BACK TO THE FUTURE: BACKTESTING SYSTEMIC RISK MEASURES DURING HISTORICAL BANK RUNS AND THE GREAT DEPRESSION*

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Abstract

We evaluate the performance of two popular systemic risk measures, CoVaR and SRISK, during eight financial panics in the era before FDIC insurance. Bank stock price and balance sheet data were not readily available for this time period. We rectify this shortcoming by constructing a novel dataset for the New York banking system before 1933. Our evaluation exercise focuses on assessing whether systemic risk measures were able to detect systemically important financial institutions and to provide early warning signals of aggregate financial sector turbulence. The predictive ability of CoVaR and SRISK is measured controlling for a set of commonly employed market risk measures and bank ratios. We find that CoVaR and SRISK help identifying systemic institutions in periods of distress beyond what is explained by standard risk measures up to six months prior to the panic events. Increases in aggregate CoVaR and SRISK precede worsening conditions in the financial system; however, the evidence of predictability is weaker.

Keywords: Systemic Risk, Financial Crises, Risk Measures

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"In 1907, no one had ever heard of an asset-backed security, and a single private individual could command the resources needed to bail out the banking system; and yet, fundamentally, the Panic of 1907 and the Panic of 2008 were instances of the same phenomenon, ... The challenge for policymakers is to identify and isolate the common factors of crises, thereby allowing us to prevent crises when possible and to respond effectively when not."

Chairman Ben S. Bernanke

Speech November 8, 2013 - *The Crisis as a Classic Financial Panic*

1 Introduction

The 2008 financial crisis elevated the measurement of systemic risk to the forefront of economists and policymakers research agendas.[1] As a result, two goals have emerged. The first is to identify and possibly regulate systemically important financial institutions (so called SIFIs). The second is to construct early warning signals of distress in the financial system which could possibly allow policymakers to attenuate or avoid future financial crises. Despite the considerable research into measures of systemic risk, neither efficacy nor best practice is firmly established in the literature.[2]

One of the main hurdles in constructing a robust measure of systemic risk is the constantly evolving U.S. financial system. Financial crisis are rare events and the financial system often evolves in response to post-crisis changes in regulation. Regulatory measures of firm level risk have traditionally focused on risky behaviors such as leverage, liquidity, or the quality of collateral backing bank loans and runnable liabilities. But the importance of these measures often changes with new regulations introduced in the wake of financial crises. Before the Civil War banks largely funded themselves by issuing private banknotes backed by collateral and state regulators monitored risk by regulating the this collateral. Bank runs nonetheless occurred when the quality of the collateral came into question.[3] Regulators responded by adopting strict collateral rules with the Civil War era National Banking Acts. These regulatory changes effectively eliminated banknote risk but made banknote financing less profitable. Banks responded by

[1] The developments of the literature are surveyed in for instance Bisias, Flood, Lo, and Valavanis (2012), Brunnermeier and Oehmke (2012), Hansen (2013) and Benoit, Colliard, Hurlin, and Pérignon (2017).

[2] A number of contributions have argued that systemic risk measures have limited ability in predicting systemic risk. See for instance the work of Giglio, Kelly, and Pruitt (2016), Danielsson, James, Valenzuela, and Zer (2012), Idier, Lamé, and Mésonnier (2014) and Benoit, Colletaz, Hurlin, and Pérignon (2013).

[3] See Rolnick and Weber (1984), Hasan and Dwyer (1994), Jaremski (2010), and Chabot and Moul (2014).

adopting uninsured deposits as their primary method of funding and regulators attempted to mitigate risk by regulating the liquidity of bank assets backing these deposits. Nonetheless, deposit runs resulted in major panics between 1873 and the Great Depression.[4] Again regulators responded. This time with FDIC insurance that effectively transformed deposits into one of the safest forms of bank funding in the United States. With deposits guaranteed and depositors no longer disciplining banks, regulation focused on bank leverage. Again, these regulations made some forms of funding more profitable and banks responded with the wholesale, derivative and off-balance sheet funding now familiar to any student of the 2008 financial crisis. The post-crisis Dodd-Frank Act is the latest regulatory response to a major crisis. The Act appears to have successfully dampened the excesses that caused the 2008 crisis but if history is any guide our new regulatory regime will almost certainly create new incentives for bank funding and risk to evolve in unforeseen ways. The challenge for regulators and economists is to develop systemic risk monitoring tools that will remain relevant to these inevitable changes.

We generally think of risk measures as robust when they are able to successfully predict multiple rare events. The constantly evolving U.S. financial system renders many historic measures obsolete. The quality of state bonds backing banknotes or the proportion of deposit funding accurately identified risky banks in the 1850s and gilded age respectively but have little power predicting which banks were risky in 2008. Likewise, the current asset stress tests, liquidity and capital regulations would likely have little power identifying systemically risky firms in the pre-FDIC era.[5] The problem is not hopeless, however. The introductory quote from the speech by Chairman Bernanke reminds us that despite the very different banking environments, there are fundamental similarities across historical financial crises. While bank funding and investments have changed across crises some traits are common. At a broad level all U.S. financial crisis occurred when bank liquid liability holders demanded their money back and bank assets proved too illiquid to meet this need. Furthermore, at least since the Civil War, the major money center banks have been publicly traded and their stockholders were acutely aware that any losses would fall directly upon them. These stockholders had incentives to monitor risks and "vote with their feet" by selling (or buying) shares whenever they perceived

[4] See Wicker (2000).

[5] We do not have the detailed balance sheet data to apply modern stress tests to pre-FDIC banks but we know that with the possible exception of the great depression asset quality was not the proximate cause of bank failures. Instead liquidity and the proportion of funding from deposits explained bank fragility. Today, deposit funding is viewed as one of the safest forms of debt finance reflected in the favored treatment of deposits in the Liquidity Coverage Ratio and Stable funding Ratio regulation.

the risks were not accurately reflected in their stock price. Two measures of systemic risk CoVaR and SRISK - proposed in the wake of the 2008 financial crisis use stock price behavior to infer the systemic risk of financial firms. Unlike era specific balance sheet measures, these stock return based measures may be able to identify systemic risk robustly even when the financial system evolves. To test the robustness of these measures we evaluate their ability to identify systemically risk firms and construct early warning signals of distress before the panics of the past 150 years.

The assessment of systemic risk measures is hindered by the lack of financial crisis episodes with suitable data. Most proposed measures require firm-level balance sheet and equity return data at a reasonably high frequency. Existing U.S. bank balance sheet and stock return data is only available for the Federal Deposit Insurance Corporation (FDIC) era when financial crises are exceedingly rare.

In this paper we tackle the problem of the evaluation of systemic risk measures by employing a novel historical dataset containing balance sheet and stock market information for the New York banking system between 1866 and 1933. In a way, the pre-FDIC era is an ideal laboratory for the evaluation of recently proposed systemic risk measures. The U.S. financial markets have evolved in many ways since the introduction of FDIC insurance. If, despite these changes, stock return based systemic risk measures designed to identify modern systemically risky firms can also identify risky firms in the pre-FDIC era it would suggest that stock holder behavior is sufficiently constant to trust these methods to identify risks before the future panics.

The pre-FDIC era is appealing in other ways as well. Throughout the period, the United States experienced frequent financial crises which provide a relatively large sample for econometric evaluation. Our sample contains eight financial panics: the panics of 1873 and 1884, the Barings Crisis of 1890, the subsequent panics of 1893 and 1896, the panic of 1907, the monetary and fiscal consolidation of 1921, and the panic of 1933.4 Bank stock price and balance sheet data were not previously available over this time period at a high enough frequency to estimate systemic risk measures. In this work we rectify these data shortcomings by constructing a new dataset spanning from the founding of the national banking system and the establishment of FDIC insurance. A key feature of the pre-FDIC era for the purposes of the analysis of this paper is that, because of the absence of deposit insurance, during panics depositors run on the banks which they ascribed a high likelihood of failure. This allows us to use bank deposits to construct an appropriate measure of financial health for individual financial institutions as well as the entire system.

A large number of systemic risk measures have proliferated following the 2008 financial crisis. Regrettably, not all are amenable to historical investigation. Here we focus on stock return based measures involving publicly available data. This excludes, for instance, scenario-based schemes such as stress tests or fire sale contingencies. In particular, we evaluate the effectiveness of CoVaR proposed by Adrian and Brunnermeier (2016) and SRISK by Brownlees and Engle (2016). The CoVaR and SRISK methodologies are used to produce measure of systemic risk for individual financial institutions as well as aggregate measures for the entire system. We choose these two systemic risk measures because they are popular measures in policy and academic circles and are relatively easy to compute using our historical dataset.

We focus on two backtesting exercises. First, we investigate whether ranking financial institutions by systemic risk can identify the institutions with notable deposit declines around panic events. We call this the cross-sectional challenge, i.e., to identify vulnerable financial institutions that might substantially contribute to the undercapitalizaion of the financial system. Second, we investigate whether aggregate systemic risk measures are significant predictors of system-wide deposit declines around panic events. We call this the time series challenge. In both backtesting exercises the performance of CoVaR and SRISK is measured relative to leverage, size and common market-based indices of risk (volatility, beta, and VaR). Put differently, our null hypothesis is that there is no additional information in the distribution of market returns besides what is captured by standard risk measures that allows us to improve systemic risk monitoring. Our backtesting exercises assess the evidence against this null.

For the cross-sectional analysis, we employ a panel regression to assess whether pre-panic measures of individual-bank CoVaR or SRISK can explain individual bank deposit declines during panic periods. The panel regressions include controls for leverage, size, volatility, beta, and VaR. We also consider different versions of the model using predictors computed 1 to 6 months ahead of each panic event. We find that CoVaR and SRISK measures identify systemic institutions in periods of distress over what is explained by standard variables up to six months ahead of a panic event. We also provide detailed statistics on individual panic events and note that for all panic events but two, CoVaR and SRISK rankings are significantly correlated with the panic-period deposit losses. Looking at the other measures of risk, we also obtain interesting results. In particular, VaR appears to be an adequate tool for systemic risk monitoring, whereas leverage cannot predict which banks will suffer deposit runs. Size performs well and is at par with CoVaR and SRISK in terms of correlations. However, the panel estimation results convey that the systemic risk measures provide important and significant incremental information over size. In order to further investigate the cross-sectional properties of CoVaR and SRISK we also estimate the panel regression during NBER expansions and recessions. We find that the during contraction periods CoVaR and SRISK predict deposit losses. By contrast, during expansions CoVaR and SRISK have little to no forecasting power. This suggests that rather than capturing specifically systemic risk arising during panics CoVaR and SRISK are correlated with general worsening conditions in the financial system irrespective of their causes. As a result, the predictive ability of these measures depends on the state of the financial system and, in particular, they become relevant only in more distressed states.

In our cross-sectional analysis we carry out an additional validation exercise for SRISK. SRISK is a prediction of the capital shortage a bank would experience conditional on a systemic event. To this extent we carry out Mincer-Zarnowitz regressions to assess if SRISK provides unbiased estimates of the actual capital shortages experienced during panic events. We find that SRISK fails to provide an unbiased estimate of actual capital shortages in panic events with one important exception which is the Great Depression. This finding highlights the fact that SRISK involves a number of tuning parameters, including the stock market decline of the financial sector. Unless the latter matches the ex post decline, we do not expect SRISK to provide an unbiased forecast of capital shortfall.

For the time-series analysis, we evaluate the ability of aggregate CoVaR and SRISK to provide early warning signals of distress in the financial systems by running a predictive regression of aggregate deposits. We run this regression by pooling together all observations in the eight panic windows spanning from 5 years before the onset of each panic until the end of the crisis. Again, the predictive regressions control for lagged aggregate deposit growth, aggregate volatility, beta, VaR, size and leverage. We consider different predictive horizons for the analysis ranging from 1 to 3 months ahead. We do find that changes in aggregate CoVaR and SRISK are significant predictors of declines in aggregate deposits. However, the evidence of predictability is rather weak. In particular, if we compute time series correlations between aggregate deposits and CoVaR/SRISK growth rates we find that these are significant in few instances only. The results also convey that finding evidence of time series predictability is much harder as none of the other risk measures produces significant signals. We also estimate the time series predictive regression during NBER expansions and contractions. Again, we find that the during contraction periods CoVaR and SRISK have significant yet weak predictability, while in deposit expansions there is no significant predictability.

Overall, our analysis shows CoVaR and SRISK perform similarly. Our historical backtesting exercise shows that there is solid evidence of cross-sectional predictability – i.e. the identification of systemic institutions – while there is only weak evidence of time series predictability – i.e. construction of early warning signal of distress in the financial system.

The rest of the paper is organized as follows. Section 2 introduces the systemic risk measures used in this work. Section 3 describes our historical dataset and defines the panic events of interest of this analysis. Section 4 analyses the evolution of systemic risk throughout the panic events. Section 5 presents the results of our backtesting study. Concluding remarks follow in Section 6.

2 Systemic Risk Measures

Several competing approaches for measuring systemic risk have been put forward in the literature in the aftermath of the crisis. Here we focus on two market-based measures: The CoVaR of Adrian and Brunnermeier (2016) and the SRISK of Brownlees and Engle (2016). There are at least two appealing reasons to focus on these two particular measures: (i) both are arguably among the most prominently featured measures currently applied and discussed in both policymaker and academic circles and (ii) both measures have relatively mild data requirements. The second reason is particularly appealing due to the historical nature of the data used in our analysis.

CoVaR and SRISK associate systemic risk with the shortfall of financial system conditional on the realization of a systemic event. There are important differences between the two approaches, in particular with respect to the definition of what a systemic event is. Broadly speaking, a common feature of CoVaR and

SRISK is that they measure the systemic risk contribution of a firm by combining a market based estimate of the degree of dependence between the firm and the entire system together with a proxy of firm size. It is important to emphasize that in this work we abstract from what CoVaR and SRISK intend to measure and simply focus on their predictive ability.

Before introducing the formal definitions of CoVaR and SRISK we need to set some appropriate notation. We are concerned with measuring systemic risk for a panel of financial firms. The number of financial entities available in the panel at a given time t is denoted by N_t. The period t arithmetic return of financial entity i is $r_{i\,t}$ and the corresponding value weighted period t arithmetic return of the entire financial system is $r_{m\,t}$. The book value of equity and debt of firm i are denoted respectively by $\mathsf{E}_{i\,t}$ and $\mathsf{D}_{i\,t}$. The market value of equity of firm i is denoted by $\mathsf{W}_{i\,t}$.

In the following subsections we introduce the definitions of firm specific and system wide CoVaR and SRISK measures. In our study we construct predictions of CoVaR and SRISK for each date t in the sample using backward looking data only to avoid any look ahead bias. To this extent systemic risk measures as well as model parameters are indexed by the subscript t throughout.

2.1 CoVaR

The CoVaR of Adrian and Brunnermeier (2016) is one of the first systemic risk measures proposed in the aftermath of the 2007–2009 financial crisis. It rapidly gained popularity among academics and supervisors as the first working paper introducing the CoVaR methodology started circulating at the same time as the financial crisis was unfolding.

Adrian and Brunnermeier (2016) define the CoVaR of firm i as the Value-at-Risk of the entire financial system conditional on institution i being distressed, that is

$$\mathrm{P}_t(r_{m\,t+1} < \mathsf{CoVaR}^{p,q}_{i\,t} | r_{i\,t+1} = \mathsf{VaR}^{q}_{i\,t}) = p\,,$$

where the distress of firm i is defined as the return of firm i being at its Value-at-Risk $\mathsf{VaR}^q_{i\,t}$. Note that we define CoVaR with respect to the conditional distribution of returns given the information available at time

t. Adrian and Brunnermeier (2016) then propose to measure the systemic risk contribution of firm i on the basis of the ΔCoVaR, which is defined as the difference between the CoVaRs of firm i conditional on its returns being at the Value-at-Risk and at the median, that is,

$$\Delta\mathsf{CoVaR}_{i\,t} = \mathsf{CoVaR}^{p,q}_{i\,t} - \mathsf{CoVaR}^{p,0.50}_{i\,t} \,. \tag{2.1}$$

The $\Delta\mathsf{CoVaR}_{i\,t}$ measure is an index of tail dependence between the entire financial system and an individual institution. It captures the increase in the Value-at-Risk of the financial system as one switches the conditioning set from the return of firm i being at its median to its $1 - q$ Value-at-Risk. Adrian and Brunnermeier (2016) classify firms with the largest ΔCoVaR as most systemic, i.e. institutions that, when in distress, predict the highest increment in the Value-at-Risk of the system. Following Adrian and Brunnermeier (2016), we also define a dollar version of ΔCoVaR that takes the size of firm i into account, that is

$$\Delta\mathsf{CoVaR}^{\$}_{i\,t} = \mathsf{W}_{i\,t}\Delta\mathsf{CoVaR}_{i\,t} \,. \tag{2.2}$$

The size adjustment is motivated by Adrian and Brunnermeier (2016) as a device to compare more easily the systemic risk contribution of different financial institutions when the degree of heterogeneity in size is large. In this work we opt for a standardized version of the dollar ΔCoVaR, that is

$$\Delta\mathsf{CoVaR}^{\%}_{i\,t} = \frac{\mathsf{W}_{i\,t}}{\sum_{j=1}^{N_t}\mathsf{W}_{j\,t}}\Delta\mathsf{CoVaR}_{i\,t} \,. \tag{2.3}$$

Since firm size changes substantially throughout our sample, the percentage ΔCoVaR% is easier to interpret than its dollar counterpart. Last, it is is also useful to introduce an aggregate ΔCoVaR index to measure the overall degree of systemic risk in the financial system. In particular, we define the value weighted aggregate $\Delta\overline{\mathsf{CoVaR}}_t$ as

$$\Delta\overline{\mathsf{CoVaR}}_t = \sum_{i=1}^{N_t}\mathsf{w}_{i\,t}\Delta\mathsf{CoVaR}_{i\,t}, \tag{2.4}$$

where $\mathsf{w}_{i\,t} = \mathsf{W}_{i\,t}/\sum_{j=1}^{N_t}\mathsf{W}_{j\,t}$.

Different approaches can be used to estimate ΔCoVaR from the data. Here we rely on a quantile regression approach as in the original contribution of Adrian and Brunnermeier (2016). We assume that the relation between the quantiles of the system returns and firm returns of firm i is linear, that is

$$\mathsf{VaR}^{p}_{m\,\tau} = \alpha^{p}_{it} + \beta^{p}_{it} r_{i\,\tau} \;, \tag{2.5}$$

for $\tau = t - T_W, \ldots, t$ where T_W is the sample size of the rolling window estimator. The coefficients of equation (2.5) can then be estimated by standard quantile regression (Koenker and Basset 1978). The CoVaR is then obtained by replacing the firm return with the VaR of firm i, that is

$$\mathsf{CoVaR}^{p;q}_{it} = \hat{\alpha}^{p}_{it} + \hat{\beta}^{p}_{it} \widehat{\mathsf{VaR}}^{q}_{it} \;, \tag{2.6}$$

where $\widehat{\mathsf{VaR}}^{q}_{it}$ is the sample q-quantile of r_{it} obtained over the t-th estimation window. In our empirical implementation the confidence levels p and q are set both to 10% and the sample size of the rolling window estimator T_W equals 5 years.

It is important to emphasize that we have opted for a basic implementation of CoVaR. Substantial refinements may be achieved, for instance, by extending the set of conditioning variables in equation (2.5). The basic CoVaR implementation we focus on however, is more straightforward to implement using our historical dataset.

2.2 SRISK

Another popular measure of systemic risk proposed in the early aftermath of the 2007–2008 financial crisis is the SRISK of Brownlees and Engle (2016). This index is inspired by the Systemic Expected Shortfall of Acharya, Pedersen, Philippon, and Richardson (2017). SRISK associates the systemic risk contribution of firm i with its expected capital shortfall conditional on a severe market downturn. This is motivated by the theoretical model of Acharya, Pedersen, Philippon, and Richardson (2017) that shows that the negative externalities of a financial firm in a crisis is proportional to the capital shortage the firm experiences during the period of turmoil.

Following Brownlees and Engle (2016), we define the capital buffer of firm i as the difference between the market value of equity minus a prudential fraction k of the market value of assets, that is $\mathsf{W}_{i\,t} - k\mathsf{A}_{i\,t}$, where $\mathsf{A}_{i\,t}$ is measured as $\mathsf{W}_{i\,t} + \mathsf{D}_{i\,t}$. The parameter k is the prudential capital fraction, that is the percentage of total assets the financial institution holds as reserves because of regulation or prudential management. Notice that when the capital buffer is negative then the firm experiences a capital shortfall. Thus, we define the capital shortfall as the negative capital buffer of the firm

$$\mathsf{CS}_{i\,t} = k\mathsf{A}_{i\,t} - \mathsf{W}_{i\,t} = k(\mathsf{D}_{i\,t} + \mathsf{W}_{i\,t}) - \mathsf{W}_{i\,t}\,. \tag{2.7}$$

Acharya, Pedersen, Philippon, and Richardson (2017) argue that capital shortfalls are systemic when they occur during periods when the entire system is in distress. This motivates Brownlees and Engle (2016) to measure systemic risk using the conditional expectation of the future capital shortfall conditional on a systemic event. Let the systemic event be $\{r_{m\,t+1} < C\}$ where C denotes the threshold loss for a systemic event. Then the (dollar) SRISK is defined as

$$\mathsf{SRISK}^{\$}_{i\,t} = \mathrm{E}_t(\mathsf{CS}_{i\,t+1}|r_{m\,t+1} < C) = k\,\mathsf{D}_{i\,t} - (1-k)\,\mathsf{W}_{i\,t}(1 - \mathsf{MES}_{i\,t})\,, \tag{2.8}$$

where $\mathsf{MES}_{i\,t} = -\mathrm{E}_t(r_{i\,t+1}|r_{m\,t+1} < C)$ is the so called Marginal Expected Shortfall, the expectation of the firm equity return conditional on the systemic event. Note that (i) we define SRISK using the conditional expectation of returns given the information available at time t, and (ii) that the last equality of (2.8) follows from assuming that in the case of a systemic event debt cannot be renegotiated hence $\mathrm{E}_t(\mathsf{D}_{i\,t+1}|r_{m\,t+1} < C) = \mathsf{D}_{i\,t}$.[6] In this work we set the prudential fraction parameter k to 20% and the systemic loss threshold C to -10%. We use the superscript \$ in equation (2.8), as the units correspond to the dollar version of ΔCoVaR, denoted as $\Delta\mathsf{CoVaR}^{\$}_{i\,t}$. In order to produce an easier to interpret index Brownlees and Engle (2016) define the $\mathsf{SRISK}^{\%}_{i\,t}$ as

$$\mathsf{SRISK}^{\%}_{it} = \frac{\mathsf{SRISK}^{\$}_{i\,t}}{\sum_{i=1}^{N_t}(\mathsf{SRISK}^{\$}_{i\,t})_+} \tag{2.9}$$

[6] It is important to emphasize that while this assumption is a reasonable approximation for today's data, in our historical sample it is clearly violated.

where $(x)_+ = \max(x, 0)$. Note that the denominator is the sum of the capital shortages of the firms in the system when such shortages are positive. Therefore, $\mathsf{SRISK}^{\%}_{it}$ can be interpreted as the capital shortage of firm i relative to the total capital shortage experienced by the financial system. Put differently, $\mathsf{SRISK}^{\%}_{it}$, when its positive, measure the contribution of firm i to the total shortfall of the system. Last, we define aggregate SRISK as

$$\overline{\mathsf{SRISK}}_t = \frac{\sum_{i=1}^{N_t} (\mathsf{SRISK}^{\$}_{i\,t})_+}{\sum_{j=1}^{N_t} \mathsf{W}_{j\,t}} ,$$

that is the total capital shortage of the financial system measured by SRISK relative to the size of the entire system. While Brownlees and Engle (2016) do not standardize the aggregate SRISK index by the total size of the market, we do so in order to make this figure more easily comparable across different time periods.

It is straightforward to compute the SRISK measure once an appropriate estimator of MES is available. Brownlees and Engle (2016) resort to a GARCH-DCC model and a simulation algorithm to produce MES estimates. Unfortunately, it is not possible to pursue the same estimation approach using our historical data and here we opt for a simplified approach.[7] We obtain estimates of MES on the basis of a linear market model. That is, we assume that

$$r_{i\,\tau} = \beta_{it} r_{m\,\tau} + \epsilon_{i\,\tau} , \tag{2.10}$$

for $\tau = t - T_W, \ldots, t$ and where $\epsilon_{i\,\tau}$ is an error term with mean zero and variance σ^2_{it}. It is important to note that these are regressions not involving the market portfolio - as it would be the case for the CAPM - but rather $r_{m\,t}$ is the return on a portfolio of financial institutions. Under these assumptions MES can then be expressed as

$$\mathsf{MES}_{i\,t} = \beta_{it} \mathsf{ES}_{m\,t} ,$$

where $\mathsf{ES}_{m\,t} = -\mathsf{E}_t(r_{m\,t+1} | r_{m\,t+1} < C)$. MES can therefore easily be estimated via the model in equation (2.10) using standard OLS and employing a nonparametric estimator for the market expected shortfall $\mathsf{ES}_{m\,t}$. Hence, the MES estimator used in this work is

$$\widehat{\mathsf{MES}}_{it} = \hat{\beta}_{it} \widehat{\mathsf{ES}}_{m\,t} ,$$

[7]GARCH-DCC models require a sample size of at least a couple of hundreds observations to deliver sufficiently stable and accurate estimates.

where

$$\widehat{\mathsf{ES}}_{m\,t} = -\frac{\sum_{\tau=t-W}^{t} r_{m\,\tau}\mathbb{I}_{\{r_{m\,\tau}<C\}}}{\sum_{\tau=t-W}^{t} \mathbb{I}_{\{r_{m\,\tau}<C\}}} \ ,$$

where $\mathbb{I}_{\{r_{m\,\tau}<C\}}$ is the indicator function that is one when $\{r_{m\,\tau} < C\}$ and zero otherwise.[8]

2.3 Alternative Measures

The performance of CoVaR and SRISK is benchmarked against commonly employed balance sheet ratios and market risk measures: Leverage, size, volatility, beta and Value-at-Risk (VaR). As for CoVaR and SRISK we construct bank specific and system wide versions of these indices. We define the leverage of bank i as the book value of debt divided by the book value of equity

$$\mathsf{Lev}_{i\,t} = \frac{\mathsf{D}_{i\,t}}{\mathsf{E}_{i\,t}} \ .$$

Analogously, we define the aggregate leverage as the ratio of aggregate debt of the financial system over the aggregate market value of equity, that is

$$\mathsf{Lev}_{t} = \frac{\sum_{i=1}^{N_t} \mathsf{D}_{i\,t}}{\sum_{i=1}^{N_t} \mathsf{E}_{i\,t}} \ .$$

We define the size of bank i as (the log of) its market value

$$\mathsf{Siz}_{i\,t} = \log\left(\mathsf{W}_{i\,t}\right) \ ,$$

and aggregate size as as (the log of) the average of the total market values of all institutions in the panel

$$\mathsf{Siz}_{t} = \log\left(\frac{1}{N_t}\sum_{i=1}^{N_t} \mathsf{W}_{i\,t}\right) \ .$$

[8] When the current estimation window does not contain any system returns smaller than the threshold, we estimate $\widehat{\mathsf{ES}}_{m\,t}$ using its sample average over the full sample.

Equity volatility is probably the most common bellwether of risk. We define the volatility of bank i as

$$\mathsf{Vol}_{i\,t} = \sqrt{\frac{1}{T_W - 1} \sum_{\tau=t-T_W}^{t} (r_{i\,\tau} - \bar{r}_{i\,t})^2}\ ,$$

where $\bar{r}_{i\,t}$ is the average return of firm i in the t-th estimation window. It's aggregated version is the square root of the value-weighted average variance, that is

$$\mathsf{Vol}_t = \sqrt{\sum_{i=1}^{N_t} \mathsf{w}_{it} \mathsf{Vol}^2_{i\,t}}\ .$$

Next, we consider beta, that is the least square estimate of the slope of the aggregate financial system return on the return of bank i, that is

$$\mathsf{Beta}_{i\,t} = \frac{\sum_{\tau=t-T_W}^{t} (r_{i\,\tau} - \bar{r}_{i\,t})(r_{m\,\tau} - \bar{r}_{m\,t})}{\sum_{\tau=t-T_W}^{t} (r_{m\,\tau} - \bar{r}_{m\,t})^2}\ .$$

We also construct an aggregated beta index as the value-weighted average of the bank betas

$$\mathsf{Beta}_t = \sum_{i=1}^{N_t} \mathsf{w}_{it} \mathsf{Beta}_{i\,t}\ .$$

Last, we consider Value-at-Risk $\mathsf{VaR}^p_{i\,t}$ defined as the p-quantile of r_{it} obtained over the t-th estimation window. The aggregated version of which is

$$\mathsf{VaR}_t = \sum_{i=1}^{N_t} \mathsf{w}_{it} \mathsf{VaR}^p_{i\,t}\ .$$

In our empirical analysis these alternative measures are used as benchmarks for the systemic risk measures.

3 Historical Data

The data required to study the historical efficacy of systemic risk measures were heretofore unavailable. We correct this shortcoming by assembling a dataset comprised of balance sheet and financial market information for a panel of New York banks and trusts from January 1866 to December 1933. The balance sheet data is sourced from information published by the New York Clearinghouse (NYCH). The NYCH was a voluntary, self-regulating association of New York City banks and trusts which stored specie, facilitated exchange and clearing, and monitored the liquidity of member institutions, in part, by publishing member institution balance sheet information at a weekly frequency.[9]

Our balance sheet data are collected from the weekly reports published by the clearinghouse. National Banking Era bankers understood that asymmetric information about the health of individual clearing house members could transform a run on a single member into a system-wide panic. The NYCH therefore attempted to minimize information asymmetries by requiring its member banks to publish weekly condensed balance sheet statements. These statements which appeared in the Saturday morning *New York Times* and *Wall Street Journal* reported the average weekly and Friday closing values of each bank's loans, deposits, excess reserves, specie, legal tenders, circulation and clearings.[10] Unfortunately, formatting changes, omitted variables, and missing tables necessitated the occasional use of alternative sources. Those include the *Commercial and Financial Chronicle*, the *Daily Indicator*, and statements from both the Superintendent of NY State and the Office of the Controller of the Currency. The variables we collect consist of: capital, loans, specie (gold and silver), circulation, deposits, legal tenders, reserves with legal depositories, and surplus. We use the balance sheet data to construct measures of debt, equity and liquidity. Debt is defined as the sum of deposits whereas equity is measured as capital plus surplus and liquidity is defined as the ratio of liquid assets to deposits. NYCH statements were carefully scrutinized by investors and unexpected changes in leverage or liquidity could set off a stock market rally or decline. In some cases, missing data could not be located, as the NYCH did not publish individual member information during periods of financial stress. As noted in Gorton (1985), during banking panics, the clearinghouse organization pooled liabilities, uniting member banks under the Clearinghouse Committee. During these times the NYCH only published aggregate balance sheet information.[11]

[9] New York Clearinghouse transactions accounted for roughly 70 percent of all clearing house transactions in 1901. Relative to the national banking sector in 1901, the New York Clearinghouse members, which included national and state banks, represented roughly 10 percent of capital, and about a third of both deposits and loans.

[10] The Clearinghouse ceased publishing information on loans, legals, and reserves at the beginning of 1928.

[11] The periods for which individual balance sheet data was not published include the Panic of 1873 (10/73-11/73), the Barings Crisis (12/90-2/91), the Panic of 1893 (7/93-10/93), the Panic of 1907 (11/07-1/08), and at the start of the First World War (8/14-11/14). In addition, we were unable to locate the balance sheet for the week ending April 29, 1892 from any possible source.

We complement the clearinghouse bank balance sheet information with bank stock return data. The stock data is consists of the price, shares outstanding, and dividends of bank trading in New York City. The stock data was hand collected from over the counter quotations and share and dividend information published in the *Commercial* and *Financial Chronicle*. The price, share and dividend data allow us to compute the market value and holding period returns for each bank stock trading between 1866 and 1933.[12]

The balance sheet and market data are collected on a 28-day sampling frequency (i.e., each Friday every four weeks) from 1866 until 1925. The 28-day frequency was selected to correspond with dates for which the authors have previously collected the price, shares outstanding and dividends of New York banks. After January 1925 and until 1933 the data are monthly. During the data collection process, we double-entered each entry and cross-checked to ensure accuracy.[13]

The result of the compilation of balance sheet data is a raw panel consisting 132 financial institutions between January 1866 and December 1933. We then merge this information to our data on stock returns. Out of these 132 institutions roughly 3/4 of the banks and trusts were publicly traded.[14] As a result, we end up with a panel of 92 institutions.[15]

Table 1 reports the list of financial institutions for which we collect balance sheet data. A number of our institutions are still in existence today (such as Bank of America, Bank of New York, Citibank, and Chase). The large majority of banks listed in Table 1 have disappeared, merged or were acquired by other banks or financial institutions.

Besides individual bank data, the estimation of both SRISK and CoVaR requires a time series of returns for the financial system. For the New York banking sector, we calculate a value-weighted index of returns using all publicly-traded banks and trusts at the time. It is important to stress that not all clearinghouse banks and trusts were publicly traded, nor were all New York financial institutions members of the clearinghouse. This

[12] Gross returns are calculated for two consecutive non-missing time periods by equally weighting the bid and ask prices at each point in time, adding any paid dividends. We also correct for capital calls and stock splits.

[13] We also subjected our data to various quality control tests (some of which reported in the paper) to ensure that the analysis we conduct and the results we report are reliable.

[14] That is, stock returns and market values were available for these organizations.

[15] It is important to note, due to the historical nature of the data, the data are typically hand-entered from 19th and 20th Century publications. In some cases the historical record might contain a blank where there should be data or an illegible entry. We treat missing returns as missing values. On the other hand, missing balance sheet data is replaced with the latest previous data point available.

implies that the financial sector index we construct includes banks and trusts that were not clearinghouse members and that some clearinghouse members are not represented in our New York financial sector index. That said, the largest institutions at the time were both publicly traded and clearinghouse members.[16]

4 Measuring Systemic Risk in the Pre–FDIC Panics

4.1 The pre-FDIC Financial Panics

The pre-FDIC era provides us with a number of financial panics to evaluate the efficacy of systemic risk measures. To perform such an analysis we require a consensus of exactly when financial panics occurred. Kemmerer (1910), Sprague (1910), DeLong and Lawrence (1986), Gorton (1988), Bordo and Wheelock (1988), Wicker (2000), and Jalil (2015) have each attempted to date pre-1914 banking panics. Although there are a number of episodes of large deposit withdrawals and financial stress that only a minority code as a financial panic each of these authors agree that major panics occurred in 1873, 1884, 1890, 1893, and 1907. To this list we add three post-1913 panics in 1914, 1921 and 1931. Table 2 reports the list of the starting months of the eight banking panic events considered in this work. For each panic event we define a panic window as the 4 months window starting from the beginning of the panic. The last column of the table includes a brief description of the panic. In the remainder of this subsection we elaborate further.

Reconstruction and westward expansion following the end of the Civil War sparked a dramatic run-up in debt-fueled railroad investment. The panic of 1873 started when one of the largest investment banks of the day–Jay Cooke and Company–suffered large loses on its railroad bond investments and was unable to meet creditor demands. Jay Cooke had borrowed heavily from national banks and its failure sparked runs on the major commercial banks of Philadelphia and New York. The bank runs forced NYC banks to call in loans extended against stock and bond collateral which in turn forced a fire sale in securities listed on the NYSE. The stock exchange made an ill-fated decision to suspend trading and close for 10 days. Banks in NYC were in the habit of placing their liquid reserves in collateralized stock market call loans. When the NYSE

[16]Our stock returns and market value data includes 141 institutions. As mentioned previously, 92 of the 132 clearinghouse institutions were publicly traded and merged to the return and market value data.

closed these banks were unable to liquidate their collateral and were forced to suspend. The panic of 1873 quickly spread throughout the country and precipitated the long depression of 1873-78.

The panic of 1884 began in May 1884 when fraud was discovered at the brokerage firm Grant and Ward. The firm was speculating with their customers' collateral and posting the same collateral to secure multiple loans. The discovery revealed a serious flaw in the custody rules for stock market call loans that brokerages relied upon to finance their inventories and bank relied upon as a safe liquid investment for their excess reserves.[17] The Marine National Bank–which shared a partner with Grant and Ward–was forced into receivership when creditors withdrew funding. The Second National Bank suffered a run when depositor withdrawals revealed a $3 million shortfall due to its presidents embezzlement and the Metropolitan National Bank was forced to suspend due to false rumors that its president had lost money speculating bank funds. The Metropolitan was a major correspondent bank and its closure sparked runs on banks throughout the eastern seaboard. The panic ended when the NYCH declared the Metropolitan solvent and pooled member resources to lend $3 million to allow the Metropolitan to satisfy depositor claims. This action re-assured the public and the panic quickly waned.

Unlike the panics of 1873 and 1884, the panic of 1890 began abroad when Barings Bank of London nearly failed due to speculative losses on South American investments. While Barings was bailed out by a Bank of England coordinated consortium, the resulting liquidity shock was felt worldwide and resulted in a sharp stock market selloff and the suspension of the brokerage firm Decker, Howell and Co. This firm relied upon the Bank of North America to finance its dealings and news of the suspension triggered a run on the Bank of North America. Runs soon spread to other brokerage firms and the banks that financed them but the panic quickly subsided when it became known that J.P. Morgan had formed a consortium of clearing house banks to extend an emergency loan to the Bank of North America.

The panic of 1893 was the most severe panics in the national banking era (Kemmerer (1910)). Unlike earlier panics, the panic of 1893 had its roots far from the financial centers of London or New York.[18] The recession that followed the Barings Crisis had resulted in a drain in the US Treasury's gold reserves and doubts about

[17] Chicago Tribune May 10, 1884. At the time, the Tribune stated "The rottenness of Wall-Street methods has never been so startlingly illustrated as by the collapse of this huge gas-bag."

[18] See Carlson (2005) for a detailed description of the events leading up to and during the panic of 1893.

the Treasury′s ability to maintain the gold standard prompted foreign depositors to withdraw money from US banks. At the same time, the recession increased loan defaults and raised fears about the solvency of country banks. In the summer of 1893 bank runs in Midwestern and Western cities resulted in over 400 bank suspensions and forced the remaining country banks to raise liquidity by withdrawing funds that had been deposited in New York to invest in the relative safe high return overnight call loan market. The NYCH banks withdrew funding to the call market forcing brokerages and stock market speculators to sell at fire-sale prices. As the stock market declined bank runs intensified and the NYCH banks were forced to slow payments to the interior. Cut off from their NY funds country banks failed throughout the nation and many clearing houses outside of New York were forced to issue script to in place of currency. The panic ended by the fall when high interest rates attracted sufficient European gold that banks throughout the nation resumed normal convertibility.

The panic of 1907 was perhaps most similar to the recent 2008 financial crisis. By 1907 trust companies had taken advantage of regulatory arbitrage to form a large "shadow" banking sector. The panic of 1907 began when Otto Heinze, the brother of copper magnate and prominent banker Augustus Heinze, attempted to corner the market in his familys publicly traded United Copper Company. When the corner failed the losses were so spectacular that depositors ran on any financial institution associated with Augustus Heinze including the Mercantile National Bank and the Knickerbocker Trust Company–the third largest trust in New York. When Knickerbocker was forced to suspend country banks feared that other Trust suspensions would endanger deposits in NYCH banks that had engaged in profitable lending to the citys Trusts. The resulting run forced widespread suspensions. The panic subsided when J.P. Morgan again organized a consortium of banks and trust companies to pool resources and provide liquidity for their weaker brethren.

Most studies that attempt to date financial panics stop after the creation of the Federal Reserve System. We also include 1914, 1921, and 1931 as years that include financial panic events with implications for the banking sector.

The commencement of hostilities and the concomitant market disruptions caused financial markets around to globe to close in the second half of 1914. In terms of the banking sector, the New York Clearinghouse ceased publishing balance sheet information from August until November. Gorton (1988) and Reinhart and

Rogoff (2013), as well as others, cite the time as a financial panic.

The panic of 1921 resembled the panic of 1893. The sharp deflation after WWI resulted in widespread farm failures throughout the Midwest in 1920 and 1921. 505 banks were suspended in 1921 when falling prices and business failures eroded depositor confidence in bank balance sheets.

Lastly, we turn to the great depression and focus on 1931 as a panic event. At the start of the Great Depression, the stock market crash of 1929 and the regional banking panics in 1930 and early 1931 caused failures in the banking system. Up until that time, though, the implications were fairly localized and did not cause major disruptions.[19] Starting in August of 1931, though, shortly after Great Britain abandoned the Gold Standard, several large banks failed and runs spread throughout the nation. Nationwide, 827 banks suspended during September and October 1931.

4.2 The New York Financial System

The National Banking Acts (NBA) of 1863 and 1864 reorganized United States banking into a nationwide system of federally chartered banks. The NBAs unified the national currency, established a federal regulator in the Office of the Controller of the Currency and, and provided regulatory incentives to pool excess reserves in central reserve cities. In particular, the NBAs encouraged the development of a nationwide inter-bank money market centered in New York City. As a result many of the most systematically important banks in the United States were located in New York and members of the New York Clearing House (NYCH).

Figure 1 reports the time series of the number of banks in the panel throughout the sample period. The figure shows that the size of the NYCH financial sector has been changing drastically through time. As seen in Figure 1, our sample has about 40 members in 1865, a number that slowly increases to around 60 members until the end of the century and that then starts declining. The primary cause of the decline in the number of banks in our sample is bank mergers, which account for nearly 45 percent of the attrition. Failures account for roughly 20 percent and departures from the clearinghouse resulted in roughly 10 percent. Of course, many mergers were the result of larger banks acquiring troubled institutions that would have likely exited

[19] See Richardson (2007).

due to failure.[20] Importantly, while the overall size of the banks in our sample reflects a substantial segment of the pre-FDIC banking sector, the declining count runs counter to the overall increase in national and state banks in the country as a whole. This is due, in part, to the emergence of the Federal Reserve as a competing institution for membership in the New York Clearinghouse.

4.3 Measuring the Health of the Financial System: Aggregate Deposits

In order to study systemic risk in the financial system, it is important to introduce an appropriate (ex-post) indicator of the health of an individual bank as well as the entire financial system. In this work we use aggregate deposits as an index of strength of the entire financial system. Typically, pre-FDIC panics are preceded by a deterioration banks' balance sheets. Specifically, most pre-FDIC panics were preceded by deposit withdrawals disproportionately drawn from the banks experiencing distress.

Figure 2 aggregate deposits in a two year window containing each of the panics. The vertical shaded areas are the panics as listed in Table 2. As mentioned earlier, during periods of financial distress, the Clearinghouse halted publication member banks' balance sheet information. The flat lines in Figure 2 reflect the lack of information on deposits. The plots show that indeed many of the panics correspond to some of the worst drops in aggregate deposits. We observe major drops during all the panics except 1921. The scale of the plots also indicate that the drops were sometimes 20% or more at the aggregate level.

4.4 Systemic Risk Measurement

In our study we produce CoVaR and SRISK for each date t in the sample using backward looking data only to avoid any look ahead bias. In particular, in this work we rely on a 5-year rolling windows estimation scheme. We include in the sub-panel all the financial institutions that are trading on the first date of the panic window that have at least 6 observations over the previous 5 years (the value of T_W).[21] Note that the sub-panels we construct are unbalanced in that banks might have not been trading for the entire 5 year

[20] For example, Bank of America's acquisition of Merrill Lynch likely forestalled Merrill's collapse in 2007.

[21] Note that the system wide index is available for each period throughout the sample. Thus, when estimating CoVaR and SRISK for firm i we are only constrained by the availability of the bank data.

window and because of missing data.

It is useful to provide more insights on the empirical characteristics of the NYCH banking system the panel around the eight panic events listed in Table 2. For each panic date we construct a sub-panel over a window spanning from 5 years before the onset of the panic until the end of the crisis.

Table 3 reports the number of banks in the panel as well as the first quartile, third quartile and mean number of time series observations available for each bank around each panic event. In line with Figure 1 the table shows that the number of banks has been changing quite drastically throughout the sample. In particular, for the last panic event the sample size contains just 16 financial institutions. The number of time series observations available also changes throughout the sample. As a result of missing values, the average number of average observations for the banks in the panel is just 28 for the first panic event. As we move towards the end of the panel data quality increases and most of the banks in each sub-panel have data available for almost the entire window.

Table 4 reports descriptive statistics on the return data around panic dates. The sample moments of the return distribution vary considerably through the different panic events. As far as the returns dynamics are concerned, we note that inspection of the price time series reveals that the stock price data in the beginning of our sample features some illiquidity patterns and exhibits “bid-ask bounce” type behavior. Accordingly, returns exhibit negative first order autocorrelation in the first part of the sample. Squared returns also exhibit autocorrelation which becomes more prominent later in the time period of interest. We observe a considerable increase in the volatility of returns in the last panic event in 1931. This is due to the fact that starting from the 1925 the stock market bubble that lead to the crisis 1929 started to inflate considerably. Accordingly, the volatility of all time series in the panel increase rapidly in the last part of our sample.

Next, we give insights on the quality of the empirical models that are the key ingredients to respectively CoVaR and SRISK calculations. For CoVaR the key ingredient is the quantile regression reported in equation (2.5) while for SRISK it is the CAPM-like regression appearing in equation (2.10).

Table 5 reports median, first quartile and third quartile of the slope coefficients (when significant), R^2 as well as the percentage of significant slope coefficients at the 10% significance level for the respective quantile regression (2.5) – left panel – and CAPM-like regression (2.10) – right panel. Let us focus first on the quantile regressions underpinning CoVaR. We observe that the R^2s are high towards the end of the historical sample, on average 50% for the 1931 crisis, but low with an average of 11% for the 1873 panic. Still, at least 75% of the quantile regressions feature significant slope coefficients even when the R^2s are low. The magnitudes of the slope coefficients are relatively stable, on average about 0.7, for most of the crises. Broadly speaking, though it seems that the quantile regressions yield sensible results in terms of (i) significance and regression fit and (i) magnitude of the parameters. It is fair to say that the data quality improved as we move from the early part of our historical sample to the end. That is in particular reflected in the significance of the slope coefficients which is 100% in 1931. Turning our attention now the second panel of Table 5 which covers the regression which is key for the calculation of MES, and therefore SRISK. As far as the goodness-of-fit is concerned, the R^2 are roughly above 10% for most of the panics and they only increase in the last two panic events. Also, the percentage of significant slope coefficients is around 50% for most of the panic events and it spikes to 100% only in for the 1931 crisis. Recall that the regressions involve the return on a portfolio of financial institutions and therefore we expect betas close to one. That is indeed what we observe in Table 5. Looking at the cross-sectional variation, we see that the interquartile range is fairly large, though, for early part of the sample – in particular 1873 and 1884. For the 1931 crisis, we observe that all betas are significant and the interquartile range is small.

In Figure 3 we report the times series plots of aggregate CoVaR and SRISK, denoted respectively $\Delta\overline{\mathsf{CoVaR}}_t$ and $\overline{\mathsf{SRISK}}_t$, over the entire sample and for two sub-periods. The time series appear against the background of vertical shaded areas corresponding to the major events we focus on. Over the entire sample (the top two panels) from 1868 to 1934 we see that both CoVaR and SRISK feature a major upward trend toward the end of the sample – i.e. the Great Depression. As can be seen in the remaining panels, $\Delta\overline{\mathsf{CoVaR}}_t$ and $\overline{\mathsf{SRISK}}_t$ appear to feature upticks during or ahead of many of the panics over the time frame of interest. That said, there are several dramatic movements in both $\Delta\overline{\mathsf{CoVaR}}_t$ and $\overline{\mathsf{SRISK}}_t$, that occur outside of periods for which there is evidence of widespread financial stress. As a result, while the time series of our systemic risk measures are informative, we need a more formal framework to accurately evaluate the efficacy of each measure.

The increases in our systemic risk metrics prior to the great depression are remarkable. The near-exponential growth seen in Figure 3 for both $\Delta\overline{\mathsf{CoVaR}}_t$ and $\overline{\mathsf{SRISK}}_t$, from 1929 onwards indicates a build up of risk in the banking sector and begs the question of whether the accumulation of risk was diffuse or the result of several systemically risky institutions. Figure 4 presents a decomposition of the aggregate CoVaR and SRISK series. The figure splits the time series and presents the SRISK and CoVaR for each individual bank. As a result, we can see that prior to the dramatic expansion of riskiness in the late 1920s the systemic risk measures provide information on individual banks' riskiness over the sample that was lost in the scale of Figure 3. Moreover, the decomposition provides evidence that the when systemic risk as measured by CoVaR and SRISK is elevated or increases, the movements and level reflect readings at several key institutions. For example, National City and Chase National Banks contribute significantly to the run-up in the riskiness of New York City banks prior to the Great Depression. We will revisit this heterogeneity and Figure 4 in the next section.

Figure 5 presents time series plots of the aforementioned alternative measures. Size, volatility, and VaR all increase dramatically in the latter part of our sample, that is, prior to the great depression, somewhat similar to the upswings in both CoVaR and SRISK. Leverage, in the first panel, while increasing from the 1870s to the 1930s, overall, stepped back a bit from its highs achieved over the 1916 to 1922 time period. Beta exhibits no discernible trend over the time frame of interest, and posts several large swings throughout the historical period of interest. It is also noteworthy that each of the measures presented in Figure 5 exhibit notable swings around our panic-periods of interest.

4.5 Systemic Rankings

Before using a more formal econometric framework to test the null that CoVaR and SRISK do not contribute more information than the standard suite of risk measures, we examine each panic event by ranking financial institutions with the largest deposit losses. With the rankings in hand, we can compare the banks and trusts with substantial deposit losses to their rankings in terms of the systemic risk measures.

Table 6 reports the ten financial institutions that suffered the largest deposit contraction during each panic date, together with the value and rank of the systemic risk measures prior to the crisis. The deposit contractions are expressed as percentages relative to the entire deposit contraction experienced by the financial system in each panic event. Note that we are reporting the value of the percent versions, i.e. $\Delta\mathsf{CoVaR}_{it}^{\%}$ and $\mathsf{SRISK}_{it}^{\%}$. For comparison purposes, the table also reports the value and rank obtained from leverage, size, volatility, beta and VaR. In what follows we provide more detailed comments of all the panic events in our sample.

The Panic of 1873. In September 1873 the post-Civil War railroad boom went bust after the Bank of Jay Cooke and Company suspended payments. As can be seen in the 1873 panel of Table 6, both Fourth National and Central National banks contributed significantly to the overall 27 percent decline in aggregate deposits. As the panic spread, market participants fled from investments that were exposed–either legitimately or through rumor–to Jay Cooke and the railroads. As was reported in the New York Times at the time, the Fourth National Bank cleared checks for Henry Clews and Co., which was exposed to large investments in railroad stocks. Fourth National bank is the top bank in the deposit loss rankings and ranks first in terms of SRISK and seventh for CoVaR. Similarly, Central National Bank, which ranked second in terms of deposit losses, maintained a relatively high CoVaR and SRISK ranking prior to the panic. Interestingly, after the panic Central National was declared to be in an "embarrassed" condition and was investigated by the New York Clearinghouse. [22]

The Panic of 1884. In late May 1884 another railroad-related downturn occurred in conjunction with the collapse of a major brokerage firm. Similar to the panic of 1873, we see the Fourth National Bank near the top of our rankings for deposit losses and maintained high rankings for our metrics of systemic risk. At the time, it is mentioned that the Fourth National Bank suffered large deposit withdrawals due to its exposure to the railroad industry.[23] Likewise, the Metropolitan bank holds a relatively elevated position in terms of CoVaR and was extensively written about at the time as being highly exposed to the railroad sector, as its president and the bank was heavily involved in railroad speculation.[24]

[22] See New York Times, September 19, 24, 25, and Nov 4, 1873.

[23] See New York Times, June 19, 1884.

[24] The president of Metropolitan Bank, George Seney, was also the president of the Georgia Railroad. See "The Metropolitan Bank, The Reasons for its Suspension," New York Times, May 15, 1884.

The Panic of 1890. The panic of 1890 spread to the United States as foreign banks withdrew deposits in the wake of the Barings Crisis in London. The months preceding the panic were characterized by slow deposit outflows rather than sharp declines and culminated with the issuance of clearing house certificates in late November 1890. As can be seen in Table 6 the aggregate deposit index declines only about 10%, substantially less than the previous two crises. For this crisis period, the relationship between deposit losses and the systemic risk measures are also not as clear cut, which is likely due to the crisis being more acute overseas. Significant domestic implications of the panic of 1890 were not felt domestically until several years later.

The Panic of 1893. The Baring crisis finally came to a head in the panic of 1893. At the time, there was also a substantial economic downturn. In contrast to the overall economic situation, aggregate deposits declined by only 11%, a magnitude similar to the 1890 panic. In addition, the metrics of systemic risk appear to have little relation to deposit losses in Table 6. Two aspects of the panic of 1893 might account for the lack of a large decline in deposits and the seemingly unrelated systemic risk measures to deposit losses. First, the financial system in New York was spared from the panic, as cities such as Chicago and Omaha suffered larger bank runs.[25] Second, the crisis partially arose from the real economy to the banking sector, as mentioned previously.

The Panic of 1907. The panic of 1907 entailed a crisis of confidence in the financial trust sector and the banks that were connected to them. As depositors ran to withdraw money from trusts they deposited these funds into many New York Clearinghouse banks. As a result a regulator using our systemic risk metrics to monitor deposit flows into clearinghouse banks would have mistakenly thought that the system was relatively stable. Unlike the previous two periods of banking stress Table 6 indicates that a large number of the banks that lost substantial deposits were ranked highly, in terms of CoVaR. Of note, the president of Mercantile Bank, which was ranked relatively highly for both measures of systemic risk, was implicated in the attempt to corner the copper market. As a result, the outflow of deposits from the Mercantile Bank were substantial, as depositors assumed the bank's assets were involved in the scheme. Moreover, the National

[25] See New York Times, June 15, 1893.

Bank of Commerce, ranked first in both deposit losses and SRISK, and ranked third in CoVaR in Table 6 was highly exposed to Knickerbocker Trust and had been extended credit to the Trust company up until the start of the crisis.[26]

The Panic of 1914. The start of the First World War and the concomitant market disruptions led to the closing of financial markets around to globe in the second half of 1914. As can be seen in Table 6, there was a dramatic decline in deposits across Clearinghouse members, particularly amongst those with high measures of systemic risk. Specifically, deposits plummeted more than 30 percent and banks with high measures of both CoVaR and SRISK, such as National City Bank, lost a substantial amount of deposits. In addition to the uncertainty and overall financial stress caused by the declarations of hostilities, the European situation initiated a large repatriation of gold stocks from the United States. Of the banks for which large gold withdrawals were made, National City Bank was particularly impacted by the withdrawal of its specie, likely leading to depositor concern about the institution's solvency.[27] Importantly, National City was ranked first in terms of both CoVaR and SRISK prior to the crisis and seen in Figure 4.

The Panic of 1921. As mentioned previously, the crisis in 1921 was a downturn resulting from post-war monetary and fiscal contraction. While the banking sector experienced a period of financial stress, it was short-lived and was tends to not be defined as a panic in previous research. Indeed, overall deposit losses were only two percent. That said, several banks, such as First National Bank, lost a substantial amount of deposits at the time and were ranked highly for our measures of systemic risk.

The Panic of 1931. At the start of the Great Depression, the stock market crash of 1929 and the regional banking panics in 1930 and early 1931 caused failures in the banking system. Up until that time, though, the implications were fairly localized and did not cause major disruptions.[28] Starting in August of 1931, though, shortly after Great Britain abandoned the Gold Standard and several large banks failed, the deposit losses and runs on various institutions grew substantially. And, as can be seen in the last panel of 6, there

[26] See Moen and Tallman (1990).
[27] See New York Times, June 12 and August 1, 1914.
[28] See Richardson (2007).

appears to be a relationship between institutions with the largest deposit losses, their systemic risk rankings, and the additional risk measures.

Overall, it is interesting to point that in most panic events the large majority of deposit losses in the financial system is concentrated in a small number of financial firms and that in a number of important cases CoVaR and SRISK measures succeed in ranking such institutions as highly systemic.

5 Backtesting Systemic Risk Measures in the Pre–FDIC Panics

The systemic risk literature typically focuses on two main challenges. One pertains to identifying systemically important financial institutions in the economy. The other relates to whether systemic vulnerabilities can be identified preventively in order to avoid or attenuate future financial crises. We call the former the cross-sectional challenge - i.e. identify across financial institutions which one(s) might be the most vulnerable. The second challenge relates to the construction of early warning signals of distress in the financial system and we call this the time series challenge.

5.1 Identifying Systemic Institutions

In this section we assess whether individual bank CoVaR and SRISK help identifying systemic institutions. It is important to stress that the focus of this analysis is to identify such institutions ahead of a panic rather than predicting financial meltdowns.

In order to carry out such an exercise it is crucial to measure ex-post the systemic importance of a financial institution. The variable we use in this section to carry this exercise is the max deposit contraction experienced by each bank during the panic window. In the pre-FDIC era panics, depositors withdraw currency out of fear that their assets', i.e. deposits, value will decline. Consequently, the largest declines in deposits are associated with banks for which depositors ascribe a high likelihood of failure.[29] Deposit declines during panic events are however hard to measure for at least three reasons. First, when the deposit

[29]It is important to stress that this relationship is not perfect, due to the possibility of scrip issuance and the suspension of withdrawals during a panic.

losses were excessive the NYCH would stop reporting balance sheet figures. Second, in panic events banks would suffer large withdrawals but as soon as the panics were over investors would return their savings to the very same banks. Third, the exact timing of the panic varies in each event, in the sense that while in some panic events the largest deposit withdrawals are sudden, in other episodes deposits withdrawals are more gradual and reach their peak at the end of the panic window.

The effects of these peculiar dynamics are apparent in Figure 2, which plots the aggregate deposits around panic events. This motivates us to use the max deposit contraction experienced by each bank during the banking panic starting from the beginning of the panic as a sensible proxy of the distress experienced by the banks in the panel for each crisis. To make this figure easier to read across different panic events, we standardize the maximum deposit loss by the sum of the max deposit contraction in each panic event. We will denote this as $\Delta\mathsf{Dep}_{it}$ for bank i. It is important to emphasize that our distress proxy is larger for those institutions that suffered larger losses in absolute terms in each panic. Note that we use again the percent versions, i.e. $\Delta\mathsf{CoVaR}^{\%}_{i\,t}$ and $\mathsf{SRISK}^{\%}_{it}$, but to simplify notation we simply refer to them as CoVaR and SRISK.

5.1.1 Predicting Individual Bank Deposit Losses Around Panic Events

We carry out a regression analysis to assess if CoVaR and SRISK are significant predictors of the deposit losses experienced by the financial firms during panic events. More specifically, we pool all panic events in our sample and we estimate a panel specification to assess whether CoVaR and SRISK provide significant signals across all events. We consider the following specification:

$$\Delta\mathsf{Dep}_{it} = \beta\,\mathsf{SRM}_{i\,t-l} + \sum_{k=1}^{p} \gamma_k\, x_{k\,i\,t-l} + \eta_i + \nu_t + u_{it} \tag{5.11}$$

where $\Delta\mathsf{Dep}_i$ is the maximum deposit contraction of institution i from the beginning of the panic until the end of the panic window, SRM_i denotes the value of the systemic risk measure CoVaR or SRISK measured in percentage terms, x_k denotes the control variables, η_i is a bank fixed effect, ν_t is a panic fixed effect, and u_{it} is an error term. The set of controls used in the regression contains size, leverage, volatility, beta and

VaR. The predictors in equation 5.11 are computed 1-month-ahead, 3-months-ahead and 6-months-ahead in order to assess how predictability is affected by the horizon. We note that the panel used to estimate the model is highly unbalanced. The total number of observations is 371 and on average a financial institution is present in 4 panics.

Table 7 reports the estimation results of the model in equation (5.11) for different horizons from the beginning of the panic (1-, 3- and 6- months ahead). The table reports estimation results for the model (5.11) under different set of restrictions: we report estimation results for CoVaR and SRISK as well as CoVaR and SRISK with the alternative risk controls. We always include bank fixed effects to the regression and report estimation results with and without panic fixed effects. The last two columns omit the control for VAR in the CoVaR regressions.

The estimation results show that, when considered individually, CoVaR and SRISK are significant predictors of the deposit losses suffered during panic events. However, when controls are included only SRISK retains significance when the full suite of controls are implemented. As mentioned, the final two columns exclude the control for Value-at-Risk. In this specification CoVaR significantly predicts deposit loss without panic fixed effects at the 1- and 3-month horizons and significantly predicts for both specifications at the 6-month horizon. Hence, it appears that VaR is a good predictor of systemic risk as well. However, in the regression models with SRISK, even controlling for VaR does not make SRISK insignificant – while it does adversely affect the significance of CoVaR.

It is important to note that the controls for leverage, size, volatility and VaR are also significant predictors of deposit losses for many specification across forecast horizons. Typically beta is not. As noted, the evidence of the importance of employing SRISK and CoVaR changes only slightly at different horizons. Overall, the measures of systemic risk improve deposit loss prediction throughout our sample, even when controlling for bank fixed effects and panic dummies. Importantly, these findings hold when controlling for a suite of additional metrics of the risk for a financial institution.

If we select the regression with the best overall fit in terms of R^2 we are looking at the specification with SRISK and all the controls included (column (8) in Table 7). It is worth noting that neither leverage nor size are significant. Only volatility and VaR are consistently significant across all horizons.

5.1.2 Cross-Sectional Correlations Around Panic Events

In order to synthesize the degree of accordance in each panic between the rankings of ex-post deposit losses and ex-ante risk measures we compute rank correlations for each panic event in our sample. The rank correlations are again computed for different horizons equal to 1, 3 and 6 months.

We report the results of the rank correlations analysis in Table 8. We expect negative rank correlations, as we associate high rankings with large deposit losses – and that is indeed what we observe. For two panic events (1893 and 1907) SRISK is the only significant systemic risk measure, that is, the signals from our measures of systemic risk are not always consistent. These results are consistent with our observations from the analysis of Table 6 that the panic of 1893 was likely transmitted from the real economy to the financial sector with financial sector stress occurring mostly in cities other than New York. Moreover, the evidence surrounding the panic of 1907 indicates that the source of financial stress originated from financial trusts, which were not en masse members of the New York Clearinghouse at the time. In all other panic events we observe that CoVaR and SRISK provides significant negative rankings. For the 1873, 1884, 1907, 1914 and 1931 we see that CoVaR and SRISK perform rather well with significant rank correlations.

The other measures of risk also provide useful information but in these cases however there is heterogeneity in terms of correlation patterns that emerge. More specifically, we note that (i) leverage is not a good predictor for systemic risk as the ranking of leverage and that of runs on deposits is almost never significant at any horizon, (ii) neither beta nor market volatility are good systemic risk measures, (iii) size performs well and is at par with CoVaR and/or SRISK in terms of rank correlations, and finally (iv) VaR is not always significant, but consistent with the results in Table (5.11), appears significant when CoVaR is not. It is interesting to note that the rankings are rather stable across horizons. In particular, 6 months before the beginning of the panic dates correlations are close to the results one gets 1 month before of the panic. Overall, the analysis that CoVaR and SRISK do contain useful information on the cross-sectional distribution of deposit losses over the crisis and that these measures help ranking institutions satisfactorily at least 6 months before the beginning of the panic events.

It is also of interest to gather how different the rankings are across the various measures. To this extent, in Table 9 we report the rank correlation between CoVaR and SRISK as well as the other measures. Specifically, the rank correlations are computed across the series - systemic risk measures as well as the alternative ones. First, we note that CoVaR and SRISK indeed provide fairly similar rankings and that the average rank correlation among the measures becomes larger in the latter part of the sample. Among the alternative measures used in this work, beta and size are the ones that are more correlated with CoVaR and SRISK, with rank correlation that are well above 0.5 for most panics. It is interesting to recall that despite beta being strongly correlated with the systemic risk measures, beta rankings do not have high rank correlation with distressed institutions. Volatility is uncorrelated for the most part with the exception of few weakly significant negative correlation with CoVaR in the first part of the sample. Last, leverage is positive correlated with SRISK and CoVaR in a number of different panic events but overall no clear pattern emerges.

5.1.3 Predicting Individual Bank Deposit Losses Around NBER Expansions and Recessions

What happens during non-panic episodes – and in particular during NBER expansions and contractions *not* associated with financial panics?[30] For expansions and contractions we take respectively the periods corresponding to the eight largest deposit increases and the eight non-panic biggest declines and run again panel regressions of the type in equation (5.11). All the regressors are the same, except for ν_t as we replace the panic fixed effect by expansion and contraction fixed effects covering each of the six selected episodes.

Table 10 reports the estimation results for contraction events. By themselves, CoVaR and SRISK are significant predictors of deposit declines in the panel. Results convey that CoVaR and SRISK flags deposit declines whether it is a financial panic or not. These results appear again to be robust across forecast horizon. Rank correlations between the risk measures and the deposit contractions in each deposit contraction events (Table 18 in the appendix) show results that are roughly in line with the evidence of Table 8, namely CoVaR and SRISK are significantly correlated with deposit contractions for the vast majority of contraction events.

[30] To be more precise the contraction dating is as follows: 01-01-1873 - 12-31-1875, 01-01-1883 - 12-31-1885, 01-01-1892 - 12-31-1896, 01-01-1903 - 12-31-1904, 01-01-1907 - 12-31-1908, 01-01-1910 - 12-31-1911, which are taken from Davis (2006), whereas the remaining are from the original NBER dating: 01-01-1913 - 12-31-1914, 08-01-1918 - 03-31-1919, 01-01-1920 - 07-31-1921, 05-01-1923 - 06-31-1924, 10-01-1926 - 09-31-1927 and 08-01-1929 - 03-31-1933. Note that Davis (2006) only provides a yearly dating, so we always take January to December from the selected year. Expansions are the compliment of contractions.

Table 11 reports the estimation results for expansion events. The findings are simple to summarize. None of the systemic risk measures are significant. This means that CoVaR and SRISK measure left tail risk rather than panic specific distress. Rank correlations between the risk measures and the deposit expansions in each deposit expansions events (Table 19 in the appendix) show that CoVaR and SRISK are typically not significantly correlated with deposit increases.

5.1.4 Predicted and Actual Capital Shortages Around Panic Events

It is possible to design an additional validation exercise for the SRISK measure only. The SRISK index is a prediction of the capital shortage a bank would experience conditional on a systemic event. This motivates us to carry out the following exercise. For each panic event we run a Mincer-Zarnowitz type regression to assess whether SRISK provides an unbiased prediction of such a shortage, that is we consider

$$\mathsf{CS}_i = \alpha_0 + \alpha_1 \mathsf{SRISK}_i + u_i \; ,$$

where CS_i is the realized capital shortage suffered by bank i at the last period of the panic window computed according to equation (2.7) and SRISK_i denotes the SRISK of firm i measured in dollars. The capital shortage and SRISK are standardized in units of billions of dollars to make the tables easier to read. Moreover, we run the regression for different values of k (15%, 20% and 25%). It is important to emphasize that SRISK is a conditional forecast (recall we set the systemic risk loss C to -10%) and is not an unbiased forecast of the capital needs of a bank in the crisis. Therefore, there is no reason *a priori* why the α_0 and α_1 coefficients in the Mincer-Zarnowitz type regression should be zero and one. Nevertheless, it is interesting to estimate this regression to gain insights into predicted and realized shortages during panic events. In particular, as SRISK is currently potentially used in policy debates regarding bailout costs it is important to understand the predictive content.

We report the estimation results of the regression in Table 12. The table shows that SRISK is a strongly significant predictor of the capital shortages and that the R^2 index is large for all panic events except 1873. Despite the strong positive correlation, the estimates of the slopes are significantly different from one, implying that SRISK fails to provide an unbiased estimate of the actual capital shortage in the panic event. In particular the slope coefficient is typically around 2, hinting that SRISK tends to underestimate the capital shortage. It is important to point out that in the panic of 1931 the slope coefficient of the regression is equal to one. This means that SRISK predicts the capital shortages during the Great Depression.[31]

5.2 Predicting Aggregate Turbulence

In this section we assess if aggregate CoVaR and SRISK are able to provide useful early warning signals of distress in the financial system as a whole. Hence, we address the time series prediction properties of aggregate systemic risk measures. We start with investigating whether increases in aggregate CoVaR and SRISK are significant predictors of changes in aggregate deposits around panic events. Next we move to expansions and non-panic recessions. Once again, in this exercise we focus on measuring the value added of the systemic risk measures over what is explained by that is volatility, beta, leverage and size.

5.2.1 Predicting System Wide Deposit Losses Around Panic Events

In order to assess the formally the predictive properties of CoVaR and SRISK we consider the following time series regressions,

$$\Delta\overline{\mathsf{Dep}}_{t+h} = \alpha_0 + \sum_{l=1}^{3} \alpha_l \Delta\overline{\mathsf{Dep}}_{t-l} + \sum_{l=1}^{3} \beta_l \Delta\overline{\mathsf{SRM}}_{t-l} + \sum_{k=1}^{p}\sum_{l=1}^{3} \gamma_{kl} x_{k\,t-l} + u_{t+h} \ , \tag{5.12}$$

where $\Delta\overline{\mathsf{Dep}}_t$ is the forward-looking 6-month change in aggregate deposits, $\Delta\overline{\mathsf{SRM}}_t$ is the monthly change is the aggregate systemic risk measures (either CoVaR or SRISK) and $x_{k\,t}$ denotes the changes in the k-th control variables and u_t is a prediction error term. It is important to emphasize that $\Delta\overline{\mathsf{Dep}}_t$ is defined as the change in deposits between period t and $t+6$. We run this regression for different horizons h ranging from 1 and 3 months ahead. We carry out inference using robust Newey-West standard errors.[32]

[31] We also estimated the Mincer-Zarnowitz equation in a panel regression context, yielding a single set of parameter estimates for which the null hypothesis of interest is also strongly rejected.

[32] When choosing the bandwidth of the Newey-West standard errors we make sure to consider a number of lags larger than $6+h$, to take into account the serial correlation arising from the definition of the dependent variable and the forecasting horizon.

The results appear in Table 13 where for each horizon we have four regression results: (a) CoVaR without and with controls and (b) SRISK with and without controls. An F-test is used to see whether the systemic risk measure are jointly significant (all three lags considered). The ΔR^2 also measures the incremental contribution of the systemic risk regressors. The results are not particularly overwhelming. Judging by the incremental R^2 and F-test we see some predictive value but it is relatively small. Both CoVaR and SRISK are significant, with one month lag for both horizons of 1- and 3-months. Among the other controls we see that leverage is significant as well as size.

5.2.2 Time-Series Correlations Around Panic Events

Table 14 reports the time series correlations between the various aggregate risk measures and aggregate deposit losses and Table 15 displays cross-correlation among the aggregate measures. The former table tells us that there is no strong predictor that consistently emerges across all panics. Sometimes CoVaR works (1907) although with the wrong sign, not much happens with SRISK, whereas leverage appears to work for 1884 and 1890, size for 1890 and 1893, and the others appear not important. Cross-sectionally, it appears from Table 15 that aggregate SRISK and leverage are highly correlated, whereas CoVaR/SRISK and size are as well. Interestingly, CoVaR and VaR are also positively correlated, particularly strongly towards the end of the sample.

5.2.3 Predicting System Wide Deposit Losses Around Deposit NBER Contractions and Expansions

We repeat the time series regressions appearing in equation (5.12) for the expansions and recession samples described in section 5.1.3. The results appear in Tables 16 (Deposit Loss Regressions Around NBER Contractions) and 17 (NBER Expansions). In the former case we see again some weak predictability from CoVaR or SRISK, even when controlling for the presence of other aggregate measures. Among the alternative measures we see that again leverage and size show up as significant. The F-tests tell us that the systemic risk measures are significant, but the increments in R^2 also tells us that the contribution is extremely marginal. For expansions none of the systemic risk measures matter, except perhaps CoVaR without controls.

6 Conclusion

This paper addressed a relatively simple question: Do CoVaR and SRISK contribute information of importance to regulators–beyond the standard measures of risk–either about identifying SIFIs or about the likelihood of a systemic event in the near future? Using a novel and unique data set covering eight historical financial crises, we find CoVaR and SRISK contain information that would allow regulators to identify SIFIs. Bank panics of the pre-FDIC era were often preceded by a deterioration of bank balance sheets as deposits were withdrawn from the money center banks that made up the NYCH. When the deposit flows were disproportionately withdrawn from banks that had high ex-ante CoVaR or SRISK rankings, financial panics were likely to occur. Our findings imply that a hypothetical regulator armed with systemic risk rankings could distinguish between benign deposit outflows and outflows likely to result in panic by paying careful attention to the systemic risk ranking of banks suffering the largest withdrawals. Therefore, CoVaR and SRISK help to identify systemic institutions in periods of distress over what is explained by standard variables. In contrast, as far as predicting when the next crisis is likely to occur, it appears we have made little progress. CoVaR and SRISK improve forecasting of the decline in aggregate deposits during panics only marginally.

We also find that VaR appears to be an adequate tool for systemic risk monitoring in lieu of CoVaR. In many of our analyses, SRISK appears to have a slight advantage over CoVaR. Nevertheless, CoVaR and SRISK provide fairly similar rankings of the most systemic institutions and their rankings are correlated with rankings based on size or beta.

SRISK is also a prediction of the capital shortage a bank would experience conditional on a systemic event. We find however that SRISK fails to provide an unbiased estimate of the actual capital shortage in the panic event with one important exception, SRISK predicts capital shortages during the Great Depression.

If we take various measure in isolation, it appears that leverage is not a good predictor for systemic risk as the ranking correlation between leverage and runs on deposits is almost never significant. This implies that imposing capital ratios as the single macro prudential tool appears unwise judging by its historical performance.

Overall, the conclusions of the paper suggest that we have made some progress towards answering some of the challenges posed by Ben Bernanke in his aforementioned speech. We still can answer a number of intriguing questions with the data set collected. For example, what is the relationship between systemic risk measures and the real economy? Historically, is the financial system less inter-connected that it today? These are a number of research topics we leave for future research.

References

ACHARYA, V. V., L. H. PEDERSEN, T. PHILIPPON, AND M. RICHARDSON (2017): "Measuring systemic risk," *Review of Financial Studies*, 30, 2–47.

ADRIAN, T., AND M. K. BRUNNERMEIER (2016): "CoVaR," *American Economic Review*, 106, 1705–1741.

BENOIT, S., G. COLLETAZ, C. HURLIN, AND C. PÉRIGNON (2013): "A Theoretical and Empirical Comparison of Systemic Risk Measures," Discussion paper, HEC Paris.

BENOIT, S., J.-E. COLLIARD, C. HURLIN, AND C. PÉRIGNON (2017): "Where the risks lie: A survey on systemic risk," *Review of Finance*, 21(1), 109–152.

BISIAS, D., M. FLOOD, A. W. LO, AND S. VALAVANIS (2012): "A survey of systemic risk analytics," Office of Financial Research, Working Paper.

BORDO, M. D., AND D. C. WHEELOCK (1988): "Price Stability and Financial Stability: The Historical Record," *Fed of St. Louis Review*, Sep/Oct, 41–62.

BROWNLEES, C., AND R. F. ENGLE (2016): "SRISK: A conditional capital shortfall measure of systemic risk," *Review of Financial Studies*, 30, 48–79.

BRUNNERMEIER, M. K., AND M. OEHMKE (2012): "Bubbles, financial crises, and systemic risk," Discussion paper, National Bureau of Economic Research.

CARLSON, M. (2005): "Causes of Bank Suspensions in the Panic of 1893," *Explorations in Economic History*, 42, 56–80.

CHABOT, B., AND C. C. MOUL (2014): "Bank Panics, Government Guarantees, and the Long-Run Size of the Financial Sector: Evidence from Free-Banking America," *Journal of Money, Credit and Banking*, 46, 961–997.

DANIELSSON, J., K. R. JAMES, M. VALENZUELA, AND I. ZER (2012): "Dealing with systematic risk when we measure it badly," Discussion paper, European Center for Advanced Research in Economics and Statistics.

DAVIS, J. H. (2006): "An improved annual chronology of US business cycles since the 1790s," *Journal of Economic History*, 66(01), 103–121.

DELONG, B. J., AND H. S. LAWRENCE (1986): "The Changing Cyclical Variability of Economic Activity in the United States," in *The American Business Cycle: Continuity and Change*, ed. by R. J. Gordon, pp. 679–719. Chicago University Press, Chicago.

GIGLIO, S., B. KELLY, AND S. PRUITT (2016): "Systemic risk and the macroeconomy: An empirical evaluation," *Journal of Financial Economics*, 119, 457–471.

GORTON, G. (1985): "Clearinghouses and the origin of central banking in the United States," *Journal of Economic History*, 45, 277–283.

GORTON, G. (1988): "Banking Panics and Business Cycles," *Oxford Economic Papers*, 40, 751–781.

HANSEN, L. P. (2013): "Challenges in Identifying and Measuring Systemic Risk," Becker Friedman Institute for Research in Economics Working Paper, 2012-012.

HASAN, I., AND G. P. DWYER (1994): "Bank runs in the free banking period," *Journal of Money, Credit and Banking*, 26, 271–288.

IDIER, J., G. LAMÉ, AND J.-S. MÉSONNIER (2014): "How useful is the Marginal Expected Shortfall for the measurement of systemic exposure? A practical assessment," *Journal of Banking and Finance*, 47, 134–146.

JALIL, A. J. (2015): "A new history of banking panics in the United States, 1825–1929: Construction and implications," *American Economic Journal: Macroeconomics*, 7, 295–330.

JAREMSKI, M. (2010): "Free bank failures: Risky bonds versus undiversified portfolios," *Journal of Money, Credit and Banking*, 42, 1565–1587.

KEMMERER, E. W. (1910): "Seasonal Variations in the Relative Demand for Money and Capital in the United States," in *National Monetary Commission, S.Doc.588, 61st Cong., 2d session*.

KOENKER, R., AND W. G. BASSET (1978): "Regression Quantiles," *Econometrica*, 45, 33–50.

MOEN, J., AND E. TALLMAN (1990): "Lessons from the Panic of 1907," *Federal Reserve Bank of Atlanta Economic Review*, 75, 2–13.

REINHART, C., AND K. ROGOFF (2013): "Banking Crises: An Equal Opportunity Menace," *Journal of Banking and Finance*, 37, 4557–4573.

RICHARDSON, G. (2007): "Categories and causes of bank distress during the great depression, 19291933: The illiquidity versus insolvency debate revisited," *Explorations in Economic History*, 44, 588–607.

ROLNICK, A. J., AND W. E. WEBER (1984): "The causes of free bank failures: A detailed examination," *Journal of Monetary Economics*, 14, 267–291.

SPRAGUE, O. (1910): "History of Crises Under the National Banking System," in *National Monetary Commission, S.Doc.538, 61st Cong., 2d session*.

WICKER, E. (2000): *Banking Panics of the Golden Age*. Cambridge University Press: New York.

Table 1: FINANCIAL INSTITUTIONS IN THE NEW YORK CLEARINGHOUSE

Name	Start Date	End Date	Exit Reason
American National Bank of New York	03/27/69	12/02/71	Bank Failure
American Exchange National	.	01/01/27	Merged into Am. Ex. And Irving Tst (129)
Astor National Bank (Trust in 1911-6)	03/24/99	04/06/17	Data stop 07, restart 1911;Exit CH 1917 w/Merger
Atlantic National	.	04/19/73	Bank Failure
Bank of America (America)	.	11/01/31	Merge to Federal National City Bank of NY (1st National (39))
Bank of Manhattan Company (Manhattan Co.)	.	.	
Bank of the Metropolis	12/12/84	02/08/18	Merge into Manhattan Company (6)
Bank of New Amsterdam	06/18/97	10/25/07	Bank Failure
Bank of NY NBA(87-94); Bank of NY (pre-87)	.	.	
Bankers Trust Company	07/07/11	.	
Bowery National Bank (Bowery)	03/02/67	12/01/25	Merged into Bowery and East River National Bank (128)
Brooklyn Trust	07/07/11	06/23/22	Left CH (enter FR system)
Bull's Head	.	12/02/71	Left CH
Central National	.	02/19/04	Merge National Citizens Bank (86) in 1904
Chase National Bank	10/26/78	.	
Chatham National Bank	.	03/17/11	Merger with Phoenix
Chatham-Phoenix National Bank	04/14/11	01/01/32	Mrgr of Chthm(16) and Phnix(104); merge to State Man. Tst
Chemical Nat. Bank	.	.	
Citizens-Central National	01/19/06	05/28/20	Renamed from Nat. Cit. (86); Merged into Chemical (18)
Coal and Iron National Bank	08/06/09	12/01/25	Merge to Fidelity-International Trust (36)
Columbia Bank	05/02/19	07/20/23	Taken over by Manufacturers Trust Company
Columbia Trust	07/07/11	05/10/12	Merger with Knickerbocker Trust
Column-Knick Tr Co	06/07/12	02/02/23	New Trust Merger of Columbia (22) and Knickerbocker
Commercial Exchange Bank (German Exch.)	02/12/81	05/27/21	Merged into National City Bank (87)
Commonwealth Bank	.	09/06/73	Bank Failure
Continental (Bank/National)	.	05/17/01	Merge into State Central Trust Company leave CH
Corn Exchange Bank	.	.	
Croton National	11/10/66	09/14/67	Bank Failure
Dry Dock	.	01/05/67	Purchased by 11th Ward
Dry Goods	10/07/71	09/01/77	Bank Failure
East River National Bank	.	12/01/25	Merged into Bowery and East River National Bank (128)
Eighth National	09/14/67	12/02/71	Bank Failure
Eleventh Ward	07/20/67	12/02/71	Left CH
Equitable Trust Company	10/15/20	05/01/30	Merge to Chase National (15)
Farmers' Loan and Trust Company	03/08/18	06/01/29	Merge into Bank of America (5)
Fidelity-International Trust Company	07/07/11	06/01/30	Name Change to Marine Midland (leave CH)
Fifth Avenue	04/10/80	.	
Fifth National Bank	10/19/83	05/22/25	Merged into State Manufacturers Trust
First National Bank	.	.	
First National Bank of Brooklyn	11/08/89	09/27/07	Bank Failure
Fourteenth St. Bank	05/10/07	08/04/11	Name Change to Security (107) (will need to merge)
Fourth National Bank	.	05/08/14	Merged to Mech and Metals (70)
Franklin Trust Co	07/07/11	05/28/20	Merge To State Bank of America ()
Fulton	.	12/09/87	Merged with Market (67)
Gallatin National	.	04/12/12	Merged to State Central Trust
Garfield National Bank	04/06/83	01/01/29	Merge to Chase (15)
German American (Continental)	09/10/70	.	
Germania (Commonwealth)	05/22/69	05/01/27	Merged into State Manufacturers Trust
Greenwich	.	03/01/27	Merged into State Central Union Trust (Hanover (52))
Grocers'	.	12/20/79	Bank Failure
Guaranty Trust Company	07/07/11	.	
Hanover National Bank	.	01/04/29	Merged to Central H. Bank and Trst (127)
Hide and Leather Nat.	11/03/99	01/23/03	Merged into Western National Bank (126)
Import and Traders National Bank	.	06/22/23	Merged into State Equitable Trust Company
Irving Trust Company (Broadway Trust)	03/15/12	04/02/20	Merged into Irving National Bank (56)
Irving National Bank	.	01/01/27	also Irving Bank-Columbia Trust Co; merged into Am. Ex. Irving Tst (129)
Law Title Ins and Trust	07/07/11	07/01/33	Merge into State County Trust Company leave CH
Leather Manufacturers National	.	04/15/04	Merged into Mechanics National (71)
Liberty National Bank	07/20/94	03/04/21	Merge to State New York Trust
Lincoln National	05/06/82	08/20/20	Merged to Irving National Bank (56)
Lincoln Trust	07/07/11	07/21/22	Merged to Federal Mechanics and Metals (70)
Manhattan Trust Co.	07/07/11	03/15/12	Merged to State Bankers Trust
Manufacturers	.	04/28/66	5 months; no information
Manufacturers and Builders	06/19/69	12/02/71	no information
Manufacturers and Merchants	.	01/17/80	no information
Marine	.	05/02/84	Bank Failure

Table continued on next page.

Name	Start Date	End Date	Exit Reason
Market	.	12/09/87	Merged with Fulton (44)
Market and Fulton National Bank	01/06/88	02/08/18	Merger of Market (67) and Fulton (44); become part of Irving(56)
Mechanics and Traders	.	10/25/07	Bank Failure
Mechanics and Metals Nat. (Mechanics Nat.)	02/18/10	12/04/25	Merger Copper(90) and Mechanics(71);become part of Irving(56) then Chase (15)
Mechanics' National Bank	.	01/21/10	Merged into Mechanics and Metals
Mercantile National Bank	.	05/10/12	Merged to Irving National Bank (56)
Mercantile Trust Company	07/07/11	08/04/11	2 months data; merged to State Bankers Trust
Merchants' Exchange Nat. Bank (American)	.	06/23/22	Merged to State Bank in 1922
Merchant's National Bank	.	03/05/20	Merged to Manhattan Company (6)
Metropolitan	.	12/09/21	Merged to Chase National Bank (15)
Metropolitan Trust	07/07/11	02/27/25	Merged into Chatham and Phoenix (17)
N.Y. County National Bank	06/18/70	10/14/21	Merged into Chatham and Phoenix (17)
N.Y. National Exchange	.	10/25/07	Merged into Irving National Bank (56)
Nassau National Bank (Nassau)	.	04/10/14	Merged into Irving National Bank (56)
Nassau Nat. Brooklyn	08/04/11	06/23/22	Left CH (enter FR system)
National Bank Commerce (Commerce)	.	04/01/29	Merge to State Guaranty Trust (51)
National Bank of Republic (Republic Bank)	.	08/09/01	Bank Failure
National Butchers' and Drovers'	.	06/19/25	Merged into Irving National Bank (56) in 1926
National Broadway	.	04/17/03	
National Citizen's	.	12/22/05	Renamed Citizen's-Central (19) shortly after Merger
National City Bank (City)	.	.	
National Currency	02/02/67	11/06/69	Left CH
National of N. America	.	10/25/07	Bank Failure (discussion of takeover)
National Copper Bank	07/03/08	01/21/10	Merged into Mechanics and Metals (70)
National Park Bank	.	07/01/29	Merged to Chase National Bank (15)
National Shoe and Leather	.	04/13/06	Merged to Metropolitan Bank (76)
National Union	07/20/94	03/23/00	Merged to National Bank Commerce (82)
New York Gold Exchange	10/12/67	09/11/69	Bank Failure
New York Trust Company	07/07/11	.	
Ninth National	.	12/27/01	Merge to Federal National Citizens Bank (86)
North River	.	10/17/90	Bank Failure
NY Produce Exchange	03/29/95	05/28/20	Merged to Mechanics and Metals (70)
Ocean	.	12/02/71	Failed; Taken over by NY Clearinghouse
Oriental	.	10/25/07	Bank Failure
Pacific Bank	.	07/17/25	Merged to American Exchange National Bank (2)
People's State Bank	.	08/23/18	Left CH (?) when admitted to FR
People's Trust	07/07/11	06/23/22	Acquired/Merged into Homestead Bank of Brooklyn (left CH)
Phoenix National Bank	.	02/17/11	Merged into Chatham and Phoenix (17)
Seaboard National Bank	06/26/85	08/01/29	Merged into State Equitable Trust Company; Chase (15)
Second National Bank	.	12/09/21	Merged into National City Bank (87)
Security	09/01/11	08/27/15	Merged into Chatham and Phoenix (17)
Seventh National	.	03/20/03	Merge into Federal Mercantile (72)
Sixth National Bank	07/24/85	12/30/98	Merged into Astor (3)
Standard Trust Co.	07/07/11	09/27/12	Merged to State Guaranty Trust (51)
State Bank	08/03/06	01/01/29	Merged to Central H. Bank and Trst (127)
State of New York	.	01/24/02	Bank Failure
Southern National	03/04/92	05/22/96	Merged to Market and Fulton (68)
St. Nicholas	.	12/08/93	Bank Failure
Stuyvesant	07/20/67	10/07/71	Bank Failure
Tenth National	09/15/66	11/24/77	Bank Failure
Third National Bank	02/03/66	06/18/97	Bank Failure
Title G'tee and Trust	07/07/11	.	
Tradesmen's National	.	09/09/98	Bank Failure
U.S. Mortgage and Trust	07/07/11	06/01/29	Merge to State Chemical Bank and Trust
Union	.	10/17/85	Voluntarily Close Due to NBA; refund capital and deposits
Union Exchange National Bank	10/28/10	06/23/22	Bought by Chatham-Pheonix
United States National	06/04/81	11/05/97	Bank Failure
Wall Street (Mechanics Bank Assoc.)	.	07/25/84	Bank Failure
West Side	04/03/85	05/31/18	Taken over by Manufacturers Trust Company
Western National Bank	05/27/87	10/02/03	Merged into National Bank of Commerce (82)
Central Hanover Bank and Trust	05/01/29	.	Merger of Hanover (52) and State Bank (111)
Bowery and East River National Bank	01/01/26	04/01/28	Merger of Bowrey (11) and East River (31); merge into B.of.America
American Exchange and Irving Trust	01/01/27	.	Merger of American Exchange (2) and Irving Trust (56)
Harriman National Bank and Trust	01/01/26	02/01/33	Bank Failure
Commercial National Bank and Trust	01/01/29	.	
Public National Bank and Trust	01/01/30	.	

List of financial institutions in the New York Clearing House, entry date in the panel, exit date from the panel and reason for exit (when available). A "." represents a date for an institution that entered or exited the panel before January 1866 or after Decemeber 1933.

Table 2: PANIC EVENTS

Panic	Start Date	End Date	Description
1873	Sep 1873	Dec 1873	Jay Cooke and Company bankruptcy and railroad bubble burst
1884	May 1884	Aug 1884	Brokerage firm Grant and Ward sets off banking panic
1890	Nov 1890	Mar 1891	Barings Bank crisis
1893	May 1893	Sep 1893	Bankrupcies and run on gold as an eventual result of Barings Crisis
1907	Aug 1907	Nov 1907	Failure of Knickerbocker Trust spread panic to financial trusts
1914	Jul 1914	Nov 1914	Banking panic and liquidity crisis set of by WWI
1921	Aug 1921	Dec 1921	Downturn resulting from post-war monetary and fiscal contraction
1931	Oct 1931	Mar 1932	Bank failures in Chicago–Britain's Departure from gold was March 1931

The table reports the list of financial panic events of our analysis, their corresponding dates and a short description of the events.

Table 3: PANEL DIMENSIONS DURING PANICS

Panic	N	T		
		Q_1	Mean	Q_3
1873	58	14	28	41
1884	52	14	23	31
1890	64	51	49	58
1893	62	53	54	60
1907	50	64	63	66
1914	44	60	60	66
1921	34	64	60	66
1931	18	59	57	60

The table reports the number of banks in the panel as well as the first quartile, third quartile and mean number of time series observations available for the banks in the panel around each panic event.

Table 4: DESCRIPTIVE STATISTICS AROUND PANIC EVENTS

Panic		Mean	Std Dev	Skew	Kurt	$\rho_1(r_t)$	$\rho_1(r_t^2)$
1873	Mean	0.622	1.926	0.009	3.864	-0.252	0.053
	Q_1	0.296	1.641	-0.094	3.054	-0.443	-0.126
	Q_3	0.703	2.623	0.573	4.788	-0.008	0.334
1884	Mean	0.863	3.614	0.292	5.977	-0.118	0.001
	Q_1	0.676	2.477	-0.017	2.862	-0.283	-0.201
	Q_3	1.111	4.492	1.090	6.438	0.024	0.185
1890	Mean	1.805	5.182	1.158	8.258	-0.117	0.104
	Q_1	0.995	2.503	0.251	4.250	-0.243	-0.040
	Q_3	1.950	7.748	1.828	9.636	-0.016	0.188
1893	Mean	1.090	4.120	1.057	10.815	-0.116	0.156
	Q_1	0.627	2.042	-0.493	6.272	-0.217	-0.032
	Q_3	1.299	5.508	2.530	14.052	-0.039	0.371
1907	Mean	0.340	3.021	1.012	11.959	-0.093	0.051
	Q_1	0.111	1.937	-0.293	5.788	-0.183	-0.053
	Q_3	0.380	3.565	1.994	13.410	0.011	0.066
1914	Mean	0.301	2.643	0.184	9.532	-0.094	0.082
	Q_1	0.162	1.700	-0.453	5.416	-0.166	-0.056
	Q_3	0.548	3.027	0.917	13.131	0.002	0.169
1921	Mean	0.487	4.022	0.052	12.509	0.049	0.076
	Q_1	0.316	2.626	-0.583	5.466	-0.074	-0.033
	Q_3	0.780	4.951	2.002	15.984	0.125	0.156
1931	Mean	0.322	11.757	-0.068	5.715	0.041	0.122
	Q_1	-0.290	10.207	-0.540	3.843	-0.026	0.017
	Q_3	1.197	13.380	-0.041	5.968	0.088	0.252

Descriptive statistics on the return data around panic dates listed in Table 2 are reported for a window spanning from 5 years before the beginning of the panic until the end of the panic. All the banks present in the panel at the beginning of the data window are used in the computation of the descriptive statistics.

Table 5: QUANTILE AND LINEAR REGRESSION ESTIMATION RESULTS AROUND PANIC EVENTS

Panic		CoVaR β	CoVaR R^2	CoVaR % Rej	SRISK β	SRISK R^2	SRISK % Rej
1873	Mean	0.688	12.16	0.448	1.226	15.76	0.431
	Q_1	0.000	1.52		0.709	4.67	
	Q_3	1.271	21.25		1.659	24.21	
1884	Mean	1.188	15.81	0.596	1.519	15.58	0.365
	Q_1	0.000	5.17		1.015	3.45	
	Q_3	1.977	21.75		2.492	21.37	
1890	Mean	0.829	7.71	0.625	1.032	9.77	0.453
	Q_1	0.339	0.98		0.863	1.29	
	Q_3	1.189	9.91		1.516	14.45	
1893	Mean	0.753	5.62	0.629	1.090	11.06	0.548
	Q_1	0.000	0.57		0.599	0.78	
	Q_3	1.203	7.95		1.410	17.05	
1907	Mean	0.626	7.96	0.720	0.725	10.97	0.560
	Q_1	0.000	0.06		0.433	1.68	
	Q_3	0.822	12.79		0.969	12.64	
1914	Mean	0.423	7.42	0.591	0.472	10.74	0.432
	Q_1	0.000	1.49		0.333	1.16	
	Q_3	0.643	11.62		0.954	10.64	
1921	Mean	0.503	10.68	0.647	0.600	15.49	0.618
	Q_1	0.000	2.28		0.443	1.77	
	Q_3	0.857	16.00		1.151	25.75	
1931	Mean	0.836	48.43	1.000	0.919	61.84	1.000
	Q_1	0.722	41.40		0.709	56.13	
	Q_3	0.953	62.51		1.025	75.71	

For each panic date reported in Table 2 we consider a window spanning from 5 years before the beginning of the panic until the end of the panic window and a cross-section made up of all the banks present in the panel at the beginning of the aforementioned data window. The entries are median, first quartile and third quartile of the slope coefficients (when significant), (pseudo) R^2 as well as the percentage of significant slope coefficients at the 10% significance level (column "Rej %") for respectively quantile regression (2.5) - left panel and CAPM-like regression (2.10) - right panel.

Table 6: Systemic Risk Rankings

Panic	Bank	Depos	CoVaR		SRISK		Lev		Siz		Vol		Beta		VaR	
			Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
1873	Fourth National Bank	-24.87	3.65	7	20.32	1	3.49	7	15.55	2	1.61	45	0.99	20	0.95	41
(-27%)	Central National	-13.11	3.81	6	6.49	4	2.34	16	14.83	12	2.81	22	1.40	10	2.04	24
	Import and Traders National Bank	-6.61	0.98	14	16.02	2	4.21	3	14.91	9	3.79	10	1.89	7	1.92	25
	Mercantile National Bank	-5.13	0.00	42	3.28	8	3.40	8	14.12	23	3.06	15	0.19	45	2.29	20
	Merchants National Bank	-4.12	3.94	5	3.50	7	1.51	32	15.08	6	2.49	29	1.37	11	2.85	12
	Commonwealth Bank	-4.11	0.87	17	1.52	16	2.37	13	13.34	40	2.89	18	0.73	29	2.75	14
	National Bank Commerce	-3.95	15.43	1	-9.26	52	0.53	55	16.29	1	1.89	37	1.06	17	1.38	34
	Ninth National	-2.81	-0.01	46	6.86	3	4.33	2	14.25	20	2.82	21	0.58	34	1.84	29
	American Exchange National	-2.65	10.51	3	-2.07	50	0.71	53	15.52	3	2.17	34	0.91	22	2.87	11
	First National Bank	-2.50	0.04	35	5.99	5	5.47	1	13.89	29	2.06	35	1.16	16	-0.00	50
1884	Metropolitan	-11.79	2.62	3	1.90	17	1.82	46	15.34	5	2.38	41	1.04	16	1.67	30
(-17%)	Fourth National Bank	-10.62	0.38	15	9.51	2	3.80	25	15.26	6	8.20	1	3.19	2	3.58	11
	First National Bank	-5.81	0.52	11	6.60	3	4.00	21	15.20	8	2.29	44	0.45	36	-0.00	46
	National Bank Commerce	-5.30	0.55	10	2.09	14	1.59	48	15.87	1	1.46	48	0.73	22	0.77	38
	Import and Traders National Bank	-5.24	1.28	7	12.93	1	5.51	11	15.22	7	4.36	12	2.46	6	2.85	19
	Continental	-4.85	-0.00	38	4.03	7	6.06	7	14.02	21	5.74	6	1.97	7	3.47	12
	Chase National Bank	-4.32	-0.00	34	3.00	10	9.98	3	13.23	39	3.41	24	0.73	23	-0.00	43
	United States National	-4.26	NA	53	NA	53	10.59	1	13.15	40	NA	53	NA	53	NA	53
	Ninth National	-4.24	0.10	25	2.89	11	5.76	8	13.71	27	3.63	20	1.04	15	2.31	25
	Central National	-3.65	1.21	8	4.14	6	4.77	16	14.77	14	5.21	8	1.17	12	3.04	16
1890	First National Bank	-10.36	1.53	5	5.19	6	2.59	46	16.12	3	4.68	20	1.66	8	2.23	19
(-12%)	Fourth National Bank	-7.77	1.36	6	5.19	5	3.59	28	15.54	7	2.06	52	0.39	42	0.72	46
	Mechanics National Bank	-7.75	1.01	10	0.45	50	1.31	58	15.25	9	3.80	26	1.31	12	1.97	22
	National Bank of Rep.	-6.79	0.08	28	3.26	7	4.09	23	14.86	16	1.37	58	0.30	44	0.53	51
	Merchants National Bank	-5.85	-0.45	59	0.56	46	2.11	50	14.97	13	3.84	25	-0.22	56	1.39	33
	Mechanics and Traders	-5.43	-0.00	48	1.30	24	6.78	5	13.08	52	3.75	27	1.05	18	-0.00	58
	Import and Traders National Bank	-5.10	2.38	4	6.96	2	3.33	31	15.94	4	3.51	30	1.49	10	1.42	30
	Mercantile National Bank	-4.37	0.53	14	2.89	8	4.14	22	14.56	19	2.03	53	0.88	24	1.16	39
	United States National	-3.62	0.05	31	1.75	17	4.52	18	13.82	35	6.09	11	0.72	32	1.40	31
	Corn Exchange Bank	-3.03	0.93	11	1.41	22	2.75	43	14.71	18	2.82	40	0.52	37	2.06	21
1893	Bank of America	-10.73	2.71	4	3.55	8	2.99	41	15.66	7	1.98	51	0.92	25	1.40	35
(-11%)	United States National	-8.03	0.24	22	1.96	17	5.77	6	13.90	33	2.57	41	0.42	43	1.41	34
	Fourth National Bank	-7.30	0.99	8	3.76	7	3.29	33	15.69	6	2.05	48	0.54	37	0.72	45
	Mercantile National Bank	-6.48	0.34	18	2.14	14	3.59	30	14.63	20	1.99	50	1.25	16	1.10	38
	American Exchange National	-6.42	3.30	3	2.07	16	1.93	53	15.84	5	1.48	57	0.69	30	1.07	39
	Hanover National Bank	-5.78	0.19	24	4.86	4	5.05	12	15.04	11	3.05	33	1.41	10	0.72	46
	National Bank of Rep.	-5.44	1.25	7	2.88	10	4.14	22	14.78	16	1.51	55	0.53	38	1.14	36
	Central National	-5.12	0.81	11	2.16	13	4.17	21	14.83	14	2.31	44	0.80	27	2.59	17
	First National Bank	-4.54	-0.00	45	1.36	25	2.33	50	16.34	2	3.93	22	0.84	26	-0.00	52
	Seaboard National Bank	-3.42	0.00	51	1.27	27	5.75	7	13.69	38	1.80	54	0.19	50	1.01	41

Table continued on next page.

Panic	Bank	Depos	CoVaR		SRISK		Lev		Siz		Vol		Beta		VaR	
			Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
1907	Mechanics and Traders	-20.73	0.09	21	3.23	8	6.49	4	13.95	36	4.63	9	1.01	6	4.55	3
(-14%)	National Bank Commerce	-11.60	6.19	3	15.90	1	3.08	35	17.57	3	3.84	12	1.79	2	4.17	5
	Oriental	-11.12	0.01	30	1.42	19	5.41	11	14.52	28	3.53	17	0.38	24	2.06	20
	Mercantile National Bank	-9.56	1.19	9	1.73	17	1.86	45	15.77	12	4.70	8	1.93	1	5.70	1
	Bank of Manhattan Company	-6.79	0.27	17	3.55	7	5.60	8	15.64	13	1.67	43	0.28	31	1.66	26
	Mechanics National Bank	-4.60	0.82	11	2.64	9	3.43	30	15.77	11	3.68	15	0.93	7	3.80	7
	Corn Exchange Bank	-4.10	0.78	12	6.22	5	5.63	7	16.03	8	3.33	20	0.93	8	2.90	13
	American Exchange National	-2.28	3.38	5	0.95	21	1.99	44	16.26	7	3.69	14	0.72	13	3.66	9
	Chase National Bank	-1.96	-0.00	33	6.64	4	5.80	6	16.60	4	6.48	4	0.68	15	-0.00	35
	Bank of America	-1.91	2.00	7	2.30	10	4.02	24	15.86	10	1.58	44	0.46	21	1.46	28
1914	National City Bank	-26.35	24.79	1	16.14	1	3.39	32	18.26	2	4.18	5	2.12	1	3.58	6
(-32%)	Hanover National Bank	-16.04	0.34	10	6.65	6	4.62	24	16.78	5	1.90	26	0.24	20	0.89	28
	Mechanics and Metals Nat.	-9.10	0.00	30	8.74	4	5.77	14	16.45	7	3.31	8	1.71	2	3.42	8
	National Bank Commerce	-5.97	9.06	3	9.31	3	2.83	38	17.55	3	3.85	7	1.49	3	3.45	7
	NY Produce Exchange	-5.69	0.06	15	1.00	20	5.56	17	14.29	26	1.54	34	0.16	27	1.49	23
	American Exchange National	-5.62	0.63	8	4.12	8	4.94	22	16.17	9	4.26	4	0.68	7	2.40	11
	Bank of Manhattan Company	-5.53	-0.04	40	3.90	9	6.19	12	15.68	14	1.72	27	0.30	16	2.11	13
	Chase National Bank	-5.12	1.14	5	10.06	2	7.87	5	17.16	4	4.17	6	1.15	4	1.69	20
	Corn Exchange Bank	-3.52	0.97	7	7.41	5	7.28	6	16.06	10	1.70	28	0.28	17	1.61	21
	Liberty National Bank	-2.14	0.05	16	2.14	12	6.94	7	15.61	15	2.61	14	0.19	22	1.95	15
1921	First National Bank	-25.33	36.37	2	3.29	13	3.65	28	18.25	1	2.35	27	0.65	10	3.66	9
(-2%)	N.Y. County National Bank	-16.44	-0.53	31	0.66	21	9.12	3	13.42	29	7.17	5	0.16	27	7.25	2
	American Exchange National	-10.32	3.36	7	3.50	9	6.39	12	16.26	11	3.75	17	0.97	8	3.84	7
	Bank of Manhattan Company	-7.18	0.60	14	5.36	7	5.13	19	15.72	15	3.46	19	0.60	13	2.94	12
	Chatham-Phoenix National Bank	-7.10	1.50	9	4.52	8	6.78	9	16.62	10	5.95	7	1.21	6	3.26	10
	National City Bank	-6.84	39.54	1	21.48	1	4.66	23	18.16	2	4.87	13	1.56	3	3.73	8
	Hanover National Bank	-5.87	3.18	8	3.35	12	3.99	26	16.98	7	2.11	29	0.52	17	1.42	24
	Corn Exchange Bank	-4.79	3.60	6	7.29	5	9.39	2	16.98	6	4.95	12	1.22	5	2.85	13
	Mechanics and Metals Nat.	-3.87	4.36	5	5.57	6	5.06	20	17.17	5	3.67	18	1.31	4	2.15	18
	Bank of America	-2.31	1.07	10	1.88	14	4.23	25	16.07	12	2.58	26	0.57	15	2.49	16
1931	Chase National Bank	-23.78	198.60	3	22.77	1	3.89	10	18.14	3	11.84	9	1.00	6	17.69	3
(-21%)	Guaranty Trust Company	-16.96	81.01	6	11.32	3	3.16	12	19.56	1	11.86	8	1.03	4	12.14	12
	Bank of America	-10.83	7.94	13	2.72	9	2.28	16	16.55	9	16.17	2	0.94	9	17.87	2
	Bankers Trust Company	-9.50	94.26	4	9.39	4	4.51	5	16.75	8	11.70	10	0.96	7	11.36	14
	Chatham-Phoenix National Bank	-9.50	51.08	8	2.61	10	4.39	6	15.50	16	10.21	14	0.78	13	15.28	5
	National City Bank	-7.23	231.29	1	20.53	2	5.04	3	18.10	4	14.99	3	1.20	2	12.86	10
	American Exchange and Irving Trust Company	-7.19	81.41	5	7.80	6	3.33	11	16.32	12	12.53	6	1.03	5	14.08	7
	Central Hanover Bank and Trust Company	-5.47	0.00	17	8.87	5	4.77	4	17.41	5	12.51	7	0.90	10	16.38	4
	Bank of Manhattan Company	-3.84	11.99	12	5.45	7	4.02	9	16.21	13	19.04	1	1.35	1	13.27	9
	New York Trust Company	-2.18	44.81	9	3.76	8	4.37	7	16.40	10	11.47	11	0.95	8	15.17	6

The table reports the ten financial institutions that suffered the largest max deposit contraction during each panic date, together with the value and rank of the systemic risk measures $\Delta\mathsf{CoVaR}^{\%}_{i\,t}$ and $\mathsf{SRISK}^{\%}_{it}$ prior to the crisis. For comparison, the table also reports the value and rank obtained from leverage, size, volatility, beta and VaR. We use "NA" to denote value of the market risk measures that could not be computed due to lack of data.

Table 7: Bank Deposits Loss Regressions Around Panic Events

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Horizon					1					
CoVaR	-0.036^{***}	-0.023^{*}			-0.013	-0.008			-0.022^{**}	-0.012
	(0.010)	(0.015)			(0.012)	(0.015)			(0.012)	(0.015)
SRISK			-0.608^{***}	-0.564^{***}			-0.562^{***}	-0.565^{***}		
			(0.068)	(0.070)			(0.079)	(0.083)		
Lev					-0.290^{**}	-0.380^{***}	-0.063	-0.046	-0.235^{**}	-0.286^{**}
					(0.132)	(0.154)	(0.125)	(0.150)	(0.131)	(0.150)
Siz					-1.014^{***}	-1.343^{***}	-0.468^{**}	-0.318	-0.982^{***}	-1.082^{***}
					(0.294)	(0.420)	(0.267)	(0.401)	(0.297)	(0.407)
Vol					0.157^{*}	0.177^{*}	0.189^{**}	0.200^{**}	-0.028	0.005
					(0.114)	(0.125)	(0.104)	(0.114)	(0.083)	(0.100)
Beta					-0.064	-0.019	0.289^{*}	0.256	-0.164	-0.171
					(0.217)	(0.230)	(0.205)	(0.215)	(0.215)	(0.222)
VaR					-0.272^{***}	-0.297^{**}	-0.238^{***}	-0.185^{*}		
					(0.116)	(0.131)	(0.101)	(0.121)		
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓		✓
R^2	4.47	7.58	23.32	25.48	12.21	13.24	26.33	26.78	10.32	11.47
Horizon					3					
CoVaR	-0.051^{***}	-0.035^{**}			-0.021	-0.012			-0.034^{**}	-0.020
	(0.014)	(0.020)			(0.017)	(0.021)			(0.016)	(0.021)
SRISK			-0.753^{***}	-0.715^{***}			-0.719^{***}	-0.729^{***}		
			(0.067)	(0.069)			(0.077)	(0.081)		
Lev					-0.447^{***}	-0.561^{***}	-0.182^{*}	-0.163	-0.388^{***}	-0.459^{***}
					(0.127)	(0.145)	(0.113)	(0.134)	(0.127)	(0.142)
Siz					-0.925^{***}	-1.374^{***}	-0.220	-0.006	-0.888^{***}	-1.075^{***}
					(0.296)	(0.418)	(0.249)	(0.378)	(0.299)	(0.408)
Vol					0.192^{**}	0.218^{**}	0.220^{**}	0.238^{**}	-0.011	0.018
					(0.114)	(0.125)	(0.099)	(0.107)	(0.085)	(0.101)
Beta					-0.006	0.053	0.395^{**}	0.358^{**}	-0.132	-0.139
					(0.213)	(0.224)	(0.188)	(0.197)	(0.210)	(0.215)
VaR					-0.297^{***}	-0.342^{***}	-0.257^{***}	-0.209^{**}		
					(0.113)	(0.127)	(0.094)	(0.111)		
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓		✓
R^2	4.91	7.81	32.90	34.51	14.66	16.13	36.16	36.59	12.34	13.67
Horizon					6					
CoVaR	-0.057^{***}	-0.044^{**}			-0.025^{*}	-0.021			-0.038^{**}	-0.028^{*}
	(0.014)	(0.021)			(0.017)	(0.022)			(0.017)	(0.022)
SRISK			-0.566^{***}	-0.527^{***}			-0.513^{***}	-0.510^{***}		
			(0.064)	(0.066)			(0.072)	(0.075)		
Lev					-0.305^{***}	-0.392^{***}	-0.102	-0.121	-0.245^{**}	-0.314^{**}
					(0.123)	(0.144)	(0.115)	(0.138)	(0.122)	(0.141)
Siz					-0.919^{***}	-1.227^{***}	-0.499^{**}	-0.429	-0.881^{***}	-1.036^{***}
					(0.301)	(0.418)	(0.262)	(0.387)	(0.304)	(0.414)
Vol					0.192^{**}	0.190^{*}	0.217^{**}	0.233^{**}	-0.002	0.010
					(0.116)	(0.126)	(0.106)	(0.114)	(0.086)	(0.101)
Beta					-0.099	-0.101	0.239	0.213	-0.182	-0.213
					(0.220)	(0.228)	(0.206)	(0.214)	(0.220)	(0.225)
VaR					-0.281^{***}	-0.287^{***}	-0.260^{***}	-0.225^{**}		
					(0.114)	(0.122)	(0.100)	(0.112)		
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓		✓
R^2	5.62	8.26	23.67	25.79	13.21	14.26	27.22	27.70	11.10	12.32

Entries are estimates of panel regression model (5.11) pooling all panic events and regressing $\Delta\mathsf{Dep}_i$, the maximum deposit loss of institution i from the beginning of the panic until the end of the panic window, onto the value of the systemic risk measure ΔCoVaR or SRISK measured in percentage terms, bank fixed effect, panic fixed effect, and a set of controls – level of volatility, beta, leverage, VaR and size. The regressions are computed 1-month-ahead, 3-months-ahead and 6-months-ahead in order to assess how predictability is affected by the horizon.

Table 8: CROSS-SECTIONAL CORRELATIONS WITH BANK DEPOSITS AROUND PANIC EVENTS

Panic	Horizon	CoVaR	SRISK	Lev	Siz	Vol	Beta	VaR
1873	1	-0.382^{***}	-0.209	0.028	-0.643^{***}	0.057	-0.213	-0.140
	3	-0.370^{***}	-0.475^{***}	-0.105	-0.639^{***}	0.044	-0.208	-0.097
	6	-0.361^{***}	-0.166	0.038	-0.638^{***}	0.007	-0.225	-0.150
1884	1	-0.332^{**}	-0.611^{***}	-0.260^{*}	-0.395^{***}	-0.230	-0.347^{**}	-0.019
	3	-0.303^{**}	-0.707^{***}	-0.321^{**}	-0.391^{***}	-0.195	-0.340^{**}	0.052
	6	-0.368^{**}	-0.649^{***}	-0.212	-0.386^{***}	-0.072	-0.306^{**}	0.060
1890	1	-0.276^{**}	-0.190	0.069	-0.263^{**}	0.276^{**}	0.034	0.199
	3	-0.266^{**}	-0.256^{*}	0.023	-0.271^{**}	0.274^{**}	0.047	0.196
	6	-0.291^{**}	-0.249^{*}	0.008	-0.277^{**}	0.254^{*}	0.046	0.161
1893	1	-0.151	-0.161	-0.043	-0.154	0.286^{**}	0.126	0.268^{**}
	3	-0.107	-0.264^{**}	-0.152	-0.161	0.190	0.091	0.277^{**}
	6	-0.096	-0.265^{**}	-0.179	-0.168	0.211	0.127	0.251^{*}
1907	1	-0.211	-0.472^{***}	-0.296^{**}	-0.301^{**}	-0.395^{***}	-0.300^{**}	-0.293^{**}
	3	-0.223	-0.492^{***}	-0.323^{**}	-0.297^{**}	-0.379^{***}	-0.342^{**}	-0.263^{*}
	6	-0.106	-0.502^{***}	-0.220	-0.314^{**}	-0.329^{**}	-0.245	-0.286^{*}
1914	1	-0.422^{***}	-0.687^{***}	-0.264^{*}	-0.609^{***}	-0.283^{*}	-0.396^{**}	-0.433^{***}
	3	-0.485^{***}	-0.747^{***}	-0.410^{***}	-0.617^{***}	-0.288^{*}	-0.393^{**}	-0.474^{***}
	6	-0.568^{***}	-0.703^{***}	-0.312^{**}	-0.616^{***}	-0.233	-0.390^{**}	-0.448^{***}
1921	1	-0.326^{*}	-0.370^{**}	0.023	-0.318^{*}	0.111	-0.122	-0.218
	3	-0.317^{*}	-0.425^{**}	-0.135	-0.311^{*}	0.102	-0.117	-0.190
	6	-0.296	-0.391^{**}	0.024	-0.295	0.087	-0.131	-0.210
1931	1	-0.484^{**}	-0.868^{***}	-0.022	-0.472^{**}	-0.515^{**}	-0.649^{***}	-0.560^{**}
	3	-0.499^{**}	-0.820^{***}	-0.063	-0.437^{*}	-0.360	-0.628^{***}	-0.453^{*}
	6	-0.483^{**}	-0.816^{***}	-0.044	-0.437^{*}	-0.323	-0.604^{***}	-0.513^{**}

Cross-sectional rank correlations for horizons equal to 1, 3 and 6 months ahead between risk measures (CoVaR, SRISK, leverage, size, volatility, beta and VaR) and bank deposition losses during panic events.

Table 9: CROSS-SECTIONAL CORRELATIONS AMONG RISK MEASURES AROUND PANIC EVENTS

Panic		CoVaR	SRISK	Lev	Siz.	Vol	Beta	VaR
1873	CoVaR		-0.040	-0.370^{***}	0.493^{***}	-0.011	0.483^{***}	0.218
	SRISK	-0.040		0.755^{***}	-0.115	0.204	0.418^{***}	-0.019
1884	CoVaR		0.294^{**}	-0.201	0.324^{**}	0.068	0.574^{***}	0.078
	SRISK	0.294^{**}		0.503^{***}	0.402^{***}	0.195	0.352^{**}	-0.052
1890	CoVaR		0.203	-0.264^{**}	0.430^{***}	-0.402^{***}	0.287^{**}	-0.009
	SRISK	0.203		0.522^{***}	0.389^{***}	-0.006	0.248^{*}	-0.106
1893	CoVaR		0.373^{***}	-0.377^{***}	0.582^{***}	-0.455^{***}	0.393^{***}	0.151
	SRISK	0.373^{***}		0.374^{***}	0.712^{***}	-0.151	0.244^{*}	-0.262^{**}
1907	CoVaR		0.590^{***}	-0.280^{*}	0.574^{***}	-0.103	0.663^{***}	0.710^{***}
	SRISK	0.590^{***}		0.283^{*}	0.687^{***}	0.156	0.594^{***}	0.378^{***}
1914	CoVaR		0.562^{***}	-0.135	0.623^{***}	0.140	0.490^{***}	0.169
	SRISK	0.562^{***}		0.296^{*}	0.700^{***}	0.245	0.497^{***}	0.335^{**}
1921	CoVaR		0.758^{***}	-0.231	0.831^{***}	-0.204	0.657^{***}	0.459^{***}
	SRISK	0.758^{***}		0.106	0.857^{***}	0.073	0.623^{***}	0.402^{**}
1931	CoVaR		0.553^{**}	-0.080	0.369	0.028	0.474^{**}	-0.097
	SRISK	0.553^{**}		0.201	0.492^{**}	0.587^{**}	0.810^{***}	0.465^{*}

The table reports the rank correlation between CoVaR and SRISK, i.e. systemic risk measures as well as the alternative ones - Beta, Volatility, Leverage, VaR and Size.

Table 10: BANK DEPOSITS LOSS REGRESSIONS AROUND NBER CONTRACTIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon					1			
CoVaR	-0.029^{***}	-0.029^{***}			-0.030^{***}	-0.031^{***}		
	(0.006)	(0.006)			(0.009)	(0.009)		
SRISK			-0.353^{***}	-0.354^{***}			-0.217^{*}	-0.213^{*}
			(0.114)	(0.115)			(0.133)	(0.135)
Lev					0.051	0.042	0.084	0.079
					(0.112)	(0.116)	(0.115)	(0.119)
Siz					-0.554^{**}	-0.557^{**}	-0.546^{*}	-0.551^{*}
					(0.323)	(0.326)	(0.336)	(0.340)
Vol					0.062^{*}	0.070^{*}	0.030	0.032
					(0.047)	(0.052)	(0.048)	(0.053)
Beta					-0.454	-0.505	-0.162	-0.193
					(0.397)	(0.405)	(0.443)	(0.453)
VaR					-0.744^{*}	-0.836^{*}	-0.594	-0.620
					(0.552)	(0.612)	(0.575)	(0.637)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓
R^2	9.40	9.58	4.36	4.43	11.75	12.01	8.12	8.20
Horizon					3			
CoVaR	-0.033^{***}	-0.033^{***}			-0.029^{***}	-0.030^{***}		
	(0.007)	(0.007)			(0.010)	(0.010)		
SRISK			-0.472^{***}	-0.472^{***}			-0.315^{**}	-0.309^{**}
			(0.120)	(0.121)			(0.142)	(0.143)
Lev					0.003	-0.006	0.049	0.046
					(0.105)	(0.108)	(0.106)	(0.109)
Siz					-0.552^{**}	-0.550^{**}	-0.492^{*}	-0.498^{*}
					(0.325)	(0.327)	(0.335)	(0.338)
Vol					0.049^{*}	0.057^{*}	0.031	0.037
					(0.035)	(0.039)	(0.036)	(0.040)
Beta					-0.451	-0.518	-0.037	-0.084
					(0.427)	(0.436)	(0.469)	(0.481)
VaR					-0.761^{*}	-0.886^{*}	-0.741^{*}	-0.836^{*}
					(0.501)	(0.557)	(0.510)	(0.570)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓
R^2	9.83	9.97	6.83	6.87	12.30	12.63	10.86	10.99
Horizon					6			
CoVaR	-0.031^{***}	-0.031^{***}			-0.024^{**}	-0.024^{**}		
	(0.007)	(0.007)			(0.011)	(0.011)		
SRISK			-0.362^{***}	-0.362^{***}			-0.175	-0.171
			(0.119)	(0.120)			(0.138)	(0.140)
Lev					0.039	0.029	0.073	0.066
					(0.105)	(0.108)	(0.106)	(0.109)
Siz					-0.528^{*}	-0.517^{*}	-0.492^{*}	-0.487^{*}
					(0.328)	(0.330)	(0.336)	(0.339)
Vol					0.025	0.028	0.017	0.019
					(0.024)	(0.025)	(0.024)	(0.025)
Beta					-0.400	-0.448	-0.149	-0.190
					(0.433)	(0.442)	(0.477)	(0.489)
VaR					-0.528^{*}	-0.572^{*}	-0.655^{**}	-0.695^{**}
					(0.360)	(0.380)	(0.356)	(0.378)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓
R^2	9.19	9.31	4.21	4.26	11.74	11.92	10.29	10.39

Entries are estimates of panel regression model (5.11) pooling all contraction events and regressing $\Delta\mathsf{Dep}_i$, the maximum deposit loss of institution i from the beginning of the contraction until the end of the contraction window, onto the value of the systemic risk measure ΔCoVaR or SRISK measured in percentage terms, bank fixed effect, contraction fixed effect, and a set of controls – level of volatility, beta, leverage, VaR and size. The regressions are computed 1-month-ahead, 3-months-ahead and 6-months-ahead in order to assess how predictability is affected by the horizon.

Table 11: Bank Deposits Loss Regressions Around NBER Expansions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon	1							
CoVaR	-0.133	-0.132			-0.201	-0.129		
	(0.206)	(0.236)			(0.264)	(0.275)		
SRISK			0.015	0.036			-0.111	-0.072
			(0.182)	(0.193)			(0.224)	(0.229)
Lev					0.674^{**}	0.650^{*}	0.791^{**}	0.726^{**}
					(0.408)	(0.420)	(0.413)	(0.427)
Siz					1.455	1.827^{*}	1.253	1.714
					(1.200)	(1.389)	(1.163)	(1.355)
Vol					-0.908^{*}	-0.739	-0.970^{*}	-0.722
					(0.647)	(1.846)	(0.686)	(1.863)
Beta					-0.470	-0.599	-0.301	-0.497
					(0.828)	(0.843)	(0.872)	(0.894)
VaR					-0.264	-4.301	-0.337	-4.600
					(1.492)	(3.858)	(1.493)	(3.781)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓
R^2	0.54	0.85	0.01	0.47	5.73	7.77	5.29	7.61
Horizon	3							
CoVaR	-0.038	-0.003			-0.024	0.057		
	(0.271)	(0.295)			(0.326)	(0.333)		
SRISK			0.074	0.088			-0.010	0.002
			(0.147)	(0.154)			(0.165)	(0.168)
Lev					0.690^{**}	0.705^{**}	0.704^{**}	0.682^{*}
					(0.403)	(0.427)	(0.395)	(0.424)
Siz					1.366	2.156^{*}	1.351	2.231^{*}
					(1.180)	(1.434)	(1.130)	(1.387)
Vol					-1.640^{*}	-0.729	-1.651^{*}	-0.747
					(1.192)	(2.288)	(1.216)	(2.286)
Beta					-0.278	-0.516	-0.263	-0.518
					(0.813)	(0.829)	(0.840)	(0.859)
VaR					0.408	-4.285	0.397	-4.145
					(1.599)	(3.866)	(1.592)	(3.782)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓
R^2	0.03	0.78	0.34	1.22	5.32	8.76	5.32	8.72
Horizon	6							
CoVaR	-0.141	-0.127			-0.207	-0.214		
	(0.245)	(0.266)			(0.308)	(0.319)		
SRISK			0.155	0.185			0.076	0.090
			(0.169)	(0.178)			(0.190)	(0.201)
Lev					0.663^{**}	0.609^{*}	0.732^{**}	0.679^{*}
					(0.376)	(0.441)	(0.356)	(0.419)
Siz					2.590^{**}	2.616^{**}	1.992^{*}	2.046^{*}
					(1.402)	(1.498)	(1.329)	(1.431)
Vol					-2.589^{**}	-2.916	-2.380^{**}	-2.344
					(1.260)	(3.206)	(1.289)	(3.164)
Beta					-0.731	-0.916	-0.787	-1.014
					(0.896)	(0.975)	(0.927)	(1.013)
VaR					1.442	-1.493	1.346	-1.836
					(1.593)	(5.620)	(1.596)	(5.616)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Panic FE		✓		✓		✓		✓
R^2	0.44	1.05	1.13	2.23	9.10	9.67	8.71	9.34

Entries are estimates of panel regression model (5.11) pooling all expansion events and regressing $\Delta\mathsf{Dep}_i$, the maximum deposit loss of institution i from the beginning of the expansion until the end of the expansion window, onto the value of the systemic risk measure ΔCoVaR or SRISK measured in percentage terms, bank fixed effect, expansion fixed effect, and a set of controls – level of volatility, beta, leverage, VaR and size. The regressions are computed 1-month-ahead, 3-months-ahead and 6-months-ahead in order to assess how predictability is affected by the horizon.

Table 12: PREDICTED VS ACTUAL CAPITAL SHORTAGES AROUND PANIC EVENTS

	$k = 0.15$			$k = 0.20$			$k = 0.25$		
Panic	α_0	α_1	R^2	α_0	α_1	R^2	α_0	α_1	R^2
1873	0.0021^{***}	-0.4809^{***}	0.05	0.0021^{***}	0.4256^{**}	0.05	0.0017^{***}	0.8302	0.27
	(0.0003)	(0.2894)		(0.0003)	(0.2611)		(0.0003)	(0.1914)	
1884	0.0023^{***}	0.7036	0.11	0.0016^{***}	1.1468	0.40	0.0010^{**}	1.2045^{*}	0.61
	(0.0004)	(0.2951)		(0.0004)	(0.2059)		(0.0004)	(0.1432)	
1890	0.0028^{***}	1.3881	0.14	0.0012^{**}	2.1136^{***}	0.57	0.0004	1.8907^{***}	0.79
	(0.0005)	(0.4583)		(0.0005)	(0.2430)		(0.0004)	(0.1303)	
1893	0.0024^{***}	1.4542	0.16	0.0006	2.0362^{***}	0.64	0.0001	1.7334^{***}	0.85
	(0.0005)	(0.4449)		(0.0004)	(0.2027)		(0.0003)	(0.0965)	
1907	0.0044^{*}	2.6414^{***}	0.41	0.0011	2.1600^{***}	0.76	0.0002	1.6890^{***}	0.87
	(0.0022)	(0.4799)		(0.0016)	(0.1839)		(0.0013)	(0.0977)	
1914	0.0090^{**}	1.7083^{*}	0.27	0.0027	1.9262^{***}	0.68	0.0005	1.6738^{***}	0.85
	(0.0039)	(0.4445)		(0.0030)	(0.2135)		(0.0022)	(0.1108)	
1921	0.0058	2.0834^{***}	0.80	0.0023	1.7442^{***}	0.91	0.0008	1.5243^{***}	0.95
	(0.0054)	(0.1962)		(0.0043)	(0.1047)		(0.0037)	(0.0663)	
1931	0.0352	0.9831	0.58	0.0171	1.0250	0.80	0.0054	1.0042	0.90
	(0.0263)	(0.2071)		(0.0231)	(0.1285)		(0.0200)	(0.0852)	

For each panic event we run a Mincer-Zarnowitz type regression to assess whether SRISK provides an unbiased prediction of such a shortage, that is we consider $\mathsf{CS}_i = \alpha_0 + \alpha_1\ \mathsf{SRISK}_i + u_i$, where CS_i is the realized capital shortage suffered by bank i at the end of the panic window and SRISK_i is measured in dollars.

Table 13: AGGREGATE DEPOSIT LOSS REGRESSIONS AROUND PANIC EVENTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon	1				3			
DG_t	0.925^{***}	0.924^{***}	0.942^{***}	0.946^{***}	0.717^{***}	0.728^{***}	0.766^{***}	0.794^{***}
	(0.051)	(0.062)	(0.053)	(0.060)	(0.074)	(0.067)	(0.075)	(0.072)
DG_{t-1}	0.060^{**}	-0.168^{***}	0.052^{*}	-0.303^{***}	0.026	-0.124^{**}	-0.015	-0.118
	(0.028)	(0.053)	(0.027)	(0.059)	(0.044)	(0.058)	(0.046)	(0.091)
DG_{t-2}	-0.001	-0.004	0.035	0.028	0.025	0.028	0.026	0.006
	(0.064)	(0.075)	(0.064)	(0.077)	(0.060)	(0.061)	(0.071)	(0.067)
CoVaR_t	-0.039		-0.035		-0.022		-0.071	
	(0.028)		(0.030)		(0.040)		(0.051)	
CoVaR_{t-1}	-0.119^{***}		-0.116^{***}		-0.338^{***}		-0.371^{***}	
	(0.042)		(0.044)		(0.064)		(0.058)	
CoVaR_{t-2}	0.006		-0.023		0.102^{**}		0.015	
	(0.029)		(0.025)		(0.050)		(0.053)	
SRISK_t		-0.039		-0.091		0.007		0.077
		(0.046)		(0.073)		(0.044)		(0.085)
SRISK_{t-1}		-0.074^{*}		-0.060		-0.327^{***}		-0.372^{***}
		(0.041)		(0.045)		(0.070)		(0.068)
SRISK_{t-2}		-0.009		0.026		0.024		0.067
		(0.031)		(0.054)		(0.059)		(0.095)
Lev_t			-0.023	0.026			0.015	0.067
			(0.025)	(0.054)			(0.053)	(0.095)
Lev_{t-1}			-0.164^{***}	-0.065^{**}			-0.135^{***}	-0.096^{***}
			(0.017)	(0.026)			(0.025)	(0.034)
Lev_{t-2}			-1.848	-9.999^{***}			-0.181	-3.606
			(1.124)	(2.023)			(1.600)	(2.879)
Siz_t			0.031	0.003			0.084	0.070
			(0.056)	(0.046)			(0.177)	(0.180)
Siz_{t-1}			-0.003	-0.014			-0.085	-0.069
			(0.051)	(0.049)			(0.113)	(0.110)
Siz_{t-2}			-0.029	0.038			0.084	0.068
			(0.067)	(0.065)			(0.157)	(0.158)
Vol_t			-0.031^{**}	-0.003			0.006	-0.016
			(0.015)	(0.022)			(0.024)	(0.032)
Vol_{t-1}			-0.353	-3.040			1.668	3.875
			(1.607)	(2.224)			(1.468)	(2.512)
Vol_{t-2}			0.084	0.106^{***}			0.020	0.031
			(0.056)	(0.040)			(0.094)	(0.086)
Beta_t			-0.034	-0.047			-0.024	-0.006
			(0.051)	(0.041)			(0.082)	(0.078)
Beta_{t-1}			-0.081	-0.099			0.126	0.056
			(0.072)	(0.064)			(0.114)	(0.105)
Beta_{t-2}			0.009	-0.010			0.029	0.007
			(0.016)	(0.019)			(0.022)	(0.030)
VaR_t			0.256	1.812			2.617	4.788^{*}
			(1.166)	(1.486)			(2.054)	(2.565)
VaR_{t-1}			-0.102	-0.041			-0.085	-0.077
			(0.105)	(0.112)			(0.103)	(0.105)
VaR_{t-2}			0.065	0.034			0.008	0.004
			(0.070)	(0.069)			(0.102)	(0.109)
F-test	3.308^{**}	1.498	3.008^{**}	1.037	9.925^{***}	9.091^{***}	13.867^{***}	11.863^{***}
R^2	73.26	71.20	78.17	76.50	31.22	30.43	36.40	36.13
ΔR^2	2.35	0.29	7.26	5.59	1.37	0.58	6.55	6.29

The entries pertain to the time series regressions appearing in equation (5.12) projecting $\Delta\overline{\mathsf{Dep}}_t$, is the monthly change in aggregate deposits onto its own lags as well as lags of $\Delta\overline{\mathsf{SRM}}_t$, the monthly change is the aggregate systemic risk measures (either CoVaR or SRISK) and controls. An F-test is used to see whether the systemic risk measure are jointly significant (all three lags considered). The ΔR^2 also measures the incremental contribution of the systemic risk regressors.

Table 14: TIME-SERIES CORRELATION WITH AGGREGATE DEPOSITS AROUND PANIC EVENTS

Panic	Horizon	CoVaR	SRISK	Lev	Siz	Vol	Beta	VaR
1873	1	0.160	-0.051	-0.026	-0.190	0.001	-0.234^{*}	-0.069
	2	0.124	-0.132	-0.138	-0.084	-0.034	-0.129	-0.011
	3	0.195	-0.156	-0.159	-0.171	-0.154	-0.098	0.075
1884	1	0.060	-0.202^{*}	-0.211^{*}	-0.076	0.143	-0.066	0.031
	2	0.018	-0.210^{*}	-0.253^{**}	-0.096	-0.020	-0.184	-0.036
	3	-0.010	-0.117	-0.144	0.035	-0.195	-0.153	-0.047
1890	1	0.029	-0.052	-0.171	-0.208^{*}	-0.175	-0.205^{*}	0.043
	2	-0.041	-0.220^{*}	-0.276^{**}	-0.103	-0.189	-0.117	-0.069
	3	-0.155	-0.036	-0.119	-0.139	-0.053	-0.050	-0.107
1893	1	-0.067	0.107	0.032	-0.232^{*}	0.189	-0.041	-0.130
	2	-0.087	-0.017	-0.101	-0.269^{**}	0.109	0.017	-0.128
	3	-0.061	-0.057	-0.168	-0.316^{***}	0.069	-0.051	-0.085
1907	1	0.189	0.078	0.076	0.005	0.134	0.134	0.070
	2	0.257^{**}	-0.086	-0.094	0.073	0.152	0.148	0.115
	3	0.292^{**}	-0.048	-0.032	0.150	0.079	0.246^{**}	0.228^{*}
1914	1	-0.067	0.039	0.067	0.084	0.003	-0.100	-0.044
	2	-0.080	0.039	0.047	0.031	0.047	-0.020	-0.032
	3	-0.016	-0.019	-0.025	0.010	0.201	0.006	0.036
1921	1	-0.058	-0.126	0.064	0.235^{*}	0.118	0.163	-0.095
	2	0.053	-0.149	0.021	0.159	0.131	0.202^{*}	-0.060
	3	-0.042	-0.025	0.110	0.069	0.120	0.207^{*}	-0.143
1931	1	-0.065	-0.014	-0.114	0.154	0.031	-0.148	-0.055
	2	-0.019	-0.052	-0.103	0.112	0.071	-0.188	-0.035
	3	-0.003	-0.062	-0.185	0.126	0.032	-0.167	-0.033
Mean	1	0.023	-0.028	-0.035	-0.029	0.056	-0.062	-0.031
	2	0.028	-0.103	-0.112	-0.022	0.033	-0.034	-0.032
	3	0.025	-0.065	-0.090	-0.030	0.012	-0.007	-0.009

Time series correlations for horizons equal to 1, 3 and 6 months ahead with aggregate bank deposit losses

Table 15: TIME SERIES CORRELATION AMONG RISK MEASURES AROUND PANIC EVENTS

Panic		CoVaR	SRISK	Lev	Siz	Vol	Beta	VaR
1873	CoVaR		0.005	-0.079	-0.638^{***}	0.104	-0.455^{***}	0.425^{***}
	SRISK	0.005		0.961^{***}	-0.041	0.089	-0.164	0.038
1884	CoVaR		-0.089	-0.135	-0.145	-0.107	-0.003	0.235^{**}
	SRISK	-0.089		0.959^{***}	-0.304^{**}	0.254^{**}	0.256^{**}	0.119
1890	CoVaR		0.102	-0.002	-0.047	-0.161	-0.265^{**}	0.390^{***}
	SRISK	0.102		0.837^{***}	-0.245^{**}	0.074	-0.068	0.152
1893	CoVaR		0.117	0.004	-0.039	0.056	-0.198	0.566^{***}
	SRISK	0.117		0.911^{***}	-0.148	0.265^{**}	-0.045	0.022
1907	CoVaR		0.154	0.019	-0.320^{***}	0.084	-0.034	0.638^{***}
	SRISK	0.154		0.850^{***}	-0.407^{***}	-0.133	-0.279^{**}	0.096
1914	CoVaR		0.162	0.074	-0.076	0.339^{***}	-0.140	0.705^{***}
	SRISK	0.162		0.896^{***}	-0.358^{***}	-0.233^{*}	-0.200^{*}	0.160
1921	CoVaR		0.140	0.012	-0.251^{**}	0.206^{*}	0.026	0.479^{***}
	SRISK	0.140		0.779^{***}	-0.442^{***}	-0.202^{*}	-0.238^{**}	0.114
1931	CoVaR		0.675^{***}	0.202	-0.653^{***}	0.335^{***}	-0.350^{***}	0.870^{***}
	SRISK	0.675^{***}		0.240^{*}	-0.903^{***}	-0.014	-0.584^{***}	0.689^{***}

The table reports the times series correlation between aggregate CoVaR and SRISK as wel as time series correlation between CoVaR and SRISK with the alternative measures - Beta, Volatility, Leverage, VaR and Size.

Table 16: AGGREGATE DEPOSIT LOSS REGRESSIONS AROUND NBER CONTRACTIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon	1				3			
DG_t	1.009^{***}	1.012^{***}	1.017^{***}	1.005^{***}	0.902^{***}	0.917^{***}	0.948^{***}	0.992^{***}
	(0.055)	(0.065)	(0.054)	(0.064)	(0.086)	(0.087)	(0.100)	(0.101)
DG_{t-1}	−0.010	-0.098^{**}	−0.041	-0.231^{***}	0.003	−0.069	−0.113	-0.167^{*}
	(0.033)	(0.046)	(0.044)	(0.088)	(0.054)	(0.045)	(0.077)	(0.092)
DG_{t-2}	−0.013	−0.018	0.044	0.055	0.020	0.019	0.036	0.015
	(0.072)	(0.086)	(0.075)	(0.086)	(0.072)	(0.071)	(0.089)	(0.080)
$CoVaR_t$	0.014		−0.030		0.044		−0.036	
	(0.032)		(0.034)		(0.042)		(0.060)	
$CoVaR_{t-1}$	-0.142^{***}		-0.144^{***}		-0.405^{***}		-0.439^{***}	
	(0.045)		(0.046)		(0.065)		(0.059)	
$CoVaR_{t-2}$	0.000		−0.024		0.100^{*}		−0.024	
	(0.032)		(0.028)		(0.058)		(0.062)	
$SRISK_t$		0.002		−0.102		0.027		0.102
		(0.041)		(0.086)		(0.044)		(0.076)
$SRISK_{t-1}$		-0.118^{**}		-0.107^{**}		-0.414^{***}		-0.457^{***}
		(0.050)		(0.047)		(0.066)		(0.067)
$SRISK_{t-2}$		−0.018		0.018		0.034		0.120
		(0.034)		(0.059)		(0.051)		(0.102)
Lev_t			−0.024	0.018			−0.024	0.120
			(0.028)	(0.059)			(0.062)	(0.102)
Lev_{t-1}			-0.134^{***}	-0.079^{***}			-0.108^{***}	-0.066^{**}
			(0.013)	(0.024)			(0.020)	(0.029)
Lev_{t-2}			-2.147^{*}	-7.337^{***}			−0.985	-4.916^{*}
			(1.105)	(2.311)			(1.328)	(2.900)
Siz_t			0.085	0.038			0.192	0.095
			(0.097)	(0.103)			(0.149)	(0.147)
Siz_{t-1}			−0.026	0.016			0.105	0.164
			(0.114)	(0.102)			(0.236)	(0.227)
Siz_{t-2}			−0.017	−0.022			0.220	0.127
			(0.088)	(0.057)			(0.173)	(0.127)
Vol_t			−0.013	0.009			0.021	0.004
			(0.011)	(0.019)			(0.023)	(0.028)
Vol_{t-1}			−0.006	−2.577			2.055	4.467
			(1.054)	(2.127)			(1.645)	(2.777)
Vol_{t-2}			−0.015	−0.016			−0.095	−0.069
			(0.081)	(0.078)			(0.121)	(0.114)
$Beta_t$			0.145^{*}	0.109			0.341^{**}	0.304^{*}
			(0.077)	(0.081)			(0.158)	(0.157)
$Beta_{t-1}$			0.037	0.044			0.212	0.170
			(0.080)	(0.064)			(0.150)	(0.127)
$Beta_{t-2}$			0.020	0.011			0.047^{**}	0.021
			(0.013)	(0.016)			(0.023)	(0.028)
VaR_t			0.877	1.983			2.265	5.584^{**}
			(0.967)	(1.491)			(1.526)	(2.318)
VaR_{t-1}			−0.081	−0.022			0.033	0.071
			(0.097)	(0.104)			(0.162)	(0.180)
VaR_{t-2}			0.006	−0.003			0.136	0.147
			(0.091)	(0.090)			(0.173)	(0.167)
F-test	3.422^{**}	3.059^{**}	3.665^{**}	2.389^{*}	17.087^{***}	13.435^{***}	18.447^{***}	18.138^{***}
R^2	80.39	79.78	85.28	84.45	43.68	43.51	49.31	48.75
ΔR^2	0.63	0.01	5.51	4.68	0.54	0.37	6.16	5.61

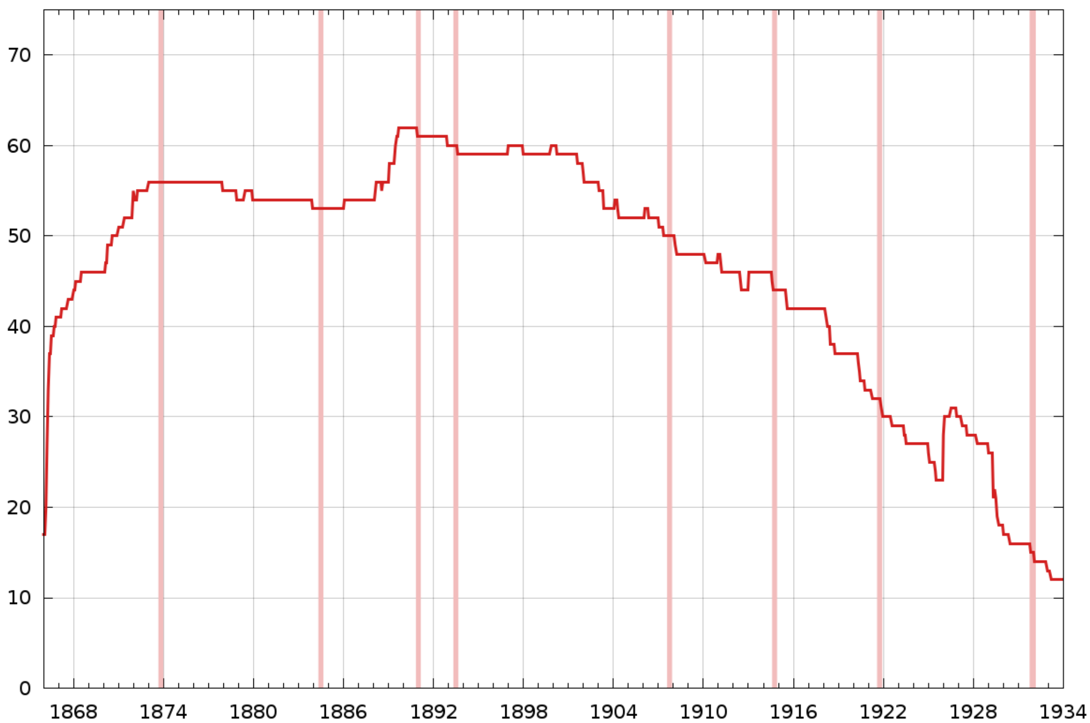
The entries pertain to the time series regressions appearing in equation (5.12) projecting $\Delta\overline{\mathsf{Dep}}_t$, is the monthly change in aggregate deposits onto its own lags as well as lags of $\Delta\overline{\mathsf{SRM}}_t$, the monthly change is the aggregate systemic risk measures (either CoVaR or SRISK) and controls. An F-test is used to see whether the systemic risk measure are jointly significant (all three lags considered). The ΔR^2 also measures the incremental contribution of the systemic risk regressors.

Table 17: Aggregate Deposit Loss Regressions Around NBER Expansions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon	1				3			
DG_t	1.008^{***}	1.048^{***}	1.021^{***}	1.027^{***}	0.688^{***}	0.734^{***}	0.698^{***}	0.713^{***}
	(0.072)	(0.084)	(0.081)	(0.083)	(0.138)	(0.160)	(0.159)	(0.169)
DG_{t-1}	−0.010	-0.279^{***}	−0.013	-0.306^{**}	−0.028	-0.219^{***}	−0.069	−0.106
	(0.034)	(0.050)	(0.035)	(0.126)	(0.063)	(0.057)	(0.067)	(0.119)
DG_{t-2}	-0.159^{***}	-0.168^{***}	-0.165^{***}	-0.160^{***}	−0.044	−0.038	−0.032	−0.027
	(0.054)	(0.061)	(0.061)	(0.060)	(0.083)	(0.096)	(0.096)	(0.099)
$CoVaR_t$	-0.063^{**}		-0.056^{*}		0.047		0.041	
	(0.032)		(0.029)		(0.053)		(0.052)	
$CoVaR_{t-1}$	−0.015		0.067^{*}		−0.141		−0.075	
	(0.044)		(0.040)		(0.091)		(0.104)	
$CoVaR_{t-2}$	0.052		−0.009		0.149^{**}		0.052	
	(0.036)		(0.036)		(0.059)		(0.057)	
$SRISK_t$		−0.003		0.019		0.065		0.143
		(0.028)		(0.040)		(0.062)		(0.087)
$SRISK_{t-1}$		0.006		0.071^{*}		−0.172		−0.102
		(0.045)		(0.041)		(0.112)		(0.116)
$SRISK_{t-2}$		−0.022		0.008		0.098^{*}		0.176^{**}
		(0.030)		(0.065)		(0.058)		(0.084)
Lev_t			−0.009	0.008			0.052	0.176^{**}
			(0.036)	(0.065)			(0.057)	(0.084)
Lev_{t-1}			-0.172^{***}	-0.071^{*}			-0.185^{***}	-0.146^{***}
			(0.018)	(0.042)			(0.025)	(0.048)
Lev_{t-2}			−3.748	-10.481^{**}			−5.784	−7.125
			(3.026)	(4.483)			(3.930)	(5.235)
Siz_t			0.077	0.038			−0.022	−0.062
			(0.091)	(0.091)			(0.144)	(0.151)
Siz_{t-1}			0.007	0.033			0.031	0.076
			(0.062)	(0.054)			(0.114)	(0.120)
Siz_{t-2}			−0.077	−0.049			0.124	0.090
			(0.066)	(0.055)			(0.128)	(0.122)
Vol_t			−0.013	−0.022			−0.008	−0.051
			(0.016)	(0.017)			(0.034)	(0.036)
Vol_{t-1}			−0.677	0.402			−1.036	2.229
			(1.141)	(1.638)			(2.071)	(3.109)
Vol_{t-2}			0.032	−0.002			−0.045	−0.063
			(0.068)	(0.066)			(0.105)	(0.104)
$Beta_t$			0.006	0.021			0.014	0.000
			(0.049)	(0.045)			(0.096)	(0.091)
$Beta_{t-1}$			0.001	−0.002			0.143	0.190
			(0.077)	(0.071)			(0.151)	(0.150)
$Beta_{t-2}$			−0.028	−0.035			−0.003	−0.059
			(0.019)	(0.029)			(0.041)	(0.049)
VaR_t			−1.956	−0.840			−3.917	−0.207
			(1.242)	(2.327)			(2.707)	(2.924)
VaR_{t-1}			−0.095	−0.074			0.027	0.080
			(0.073)	(0.078)			(0.143)	(0.147)
VaR_{t-2}			0.051	0.035			−0.038	−0.095
			(0.047)	(0.051)			(0.117)	(0.114)
F-test	2.278^{*}	0.191	2.366^{*}	1.488	2.882^{**}	1.057	0.508	1.739
R^2	82.55	80.03	85.17	84.35	38.31	36.71	43.25	42.82
ΔR^2	2.71	0.19	5.32	4.51	2.29	0.70	7.24	6.81

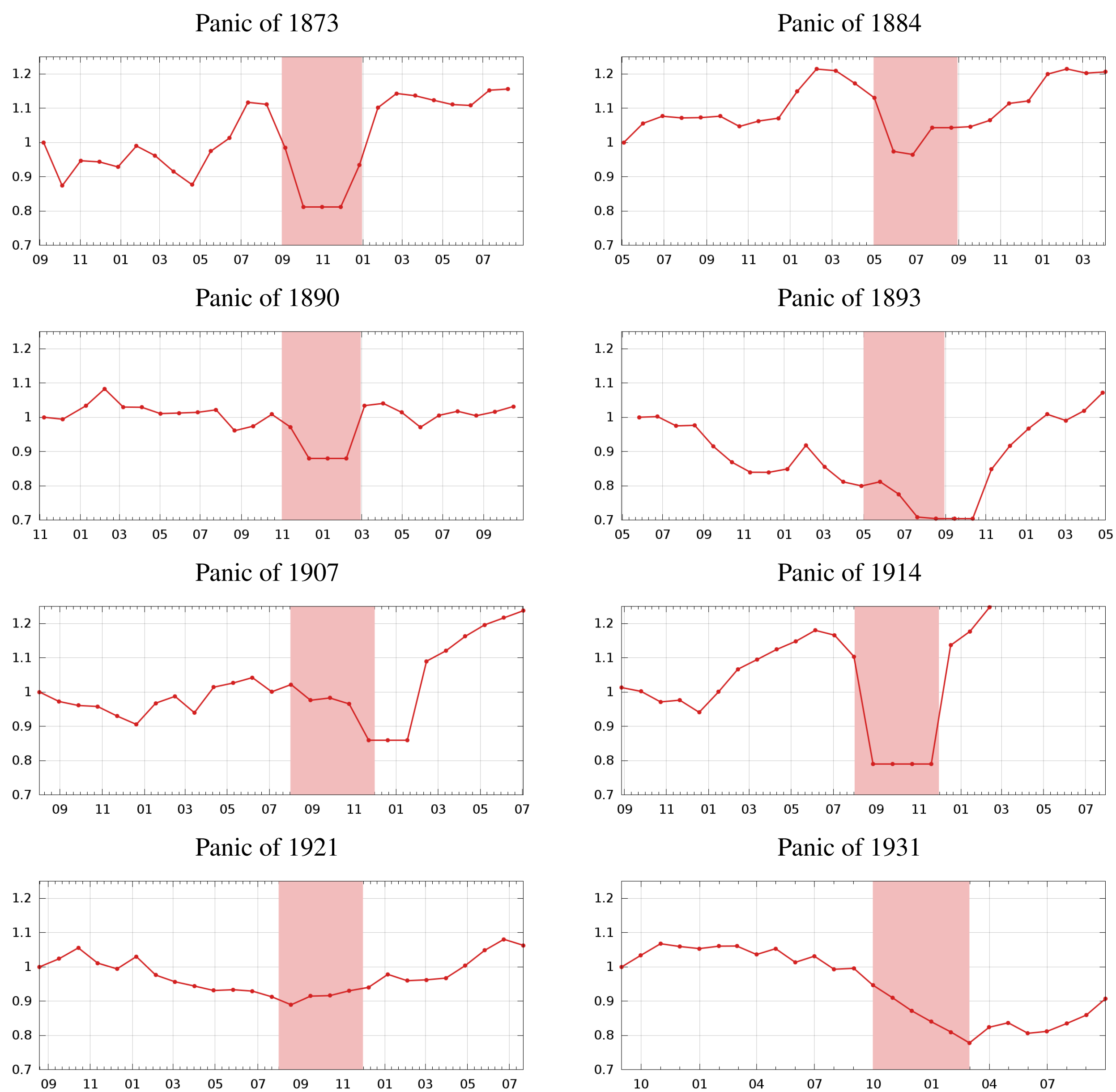
The entries pertain to the time series regressions appearing in equation (5.12) projecting $\Delta\overline{\mathsf{Dep}}_t$, is the monthly change in aggregate deposits onto its own lags as well as lags of $\Delta\overline{\mathsf{SRM}}_t$, the monthly change is the aggregate systemic risk measures (either CoVaR or SRISK) and controls. An F-test is used to see whether the systemic risk measure are jointly significant (all three lags considered). The ΔR^2 also measures the incremental contribution of the systemic risk regressors.

Figure 1: NUMBER OF BANKS



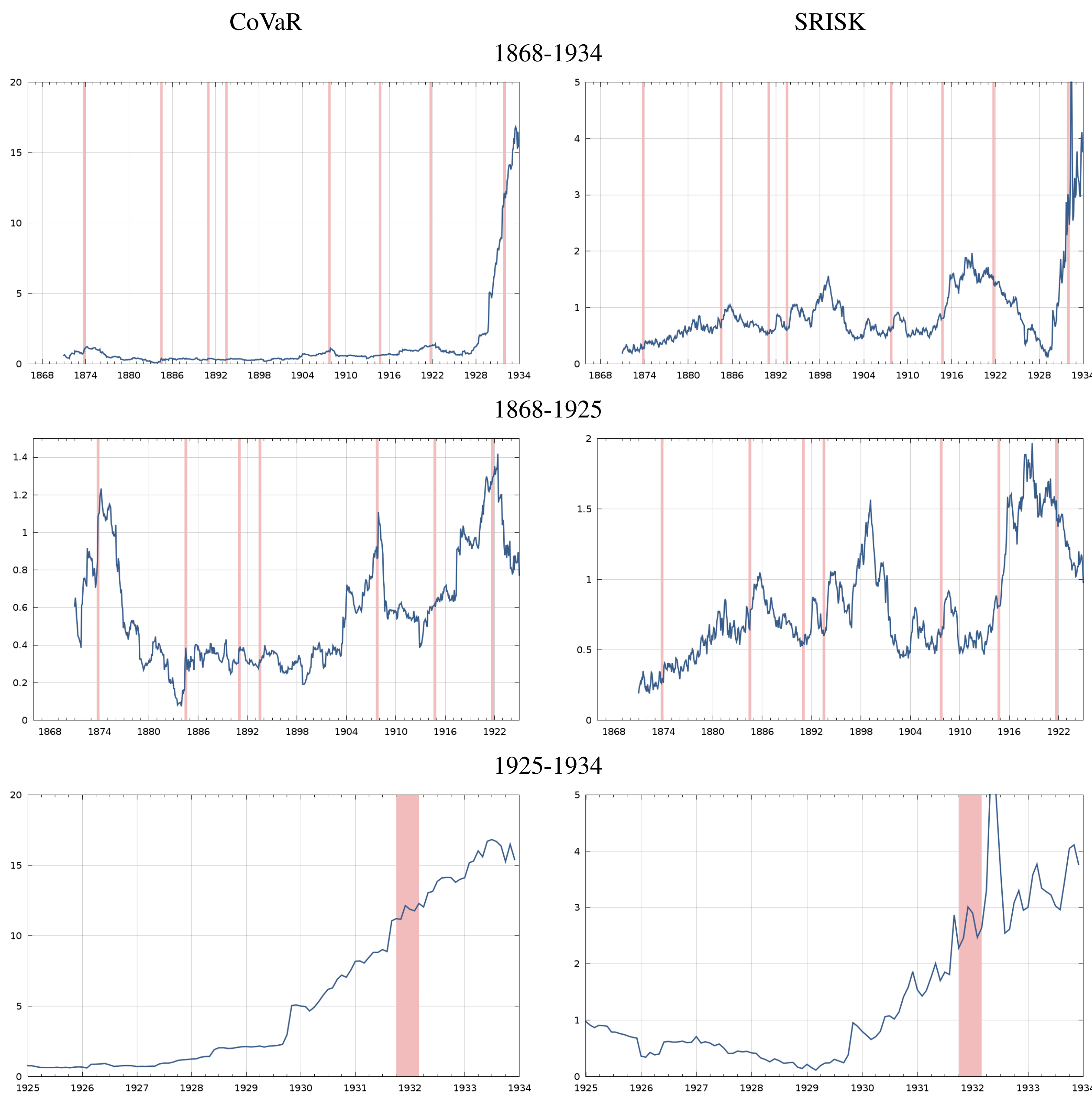
Our historical dataset comprises balance sheet and market information for a panel of New York banks and trusts from January 1866 to Decemeber 1933. The figure reports the time series of the number of banks in the panel throughout the sample period. The red vertical shaded area represent the panic periods described in table 2

Figure 2: AGGREGATE DEPOSITS AROUND PANIC EVENTS



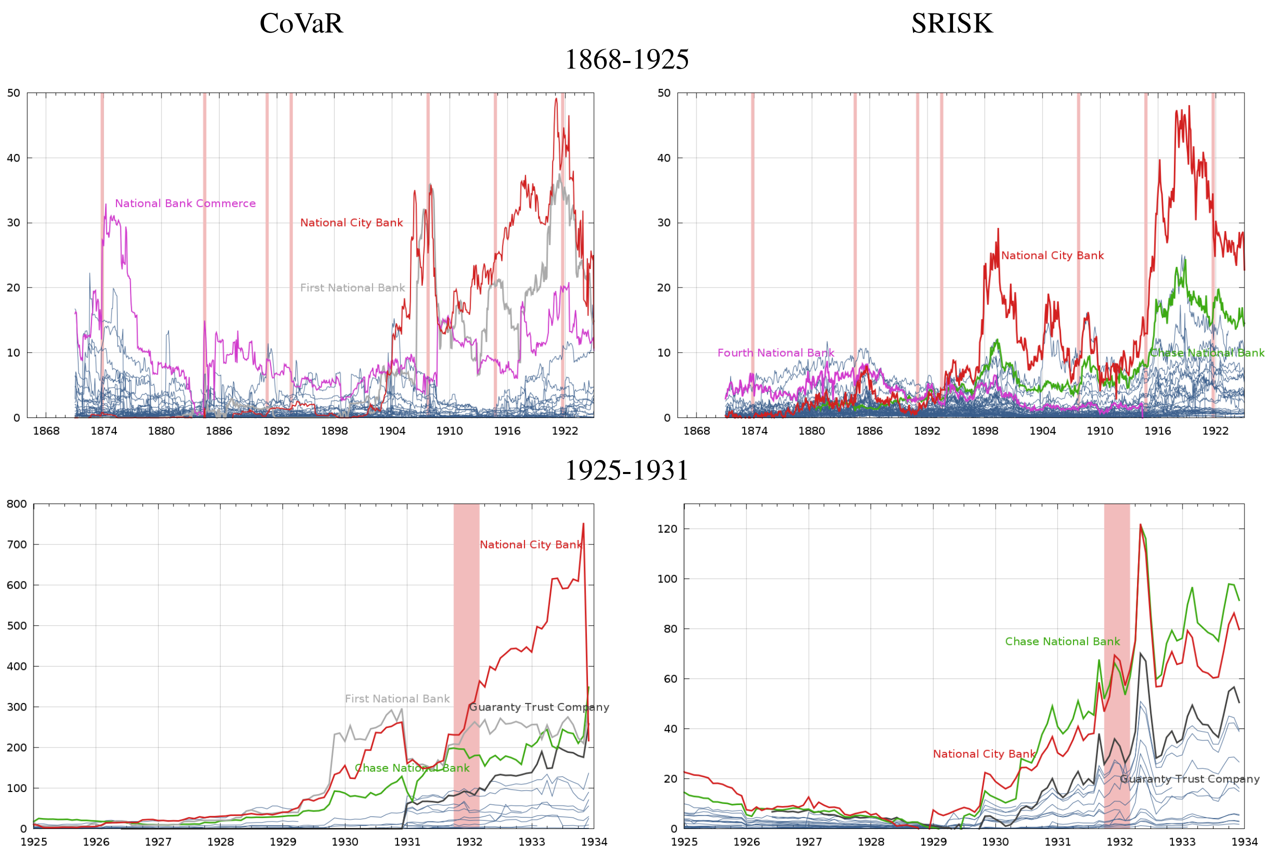
Plots of aggregate deposits in a two year window containing each of the panics. The vertical shaded areas are the panics as listed in Table 2.

Figure 3: SYSTEMIC RISK MEASURES



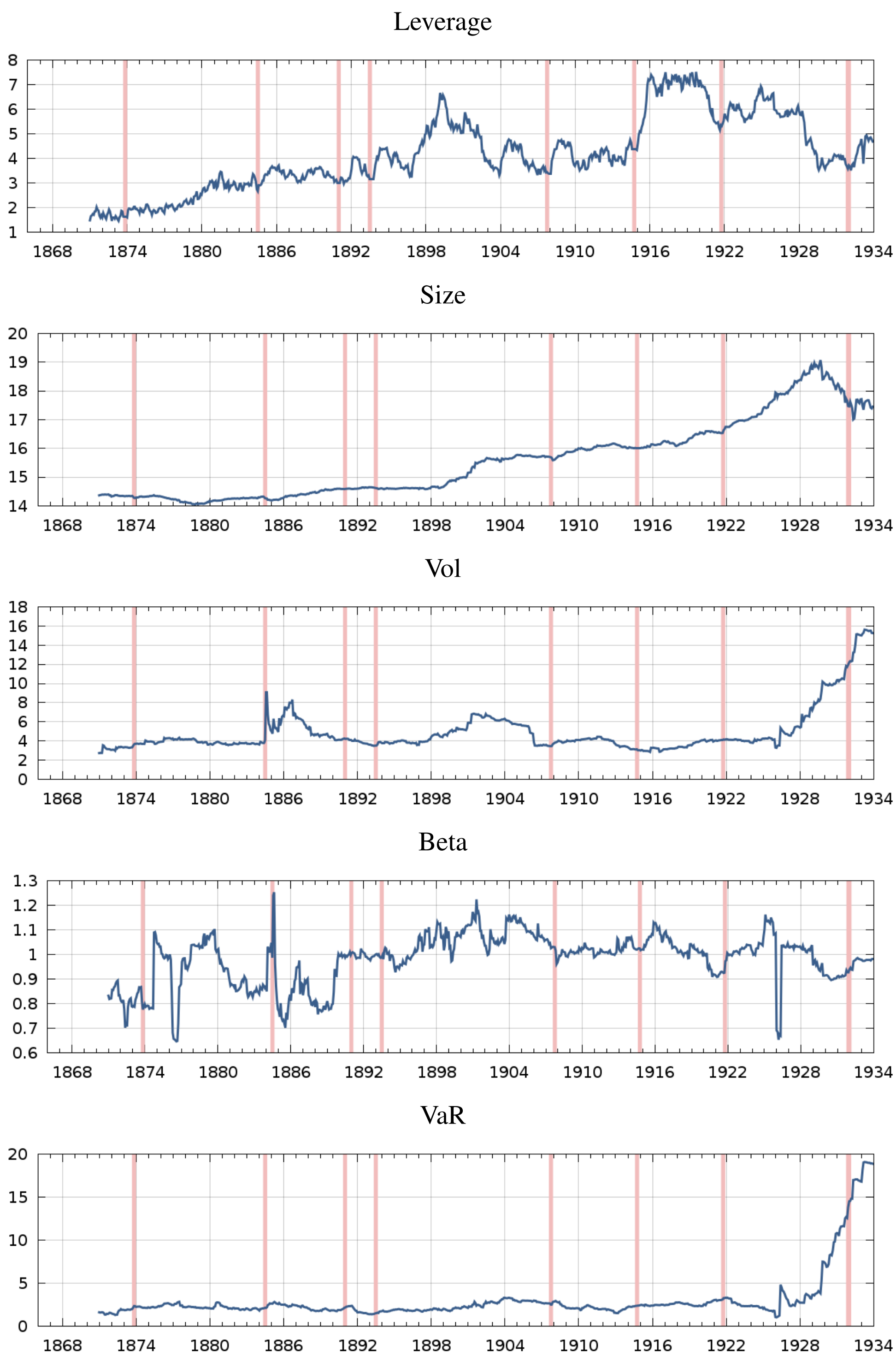
The figures plot the time series of aggregate CoVaR and SRISK over the full sample and over the sub-samples 1868-1925 and 1925-1934. The red vertical shaded area represent the panic periods described in table 2.

Figure 4: DECOMPOSITION OF SYSTEMIC RISK



Note: The red vertical shaded area represent the panic periods described in table 2.

Figure 5: TIME SERIES PLOT OF ALTERNATIVE RISK METRICS



Plots of aggregate dollar systemic risk measures, volatility, beta, leverage and size. The vertical shaded areas are the panics as listed in Table 2.

A Additional Tables and Figures

Table 18: CROSS-SECTIONAL CORRELATIONS AMONG RISK MEASURES AROUND DEPOSIT CONTRACTION EVENTS

Panic	Horizon	CoVaR	SRISK	Lev	Siz	Vol	Beta	VaR
1896-08-14	1	-0.516^{***}	-0.687^{***}	-0.046	-0.716^{***}	-0.434^{***}	-0.005	-0.344^{***}
	3	-0.468^{***}	-0.784^{***}	-0.114	-0.715^{***}	-0.397^{***}	-0.042	-0.324^{**}
	6	-0.482^{***}	-0.740^{***}	-0.059	-0.721^{***}	-0.412^{***}	-0.078	-0.356^{***}
1903-03-20	1	-0.494^{***}	-0.494^{***}	0.116	-0.636^{***}	0.093	-0.443^{***}	0.126
	3	-0.390^{***}	-0.566^{***}	0.130	-0.640^{***}	0.105	-0.427^{***}	0.134
	6	-0.461^{***}	-0.564^{***}	0.075	-0.645^{***}	0.191	-0.408^{***}	0.185
1910-10-28	1	-0.417^{***}	-0.434^{***}	0.154	-0.645^{***}	-0.322^{**}	-0.422^{***}	-0.103
	3	-0.414^{***}	-0.504^{***}	0.065	-0.646^{***}	-0.354^{**}	-0.411^{***}	-0.140
	6	-0.403^{***}	-0.428^{***}	0.153	-0.654^{***}	-0.323^{**}	-0.401^{***}	-0.171
1913-12-19	1	-0.269^{*}	-0.513^{***}	-0.130	-0.517^{***}	0.071	-0.369^{**}	0.045
	3	-0.281^{*}	-0.522^{***}	-0.198	-0.520^{***}	0.059	-0.397^{***}	0.140
	6	-0.272^{*}	-0.495^{***}	-0.231	-0.524^{***}	0.067	-0.354^{**}	0.111
1918-11-15	1	-0.674^{***}	-0.709^{***}	0.056	-0.648^{***}	0.162	-0.501^{***}	-0.123
	3	-0.690^{***}	-0.709^{***}	0.016	-0.646^{***}	-0.039	-0.610^{***}	-0.041
	6	-0.662^{***}	-0.700^{***}	-0.030	-0.653^{***}	0.122	-0.577^{***}	0.116
1923-08-17	1	-0.619^{***}	-0.568^{***}	-0.009	-0.598^{***}	0.069	-0.672^{***}	0.131
	3	-0.652^{***}	-0.718^{***}	-0.078	-0.594^{***}	0.069	-0.682^{***}	0.131
	6	-0.659^{***}	-0.705^{***}	-0.106	-0.588^{***}	0.187	-0.702^{***}	0.225
1927-02-01	1	-0.212	-0.298^{*}	-0.163	-0.284	0.271	-0.133	0.262
	3	-0.224	-0.254	-0.302	-0.272	0.271	-0.126	0.262
	6	-0.208	-0.226	-0.298	-0.259	0.330^{*}	-0.173	0.257
1933-02-01	1	-0.737^{***}	-0.969^{***}	-0.275	-0.895^{***}	0.099	-0.684^{***}	0.099
	3	-0.737^{***}	-0.960^{***}	-0.288	-0.895^{***}	0.099	-0.719^{***}	0.099
	6	-0.737^{***}	-0.952^{***}	-0.270	-0.890^{***}	0.099	-0.662^{**}	0.099

Cross-sectional rank correlations for horizons equal to 1, 3 and 6 months ahead between risk measures (CoVaR, SRISK, leverage, size, volatility, beta and VaR) and bank deposit losses during deposit contractions.

Table 19: CROSS-SECTIONAL CORRELATIONS AMONG RISK MEASURES AROUND DEPOSIT EXPANSION EVENTS

Panic	Horizon	CoVaR	SRISK	Lev	Siz	Vol	Beta	VaR
1868-02-01	1	-0.142	-0.221	-0.062	-0.506^{***}	-0.080	-0.393^{**}	-0.389^{**}
	3	-0.127	-0.051	-0.034	-0.519^{***}	-0.128	-0.369^{**}	-0.375^{**}
	6	-0.094	0.002	0.110	-0.509^{***}	-0.145	-0.324^{*}	0.013
1879-05-10	1	0.047	0.060	0.016	-0.019	0.074	-0.046	-0.128
	3	0.063	-0.027	-0.024	-0.018	0.041	-0.014	-0.131
	6	0.073	-0.020	-0.044	0.005	0.021	0.088	-0.125
1892-01-08	1	0.002	0.164	0.013	0.181	-0.022	-0.192	-0.072
	3	-0.001	0.074	-0.098	0.170	-0.032	-0.198	-0.103
	6	0.052	0.139	-0.022	0.168	-0.067	-0.194	-0.106
1901-01-25	1	0.053	0.380^{***}	0.455^{***}	0.251^{**}	-0.191	0.232^{*}	-0.116
	3	0.066	0.359^{***}	0.396^{***}	0.264^{**}	-0.246^{*}	0.272^{**}	-0.107
	6	0.072	0.371^{***}	0.445^{***}	0.259^{**}	-0.245^{*}	0.251^{**}	-0.091
1907-01-18	1	0.213	0.028	-0.029	0.029	-0.065	0.247^{*}	-0.068
	3	0.196	-0.098	-0.104	0.030	-0.063	0.229	-0.069
	6	0.198	-0.004	-0.017	0.045	-0.056	0.227	-0.020
1912-01-19	1	0.138	0.221	0.085	0.207	0.178	0.075	0.138
	3	0.187	0.172	0.005	0.209	0.150	0.072	0.108
	6	0.075	0.186	0.046	0.204	0.155	0.056	0.118
1915-10-22	1	0.105	0.141	0.114	0.122	-0.069	0.233	0.066
	3	0.162	0.121	0.114	0.131	-0.065	0.220	0.094
	6	0.200	0.122	0.142	0.139	-0.026	0.227	0.038
1928-04-01	1	-0.219	-0.607^{***}	-0.360^{*}	-0.673^{***}	0.115	-0.373^{**}	0.108
	3	-0.298	-0.669^{***}	-0.395^{**}	-0.636^{***}	0.211	-0.542^{***}	0.139
	6	-0.213	-0.630^{***}	-0.405^{**}	-0.646^{***}	0.223	-0.520^{***}	0.153

Cross-sectional rank correlations for horizons equal to 1, 3 and 6 months ahead between risk measures (CoVaR, SRISK, leverage, size, volatility, beta and VaR) and bank deposit losses during deposit epxansions.