution j into a weighted adjacency matrix, where the active set is derived from the usual 63 day moving window. From this matrix we can derive the network's nodes' centrality and link strength, see Figure 7 for an example of $FRM@Americas$. Here we follow **Nieminen:1974** for a simple and general measure of total network centrality. The dates chosen are right ahead of the Bear Stearns Companies, Inc. offer by JPMorgan Chase on 14 March 2008 when the earlier was failing due to involvement in the subprime mortgage crisis, and 5 September 2008 just ahead of the US Treasury announcement to take over the mortgage buyers FNMA and FHLMC, and a weak ahead of the Lehman Brothers failure. Between the two networks, one can observe the increasing centrality of Wachovia, which later had to merge with Wells Fargo (WFC) so as to prevent further market

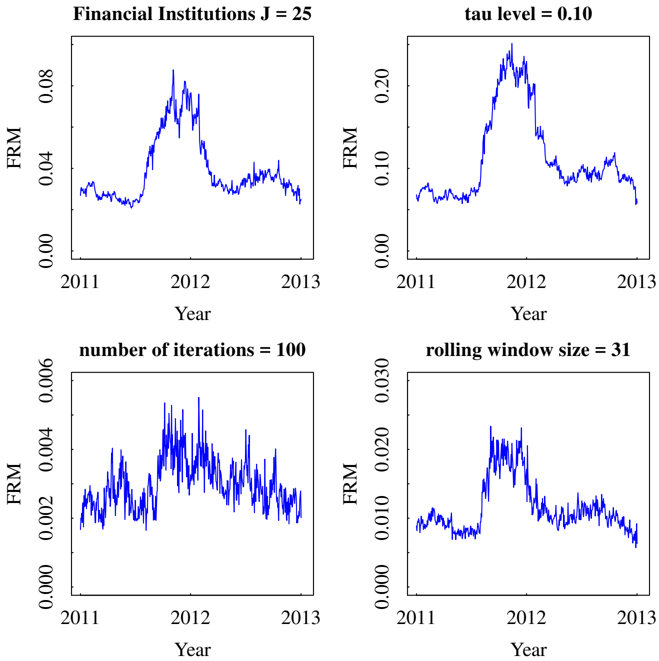

Fig. 6 FRM@Europe between 2011 and 2012 with a variety of settings and 25 financial institutions

disruption. Also, AIG's node has increased in size, reflecting the market's risk perception towards the insurer. AIG received a 85 billion USD two-year loan by the Federal Reserve so as to prevent its bankruptcy and thereby further stress to the global economy. An earlier dealing with these potential activators of crisis could have possibly reduced the contagion to the system later on.

As for the high and low co-stress ID's on September 5th, the top five co-stress identities where in descending order Visa Inc, Toronto Dominion Bank, US Bancorp, American Express Co, and American International Group (AIG) Inc. On the low side, Mastercard Inc, Bank of America Corp, Bank of Nova Scotia, Goldman Sachs Group Inc and Merrill Lynch Co Inc.

We also show the financial network in the case of Europe in Figure 8 on 20 January 2012, just after the downgrade of France by credit rating agency Standard & Poors including eight other Eurozone countries. Also that same day, Greece and private investor talks had stalled. Quite apparent are the Italian banks UniCredit SpA (UCG) and Intesa Sanpaolo SpA (ISP) and link's strength between them, reflecting the so called peripheral country risk perception that spilled over from the Eurozone government debt crisis. We will look the Eurozone government debt crisis in detail in section 4.2.

4.2 The Sovereign Risk Meter

The FRM technology can by applied to other asset classes. The discussion on $FRM@Europe$ on the Euro Area's government debt crisis motivates us to an analysis of the network behaviour of the Euro Areas government debt markets. For this task, we take the changes in constant maturity ten year government debt levels of eleven Euro Area countries, namely Belgium, Spain, Italy, Austria, Germany, France, Portugal, Ireland, Finland, the Netherlands and Greece. As for macroeconomic risk factors we take a reduced set including Euro Area REIT returns, Euro Stoxx 50 returns, Euro Stoxx 50 Volatility Index returns, the Germany treasury yield curve slope, and finally a liquidity measure consisting of ten year Kreditanstalt für Wiederaufbau (KfW) ten year yields as a spread to German ten year treasury yields. The latter are both ultimately guaranteed by the German government, however differ in market size and thus liquidity. We will refer to it as the Sovereign Risk Meter (SRM), and for the exemplary case of the Euro Area: $SRM@EuroArea$. Figure 9 shows the $SRM@EuroArea$ for $\tau = 0.05$.

As expected, the SRM is soaring during the 2011-2012 Euro Area government debt crisis, which culminated in Greece's debt restructuring deal in March 2012. However, the $SRM@EuroArea$ reaches similarly high levels around the Greek bailout referendum on July 5, 2015 on the acceptance of the bailout conditions in the country's government debt crisis. When looking at the yield level developments throughout 2014 and into the referendum 2015, the SRM's technology is exemplified. Whilst Greece' yield levels sell off in the second half of 2014 already, the SRM level only increases when the other countries' yield levels jointly move higher by end of April 2015, right when the issue became systemic in the eyes of investors, see figure 10.

Further applications in the realm of bond yield levels will be the focus of future work. Such applications could be to emerging market government debt denominated in local or foreign currency, or local government debt in the case of China.

In a similar fashion to the ECB's equally weighted CISS measure, the average of normalised level of the $FRM@Europe$ and $SRM@EuroArea$ shown in Figure 11. Both have very similar patterns, but our measure captures better the systemic risk increase around June 2013, when equity index provider MSCI Inc. reclassified Greece as an emerging market, given failure to qualify on several criteria for market accessibility. Again, this points to the advantage of including the FRM technology when estimating system risk levels.

For the Euro Area policy makers, understanding the networks key nodes is of importance. Figures 12 and 13 show the total degree of centrality early May 2015, when the FRM was at local lows, on July 3rd 2015 just ahead of the Greek referendum. The spread of contagion to Italy is clearly visible. As of July 10th, 2019, the centrality graph points to much calmer times, see Figure 14.

4.3 FRM and Credit Default Swaps

We now want to take it one step further, by calculating the FRM on credit default swap (CDS) spread changes of specific CDS index members. Credit default swaps have been widely used as a key tool in risk management over the last two decades. It is a financial swap agreement between a protection buyer and a protection seller on a specific reference bond. The protection seller receives a series of payments ("spread") and the protection buyer receives a payoff if there is a default on the underlying asset. The spread is an expression of expected loss given default and the probability of default. The maturities of these contracts range from short one year to ten year and longer, and are available on sovereign debt issuers from developed and emerging markets, corporate debt issuers, and even supranational agency issuers.

Our focus is on financial institutions and specifically the Markit iTraxx credit default swap indices on iTraxx European Financials Senior, which includes currently 30 of the most liquid equally weighted senior subordination financial names. Starting 2004 iTraxx European Financials Senior roll in series every six months in March and September, and a polling procedure obtains the constituents with index rule considerations regarding outstanding debt, corporate events, business sector and so on. For our study, we obtained the iTraxx European Financials Senior index constituents for all series starting in September 2005 and up to the current series 32 for five year maturity CDS. We then obtain the CDS spread history of each if these historical constituents. The first series start with 25 index members, but they currently encompass 30 index members. The macroeconomic risk factors selected were Euro Area REIT returns, Euro Stoxx 600 returns, Euro Stoxx 50 Volatility Index returns, the Germany treasury one year yield level and curve slope to ten year bonds, the corporate credit spread and the yield spread between German and Italian ten year government bond yields.

Figure 15 shows the $FRM@iTraxx$ as an example for CDS spread change tail event network behaviour. Importantly, the aforementioned August 2007 liquidity stress situation is very well captured by a sharp rise in the FRM, spiking to levels close to what will later be observed in 2008. Judging by the FRM, there was imminent risk of a systemic crisis and the ECB was correctly assessing its need to address the banks' provision of credit and liquidity.

Figure 16 shows the $FRM@iTraxx$ adjacency matrix as of 07 October 2019. The columns show company j's marginal contribution to the other network members' returns. In rows, we see each company j's marginal return contribution from the remaining companies. In Figure 17 the exemplary spill over effects from activator Deutsche Bank (DB) are being depicted, indicating the potentially "activated entities". In fact, DB only has to significant marginal return contributions in the tail event scenario, namely to Swiss Re (SRENVX) and Commerzbank (CMZB), the latter probably less surprising. CMZB itself has a sizeable marginal return contribution to Allianz (ALVGR), which itself impacts large parts of the network. The total network degree centrality is again depicted in Figure 18. Expectedly, the linkages between national banking and insurance sectors are generally strong, for example Aviva and the British banking sector, or between Swiss Re and Zurich Insurance as well as UBS and Credit Swiss in the Swiss case.

4.4 FRM as the Predictor of Recessions

The FRM dynamics in Figure 2 reveals several peaks in the FRM series. "Peaks" at the financial crises in 2000, 2008 and 2013 motivate us to study the role of the FRM in the recession prediction. There exists a variety of recession indicators, such as the term structure of yield curve or interest rate, monetary policy-related predictors, that are employed as recession predictors (see **Estrella:1991** and **Estrella: 1996**). These indicators carry information about the monetary and bond markets, whereas the FRM is measuring the strengths of tail dependence of the entire financial system.

We collect the National Bureau of Economic Research (NBER) recession indicator data and the Centre for Economic Policy Research (CEPR). More detail can be found at `https://fred.stlouisfed.org/series/USREC` and `https://cepr.org/content/`. According to the NBER, a recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. The recession indicator has a value of 1 in a recessionary period, while a value of 0 indicates an expansionary period. The complete recession data is spanning from 1855 up to today, on a monthly basis. As for Europe, the CEPR analogously publishes recession periods following the NBER's trough method.

To examine whether the FRM can be a predictor for the NBER recession indicator or for the CEPR indicator, we perform a univariate linear logistic regression. Between the predictor, the FRM at the past k-month, and the recession probability as follows

$$\log \frac{\mathrm{P}(Y_t = 1 | x_{t-k}; \theta)}{\mathrm{P}(Y_t = 0 | x_{t-k}; \theta)} = \theta_{0,k} + \theta_{1,k} x_{t-k} \quad where \ \ k = 1, ..., 6 \tag{14}$$

where x_{t-k} is the $FRM@Americas$ ($FRM@Europe$) at time $t-k$ which can be obtained by averaging the daily FRM within the $t-k$ month, Y_t is NBER (CEPR) recession indicator with binary value 1 or 0 at time t to indicate the presence ($Y_t = 1$) or absence ($Y_t = 0$) of a recession. To be precise, we only use the $t-k$ predictor, since this was more significant compared to using all $t-1$ to $t-k$ predictors. After aligning the two FRM with the recession series in the Americas and Europe, we end up a time frame from January 2000 to July 2019 on a monthly basis. An alternative is to take the median of daily FRM in month $t-k$, but the two are not meaningfully different.

Table 1 reports the regression coefficients, $\theta_{1,k}$ in (14) as $k = 1, ..., 6$, and documents their statistical significance and R-square values. This indicates that FRM is capable of predicting the upcoming recession up to $t+6$ month,

with the R-squared value from 10%(lag 6) up to 36% (lag 1) in the US recession forecast. As can be understood, the statistical significance declines as the lag increases. The forecast in the EU market exhibits the comparable performance.
Having the estimated logistic regression, one may calculate the FRM-implied recession probability. This implied recession probability indicates the probability of recession attributed to the quantified systemic risk measure, at 5% level of FRM. Figure 19 depicts the recession probability implied by the generated FRM, the FRM series and the dated recession periods. In order to have more recession periods under consideration, we would need to extend to the next NBER recession in the early 1990s. In Chapter 4.1 we lengthened the FRM back to 1990 for the US' S&P 500. In Figure 21 the resulting recession probability is shown for the the longer 30 year period between 1990 and 2020, now encompassing three official NBER recession periods. The FRM derived recession probability captures well the spill over from the Asian Crisis 1997-1998. There is also a rise in recession probability around 1990 on the back of the restrictive US Federal Reserve's policy mix. However, given the limited availability of index membership data prior to 1990s, there is not enough data to perform the univariate linear logistic regression on in the early stages.

Figure 22 compares the recession probability obtain from the FRM for the US with those obtained from smoothed recession probability calculation by the St. Louis Federal Reserve, as well as the yield curve slope derived probability by the New York Federal Reserve. Around 2008, the FRM recession probability indicator rises earlier than the St.Louis Fed's, however later than the New York Fed's yield curve implied probability. Against that, the FRM captures the 2001 recession earlier than the other two measures. What is more, the FRM derived recession probability captures the spill over from the 2011 Euro Area debt crisis, which was impacting European banks especially. This supports the FRM's capability to indicate stress stemming from global linkages in the financial network. More recently, the FRM's recession probability has risen somewhat, but less so compared to the New York Fed's recession indicator.

In sum, the FRM shows a predictability to an imminent recession and serves therefore as an indicator for systemic risk in a variety of world regions. We, therefore, suggest that FRM can be considered in the inclusion of the list of leading indicators and is informative in terms of predicting upcoming recessions.

4.5 Further implications and extensions

With the onset of the financial crisis 2008, and its implications on the systemic risk character of the financial market and the functioning thereof, more focus has shifted to so called macro-prudential policy making. For example, the European Central Bank has included macro-prudential policies aiming at risk build-up prevention, to improve the financial sector's resilience and limit contagion effects, and lastly improvement of market participants' incentives.

	US recession			EU recession		
k-month ahead	coefficient	std	R^2	coefficient	std	R^2
1	69.43*	14.44	0.36	77.07*	13.95	0.27
2	54.87*	11.55	0.29	65.12*	12.30	0.22
3	47.12*	9.84	0.23	56.65*	11.18	0.18
4	42.12*	8.77	0.19	50.83*	10.45	0.14
5	35.83*	7.59	0.14	45.68*	9.86	0.12
6	29.77*	6.70	0.10	38.56*	9.16	0.09

Table 1 Predicting future recession

The coefficient $\theta_{1,k}$ defined in (14, the standard error of coefficient and R-square value are reported. * indicates significance at the 1% level.

For more details, see `https://www.ecb.europa.eu/ecb/tasks/stability/html/index.en.html`. Similarly, the Federal Reserve has included a Division of Financial Stability, which includes macro-prudential analysis ultimately with the aim to improve the financial market's resilience. This inclusion of macro-prudential variables has also been studied in academia. For example **Edge:2017** analyse the implementation of macro-prudential policies across countries and the functioning of respective institutions tasked to improve financial stability. But already pre-crisis, **Bodie: 2007** outlined the necessity to include contingent claims analysis and their sensitivity to shocks and the resulting necessity for macro-prudential policy sets. Post-crisis, a good overview of macro-prudential policies and its benchmarking is given laid out by **Lombardi:2016**

There are two ways in which the FRM helps to improve on financial stability stability management. First, the FRM is an aggregated tail event network's risk measure, which, as shown in the previous sections, is an early detector of financial distress in the market. As λ_j rise, and with that, the overall FRM, the J companies returns are driven by a decreasing number of companies and macroeconomic risk factors, that is, a smaller active set. Under the assumptions that company returns reflect the changing investment behaviour into a more distressed scenario, and early indication thereof is available with the FRM. Secondly, the FRM is a rich measure in that one can infer which nodes of the financial network are in distress, and the potential chain of spillover into the general financial market. By analysis of the active set, the financial institutions with significant marginal effect on returns of a large number other companies can be detected, the so-called "activators". Further, the individual λ_j indicates that select company j is a risk of driven further by external factors, be it other financial institutions or macroeconomic risk factors. This enhances the understanding of empirical properties of tail event network stress unfolding.

In fact, the FRM addresses several points which the BIS' **Gadanecz:2015** raise. Not only does the FRM show the financial cycle dynamics at the early stages of distress, thereby giving necessary lead time to decision makers, but it also indicates where exactly in the financial system network to put in place measures that can prevent a crisis at the early stages. By not only focusing on banks, but by including the entire financial industry, the FRM measure detects appearing risks in non-bank financial sectors. Systemic risks emerging in the so called "shadow banking system", which is in need of regulation and oversight, can be detected by looking at sub-sector aggregation of the FRM's composition. The shadow banking system is described by the Federal Reserve's Financial Stability Board as credit intermediation involving entities and activities outside the regular banking system. By inclusion of a broad set of financial sector entities, the FRM captures risks emerging from any potential subsector. Secondly, a truncated version of the FRM can be analysed, by for example only including the bottom third in terms of market capitalisation of the financial industry. Distress in the smaller capitalisation financial industry could lead to spill over to the broader market, as had happened with the onset of the financial crisis in early 2007. Further, the FRM can be measured on a global level. As Figure 2 shows, the 2012 Eurocentric crisis had ripple through effects to the US' financial system, where it did not lead to a recession as with the Euro Area, but had increased financial market distress levels as per the FRM. A global model can directly detect the banks via which the spillovers into another region might happen.

The FRM's forward looking character is a key ingredient to successful employment of circuit breaking tools. By understanding which financial institutions and sectors are leading the increase in λ_j and FRM overall, potential spill-over paths can be forecast and successfully put to a halt. This addresses the clear need of interaction of monetary policy, financial stability related policy sets, but also fiscal policy as it relates to for example forced recapitalisation of detected nodes in the system. So as outlined in **Gauthier:2016** who use a network based structural model to measure systemic risk and how it changes with bank capital, the FRM can further improve macro-prudential financial system capital requirements by detecting the specifically important companies j which are at risk of creating spill-overs to the entire financial sector,that is the activators, the activated entities and the co-stress IDs. Regulatory entities are thereby able to limit contagion within a crisis scenario.

For the investment management industry, the FRM's appeal is in its detection of risk concentration in tail event network distress scenarios. Or in a broader sense, an economies savings are better protected from tail event risks when following similarly prudent measures on an investment portfolio level. The FRM technology detects the financial institutions from which spill-overs emerge, and which other financial institutions in the network will be detected. As a result, the savings can be protected from clustered tail-even risk and invested in nodes further away from the crisis' epicentre. A given company's λ_j can therefore act as a penalising factor allocation of capital within a portfolio management set-up and optimisation. Thereby the full distribution of and interlinkages at all quantile levels can be taken into consideration for an improved and more robust portfolio management strategy. As a consequence, this adaptive portfolio risk management approach including quantile levels has a self-regulating effect. Early detection of risky nodes and nearby co-stress IDs lead to earlier disinvestment and thus an early stoppage to systemic risk building up in a system. Prudent portfolio management quality assessment should therefore include not only the standard risk and reward ratios, but also tail event risk behaviour and exposures to it.

Together, both from a regulatory as well as a portfolio construction point of view, the FRM technology provides a return based measure of systemic risk without the pitfalls embedded in some of them, as have been outlined in **Loeffler:2018** A respective bank's size in terms of market capitalisation relative to others does not have an impact. The FRM is simply the mean of all λ_j. Further, an increasingly infectious bank within the previously studied contagion scenarios of 2008 for the Americas, and 2011 for Europe, indicates that the FRM can detect activators and activated entities, and it is those banks themselves that would be charged with holding more capital or similar risk diminishing measures.

5 Conclusions

In this paper we propose and develop the Financial Risk Meter (FRM), a measure for systemic network risk in financial markets. The FRM is derived from a distribution of penalty terms λ of the linear quantile Lasso regression in a daily rolling window scheme. The FRM is simply the average of the λ series over the 100 largest publicly traded financial institutions in the US and EU, respectively.The up-to-date FRM can be found on `http://hu.berlin/frm` and also on `https://firamis.de`. Modeling the joint tail event network distress is however challenging given a high-dimensional node structure. The FRM is useful since it boils down to a real number, allowing the authorities to manage the systemic risk effectively and further prepare for upcoming economic recessions. The construction of FRM measures though is simple but concise to encompass the joint tail event distress. The FRM technology is applied to the asset class of government bonds. The derived Sovereign Risk Meter (SRM) can be combined with the FRM, to construct a holistic systemic risk measure which can be extended to include further asset classes. The FRM is an early recession indicator as has been shown for the Americas and Europe. Further, the FRM can help to detect distressed areas in the financial system network consisting of banks and non-banks, and thereby can help prevent spill-overs into the wider financial industry. Finally, FRM successfully measures tail event risk, accounts for network dynamics characteristics and offers a flexible risk measuring platform.

References

1. Adrian, T. and Brunnermeier, M. K. (2016) CoVaR, *American Economic Review*, **106**(7):1705–1741
2. Bodie, Z., Gray, F.F., and Merton, R.C. (2007b), New Framework for Measuring and Managing Macrofinancial Risk and Financial Stability, *NBER Working Paper* (13607)

3. Belloni, A. and Chernozhukov, V. (2011), l_1-Penalized Quantile Regression in High-Dimensional Sparse Models,*The Annals of Statistics* **39**: 82–130
4. Chauvet, M. and Piger, J. (2008), A Comparison of the Real-Time Performance of Business Cycle Dating Methods, *Journal of Business and Economic Statistics*, **26**: 42–49
5. Cont, R. and Schaaning, E. (2019) Monitoring indirect contagion, *Journal of Banking & Finance*, **104**: 85–102
6. Edge, R.M., and Liang, N. (2017), New Financial Stability Governance Structures and Central Banks, *Hutchins Center Working Paper* **32**(Brookings Institution)
7. Elton, E.J., ,Gruber, M. J. and Blake, C. R. (1996), Survivor Bias and Mutual Fund Performance, *The Review of Financial Studies*, **9**(4): 1097–1120
8. Estrella, A. and Hardouvelis, G.A. (1991) The Term Structure as a Predictor of Real Economic Activity, *The Journal of Finance*, **46**(2):555–576
9. Estrella, A. and Mishkin, F.S. (1996) The Yield Curve as a Predictor of U.S. Recessions, *Current Issues in Economics and Finance*, **2** 7
10. Gadanecz, B., and Jayaram, K. (2015) Macroprudential policy frameworks, instruments and indicators: a review, *Bank for International Settlements*(Irving Fisher Committee on Central Bank Statistics)
11. Gauthier, C., Lehar, A.,, and Souissi, M. (2012) Macroprudential Capital Requirements and Systemic Risk. *Journal of Financial Intermediation*,**21**(4): 594–618
12. Härdle, W. K., Wang, W. and Yu, L. (2016) TENET: Tail-Event driven NETwork risk, *Journal of Econometrics*, **192**(2):499–513
13. Zbonakova, L., Wang, W., and Härdle, W. K. (2019), Time Varying Quantile Lasso, *SFB 649 Discussion Paper*,**2016** (047) ISSN 1860-5664
14. Chernozhukov, V., Härdle, W. K., Huang, C. and Wang, W. (2018) Lasso-Driven Inference in Time and Space, *IRTG 1792 Discussion Paper 2018-021, ISSN 2568-5619* Annals of Statistics: revised and resubmitted
15. Zbonakova, L., Monti, R. P., and Härdle, W. K. (2019) Towards the interpretation of time-varying regularization parameters in streaming penalized regression models, *Pattern Recognition Letters***125**:542–548
16. Härdle, W. K., Franke, J. and Hafner, C.M. (2019) Value at Risk and Backtesting, *Statistics of Financial Markets*
17. Hastie, T., Tibshirani, R. and Friedman, J. (2009),*The Elements of Statistical Learning: Data mining, Inference and Prediction*, **2nd ed**(Springer Verlag, New York.)
18. Hollo, D., Kremer, M., and Lo Duca, M. (2012) CISS A Composite Indicator of Systemic Stress in the Financial System, *ECB Working Paper Series***1426**
19. Kristoufek, L. (2013) Can Google Trends search queries contribute to risk diversification? *Scientific Reports***3**:2713 (2013)
20. Leng, C., Lin, Y. and Wahba, G. (2006), A Note on the Lasso and Related Procedures in Model Selection, Statistica Sinica **16**: 1273–1284.
21. Li, Y. and Zhu, J. (2008) L_1-Norm Quantile Regression, *Journal of Computational and Graphical Statistics*, **17**(1):163–185
22. Löffler, G. and Raupach, P. (2018), Pitfalls in the Use of Systemic Risk Measures, *Journal of Financial and Quantitative Analysis***53**(1): 269–298
23. Bassett, G. W., and Koenker, R. (1976) Regression Quantiles, *Econometrica* **46**(1): 33–50
24. Koenker, R., Bassett, G. W., (1978) Asymptotic Theory of Least Absolute Error Regression, *Journal of the American Statistical Association*, **73**(363): 618–622
25. Lombardi, D. and Siklos, P., (2016), Benchmarking Macroprudential Policies: An Initial Assessment *Journal of Financial Stability***27**: 35–49
26. Nieminen, J., (1974), On the centrality in a graph *Scandinavian Journal of Psychology***15**(1): 332–336
27. Osborne, M. R. (1985)*Finite Algorithms in Optimization and Data Analysis*, Wiley Series in Probability and Mathematical Statistics, Chichester, Wiley.
28. Osborne, M. R., Presnell, B. and Turlach, B. A. (2000), On the LASSO and its Dual, *Journal of Computational and Graphical Statistics* **9**: 319–337.
29. Quint, D., Tristani, O. (2017), Liquidity provision as a monetary policy tool: the ECBs non-standard measures after the financial crisis, *ECB Working Paper Series***2113**
30. R Core Team (2019) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna. `http://www.R-project.org/`

31. Tibsirani, R. (1996) Regression Shrinkage and Selection via the Lasso, *Journal of the Royal Statistical Society. Series B (Methodological)*, **58**(1):267–288
32. Wang, H., Li, B. and Leng, C. (2009), Shrinkage Tuning Parameter Selection with a Diverging Number of Parameters, Journal of the Royal Statistical Society: Series B **71**: 671–683.
33. Yu, L., Härdle, W. K., Borke, L., Benschop, T. (2017), FRM: a Financial Risk Meter based on penalizing tail events occurrence, *SFB 649 Discussion Paper* (0003) ISSN 1860-5664
34. Yuan, M. (2006), GACV for Quantile Smoothing Splines, *Computational Statistics & Data Analysis*, **50**: 813–829
35. Zhu, X., Wang, W., Wang, H. and Härdle, W. K. (2019) Network quantile autoregression, *Journal of Econometrics*, `https://doi.org/10.1016/j.jeconom.2019.04.034`

6 Appendix

Table 2 FRM Macroeconomic risk factors in *FRM@Americas* and *FRM@Europe*

(a) *FRM@Americas*	(b) *FRM@Europe*
S&P 500 Index Returns	S&P Europe 600 Index Returns
CBOE Volatility Index (VIX) Returns	Euro Stoxx 50 Volatility Index Returns
REIT Index Returns	MSCI Europe REIT Index Returns
3 months Treasury Constant Maturity Rate Differences	1 year German Treasury Constant Maturity Rate Differences
3 months Treasury Constant Maturity Rate to 10 year Treasury Constant Maturity Rate Spread Differences	German Treasury Constant Maturity Rate 1 to 10 year Slope Spread Differences
Moodys Seasoned Baa Corp Bond Yield Spread to 10 year Treasury Constant Maturity Rate Spread Differences	Barclays Bloomberg EuroAgg Corporate Yield Spread to 10 year German Treasury Constant Maturity Rate Spread Differences
	10 year Italy Treasury to 10 year German Treasury Constant Maturity Rate Spread Differences

Table 3 FRM Preparation, estimation and reporting algorithm steps

(a) FRM Statistics and Data
Obtain past and present index constituents over entire period
Load daily closing prices of selected companies
Load daily market capitalisation in USD
Load daily closing levels of exogenous macroeconomic risk factors
Merge matrix of prices and market capitalisation for all financial markets
Merge Stock price and macroeconomic risk factor level matrices
Calculate the daily return matrix for all selected financial companies and macroeconomic risk factors

function sorting market capitalisation (
 sort market capitalisation table per trading day in descending order
 determine company index number on descending order
 determine respective companies market capitalisation values in USD
)

Save results in three matrices:
 FRM Stock Market Returns
 Market Capitapisation Index
 Market Capitalisation Value

(b) FRM Statistics and Estimation
Load the Stock Returns Data Matrix for all K financial companies
Load the market capitalisation index for all financial companies, sorted by market capitalisation
Load the market capitalisation values for all financial companies, sorted by magnitude
Set the number of largest financial companies J,
 the estimation window size s,
 tail risk level τ,
 number of iterations I
Determine the ending and start date
Count the number of trading days r between the selected ending and start dates
Determine the data matrix row index at the ending date

from start date to end date (
 obtain the daily largest J companies' index number
  for each company j in J
   create the daily data matrix of their stock price returns of the largest J and all L macroeconomic risk factors
   estimate per company active set, λ and design matrix condition number c

Create a data matrix that collects all empirical results:
the matrix has r rows and $K\,(K+2)$ columns,
containing K^2 columns for estimated parameters,
K columns for the estimated λ,
K columns for the estimated condition number c

for example:
$FRM^o Americas$ contains $K = 706$ and the data matrix correspondingly is of dimension $r \times 499848$

(c) FRM Results and Reporting
Load the FRM Empirical Results data matrix
 calculate the FRM measure as the mean of λ for all J companies
 calculate the count of company j being in the active set of all other companies $J-1$
 calculate the count of macroeconomic variable l being in the active set of all J companies
 calculate the mean of c design matrix condition number

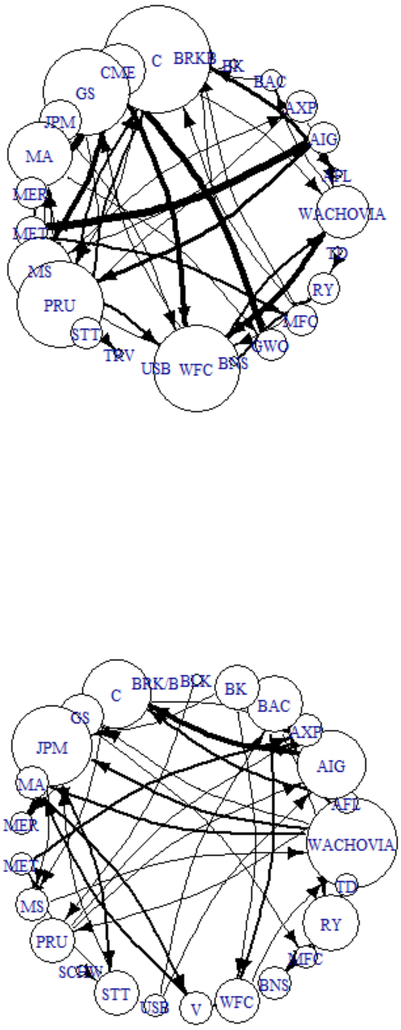

Fig. 7 Depicting the network centrality and link strength
The *FRM@Americas* on 14 March 2008 (top) and 05 September 2008 (bottom)

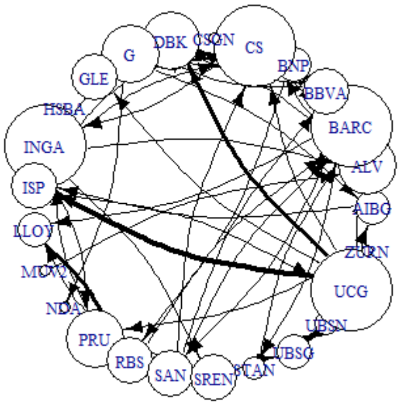

Fig. 8 Depicting the network centrality and link strength
The $FRM@Europe$ on 20 January 2012

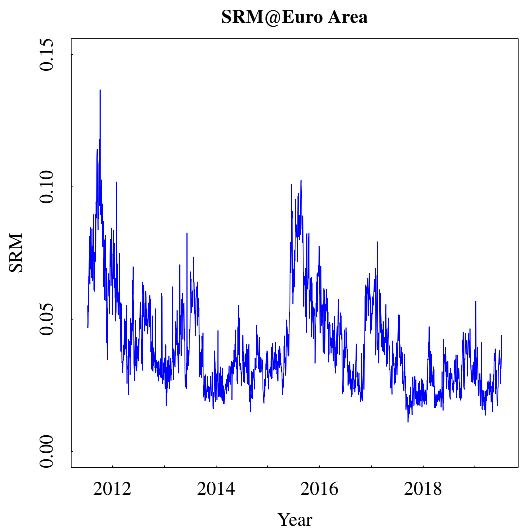

Fig. 9 $SRM@EuroArea$ from 2011 until 2019 for $\tau = 0.05$

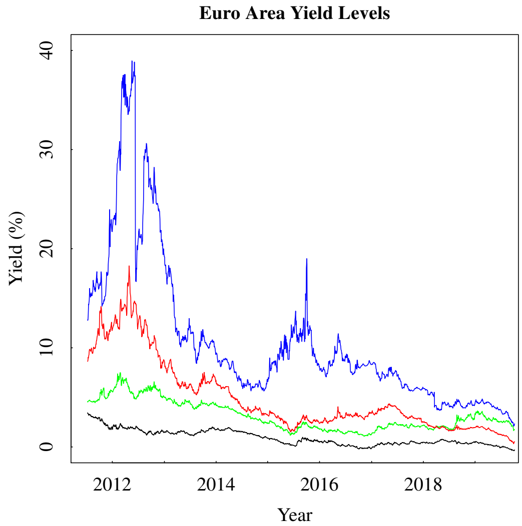

Fig. 10 Ten year government bond yields for Greece, Portugal, Italy, and Germany

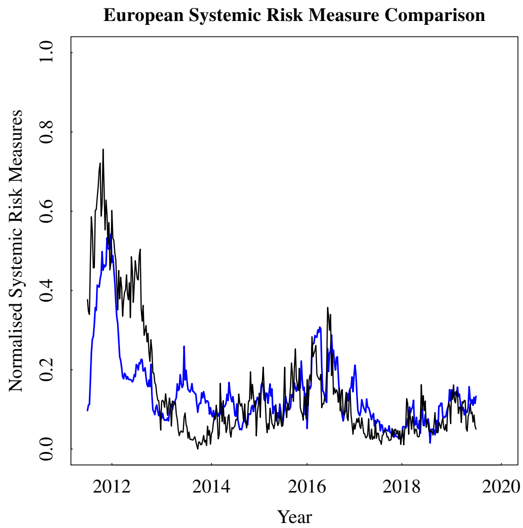

Fig. 11 Average of *FRM@Europe* and *SRM@EuroArea* versus CISS

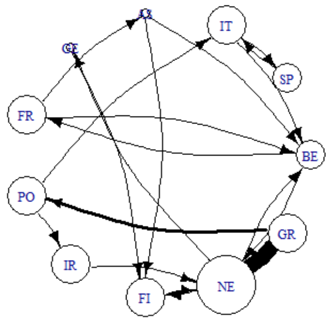

Fig. 12 *SRM@EuroArea* constituent network total degree of centrality May 4th, 2015

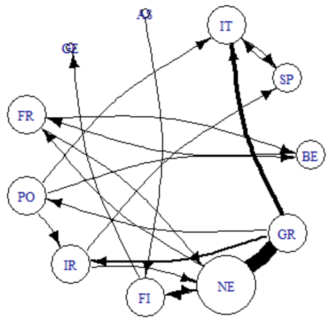

Fig. 13 *SRM@EuroArea* constituent network total degree of centrality July 3rd, 2015

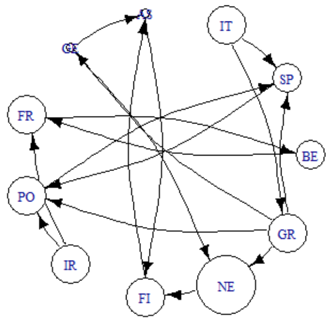

Fig. 14 *SRM@EuroArea* constituent network total degree of centrality July 10th, 2019

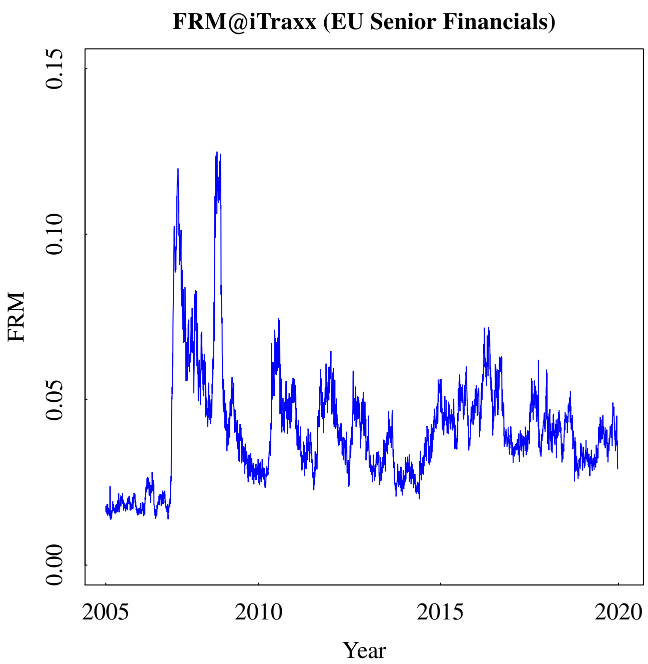

Fig. 15 *FRM@iTraxx* Eu Senior Financials, 25 to 30 financial institutions

	AEGON	ALVGR	ASSGEN	AVLN	AXASA	ISPIM	BACRED	CS	HANRUE	INTNED	MUNRE	PRUFIN	RABOBK	SRENVX	STANLN	RBS	LLOYDS	HSBC	UCGIM	BACR	UBS	BBVASM	BNP	ACAFP	SOCGEN	SANTAN	DB	DANBNK	CMZB	ZURNVX
AEGON		0.131	0.038	0.035						0.117		0.152	0.000													0.184			0.111	0.026
ALVGR			0.419						0.116		0.280		(0.346)											0.052					0.404	(0.000)
ASSGEN		0.226		0.051	0.213			0.040											0.042				(0.133)			0.233				
AVLN	0.248				0.145					0.229		(0.000)		(0.118)				0.118					0.174							
AXASA												0.330	0.216					0.011						0.321						
ISPIM		(0.021)					0.519								(0.063)	0.082			0.311							0.064				0.071
BACRED			0.081		0.112	0.732							0.046	(0.093)	0.009	0.025								0.157	0.051			0.090	0.067	
CS									(0.041)	0.030				(0.000)					0.323		0.082							0.292		
HANRUE		0.123			0.151			(0.331)				0.699									0.141									0.365
INTNED					0.298								0.031	0.003	0.263									0.023					0.025	
MUNRE		0.151				0.015			0.522	(0.107)		0.312		0.054				0.052			(0.063)	0.117						0.240		
PRUFIN	0.070	0.197		0.179	0.175					0.127	0.119							0.355			(0.047)				(0.137)					(0.000)
RABOBK		(0.210)		(0.163)			0.038		0.059			0.250			(0.116)									0.495		0.416			(0.003)	(0.003)
SRENVX				(0.259)	0.168			(0.066)		0.164	0.089		0.041													(0.291)	0.123	0.397		0.349
STANLN	(0.039)		(0.014)						0.192									0.259		0.473			0.114			0.028				
RBS		(0.020)								0.044			(0.032)		0.123			0.000		0.718			0.052							
LLOYDS		0.081					0.038								0.102	0.417		0.220												
HSBC		(0.175)					0.367					0.168			0.476		0.292													
UCGIM						0.699	0.179					0.031				0.023								0.006						
BACR				0.055						0.056				0.045	0.048	0.366	0.297													0.050
UBS		(0.225)						0.543	0.069	0.000			0.022	0.180			0.047					0.015			0.017					
BBVASM													0.015				0.069	0.148								0.207				
BNP		(0.095)				0.129	0.004						(0.013)			0.225		(0.007)	(0.000)					0.795	0.237	(0.119)				
ACAFP											0.014		0.229										0.691		0.133	0.128				
SOCGEN			0.128	0.031															0.132				0.227	0.077		0.286				
SANTAN		(0.105)	0.228	0.060		0.240			0.249				0.000		0.062						0.006	0.301	(0.076)							
DB			0.041		0.064							0.068		0.059			0.049				0.058								0.136	
DANBNK		(0.187)					0.244				0.494		(0.036)	0.097		(0.000)	(0.059)		0.021	(0.369)	0.057									
CMZB		0.002	0.176	0.143		0.265			0.092	0.002									0.129								0.131			
ZURNVX						0.187					0.202			0.261		0.103														

Fig. 16 *FRM@iTraxx* Eu Senior Financials adjacency matrix as of October 7th, 2019

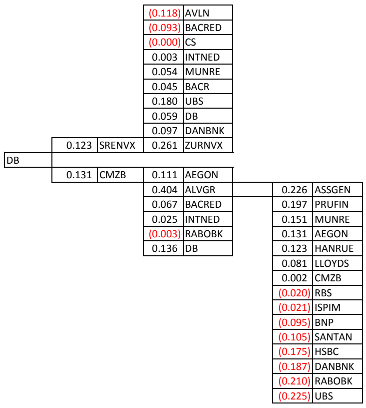

Fig. 17 *FRM@iTraxx* spill-over channel as of October 7th, 2019, activators Deutsche Bank (DB) and Allianz (ALVGR)

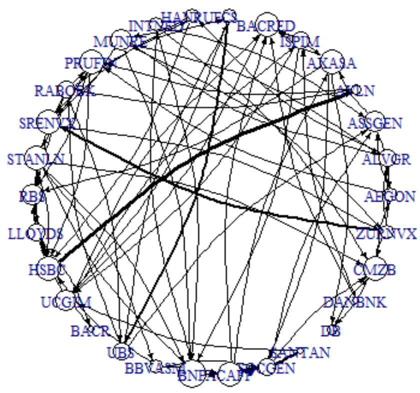

Fig. 18 *FRM@iTraxx* Eu Senior Financials constituent network total degree of centrality October 7th, 2019

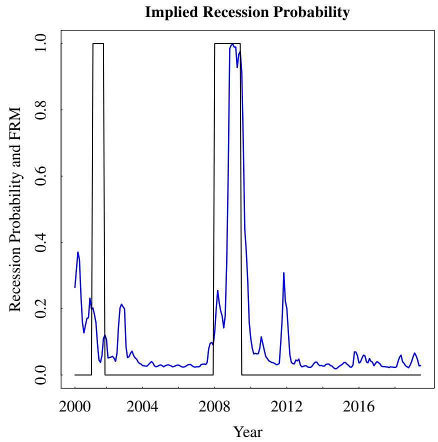

Fig. 19 The FRM-implied recession probability in the US
The implied recession probability from the fitted logistic regression, and dated NBER recession periods

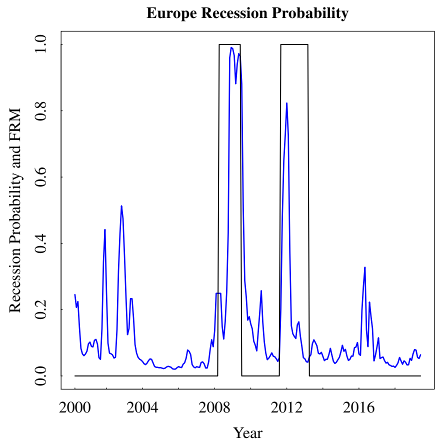

Fig. 20 The FRM-implied recession probability in the Europe
The implied recession probability from the fitted logistic regression, and dated CEPR recession periods

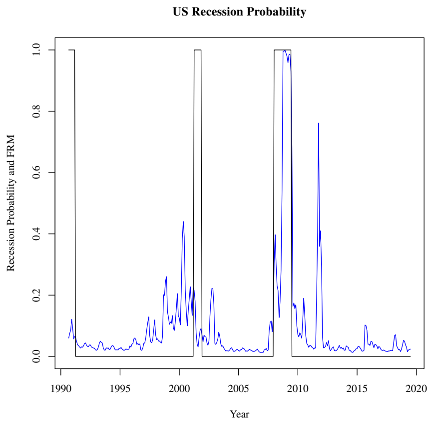

Fig. 21 The FRM-implied recession probability in the US (S&P500)
The implied recession probability from the fitted logistic regression, and dated CEPR recession periods

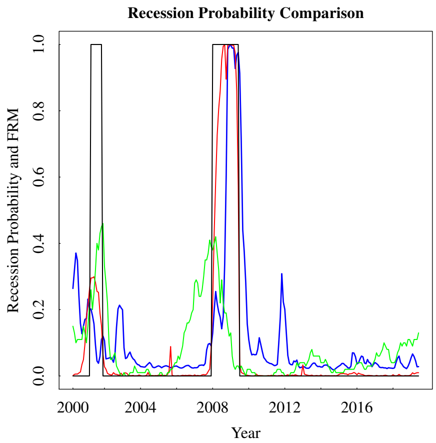

Fig. 22 The FRM-implied recession probability in comparison in the US
NBER recession periods, *FRM@Americas* versus Smoothed US Recession Model, Yield Curve Slope Model