Systemic Risk and Bank Defaults

Assessing the Explanatory Power of
Systemic Risk Measures in Forecasting Bank Defaults

submitted by

Arndt-Gerrit Kund
Department of Bank Management
University of Cologne
Albertus-Magnus-Platz
50939 Cologne

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Contact Details: The author can be reached at kund@wiso.uni-koeln.de or +49 221 470 2628.

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Abstract

This paper contributes to the literature by assessing the predictive power of systemic risk measures (SRM) in the context of bank defaults. Quarterly forward-looking probabilities of default (PD) are estimated for a heterogeneous population of 22,751 banks using a model consisting of only idiosyncratic variables. Under the developed hypothesis, the accuracy of the model should improve, when combining measures of idiosyncratic and systemic risk. Surprisingly, β and $SRISK$ do not improve the performance to exceed a random draw. $\Delta CoVaR$ and MES enhance the accuracy of the model to 99.97%, respectively 99.90%. However, only the latter is statistically significant. In investigating explanations for the findings, bank size becomes a likely determinant. It is suggested that depending on size, banks allot different shares of their risk budget to credit and market risk. The applied metrics capture market risk more accurately than credit risk, which might explain their poor performance, as the majority of banks is rather small. The findings challenge the adequacy of current measures of systemic risk. Furthermore, it allows regulators to prioritize their use of SRM, and identify ailing banks ahead of a possible default. The results are time invariant, and robust against structural distortions such as size and winsorization.

Contents

1 Introduction

Changing perspective can be worthwhile to encourage innovative thinking about established problems. With regards to this paper, it is applied in the context of predicting bank defaults. Current models overly rely on idiosyncratic measures, and account for systemic distress with crisis innate variables. Hence, they become sumptuous when accounting for different crises, as the number of needed variables increases. This paper complements the existing literature by incorporating systemic risk measures (SRM) and thus disposing of the prevalent overfitting. In doing so, a new approach of explaining bank defaults is brought forward. The logic behind this new model is simple, yet compelling. It is assumed that bank defaults can be either idiosyncratically or systemically induced. Both grow independently from another and constitute the overall risk. As a result, they can autonomously induce bank failures by elevating the overall risk beyond the default threshold.

Idiosyncratic risk is the risk that is only borne by the institution in question. Consequently, it can be explained in its entirety by the fundamentals of this very institution. As a result, it is henceforth subsumed that the idiosyncratic risk of a bank can be fully decomposed into a function of balance sheet, as well as profit and loss information. Implicitly, microprudential regulation makes a comparable assumption by relying on fundamental data. In contrast, systemic risk is harder to conceptualize. This paper defines it as the risk that all institutions within a system are subject to, owed to the design of the system. As such, a systemic event occurs when endogenous developments become self-enforcing feedback loops. The risk of materialization in some form of an adverse shock, as for example described by Danielsson, Shin, and Zigrand (2011), constitutes the actual systemic risk. Other definitions focus on exogenous shocks such as interest spikes or unexpected changes to regulation. Examples can be found in the work of FSB, IMF, and BIS (2009), Adrian and Brunnermeier (2011), and Patro, Qi, and Sun (2013).

Throughout the analyzed data, failed banks have had rather steep default paths. Said differently, they appear arguably sound in one period, yet deteriorate alarmingly quickly in the next. Established idiosyncratic models have failed to capture this characteristic, as illustrated by examples such as Lehman Brothers and the like. This paper sets out to remedy this shortcoming. In doing so, a joint modeling approach is postulated that unifies idiosyncratic as well as systemic risk as means of predicting bank defaults. As a result, a holistic model is derived that allows for a pronounced analysis of contributing factors to bank distress.

The resulting contribution is threefold. First, it is investigated in extension to the existing literature whether the incorporation of SRM further enhances the predictive power of default forecasting models. This paper thus bridges the gap between idiosyncratic and systemic risk measures as default predictors. Second, a hierarchy of SRMs based on their predictive power is derived. This is achieved by individually adding them to the best performing model based on idiosyncratic measures and comparing the estimates in sample. Doing so allows policy makers to prioritize between measures and derive meaningful action from it. Third, explanations for the poor performance of the SRM are derived. In doing so, evidence is generated, suggesting that bank size influences how banks allot their risks. Consequently, they are more or less exposed to systemic events in credit or market risk. This observation might explain the poor performance of generic SRM, which do not differentiate between the sources of financial crises. Based on the results, future capital requirements may be computed more accurately as to address the antagonism between capital requirements and competitiveness. Similarly, heightened supervision from the regulator could be justified by identifying ailing banks based on the proposed framework. To the best of my knowledge there are no related publications on a similar topic, nor have there been approaches with comparably complex datasets.

The remainder of this paper is organized as follows. The pursuant section gives a short literature overview on the two topics that are unified in this paper. Initially, models used to predict bank defaults will be presented. After that, the SRMs which will be used to enhance the presented models will be reviewed. Section 3 describes the methodology applied in obtaining the results, while Section 4 outlines the used regression. The robustness of the obtained results will be assessed in the fifth section. The final section concludes and gives an outlook into possible research questions arising from this work.

2 Literature Review

2.1 Predicting Bank Defaults

Predicting bank defaults is a tedious task for a plurality of reasons. Unlike other companies, banks can net their exposures under certain accounting regimes, as it is the case in this dataset. This property leads to a distorted view on the actual exposures a bank may have. It is especially problematic when defaults occur, as the payments do no longer offset one another. As a result, these opaque information shed little light on the health of an institution. Furthermore, a significant imparity between assets and liabilities can be induced by the extend of maturity transformation. It constitutes a concealed default risk that materializes as illiquidity, when the required short term funding to bridge the gaps becomes constrained. In response to these deficits, a multitude of techniques have been suggested to assess the resilience of banks. The used methodologies can be divided in parametric (e.g. Merton-type models, logistic regression) and non-parametric (e.g. trait recognition) measures. A comprehensive discussion of the literature can be found in Giesecke and Kim (2010). An example for a parametric approach would be the work of Tong (2015), who uses a logistic regression on a smaller and more aggregated dataset. He derives the PD by inferring from the logistic regression function after standardizing the regressors to be normally distributed. This may be seen critical, as it changes the underlying distribution of regressors, and might redistribute the data points to be within the confidence bounds in favor of a significant result. As in Zaghdoudi (2013), the used regressors are derived by taking the discriminant analysis of Altman (1968) into account. In accordance with it, Tong finds that certain idiosyncratic ratios perform outstandingly well and contribute excessively to explaining defaults. In the context of banks, this observation is especially true for the return on equity. By plotting the Bayesian Information Criterion (BIC), relative to the number of regressors, Tong assesses the predictive power of his variables. While the function is initially diminishing, it converges towards a constant and does not appear to be convex. This would signal that no minimum has been found, which might hint at an omitted variable. As the model only consists of balance sheet information, this finding supports the hypothesis that the incorporation of SRM might further enhance the forecasting power by remedying the omitted variable problem. Consequently, this observation can be interpreted as evidence in favor of the model postulated in this paper.

A related methodology has been applied by Cox and Wang (2014). They enhance Altman's discriminant analysis by applying the "leave-one-out estimation" for cross validation. Comparably to the out of sample validations applied in time series data, one observation of the population is left out when estimating the parameters. This is repeated until each observation has been left out once. As a result, there are as many equations as observations. The aggregate error over all these equations can be collected and minimized with regards to the β error. Their method thus increases the likelihood of not overseeing an ailing bank. Despite this favorable property, their model should be taken with a grain of salt. It is centered around the recent financial crisis and the model specification correlates significantly with the drivers of the crisis. High loan growth, especially in real estate, as well as foreclosure rates, might preform well as predictors for this crisis, but underperform in other crises.

Another strand of the literature concerns non-parametric models. In this context, the work of Kolari et al. (2002) is noteworthy. They apply a trait recognition model and compare its performance to a logit model for large banks in excess of USD 250 million total assets. While both behave well in sample, the performance of the logit model deteriorates out of sample. As a result, they conclude that trait recognition is the superior method in this context. However, trait recognition yields contentious results owed to the underlying partitioning. Based on metrics such as standard deviations, cut off points are derived as to classify the data. The partitioned data is then split in groups on the basis of the previously specified traits. This procedures appears arguably arbitrary and comes short of possible economic explanations.

In conclusion, predicting bank defaults remains difficult despite the contributions of the cited literature. The meaningfulness of the provided variables is often low owed to netting rules under prominent accounting regimes. As a result, the variables become opaque and less informative. Furthermore, banks have steep default paths, making it difficult to foresee the occurrence of bankruptcy. Addressing these issues has yet to yield a satisfactory model. Despite performing well, the presented models are subject to individual shortcomings and limitations. Tong (2015) owes a clarification with regards to his normalization approach as well as the convexity of his maximum likelihood function. Moreover, the used regressors in his model are not stable over time. Cox and Wang (2014) produce a sound model, which however is overexposed to the recent financial crisis and thus questionably specified. Kolari et al. (2002) bring forward a robust model for banks in excess of USD 250 million, which is yet to be validated for smaller banks.

2.2 Quantifying Systemic Risk

Having given an overview of default prediction models in the previous section, this paragraph presents the SRM by which the initial model will be amended. In order to discuss measures of systemic risk, it will be contoured first. As per the introduction, systemic risk in the context of this paper is understood as the risk of distress that is faced by all institutions in a given system, owed to the design of the system. While the exposure of an individual institution during the materialization of the systemic risk event can be ambiguous, it is certain that it is faced by all institutions. Measuring systemic risk per se is intricate because it can only be quantified ex post, and latent states can only be estimated, but not verified through observation. Because of this property, it is difficult to benchmark the suggested metrics owed to a lack of realizations. The modeling approach pursued in this paper relies on the assumption that the latent states can be modeled, as to allow for the suggested decomposition of the overall risk into systemic and idiosyncratic risk.

With an initial definition given, the following paragraphs will focus on four distinct measures and review how systemic risk can be measured in more detail. Generally speaking, there are two possible approaches. On the one hand side, a systemic approach, which focuses on the distribution functions of banks and markets. On the other hand side, a systematic approach that assesses the correlation and covariance of bank and market returns as pointed out by Brownlees and Engle (2016), as well as Acharya et al. (2017). As such, it relates to an ubiquitous risk that cannot be diversified by market participants. These approaches can be further distinguished in macro- and microprudential measures. While macroprudential measures quantify systemic risk in the context of the market as a whole, the microprudential measures assign each member of the market a share of systemic risk. For the purpose of this paper, the latter category is of interest, as it allows to conclude on the riskiness of an individual bank. In spite of the plurality of metrics that have been postulated in the literature, β, $\Delta CoVaR$, MES, and SRISK, will be analyzed in more detail in the following. They were chosen among other for their acceptance and feasibility in the context of the research question.

For the purpose of completeness, it shall be said, that there are other strands of the literature that propose even more measures of systemic risk. Noteworthy examples are the work of Billio et al. (2012), and Patro, Qi, and Sun (2013) who assess correlation matrices. Furthermore, measures relying on the spreads of credit default sawps (CDS) are postulated by Huang, Zhou, and Zhu (2009), as well as the CoRisk technique of Chan-Lau (2010). However, they are excluded from the analysis because they cannot be computed for the majority of the analyzed institutions owed to the lack of tradable CDS in the institution. A more detailed overview regarding the universe of suggested SRMs can be obtained by the work of Hartmann and de Bandt (2000), in the ECB Financial Stability Review (2010a, b), respectively Bisias, Flood, Lo, and Valavanis (2012).

Initially, β as in the CAPM model shall be addressed. It can be understood as a measure of the sensitivity of a stock relative to changes in the market it trades in. To this day, it is used for its ease of interpretation and influences more recent measures such as SRISK by Brownlees and Engle (2016). Formally, β is defined as the covariance of the returns of a company (R_i) and the market (R_m), divided by the variance of the market returns:

$$\beta_i = \frac{Cov\left(R_i, R_m\right)}{Var\left(R_m\right)} \tag{1}$$

CoVaR, as described by Adrian and Brunnermeier (2011), is the abbreviation for the conditional, contagion, respectively comovement of the Value at Risk (VaR) of an individual institution relative to the financial sector. For the purpose of this paper $\Delta CoVaR$ will be analyzed in more detail. It measures the marginal contribution of an institution to the aggregate level of systemic risk. The computation involves multiple steps. Initially, a lagged vector M_{t-1} with the state variables is calibrated. It contains among other volatility, liquidity, and return measures to approximate the health of the market. It may be critically noted, that this vector might have to be adjusted in other studies as it is centered around the volatility and return characteristics of the S&P 500, respectively the three month U.S. treasury rate and consequently just shows different sides of the same coin. In a next step a quantile regression of the state variables on the stock return of the analyzed bank is run. The superscript i denotes the bank, while the subscript t refers to time. $\hat{\alpha}$ constitutes the intercept and $\hat{\gamma}$ captures the coefficients that are used to predict the VaR to the quantile that has been specified in the quantile regression. As such, it is very efficient, as the estimation error is minimized at the specified quantile.

$$VaR_t^i = \hat{\alpha}_t^i + \hat{\gamma}_t^i M_{t-1} \tag{2}$$

Subsequently, the return of the analyzed bank is regressed along the state variables on the market return. In doing so, an estimate for β is obtained, that is used to weight the difference of the bank specific VaR at a certain quantile denoted by q.

$$\Delta CoVaR_t^i = \hat{\beta}^{system|i}(VaR_t^i(q) - VaR_t^i(50\%)) \tag{3}$$

As a result, one obtains the risk adjusted downturn return of the analyzed institution, relative to the market, or more generally speaking the marginal contribution to aggregate systemic risk.

Another metric that assesses systemic risk is the marginal expected shortfall (MES). It borrows from the expected shortfall (ES), which is the equally weighted average of the returns in excess of the VaR computed to an ex ante defined quantile (q). As ES is an idiosyncratic variable, some sort of transformation is necessary to derive a systemic measure. This is achieved by sorting the return vector of the market and calculating the mean of the corresponding values from the return vector of the bank that are in excess of the confidence level initially specified. The information which values are to be contained is denoted by the vector I.

$$MES_q^i = -\mathbb{E}\left[r_{bank} \mid I_{market,q}\right] \tag{4}$$

Since the distribution function of the market and bank return do not necessarily move in lockstep, the market returns might be significantly different from the returns of the bank. As a result, the ES of the bank is obtained relative to the worst outcomes of the market and not the worst outcomes of the bank itself. Consequently, the marginal contribution of the bank in the event of a market downturn can be assessed. This is a significant advance over former Merton-Style models, where the capital shortfall of an individual bank was calculated, without taking the market into consideration.

Finally, SRISK, as postulated by Brownlees and Engle (2016), will be discussed. It is defined as the expected lack of funding a bank experiences during an extended market down turn, henceforth referred to as the Long Run Marginal Expected Shortfall (LRMES). More specifically, they calculate the expected capital shortfall conditional on the occurrence of a systemic event, denoted by c. They define the materialization of systemic risk as a decline in asset prices of 10% over the course of a month. In this context, it can be understood, as yet another extension of the initially discussed ES. That is to say that the LRMES is the expected value of returns worse than c, adjusted for individual risk through β, as well as time through $\sqrt{h}$.

$$\begin{aligned} LRMES_{i,t} &= -\sqrt{h}\beta_i \mathbb{E}\left(r_{m,t+1} | r_{m,t+1} < c\right) \\ & \qquad with\, \mathbb{E}\left(r_{m,t+1} | r_{m,t+1} < c\right) = -\sigma_m \frac{\phi\left(c/\sigma_m\right)}{\Phi\left(c/\sigma_m\right)} \end{aligned} \tag{5}$$

In this notation ϕ refers to the density, and Φ to the distribution function of a standard normal distribution. σ_m measures the market volatility. After obtaining the LRMES, it is incorporated in the calculation of SRISK by multiplying one minus LRMES times the adjusted equity ($E_{i,t}$) accounting for the regulatory capital fraction k. In accordance with Brownlees and Engle (2016) it was set to 8% as approximated from the Basel accords. Pursuant, the term is deducted from the market valued debt ($D_{i,t}$) times the regulatory capital fraction. Formally:

$$SRISK_{i,t} = kD_{i,t} - (1-k)\, E_{i,t}\left(1 - LRMES_{i,t}\right) \tag{6}$$

By doing so, one obtains a SRM that contains balance sheet information (Debt and Equity), as well as market information as judged by the returns observed in LRMES. SRISK can thus be understood as the funding gap between debt and equity in the case of a systemic event. Said differently, SRISK is the required capital to survive the materialization of a market downturn with the severity c. In this interpretation, it is floored to zero, as to indicate, that a bank has no funding gap. Doing so allows to compute the percentage contribution (SRISK %) of a bank to the overall systemic risk by dividing the bank related SRISK through the aggregate system-wide SRISK:

$$SRISK(\%)_{i,t} = \frac{max(SRISK_{i,t}, 0)}{\sum_{i=1}^{I} max(SRISK_{i,t}, 0)} \tag{7}$$

However, systemic risk is overestimated because of this constraint, as the negative contribution of banks without a funding gap is left out. A negative value would thus indicate the resilience of a bank in excess of c. This suppressed interpretation is troublesome in the context of the analyzed dataset. It contains many small banks that arguably behave counter cyclical and thus appease the severity of downturns. Regarding the postulated regression, the error aggravates, as the estimated PD of counter cyclical banks should be lower during such periods, which cannot be accounted for owed to this technicality of SRISK.

In conclusion, the most common SRMs have been presented. All of them have individual strengths and weaknesses and should thus be taken with a grain salt. One of the most common critiques is that they fail to address all dimensions of systemic risk. That is to say that they may be good at estimating losses on a bank level in the case of a systemic event, yet fail to capture the pursuant contagion that ricochets through the financial system. Another critique, as voiced by the ECB (2010b), concerns the problem of identifying the masked growth of systemic risk. Imbalances in the financial system tend to build up gradually and unnoticed, yet materialize suddenly. In this context Adrian and Brunnermeier (2011) mention the volatility paradox. Systemic risk tends to build up during times of low volatility, which suggests sound markets, whereas the observation should actually be understood as a call for caution as a systemic event might be about to unfold. Daníelsson (2013) affirms this concern, and argues that systemic risk develops, despite all indicators making us believe otherwise.

3 Methodology

The analyzed data are a compilation of the Uniform Bank Performance Reports (UBPR) from the Federal Financial Institutions Examination Council (FFIEC). The dataset covers commercial and saving banks in the United States of America from 1980 until 2013. By merging profit and loss information with balance sheet data, a sample of 22,751 banks with observations on a quarterly basis is obtained. In doing so, the CERT key was used as unique identifier as it had the same cardinality in both datasets. Pursuant, the initial population is amended with information from the "Failed Bank List" as published by the Federal Deposit Insurance Corporation (FDIC). Doing so allows to conclude on the quarter of default and to mark the corresponding observation in the sample. Additional defaults were identified by investigating banks with negative equity at the end of the reporting period that were not tagged as defaulted, because they were acquired. Nevertheless, a de facto default occurred which is why they were henceforth referred to as bankrupt. The dataset has a plurality of favorable properties. While it is usually not desirable to have an unbalanced sample, it here is a positive characteristic. It means that there are plenty of defaults to observe, which allows the model to be reliably calibrated, and not only depend on a few extreme outliers that defaulted. Over the analyzed period, 1,983 banks defaulted, which translates to roughly 15 defaults per quarter. Furthermore, all banks in the sample are subject to the same set of regulations, which allows to rule out possible inference from different accounting or regulatory regimes. Lastly, limitations as in Kolari et al. (2002) are not applicable, as the dataset consists of banks of different sizes and specializations. Consequently, universal conclusions can be drawn from the findings.

In a next step, the population is amended by additional metrics. The leverage ratio (LR) is calculated as total equity divided by total assets. Furthermore, the return on assets (ROA) is computed as the ratio of net income to total assets. Moreover, the cost income ratio is derived as operating income divided by operating expenses. The percentage of non performing loans (NPL) is computed by dividing the sum of past due and non accruing loans by the total loan volume. Ultimately, the loan to deposits ratio (LTD) is calculated as the quotient of total loans and total deposits. In order to derive these measures, the reported figures were disaggregated on a quarterly basis, as they were previously reported accumulative.

With the intent to further quantify the resilience of a bank, the degree of income diversification is measured as the ratio of non interest to interest income. If earnings are well diversified, interest rate shocks as observed during the savings and loans crisis are expected to be less devastating to the bank's bottom line. Brunnermeier, Dong, and Palia (2012) support this assumption, by showing that less income diversification leads to a higher contribution to systemic risk.

$$r\_income\_div_{i,t} = \frac{non\ interest\ income_{i,t}}{interest\ income_{i,t}} \tag{8}$$

An initial deliberation considered the inclusion of the Net Stable Funding Ratio (NSFR), respectively the Liquidity Coverage Ratio (LCR), as additional regressors. It was refrained from doing so owed to the lack of sufficiently granular data for a robust computation of the measures. Nevertheless, it would have been a desirable test, as to assess, whether the postulated measures do indeed quantify bank resilience.

For the implementation of the SRMs, it is necessary to transform book to market values. This is achieved by multiplying the book values times a multiple. The multiple consists of the inverse of the market to book-ratio for the bank sector, as provided by the Fama-French 48 industries index. It is amended by the bank specific compounded annual growth rate (CAGR) in order to account for individual differences between the banks. CAGR is defined as the quotient of the last reported assets over the first reported assets to the power of one over the observed periods, minus one.

$$\begin{aligned} multiple_{i,t} =& \frac{1}{Market\ to\ Book\ Ratio_t} + CAGR_i \\ & with\ CAGR_i = \left(\frac{assets_{i,T}}{assets_{i,t}}\right)^{\frac{1}{T}} - 1 \end{aligned} \tag{9}$$

The intuition behind it is simple: it is assumed that investors are willing to pay a premium in excess of the average price for banks that are outgrowing their peers.

The observed multiples are fairly low, as illustrated by the fact that only about 50% of the data trade at a multiple relative to their book value. Owed to the absence of significant intangible values, this characteristic seems reasonable and is in accord with what can be observed on financial markets. Furthermore, banks can be viewed as institutions with a multitude of receivables, which are unlikely to trade in excess of their nominal value, as would be needed to justify a multiple larger than one.
As can be seen in Figure (1), the approximated multiples inflate in relation to the occurrence of asset pricing bubbles. This is interpreted as further evidence for the robustness of the applied transformation, as high multiples coincide with systemic crises as shown by Döring and Hartmann-Wendels (2016). The possibility of a measurement error that would systemically bias the computed multiple was discussed. The deviations between estimates and actual values – where available – however were only marginal. The theoretical and empirical values were tested for an equal mean, using a two-sided t-test, and found to be significant to a confidence level of 93.47%. It is thus assumed that the influence on pursuant calculations can be neglected.

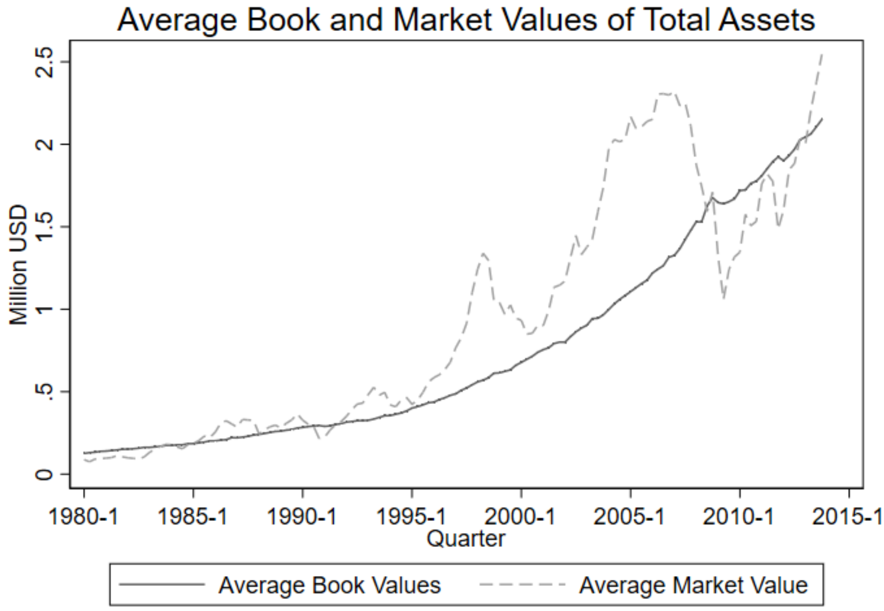


Figure 1: Average Book Value versus average Market Value of Assets.

With regards to the information vector M for the CoVaR Model the methodology of Adrian and Brunnermeier (2011) is repeated except for minor alternations. The missing data for the S&P 500 Volatility Index (VIX) are interpolated through regressing the VIX on the S&P 100 Volatility Index (VXO) and then predicting the periods in question through the regressors. However, in order to calibrate the regression, the used time frame is expanded to 2015 to account for more recent information. Owed to the lack of access to the three-month repo rate as in the original

paper, the difference between the federal funds rate and the three month bill rate is used to approximate the liquidity spread. As a positive side effect of doing so, back-dating LIBOR data for calibration purposes becomes obsolete.
In order to calculate returns, the theoretical market value of the equity was divided by the number of available common shares reported per bank. Despite the majority of banks not being listed, they have issued shares, which were used as a proxy. From this assumption, it was possible to proxy the market return as the total asset-weighted theoretical return. As a result, it became possible to calculate β.

If not indicated differently, the assumptions of the original authors have been reapplied in deriving the necessary metrics. That is to say that the threshold for c and k in the SRISK model were ten, respectively eight percent.

Ultimately, the values of cash, equity and loan exposure were logarithmized to account for differences in size as banks such as JP Morgan and Bank of America added significant skewness. Column (1) of Figure (2) depicts the raw data in million USD and illustrates the need for such transformation. With a kurtosis of 22,725.46, and a skewness of 125.45, cash has the highest asymmetry. The logarithmic values depicted in column (2) show the success of the transformation. With a skewness of 0.94, and a kurtosis of 5.86, cash behaves arguably symmetric with noteworthy tails.

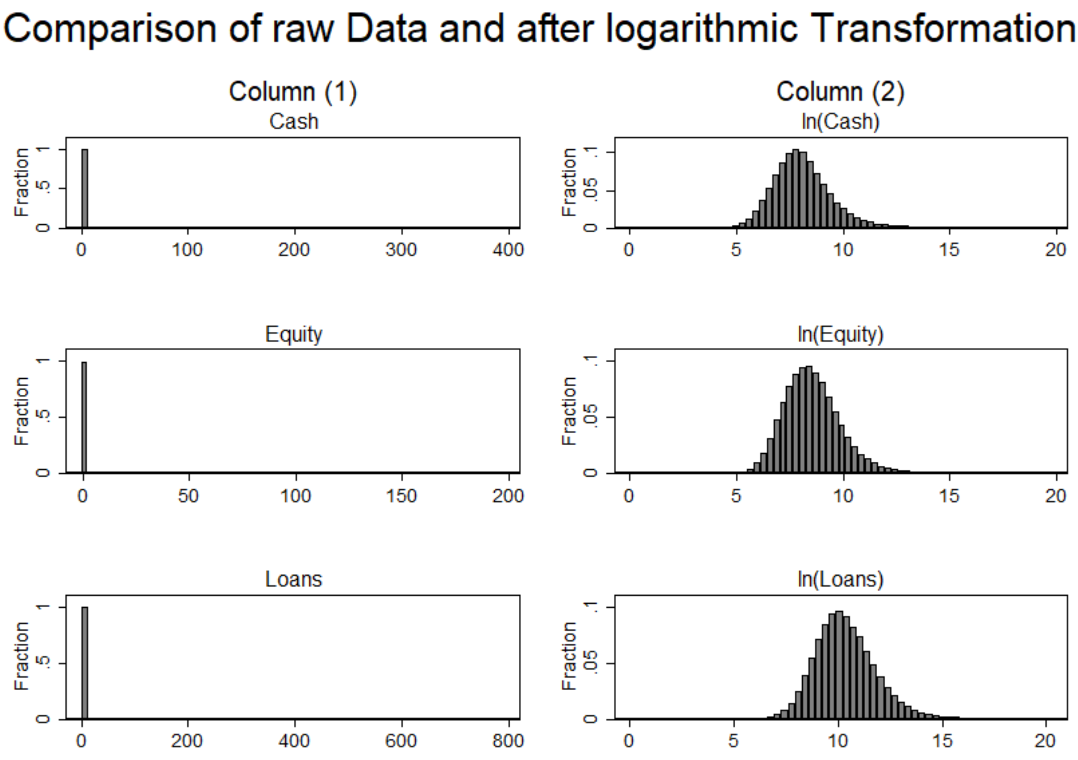


Figure 2: Adjusting size-sensitive Variables.

4 Model and Interpretation

4.1 Regression Model

As Haldane and Madiros (2012) argue, complexity creates uncertainty rather than manageable risk. Because of this deliberation, the current complexity of the financial system should not be addressed with even more voracious models. To the contrary, a parsimonious model with a simple explanation should be preferred over more complicated ones, as to not suggest a false degree of sophistication. As Pakoke (2014) has shown, the simplest models, in the context of systemic risk, tend to yield the highest explanatory power. In light of this, the suggested model is kept rather simple and can be summarized as follows:

$$D_{i,t} = \underbrace{f(balance\ sheet_{i,t-1}) + g(profit\ and\ loss_{i,t-1})}_{idiosyncratic\ risk} + \underbrace{h(SRM_{i,t-1})}_{systemic\ risk} \tag{10}$$

It is theorized that the default of a bank i at time t ($D_{i,t}$) can be fully explained by a probit regression of idiosyncratic and systemic risk measures of the previous period on the default indicator. Doing so allows to postulate a forward looking model from which predictions can be derived. Out of the multitude of possible specifications, the variables presented in equation (11) were chosen as idiosyncratic variables that constitute the universal base model. In deriving it, the deliberations of Haldane and Madouros (2012), who showed that market measures can help explain resilience towards adverse shocks, were vital. Likewise, the findings of Demirgüc-Kunt (1989), Wheelock and Wilson (2000), and Cebula (2010) were relevant in understanding which accounting information to include.

$$\begin{aligned} D_{i,t} =& \alpha + \beta_1 ln(cash) + \beta_2 ln(equity) + \beta_3 ln(total\ loans) + \beta_4 NPL\% \\ &+ \beta_5 costinc + \beta_6 incomediv + \beta_7 ltd + \beta_8 roa + \epsilon \end{aligned} \tag{11}$$

The goal was to balance the fit of the model without overcalibrating it, so that room for improvement through the addition of SRM is left. Doing so prevents a technicality which renders it impossible for systemic risk to become significant. Said differently, it allows to refute the critique that the contribution of systemic risk is underestimated owed to an already excellent fit. As a result, four different models were obtained, consisting of the initial model, of which the right hand side of the equation was amended by β, $\Delta CoVaR$, MES, and $SRISK$ (%) respectively.

$$Equation\ (11) + \beta_9 \beta_{CAPM} \tag{12.1}$$

$$Equation\ (11) + \beta_9 \Delta COVAR \tag{12.2}$$

$$Equation\ (11) + \beta_9 MES \tag{12.3}$$

$$Equation\ (11) + \beta_9 SRISK\ (\%) \tag{12.4}$$

Moreover, the decomposition in idiosyncratic and systemic risk allows for a compelling economic interpretation. Assuming that they are statistically independent from another, this paper needs not rely on overspecification of the idiosyncratic variable as in previous studies. Instead, systemic risk can be high, when idiosyncratic is low and vice versa. As both constitute the overall risk which triggers default, this premise allows for an elegant minimization of the forecasting error and remedies shortcomings of current papers. Figure (3) graphically illustrates the previous deliberations.

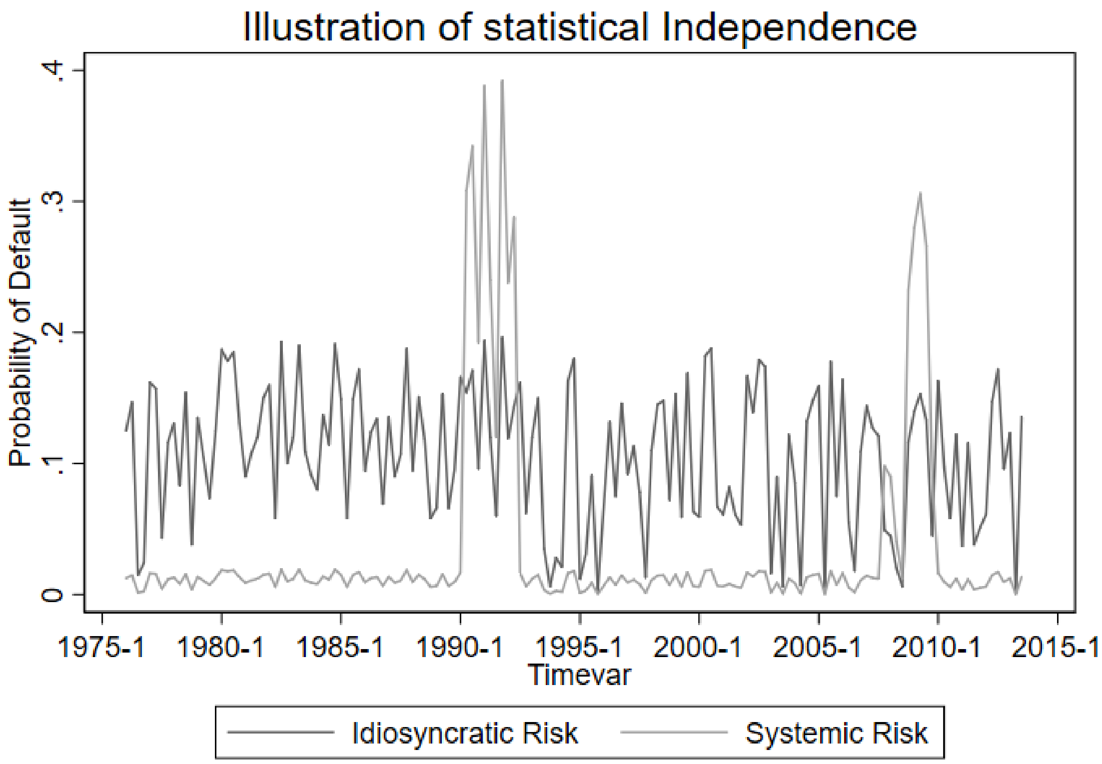


Figure 3: Statistical independence between idiosyncratic and systemic risk.

Furthermore, it solves another issue as it is unknown ex ante, whether idiosyncratic or systemic risk is the bigger contributor to the probability of default. The weighting of the idiosyncratic and systemic summand could thus only be done ex post. Acharya et al. (2017), find evidence that hints at systemic risk being the stronger influence, as their idiosyncratic variables become less significant when systemic risk is incorporated. However, some part of explanatory power is expected to be lost in one variable, when another is introduced that arguably captures the underlying effect more exactly. In line with this notion, no scaling of the types of risk was done. To the contrary, it is argued that the scaling is being accounted for by the coefficients of the respective variables.

4.2 Interpretation of Coefficients

Table (1) about here

As can be seen in Table (1), most of the regressors are highly significant and their coefficients are in line with theory. More cash and equity increase the resilience of a bank, all else being equal except for a deviation in the case of MES and $\Delta CoVaR$. Instead, income diversification determines bank stability in their cases. To the contrary, a higher exposure to loans translates to higher default risk. If the loan exposure contains a substantial proportion of non performing loans, the default risk is aggravated. Judged by the high coefficient of NPL, it contributes strongly to default, as also found by Wheelock and Wilson (2000). The cost-income-ratio at the other hand mitigates bankruptcy risk. Again, the coefficient is in line with expectations. A bank with a lower cost-income-ratio can be expected to work more efficiently and to consequently be less susceptible for a solvency induced bankruptcy. The same argumentation can be applied to ROA. If a bank is capable of producing a higher return on a given set of assets, it operates more efficiently, and has more potential to retain profits from the same assets. A comparable finding has been made by Zaghdoudi (2013). It is surprising that the coefficient deviates strongly between the idiosyncratic and joint model. Ultimately, a higher leverage ratio translates to more equity relative to the total assets. This can be understood as additional shock absorbing capacity and should thus reduce default risk, as it is the case in the model.

Unexpectedly, income diversification does not make a bank more resilient as judged from a statistical perspective except for MES and $\Delta CoVaR$. In these models, the explanatory power of equity fades to the benefit of income diversification. Still, the coefficient remains ambiguous, impeding a stringent explanation. A possible, yet contentious interpretation would be that a more even distribution between interest and non interest income would make a bank sounder, as shocks in one income class can be absorbed by the other. Consequently, the negative coefficient could be explained. Likewise, it is surprising that a larger portion of deposits relative to outstanding loans, does not result in a safer bank, speaking from a statistical point of view. It would be expected, that more deposits constitute a higher reliability of capital and thus reduce the funding risk in times of constrained liquidity.

With regards to the SRM which were used as additional regressors, it is found that none of them except for MES yielded significant additional explanatory power. This result is puzzling and against expectations. In fact, as can be inferred from the $p-values$ denoted in the brackets, none of them is close to becoming statistically significant. A possible explanation for the performance of MES might relate to the underlying methodology. It conditions returns of the bank on the state of the market. As a result, it accounts for market as well as bank specific characteristics. In spite of issues such as netting, the topology of balance sheet information appear particularly valuable for estimating the health of a bank. In general, the findings are in line with Pankoke (2014) who shows, that simple systemic risk indicators such as market capitalization and market leverage tend to outperform sophisticated ones.

The results were validated by comparing them to empirical observations. In order to do so, the estimated PDs are transformed into a dichotomous variable such as the observed default dummy. The cut off point was chosen by applying the trivial solution. All PDs in excess of 50% took the value of one, indicating default. Everything below the threshold received a non-default tag as indicated by a zero. The logic behind it is simple: the dummy should reflect, whether it is more likely than not, that the bank defaults. The number of predictions per group were then scaled relative to the total population as to equal 100% in total. Doing so allows to assess the accuracy of the model, as shown in Table (2) of the appendix. Furthermore, it remedies intricacies in the interpretation that stem from different sample sizes. Not all measures could always be calculated, owed to differences in the availability of the necessary data. However, irrespective of the number of observations, the predictive power only differs marginally between the models. β and $SRISK$ yield the worst performance with an accuracy ratio of 99.87%, which is equal to a random draw. This finding is plausible, given that both SRM are insignificant in the respective models. MES increases the performance to 99.90%, with $\Delta CoVaR$ performing best, with an accuracy ratio of 99.97%. The results are consistent, as MES is the only significant SRM, and $\Delta CoVaR$ is relatively close to significance. Evidence against a significant omitted variable is generated, as the predictive power is already substantial, and the information criteria increase, when introducing an additional regressor to the base model. The added value of the SRM however is only marginal and does not significantly improve the results, except for MES. Furthermore, it is unclear to what extend it helps reduce the α, respectively β error, as shown in Kolari et al. (2002). Given the principle of prudence, one would prefer the false prediction of a default relative to its unpredicted occurrence. Cox and Wang (2014) show a way of mitigating this issue by the means of a discriminant analysis. In applying this technique, it was found that the optimal default threshold for minimizing the probability of overseeing a bank default is as low as 1%. However, by definition, this increases false predictions of default by orders of magnitude owed to the inherent trade off between the errors. Moreover, the overall model performance deteriorates below a random draw.

Table (3) about here

Ultimately, the information criteria (AIC, BIC) are interpreted regarding the model outcomes. The most favorable model should have the lowest possible IC. However, owed to different methodologies, not all models have the same amount of information available. As the number of observations is a parameter in the calculation of BIC, a comparison of the models would not be possible. Therefore, it was decided to rerun the regression on those data points where information were available for all tested models. This led to a reduction of the sample size from up to 1,138,248 observations (β) to 550,324 joint observations. As a result, the coefficients as described in Table (3) of the appendix were derived. Again, it can be inferred that the models only differ marginally, which seems plausible, given that none of the SRM were significant and comparable likelihood functions have been estimated.

5 Robustness Tests

5.1 Size Effects

In order to validate the findings from the previous section, a plurality of robustness tests were conducted. Given the multitude of different types of banks, one issue is unaccounted for heterogeneity, which might manifest in systematic differences in the causes of default for small and large banks. Indeed, dividing the sample in its quartiles as judged by total assets shows that default peaks occurred at different periods for different bank sizes, as illustrated in Figure (4). Starting with the smallest quarter of observations in peer group one, the number of defaults per quarter has been plotted over time.

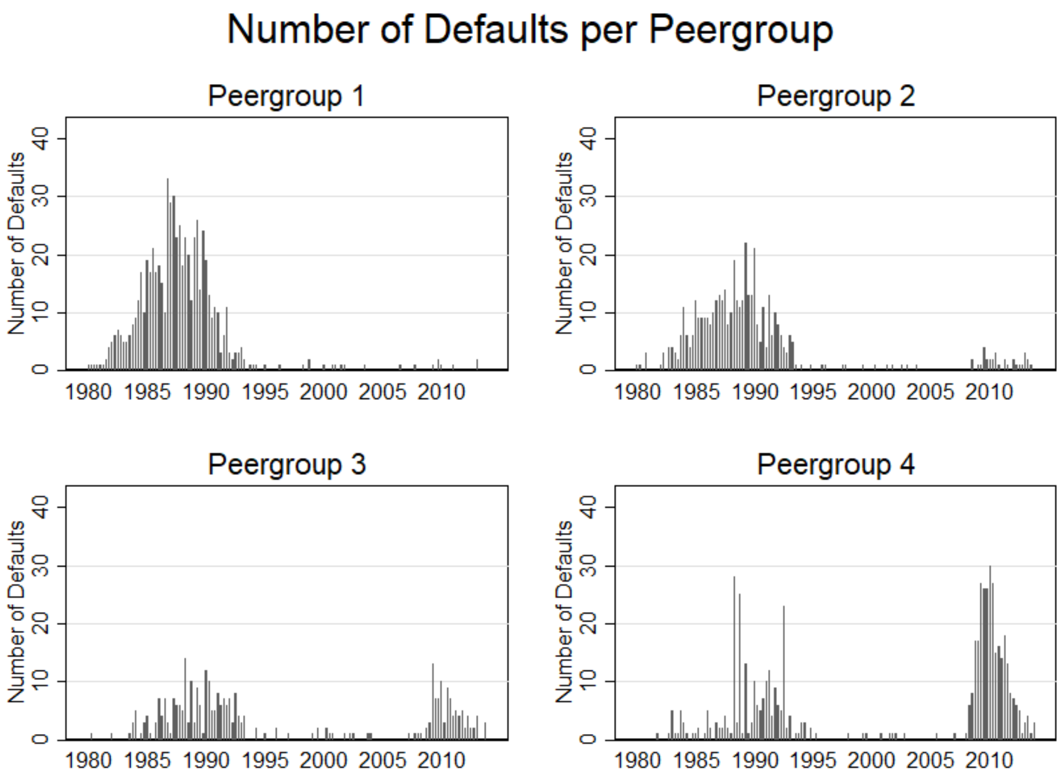


Figure 4: Number of Defaults per Peergroup over Time.

The first peer group is very sensitive to interest rate shocks and consequent defaults as prevalent during the S&L crisis of the 1980s. However, they do not seem to be influenced by the recent financial crisis. In contrast, the last peer group, containing the largest banks in the sample, was less exposed to the S&L crisis, though suffered undoubtedly from the subprime crisis. This observation might be due to different business models. While smaller banks focus on deposit taking and loan granting, larger banks are rather oriented towards the capital market. They make a large share of their assets tradable through securitization, which transforms the credit risk entailed in loan origination into market risk. When credit losses in real estate loans were soaring during the subprime crisis, this surge manifested as market risk, with mounting losses in asset-backed securities. In general, a monotonic trend can be observed, when moving from smaller to larger banks. The larger the bank, the less susceptible it is to the interest rate shocks of the 1980s and ensuing credit losses. At the same time, its vulnerability to market risk grows. Banks appear to have a risk budget, which shifts credit to market risk, with increasing size. Stringently, there are only little defaults to be observed in peer group three, as it has an efficient mixture of credit and market risk. Because of this feature, it achieves the highest degree of diversification and thus resilience towards shocks.

In order to validate these deliberations, the regressions from Equations (12.1) to (12.4) have been recalibrated including the peer group as proxy for size. If no such effect were to exist, the dummies should not be significant.

Table (4) about here

As can be inferred from the table, the added dummies are all significant, except for the case of $\Delta CoVaR$. In all cases, but the latter, size is a noteworthy characteristic that determines bank resilience. On further investigation, it is shown that all of the coefficients are negative and rising, except for peer group four. In line with previous deliberations, this finding suggests that the benefit of substituting credit for market risk peaks in the third peer group and turns negative for peer group four. Such an interpretation matches the graphical evidence from Figure (4). However, a more thorough analysis highlights another important characteristic. While the dummies are statistically significant, they do not change the actual dynamics that are observed. In comparing the original model from Table (1) and the amended model from Table (4), it is obvious that the reported coefficients have not changed. The direction of the found effects remains stable, as does the magnitude of the effects. Only two deviations in terms of magnitude can be identified. Cash becomes less significant in the MES model, as does the LR in the $\Delta CoVaR$ model. This finding suggests that size explains the magnitude of how variables influence bank stability, but not their actual effect. In order to investigate this hypothesis, a subsampling approach is applied.

Tables (5) to (8) about here

Tables 5 to 8 in the appendix show the regression models from Equations (12.1) to (12.4) run on subsamples, consisting of the quartiles of the sample. If the postulated model holds true, the findings should be replicable on a peer group level, irrespective of previous deliberations. Depending on the subset, some changes in significance of the regressors can be observed. Most notably, the changes concentrate on peer groups two and three, or more generally medium sized banks. An explanation might be related to previous deliberations. Medium sized banks benefit from an efficient mixture of credit and market risk that yields a noteworthy diversification. As a result, systemic events in credit or market risk are attenuated by opposing diversification effects within the risk types. Surprisingly, most of the found changes weaken, respectively repeal the found significance of equity. At the same time, this effect is overcompensated by an extensive rise in the size of the leverage ratio coefficient. In other words, it is not important for those banks how much equity they have, but how much they have in relation to their assets. In line with this interpretation, changes in the regressors are limited to the absolute measures, namely Cash, Equity, and Loans. All other regressors are ratios and thus size-adjusted. Notwithstanding this finding, the other coefficients behave stable irrespective of the subsampling and remain highly significant. It can thus be concluded that the assumed dynamics of the model are robust to size, which only aggravates their effect, but does not change the interactions.

The illustration of Figure (4) also shows another advantage of the proposed methodology. As previously said, the model allows for idiosyncratic and systemic risk to build up independently. As can be seen, default clustering occurred at different times for different types of banks. It can be interpreted as evidence in favor of the postulated independence between idiosyncratic and systemic risk, as each cluster is driven by a different risk type. As such, systemic events related to credit risk would be more detrimental for banks in peer group one compared to peer group four. Previous models, that only consider idiosyncratic risk measures, arguably have a poor fit because they would have to account for ailing banks, as well as sound ones with the same variables. This paper proposes a model that remedies said shortcoming and should consequently perform better.

5.2 Time Variant Influences

As another measure of assessing the validity of the previous results, the model was recalibrated on annual subsamples. If parts of the observed effects were to be time sensitive, the coefficients should fluctuate. In other words, if time is irrelevant to the model, the observed idiosyncratic coefficients should be stationary. That is to say that they have arguably little variance around the mean and are free of jumps. The SRM to the contrary are expected to be highly volatile. While they are barely noticeable during normal times, a systemic event triggers an excessive amplification as previously illustrated in Figure (3). Hence, the proposed model is simple but effective, in that it combines idiosyncratic risk with systemic risk as to account for different states of the market. Doing so remedies shortcomings of previous studies that have overspecified their models with idiosyncratic variables to fit the data to crisis level amplifications. In order to compare the severity of the changes in the reported coefficients, a transformation to percentage values was applied. This was achieved by dividing all coefficients by the first calculated value of the respective coefficient. Doing so allowed to assess the vigorousness of changes in different variables that would otherwise not be comparable. For example, an increase of 0.1 in absolute terms in the coefficient would be a strong change for Cash, while being negligible for the LR. Thanks to the transformation to percentage values, these differences in size can be easily accounted for.

Figure (5) about here

Despite the transformation, it is difficult to derive a consistent interpretation of the coefficients, as they do not move unanimously. Regarding Panel (a), it can be concluded that the coefficients are somewhat time sensitive. While their changes are indisputable, the severity is subject to discussion. The idiosyncratic coefficients do in most cases not rise beyond a fourfold increase from the base value. The strongest amplifications are shown by the LTD during times of crises. A possible interpretation would be that the origin of funding is irrelevant most of the time, except for the occurrence of crises. Likewise, the LR is unimportant during normal times, yet becomes crucial during market distortions. The included SRM leaves an inconclusive picture. It precedes the Dot-Com and subprime crises, yet lags the S&L crisis.

Panel (b) shows the evolution of the coefficients in the model incorporating MES. It is the only significant model speaking from a statistical perspective. A possible explanation can be inferred from the panel. As postulated, the idiosyncratic factors are arguably static. Subsequently, changes in the overall risk are captured by the SRM. As before, the LTD shows strong volatility during crisis times. This variability is possibly due to the origin of funding becoming highly relevant during a crisis. Spikes in the idiosyncratic variables occur after the introduction of the "Riegle-Neal Interstate Banking Act" of 1994 and might hint at a structural break induced by changes in regulation.

The findings of Panel (c) should be interpreted with caution. It was not possible to compute $\Delta CoVaR$ for all points in time owed to missing data. As a result, the observations only start in 1986, instead of 1980. In addition, the first joint occurrence of a default and being able to calculate a value for $\Delta CoVaR$ is in 2005.

Consequently, the panel only starts then, and does not illustrate how the coefficients behave around different crises. Instead, they have a significant exposure towards the recent crisis and are thus susceptible for misinterpretation. Panel (d) reflects previous findings. Again, LTD has the strongest amplifications, which coincide with the occurrence of systemic events. Changes in the idiosyncratic variables are within reasonable bounds. Notable deviations include once more the LR, as well as the cost-income ratio. The panel depicts the base model amended by SRISK in order to account for systemic risk. The theorized upticks precede financial crises as was the case in the previous panels.

In conclusion, the idiosyncratic variables appear to be influenced by time. It thus appears reasonable to attest, that they capture some of the volatility that stems from systemic events. However, the arguably small magnitude of changes in the coefficients leaves it for discussion, whether the initial deliberation of stationary idiosyncratic risk has to be refuted. For all panels, LTD shows the strongest amplifications. This finding can be explained by the origin of funding becoming highly important during financial distress. As such, it might be worth considering LTD an indicator for systemic risk. However, amplifications in LTD only become visible during the crisis and not ex ante. Consequently, it does not constitute noteworthy predictive power. Likewise, the LR is subject to significant changes during crises. The theorized model is most accurately reflected by Panel (b) which shows the coefficients of the base model, including MES. As postulated, the idiosyncratic variables are rather flat and do not capture rises in the overall risk sufficiently. Instead, this role can be attributed to the SRM, which performs outstandingly.

5.3 Spurious Results

In order to test whether the used variables are the main contributors to the observed effects, the strongest outliers of the individual regressors are deleted and the model is reevaluated. If the model fails to reproduce the previous results it can be argued that the findings were only driven by severe outliers, and not the variables themselves. In this paper it is winsorized at the 1^{st} and 99^{th} percentile of the data. The results are shown in Table (9) of the appendix.

Table (9) about here

As can be seen, the coefficients have hardly changed compared to the initial Table (1). Where a strong statistical influence could be observed before the exclusion of outliers, there can still be done so afterwards. It is noteworthy, that the sample size shrunk drastically. Upon further inspection it became clear, that a plurality of the banks resolved around a common average for most of the variables, except one outlier. There were few banks that had multiple values in excess of what could reasonably be expected. It can be concluded that the observed effects are persistent, as they can be reproduced with comparable coefficients in a much smaller sample. If significance were to be induced by the large sample size, this observation would not be the case. Hence, further evidence highlighting the robustness of the postulated model is generated.

Table (10) about here

Table (10) illustrates the influence of the winsorization in contrast to the original values. The first column of each calculation depicts the original value, while the adjacent column inherits the winsorized values. In doing so, the effect of excluding the outliers becomes more obvious. It can be concluded that no such effect can be inferred from leaving out extreme values. As a result it can be said with reasonable certainty, that the findings made in the previous section were not induced by excessively large values.

Table (11) about here

Ultimately, it is shown in Table (11) of the appendix, that the correlation between regressors and regressand is within reasonable bounds. From this analysis, it is concluded that distortions from multicollinearity can be neglected.

In conclusion, it was tested for size effects, originating in the magnitude of the coefficients, as well as the size of the bank itself. Furthermore, influences stemming from time variant factors were investigated by running the model on annual subsets. It was found that such effects can be disregarded. Ultimately, evidence against multicollinearity has been generated. It would be interesting to see how the results are influenced from a change in the methodology of deriving market prices from accounting information as to rule out a possible measurement error. Moreover, substituting the regressors with highly comparable, respectively correlating measures, would be a useful control for variable intrinsic effects. Owed to the lack of adequate options it was refrained from doing so. Another possibility of assessing the robustness of the model would be to verify the results for non financial firms. Doing so would allow to exclude the possibility that the observed results are based on an omitted factor that is inherent to banks. As some of the regressors are specific to the banking industry, this approach cannot be pursued. Likewise, it is difficult to replicate the study for another geography owed to the lack of defaults that can be observed and thus used to calibrate the model. Consequently, this endeavor was not undertaken. The issue of reverse causality, respective simultaneity cannot be fully excluded. Nevertheless, the conducted tests rule out a significant proportion of alternative explanations that might have questioned the validity of the results and subsequent conclusions.

6 Conclusion

This research extends the knowledge on bank defaults by investigating the predictive power of SRM and identifying mechanisms that contribute to bankruptcies of financial institutions. The results are important because they allow to identify troubled banks before they default. As a result, they can be recapitalized in advance as to prevent bankruptcy and thus minimize costs borne by society. The severity of economic distortions caused by bank defaults underlines the necessity of the conducted research.

At the moment, forecasting models overly rely on idiosyncratic variables to predict defaults. In doing so, they lack the ability to capture systemic risk. From this observation, it was hypothesized that more accurate projections of bank solvency could be made when incorporating SRM. To test this theory, an idiosyncratic base model was derived. Under the postulated hypothesis, it should improve, when amended with measures of systemic risk. It was found that β and $SRISK$ do not improve the performance beyond a random draw. While $\Delta CoVaR$ and MES benefit the model accuracy, only the latter is statistically significant. In investigating the reasons for the surprising performance of the SRM, two findings stood out. First, bank size determines exposure to credit or market risk. Smaller banks tend to allocate more of their risk budget to credit risk. However, systemic events originating in credit risk are not efficiently incorporated in current metrics. As a result, they do not capture the riskiness of smaller banks. Second, idiosyncratic measures are surprisingly volatile, and thus capture a noteworthy share of risk which was ex ante attributed to SRM.

Interestingly, LTD showed characteristics of a SRM by moving in parallel with systemic events. However, the amplifications did not manifest timely enough to function as an indicator of impending financial distress. Furthermore, it was found that a few idiosyncratic measures perform outstandingly at predicting defaults. Most notably, NPL, ROA, and LR produce consistent results. These findings suggest, that prudent credit risk management should be of utmost importance to banks, as the return generated on a portfolio of assets and the subsequent management of delinquencies has considerable predictive power of potential defaults. Given the inherent risk and illiquidity of loans, this finding is evident. Surprisingly, it was shown, that income diversification and cost efficiency do not explain bank resilience. Likewise, the origin of funding only yields explanatory power during financial crises.

To rule out distortions in the presented results, they were subject to a plurality of robustness checks. It was assessed, whether structural or temporal effects were responsible for the findings. Furthermore, the data were winsorized in order to rule out that the observed effects were due to outliers. No change in the dynamics of the model were observed. Neither of the robustness tests showed signs of inadequacy of the model. It was found though, that bank size can amplify the severity with which these dynamics function. In addition, the results were derived based on a heterogeneous population of banks that was exposed to different sources of systemic risk and free of a selection bias. At the same time, the investigated banks were subject to a homogeneous accounting as well as regulatory regime. It can thus be concluded that the findings are robust to externalities and universally valid.

Taken together, the findings made in this paper generate evidence challenging the status quo in measuring systemic risk. Assuming that the PD of a bank can be decomposed into idiosyncratic and systemic risk, the current measures fail to capture systemic risk. Possible explanations might be the lack of incorporating sufficient dimensions of systemic risk at the same time. In other words, they may perform well at predicting losses on a bank level, yet fail to account for possible contagion effects. What is more, the contribution of credit risk to systemic risk is underestimated. Hence, the paper accentuates the need for further research on systemic risk. At the same time, it gives regulators substantiated evidence in prioritizing their use of SRM in favor of MES. As a result, a more differentiated calculation of capital requirements might be derived based in order to account for banks that mitigate or amplify systemic events.

Further research should try to reinstate the made findings for other geographies and jurisdictions. It would be interesting to assess the inclusion of the liquidity coverage ratio (LCR) and net stable funding ratio (NSFR) in the model. Doing so would allow to conclude whether they indeed capture the stability of a bank as envisaged by the regulator. Owed to the lack of sufficiently granular information the two metrics were not included in this paper. Another endeavor of worthy pursuit would be the replication of the applied methodology for other SRM, as to investigate their contribution. Lastly, future research might resort to a study that does not need the transformation of accounting to market data.

7 Appendix

Table 1: Probit Regression on the Default Dummy.

	(1) Base Case	(2) β	(3) MES	(4) Δ CoVaR	(5) SRISK %
ln(Cash) (USD)	-0.1163***	-0.1155***	-0.0433	0.0724	-0.1026***
	(0.0000)	(0.0000)	(0.0536)	(0.1434)	(0.0000)
ln(Equity) (USD)	-0.2420***	-0.2089***	-0.1650***	-0.6632***	-0.2405***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln(Loans) (USD)	0.2824***	0.2548***	0.1794***	0.6231***	0.2796***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NPL (%)	5.3903***	5.1146***	5.3908***	5.4006***	5.1592***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cost-Income (%)	-0.0008	-0.0013	-0.0031	-0.0027	-0.0005
	(0.7248)	(0.7802)	(0.3994)	(0.5982)	(0.9332)
Income-Div. (%)	-0.0029	-0.0255	-0.0319*	0.0040***	-0.0257
	(0.2356)	(0.0703)	(0.0470)	(0.0006)	(0.0680)
LTD (%)	-0.0016	-0.0014	-0.0006	0.0000	-0.0012
	(0.7131)	(0.7351)	(0.9600)	(0.8745)	(0.7821)
ROA (%)	-0.0454**	-9.0516***	-9.3031***	-6.4122***	-9.1527***
	(0.0033)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LR (%)	-23.9456***	-22.9026***	-25.7374***	-21.5728***	-22.7600***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β		-0.0000			
		(0.3654)			
MES			-0.4915***		
			(0.0000)		
Δ CoVaR				-1.0726	
				(0.1193)	
SRISK (%)					-0.8584
					(0.9134)
N	1,189,151	1,138,248	855,980	669,345	1,021,363

Note: p-values can be inferred from the brackets. Significance is denoted at the 5% (*), 1% (**), and 0.1% (***) significance level.

Table 2: Accuracy per Model.

Random Draw	0	1	Total
0	99.7606%	0.1196%	99.8802%
1	0.1196%	0.0001%	0.1198%
Total	99.8802%	0.1198%	100.0000%

Base Case	0	1	Total
0	99.8669%	0.0080%	99.8749%
1	0.1213%	0.0038%	0.1251%
Total	99.9882%	0.0118%	100.0000%

β	0	1	Total
0	99.8639%	0.0076%	99.8716%
1	0.1242%	0.0042%	0.1284%
Total	99.9881%	0.0119%	100.0000%

MES	0	1	Total
0	99.9003%	0.0051%	99.9055%
1	0.0908%	0.0037%	0.0945%
Total	99.9911%	0.0089%	100.0000%

$\Delta CoVaR$	0	1	Total
0	99.9700%	0.0009%	99.9709%
1	0.0288%	0.0003%	0.0291%
Total	99.9988%	0.0012%	100.0000%

SRISK Percent	0	1	Total
0	99.8703%	0.0085%	99.8788%
1	0.1160%	0.0052%	0.1212%
Total	99.9863%	0.0137%	100.0000%

Note: The tables above depict the accuracy of the applied models. Empirical observations are denoted row-wise, whereas the columns contain predictions made from the model. As such, the first cell of the first table (99.7606%) depicts the share of banks that did not default and were identified as not defaulting. The adjacent second cell (0.1196%) of the row contains the share of banks for which a default was previsioned, yet did not occur. Analogously, the second row shows the results with regards to bank failure. The first table shows the results as they would be expected after a random draw from the full sample. The diagonal from the top left to the bottom right yields the number of correct identifications, of which the sum shall be maximal. As the can be seen, the base case already yields an improvement over a random procedure. It can be seen that all models have a high accuracy ratio as judged by the correct identifications. The model is rather conservative, in that the default threshold has been chosen at 50%. It would be desirable to minimize the α error, as to not oversee ailing banks. After optimizing the discriminatory function, it was found that an even lower default threshold accomplishes this property. However, at the same this aggravates the β error, reducing the overall model accuracy.

Table 3: Information Criteria of the Models.

	Obs.	AIC	BIC
Base Case	550,324	1,293.01	1,416.41
β	550,324	1,295.01	1,429.63
MES	550,324	1,294.63	1,429.25
$\Delta CoVaR$	550,324	1,293.44	1,428.06
SRISK Percent	550,324	1,294.86	1,429.48

Note: The table above shows the information criteria after readjusting the sample to only include banks where all SRM could be computed. Doing so allows to compare the results net of noise originating from different sample sizes. It can be inferred from the table, that the models only differ marginally. This finding is in line with previous results. As has been shown, the SRM did not provide significant explanatory power. To the contrary, the information criteria increase in size, suggesting that the more parsimonious base case was the more desirable model. It is thus evident, that a local minimum of the maximum likelihood function has been reached in the base case. Consequently, an omitted variable problem appears unlikely, as further variables lessen the accuracy of the forecast.

Table 4: Probit Regression on Default Dummy incl. Controls.

	(1) β	(2) MES	(3) Δ CoVaR	(4) SRISK %
ln(Cash) (USD)	-0.1164***	-0.0498*	0.0493	-0.1019***
	(0.0000)	(0.0269)	(0.3567)	(0.0000)
ln(Equity) (USD)	-0.1858***	-0.1633***	-0.9274***	-0.2151***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln(Loans) (USD)	0.2959***	0.2002***	0.9637***	0.3248***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NPL (%)	5.1208***	5.3951***	4.9779***	5.1716***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cost-Income (%)	-0.0010	-0.0033	-0.0024	-0.0001
	(0.8434)	(0.3682)	(0.6802)	(0.9820)
Income-Div. (%)	-0.0261	-0.0321*	-0.0504*	-0.0259
	(0.0559)	(0.0426)	(0.0464)	(0.0644)
LTD (%)	-0.0021	-0.0025	-0.0001	-0.0018
	(0.6870)	(0.8964)	(0.9737)	(0.7318)
ROA (%)	-8.7327***	-9.0514***	-10.2880***	-8.7662***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
LR (%)	-23.5072***	-25.7987***	-16.8343***	-23.4011***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	-0.0000			
	(0.3366)			
MES		-0.4910***		
		(0.0000)		
Δ CoVaR			-1.2457	
			(0.0856)	
SRISK %				-17.3506
				(0.4116)
Peergroup (2)	-0.2512***	-0.2444***	-0.0957	-0.2476***
	(0.0000)	(0.0000)	(0.7410)	(0.0000)
Peergroup (3)	-0.3740***	-0.2413***	-0.2219	-0.3816***
	(0.0000)	(0.0001)	(0.4325)	(0.0000)
Peergroup (4)	-0.3182***	-0.1567	-0.4495	-0.3602***
	(0.0000)	(0.0651)	(0.1432)	(0.0000)
N	1,132,169	850,678	127,989	1,021,363

Note: p-values can be inferred from the brackets. Significance is denoted at the 5% (*), 1% (**), and 0.1% (***) significance level.

Table 5: Regression incl. β on the Default Dummy separated by quartiles.

	(1) Quartile	(2) Quartile	(3) Quartile	(4) Quartile	Full Sample
ln(Cash) (USD)	-0.1534***	-0.1899***	-0.1701***	-0.0156	-0.1155***
	(0.0000)	(0.0000)	(0.0001)	(0.6199)	(0.0000)
ln(Equity) (USD)	-0.2405***	-0.1138	-0.0484	-0.3631***	-0.2089***
	(0.0000)	(0.0566)	(0.4864)	(0.0000)	(0.0000)
ln(Loans) (USD)	0.3463***	0.6761***	0.2975**	0.3667***	0.2548***
	(0.0000)	(0.0000)	(0.0069)	(0.0000)	(0.0000)
NPL (%)	4.6354***	5.4473***	4.5842***	5.5721***	5.1146***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cost-Income (%)	-0.0511	-0.0026	0.0061	-0.0094	-0.0013
	(0.1394)	(0.6488)	(0.5292)	(0.1560)	(0.7802)
Income-Div. (%)	0.0048	0.0040*	-0.0297	-0.0314*	-0.0255
	(0.2959)	(0.0365)	(0.2455)	(0.0394)	(0.0703)
LTD (%)	-0.0002	-0.0034	-0.1500	-0.3216	-0.0014
	(0.9026)	(0.7914)	(0.5609)	(0.0639)	(0.7351)
ROA (%)	-7.1464***	-5.6834**	-11.1788***	-11.2021***	-9.0516***
	(0.0000)	(0.0016)	(0.0000)	(0.0000)	(0.0000)
LR (%)	-17.1565***	-24.1204***	-30.0627***	-27.0315***	-22.9026***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	-0.0000	-0.0007**	-0.0000	-0.0001	-0.0000
	(0.9436)	(0.0042)	(0.5138)	(0.7373)	(0.3654)
N	177,270	279,464	332,990	342,445	1,138,248

Note: p-values can be inferred from the brackets. Significance is denoted at the 5% (*), 1% (**), and 0.1% (***) significance level.

Table 6: Regression incl. MES on the Default Dummy separated by quartiles.

	(1) Quartile	(2) Quartile	(3) Quartile	(4) Quartile	Full Sample
ln(Cash) (USD)	-0.0230	-0.1660**	-0.1319*	-0.0261	-0.0433
	(0.6613)	(0.0094)	(0.0233)	(0.4891)	(0.0536)
ln(Equity) (USD)	-0.3860***	-0.1933*	-0.1033	-0.1767*	-0.1650***
	(0.0000)	(0.0284)	(0.2819)	(0.0199)	(0.0000)
ln(Loans) (USD)	0.4139***	0.6474***	0.2627	0.2044*	0.1794***
	(0.0000)	(0.0000)	(0.0818)	(0.0194)	(0.0000)
NPL (%)	5.1957***	6.0952***	5.0782***	5.4487***	5.3908***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cost-Income (%)	0.0076	-0.0023	-0.2921***	-0.1918***	-0.0031
	(0.8843)	(0.7403)	(0.0000)	(0.0000)	(0.3994)
Income-Div. (%)	0.0122*	0.0037	-0.0572	-0.0427*	-0.0319*
	(0.0158)	(0.0505)	(0.1825)	(0.0205)	(0.0470)
LTD (%)	0.0030	0.0057	-0.4183	-0.4351	-0.0006
	(0.3692)	(0.7617)	(0.2470)	(0.0524)	(0.9600)
ROA (%)	-8.1008***	2.3510	-8.7639**	-10.1475***	-9.3031***
	(0.0004)	(0.4894)	(0.0035)	(0.0000)	(0.0000)
LR (%)	-14.6619***	-21.5115***	-26.9751***	-32.1092***	-25.7374***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MES	-0.3527	-0.6252**	-0.0106	-0.8499***	-0.4915***
	(0.1032)	(0.0045)	(0.9174)	(0.0006)	(0.0000)
N	114,652	199,734	254,558	281,734	855,980

Note: p-values can be inferred from the brackets. Significance is denoted at the 5% (*), 1% (**), and 0.1% (***) significance level.

Table 7: Regression incl. $\Delta CoVaR$ on the Default Dummy separated by quartiles.

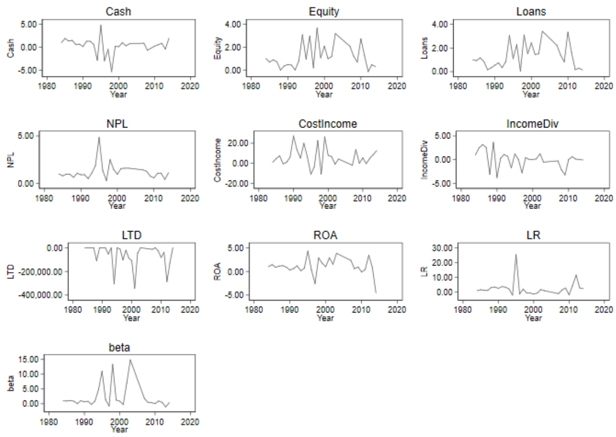
	(1) Quartile	(2) Quartile	(3) Quartile	(4) Quartile	Full Sample
ln(Cash) (USD)	0.3534	-0.1052	0.0233	0.0844	0.0724
	(0.2644)	(0.5642)	(0.8280)	(0.2181)	(0.1434)
ln(Equity) (USD)	-0.8976*	-0.3308	-0.4341*	-0.6876***	-0.6632***
	(0.0415)	(0.2854)	(0.0295)	(0.0001)	(0.0000)
ln(Loans) (USD)	2.0865**	1.2247*	0.5881*	0.6946***	0.6231
	(0.0012)	(0.0180)	(0.0158)	(0.0001)	(0.0000)
NPL (%)	7.1688**	7.5547***	5.1998***	5.8158***	5.4006***
	(0.0081)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cost-Income (%)	-0.2463	-0.0040	-0.2668**	-0.1600***	-0.0027
	(0.2772)	(0.7591)	(0.0035)	(0.0005)	(0.5982)
Income-Div. (%)	-0.9651	0.0049	-0.0752	-0.2178	0.0040***
	(0.2926)	(0.3428)	(0.1151)	(0.0755)	(0.0006)
LTD (%)	-0.0242	0.0003	0.0005	-0.0001	0.0000
	(0.9275)	(0.9922)	(0.9550)	(0.9776)	(0.8745)
ROA (%)	-0.5392	-8.9111**	-6.9923***	-9.7675**	-6.4122***
	(0.5923)	(0.0063)	(0.0004)	(0.0069)	(0.0000)
LR (%)	3.6921	-26.6214**	-21.5884***	-26.4942***	-21.5728***
	(0.6884)	(0.0060)	(0.0005)	(0.0000)	(0.0000)
Δ CoVaR	-6.4686	2.6746	-0.7943	-2.0291*	-1.0726
	(0.1559)	(0.3764)	(0.5771)	(0.0204)	(0.1193)
N	89,805	162,219	200,612	216,709	669,345

Note: p-values can be inferred from the brackets. Significance is denoted at the 5% (*), 1% (**), and 0.1% (***) significance level.

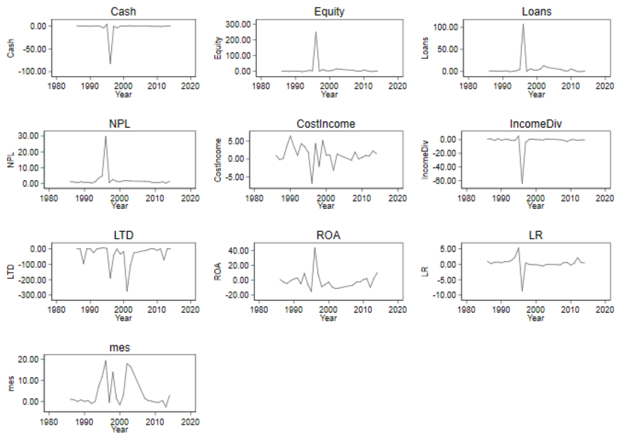
Table 8: Regression incl. $SRISK$ on the Default Dummy separated by quartiles.

	(1) Quartile	(2) Quartile	(3) Quartile	(4) Quartile	Full Sample
ln(Cash) (USD)	-0.1511***	-0.1937***	-0.1475**	0.0141	-0.1026***
	(0.0000)	(0.0000)	(0.0014)	(0.6759)	(0.0000)
ln(Equity) (USD)	-0.2796***	-0.1240	-0.0448	-0.3806***	-0.2405***
	(0.0000)	(0.0631)	(0.5609)	(0.0000)	(0.0000)
ln(Loans) (USD)	0.3886***	0.6407***	0.3476**	0.3867***	0.2796***
	(0.0000)	(0.0000)	(0.0035)	(0.0000)	(0.0000)
NPL (%)	4.6115***	5.4243***	4.7301***	5.6510***	5.1592***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cost-Income (%)	-0.0528	-0.0023	0.0065	-0.0088	-0.0005
	(0.1276)	(0.7159)	(0.5251)	(0.2371)	(0.9332)
Income-Div. (%)	0.0046	0.0041*	-0.0309	-0.0296	-0.0257
	(0.3591)	(0.0335)	(0.2303)	(0.0769)	(0.0680)
LTD (%)	-0.0003	-0.0032	-0.0883	-0.1676	-0.0012
	(0.9156)	(0.8131)	(0.7458)	(0.3354)	(0.7821)
ROA (%)	-7.0894***	-5.8316**	-11.6679***	-11.3909***	-9.1527***
	(0.0000)	(0.0043)	(0.0000)	(0.0000)	(0.0000)
LR (%)	-16.3084***	-25.1542***	-31.1181***	-26.4613***	-22.7600***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SRISK (%)	141.8470	284.0346***	3.4246	-82.6026	-0.8584
	(0.7144)	(0.0001)	(0.9408)	(0.1184)	(0.9134)
N	154,388	248,221	302,290	316,464	1,021,363

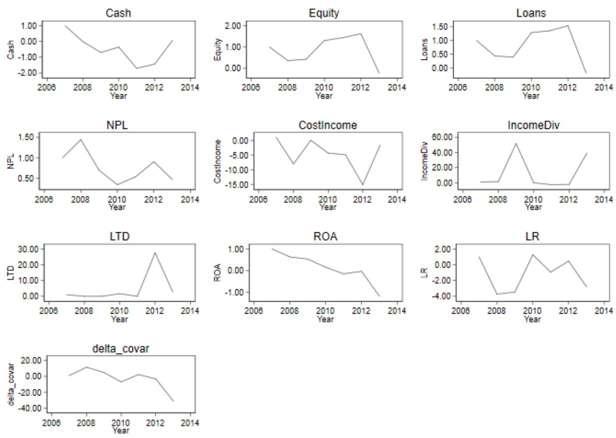
Note: p-values can be inferred from the brackets. Significance is denoted at the 5% (*), 1% (**), and 0.1% (***) significance level.



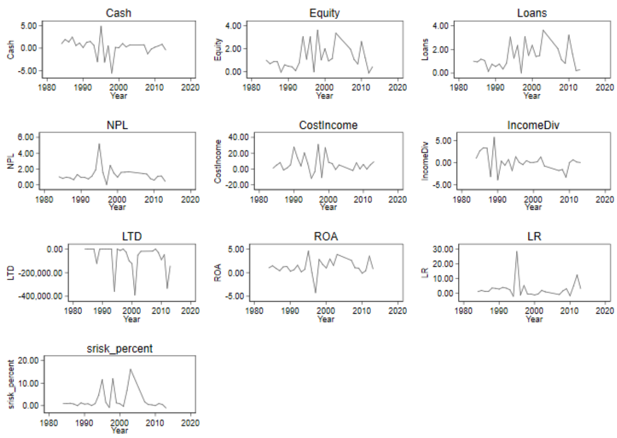
(a) Coefficients of *Equation* (11) including β.



(b) Coefficients of *Equation* (11) including *MES*.



(c) Coefficients of *Equation* (11) including $\Delta CoVaR$.



(d) Coefficients of *Equation* (11) including $SRISK(\%)$.

Figure 5: Development of coefficients over time.

Note: The table above depicts the coefficients of the model when run on an annual basis instead of the full sample. If the postulated model were to be robust regarding time variant effects, the coefficients should behave rather static. In order to visualize the severity of possible deviations, the coefficients were index-linked with the first observation denoted as 100%. As can be seen the coefficients are in most cases flat, indicating the absence of time related fluctuations. Notable exceptions are constituted by the LTD and LR. The first captures all crises reliably, irrespective of the model. The latter, fluctuates strongly in advance to the dot-com-bubble, and the financial crisis of 2008. Likewise, ROA is arguably different from a constant and precedes the occurrence of the dot-com-bubble, too. The results of $\Delta CoVaR$ appear to be more time variant. However, this impression is due to a technicality: the data only starts in 2005 as no previous estimates coincide with defaults in the preceding time.

Table 9: Probit Regression on Default Dummy.

	(1) Base Case	(2) β	(3) MES	(4) Δ CoVaR	(5) SRISK %
ln(Cash) (USD)	-0.1186***	-0.1162***	-0.0466	0.0762	-0.1071***
	(0.0000)	(0.0000)	(0.0885)	(0.2332)	(0.0000)
ln(Equity) (USD)	-0.1953***	-0.1732***	-0.1263**	-0.5999***	-0.1995***
	(0.0000)	(0.0000)	(0.0041)	(0.0003)	(0.0000)
ln(Loans) (USD)	0.2400***	0.2219***	0.1388**	0.5532***	0.2481***
	(0.0000)	(0.0000)	(0.0015)	(0.0003)	(0.0000)
NPL (%)	3.9741***	3.8507***	4.3601***	4.5220***	3.8687***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cost-Income (%)	0.0003	0.0009	-0.0021	-0.0019	0.0014
	(0.9420)	(0.8637)	(0.6168)	(0.7285)	(0.7850)
Income-Div. (%)	-0.0023	-0.0233*	-0.0314*	-0.0608**	-0.0230
	(0.3051)	(0.0415)	(0.0383)	(0.0093)	(0.0514)
LTD (%)	-0.0074	-0.0064	-0.0050	-0.0001	-0.0058
	(0.5766)	(0.5978)	(0.8371)	(0.9688)	(0.6285)
ROA (%)	-0.0388*	-6.3594***	-6.2975***	-1.1230***	-6.3712***
	(0.0402)	(0.0000)	(0.0000)	(0.0004)	(0.0000)
LR (%)	-22.2198***	-21.5666***	-27.2622***	-26.6082***	-21.4204***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β		-0.0001			
		(0.7252)			
MES			-0.6433***		
			(0.0000)		
Δ CoVaR				-1.0260	
				(0.2636)	
SRISK (%)					-25.9131
					(0.3807)
N	99,704	88,826	58,632	41,847	79,192

Note: p-values can be inferred from the brackets. Significance is denoted at the 5% (*), 1% (**), and 0.1% (***) significance level.

Table 10: Comparison between Probit Regression on Default Dummy with full and winsorized Sample.

	(1) Base Case	(2) winsorized	(3) β	(4) winsorized	(5) MES	(6) winsorized	(7) Δ CoVaR	(8) winsorized	(9) SRISK %	(10) winsorized
ln(Cash) (USD)	-0.1163***	-0.1186***	-0.1155***	-0.1162***	-0.0433	-0.0466	0.0724	0.0762	-0.1026***	-0.1071***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0536)	(0.0885)	(0.1434)	(0.2332)	(0.0000)	(0.0000)
ln(Equity) (USD)	-0.2420***	-0.1953***	-0.2089***	-0.1732***	-0.1650***	-0.1263**	-0.6632***	-0.5999***	-0.2405***	-0.1995***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0041)	(0.0000)	(0.0003)	(0.0000)	(0.0000)
ln(Loans) (USD)	0.2824***	0.2400***	0.2548***	0.2219***	0.1794***	0.1388**	0.6231***	0.5532***	0.2796***	0.2481***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0015)	(0.0000)	(0.0003)	(0.0000)	(0.0000)
NPL (%)	5.3903***	3.9741***	5.1146***	3.8507***	5.3908***	4.3601***	5.4006***	4.5220***	5.1592***	3.8687***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cost-Income (%)	-0.0008	0.0003	-0.0013	0.0009	-0.0031	-0.0021	-0.0027	-0.0019	-0.0005	0.0014
	(0.7248)	(0.9420)	(0.7802)	(0.8637)	(0.3994)	(0.6168)	(0.5982)	(0.7285)	(0.9332)	(0.7850)
Income-Div. (%)	-0.0029	-0.0023	-0.0255	-0.0233*	-0.0319*	-0.0314*	0.0040***	-0.0608**	-0.0257	-0.0230
	(0.2356)	(0.3051)	(0.0703)	(0.0415)	(0.0470)	(0.0383)	(0.0006)	(0.0093)	(0.0680)	(0.0514)
LTD (%)	-0.0016	-0.0074	-0.0014	-0.0064	-0.0006	-0.0050	0.0000	-0.0001	-0.0012	-0.0058
	(0.7131)	(0.5766)	(0.7351)	(0.5978)	(0.9600)	(0.8371)	(0.8745)	(0.9688)	(0.7821)	(0.6285)
ROA (%)	-0.0454**	-0.0388*	-9.0516***	-6.3594***	-9.3031***	-6.2975***	-6.4122***	-1.1230***	-9.1527***	-6.3712***
	(0.0033)	(0.0402)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)
LR (%)	-23.9456***	-22.2198***	-22.9026***	-21.5666***	-25.7374***	-27.2622***	-21.5728***	-26.6082***	-22.7600***	-21.4204***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β			-0.0000	-0.0001						
			(0.3654)	(0.7252)						
MES					-0.4915***	-0.6433***				
					(0.0000)	(0.0000)				
Δ CoVaR							-1.0726	-1.0260		
							(0.1193)	(0.2636)		
SRISK (%)									-0.8584	-25.9131
									(0.9134)	(0.3807)
N	1,189,151	99,704	1,138,248	88,826	855,980	58,632	669,345	41,847	1,021,363	79,192

Note: p-values can be inferred from the brackets. Significance is denoted at the 5% (*), 1% (**), and 0.1% (***) significance level.

Table 11: Correlations of Regressand and Regressors

	Default	ln(Cash)	ln(Equity)	ln(Loans)	NPL(%)	Cost-Income	Income-Div.	LTD	ROA	LR	β	MES	$\Delta CoVaR$	SRISK
Default	1.0000													
ln(Cash)	0.0231	1.0000												
ln(Equity)	-0.0017	0.8449	1.0000											
ln(Loans)	0.0183	0.8324	0.9331	1.0000										
NPL(%)	0.1018	0.0585	-0.0092	-0.0077	1.0000									
Cost-Income	-0.0101	0.0317	0.0644	0.0439	-0.0362	1.0000								
Income-Div.	-0.0003	0.0040	0.0110	-0.0195	-0.0008	0.0022	1.0000							
LTD	-0.0001	0.0167	0.0219	0.0234	0.0016	0.0190	-0.0001	1.0000						
ROA	-0.1100	-0.0225	0.0595	0.0133	-0.2445	0.1117	0.0806	-0.0023	1.0000					
LR	-0.0334	-0.1249	0.0906	-0.1815	-0.0090	0.0952	0.0977	-0.0031	0.1404	1.0000				
β	-0.0001	0.0045	0.0076	0.0066	-0.0011	0.0002	-0.0000	-0.0000	0.0016	0.0048	1.0000			
MES	-0.0026	0.0198	0.0241	0.0271	0.0056	0.0024	0.0005	0.0006	0.0056	-0.0002	-0.0025	1.0000		
$\Delta CoVaR$	-0.0020	0.1665	0.1509	0.1582	0.0188	0.0081	0.0086	0.0102	-0.0137	-0.0299	0.0027	0.0056	1.0000	
SRISK	0.0003	0.0452	0.0488	0.0456	0.0020	0.0016	0.0002	0.0010	0.0019	-0.0003	0.3332	-0.0002	0.0132	1.0000

Note: The table above shows the correlation of the regressors and the regressand (default). It can be seen that the strongest positive correlation is between equity and loans (0.9311), respectively between NPL and ROA as for the negative correlation (-0.2435). The findings make sense with regards to the low leverage ratio, which suggests that the majority of loans is backed by equity. As a result, loans and equity reflect the assets, respectively liabilities of the company, net of residual values. Likewise, the return on assets is low, when the percentage of non performing loans is high. As no payments are received by the delinquent loans, no returns are made, thus lowering the ratio relative to the assets. While the correlation is undoubtedly high, it poses no threat to the analysis, as it merely captures the structural characteristic of high equity funding in the investigated sample.

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