

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 two challenges: the ranking of systemically important financial institutions (SIFIs) and financial crisis prediction. We find that CoVaR and SRISK meet the SIFI ranking challenge, i.e. help identifying systemic institutions in periods of distress beyond what is explained by standard risk measures up to six months prior to panics. In contrast, aggregate CoVaR and SRISK are only somewhat effective at predicting financial crises.

Keywords: Systemic Risk, Financial Crises, Risk Measures

JEL: G01, G21, G28, N21

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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 SIFI’s). 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 financial system. Financial crises are rare events and the system often evolves in response to post-crisis changes in regulation. Regulatory measures of firm level risk have traditionally focused on risky behavior associated with 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 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 adopting uninsured deposits as their primary method

¹The 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).

²A 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).

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

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 (see Wicker (2000a)). 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.⁴ 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 crises 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 the risks were not accurately reflected in their stock price. Two measures of systemic risk proposed in the

⁴We 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.

wake of the 2008 financial crisis – CoVaR and SRISK – use stock price behavior to infer the systemic risk of financial firms. Unlike era-specific balance sheet measures, these measures based on stock returns 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 risky 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, 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 future panics.

The pre-FDIC era is appealing in other ways as well. Throughout the period, the U.S. 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. 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 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 SIFI ranking challenge, i.e., to identify vulnerable financial institutions that might substantially contribute to the undercapitalization 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 financial crisis prediction 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 SIFI ranking 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 subsequent 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 SIFI's in periods of distress over what is explained by standard variables up to six months ahead of a panic event. We 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 obtain additional 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 SIFI ranking properties of CoVaR and SRISK we also estimate the panel regression during NBER expansions and recessions. We find that 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.

We carry out an additional validation exercise for SRISK which provides a prediction of the capital shortage a bank would experience conditional on a systemic event. We run Mincer-Zarnowitz type regressions to assess whether 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 crisis prediction 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 for 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, and 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, when we compute time series correlations between aggregate deposits and CoVaR/SRISK growth rates we find that these are significant in a few instances only. The results also

convey that finding evidence of time series predictability is much harder as none of the other risk measures produce 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 during 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 SIFI 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, describes our historical dataset, and defines the panic events of interest of this analysis. Section 3 analyses the evolution of systemic risk around panic events. Section 4 tests the ability of systemic risk measures to identify systemic important financial institutions prior to panic events. Section 5 presents evidence on the predictive content of aggregate CoVaR and SRISK. Concluding remarks follow in Section 6.

2 Systemic Risk Measures and Historical Data

In a first subsection we provide a short introduction to the systemic risk measures used in the paper. 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. We only provide a short introduction to CoVaR and SRisk since both measures are described and studied in detail in the aforementioned papers.⁵

⁵In the Online Appendix to the paper – specifically in Section OA.1 – we provide further details regarding the specific implementation in the current paper.

A second subsection covers the details of the unique data set on which we rely, while a third provides an overview of the different financial crisis panic periods we study.

2.1 CoVaR and SRisk

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. 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_{it} and the corresponding value weighted period t arithmetic return of the entire financial system is r_{mt} . The book value of equity and debt of firm i are denoted respectively by E_{it} and D_{it} . The market value of equity of firm i is denoted by W_{it} .

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

$$P_t(r_{mt+1} < \text{CoVaR}_{it}^{p,q} | r_{it+1} = \text{VaR}_{it}^q) = p,$$

where the distress of firm i is defined as the return of firm i being at its Value-at-Risk VaR_{it}^q . 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,

$$\Delta\text{CoVaR}_{it} = \text{CoVaR}_{it}^{p,q} - \text{CoVaR}_{it}^{p,0.50}. \quad (1)$$

The ΔCoVaR_{it} measure is an index of tail dependence between the entire financial system and an individual institution. We also define a dollar version of ΔCoVaR that takes the size of firm i into account, that is

$$\Delta\text{CoVaR}_{it}^{\$} = W_{it}\Delta\text{CoVaR}_{it}. \quad (2)$$

In this work we opt for a standardized version of the dollar ΔCoVaR , that is

$$\Delta\text{CoVaR}_{it}^{\%} = \frac{W_{it}}{\sum_{j=1}^{N_t} W_{jt}} \Delta\text{CoVaR}_{it}. \quad (3)$$

Since firm size changes substantially throughout our sample, the percentage $\Delta\text{CoVaR}^{\%}$ is easier to interpret than its dollar counterpart. Last, we define the value weighted aggregate $\overline{\Delta\text{CoVaR}_t}$ as

$$\overline{\Delta\text{CoVaR}_t} = \sum_{i=1}^{N_t} w_{it} \Delta\text{CoVaR}_{it}, \quad (4)$$

where $w_{it} = W_{it} / \sum_{j=1}^{N_t} W_{jt}$.

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). Following their approach, 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 $W_{it} - kA_{it}$, where A_{it} is measured as $W_{it} + D_{it}$. 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. Note that when the capital buffer is negative then the firm experiences a capital shortfall. Therefore, we define the capital shortfall as the negative capital buffer of the firm

$$\text{CS}_{it} = kA_{it} - W_{it} = k(D_{it} + W_{it}) - W_{it}. \quad (5)$$

Brownlees and Engle (2016) 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

$$\text{SRISK}_{it}^{\$} = E_t(\text{CS}_{it+1} | r_{m,t+1} < C) = k D_{it} - (1 - k) W_{it} (1 - \text{MES}_{it}), \quad (6)$$

where $\text{MES}_{it} = -E_t(r_{it+1} | r_{m,t+1} < C)$ is the so called Marginal Expected Shortfall, the expectation of the firm equity return conditional on the systemic event. 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 (6), as the

units correspond to the dollar version of ΔCoVaR , denoted as $\Delta\text{CoVaR}_{it}^{\$}$. In order to produce an easier to interpret index Brownlees and Engle (2016) define the $\text{SRISK}_{it}^{\%}$ as

$$\text{SRISK}_{it}^{\%} = \frac{\text{SRISK}_{it}^{\$}}{\sum_{i=1}^{N_t} (\text{SRISK}_{it}^{\$})_+} \quad (7)$$

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, $\text{SRISK}_{it}^{\%}$ can be interpreted as the capital shortage of firm i relative to the total capital shortage experienced by the financial system. Last, we define aggregate SRISK as

$$\overline{\text{SRISK}}_t = \frac{\sum_{i=1}^{N_t} (\text{SRISK}_{it}^{\$})_+}{\sum_{j=1}^{N_t} W_{jt}},$$

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.⁶

Finally, 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).⁸

2.2 Historical Data from the New York Clearinghouse

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 provided regulatory incentives to pool excess reserves in central reserve cities. In particular, the NBAs encouraged the development of a nationwide inter-bank

⁶All the technical details about the actual implementation of CoVaR and SRISK appear in the Online Appendix Section OA.1, where we also provide insights regarding the quality of the empirical models that are the key ingredients to respectively CoVaR and SRISK calculations. In particular, we document that the key parameter estimates are all statistically significant and within economically plausible range. Moreover,

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).⁷ Note that the sub-panels we construct are unbalanced in that banks might not have been trading for the entire 5 year window and because of missing data.

⁸Online Appendix subsection OA.1.3 provides the details regarding the computations of Leverage, size, volatility, beta and Value-at-Risk (VaR).

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).

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 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

Many cities across the U.S. had clearinghouses. Focusing only on the NYCH may therefore appear as if we are examining a sample that is not representative.¹⁰ Our use of NYCH banks was motivated by both the importance of the NYCH and by data availability. The NYCH is an ideal laboratory for out-of-sample tests of CoVaR and SRISK. The U.S. banking system before WWII consisted of thousands of banks with deposits and capital concentrated in the clearing house member banks of the largest cities. Of these clearing house cities New York was the most important and had many of the most systemically important banks. National banking act reserve requirements encouraged the pooling of country bank reserves in central reserve cities and New York banks attracted the vast majority of these reserves because of their proximity to the NYSE call money market (Bordo and Landon-Lane (2010)). Because of this pooling of reserves in New York, Wicker (2000b) argued that U.S. bank panics prior to 1914 were always centered in the New York money market and then spread via the vagaries of the National banking system to rest of the country.¹¹ Secondly, calculating CoVaR and SRISK requires high-frequency balance sheet and stock return data. New York clearing house banks are the only banks in the U.S. that both reported weekly balance sheet data and had shares quoted regularly for our entire period of study.¹²

⁹New 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.

¹⁰Details regarding the NYCH historical data appear in Online Appendix Section OA.2.

¹¹Mitchener and Richardson (2016) provide evidence that transmission of withdrawal pressure in many cases flowed from small to large banks, amplifying liquidity constraints during banking panics.

¹²It is important to note that, the vast majority of modern U.S. banks are too small to have publicly traded equity. As a result modern applications of CoVaR and SRISK which seek to either identify systemically risky financial institutions or construct an

NYCH balance sheet statements 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.¹³ The variables we collect consist of: capital, loans, specie (gold and silver), circulation, deposits, legal tenders, reserves with legal depositories, and surplus.

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 (that is, stock returns and market values were available for these organizations). As a result, we end up with a panel of 92 institutions.¹⁴

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 due to failure.¹⁵

The thick black line in Figure 1 presents the total deposits of NYCH members. It is important to note, that while the number of NYCH institutions begins to trend downward around 1900, the total size and thereby importance of NYCH members continues to increase. To be sure, the decline in the the number of clearinhouse members runs counter to the overall increase in the number of national and state banks

aggregate measure of systemic risk in the U.S. financial system are limited to the largest U.S. banks by design. This is not viewed as a shortcoming because these tests do not require a representative sample. Rather they should be evaluated with banks that are likely to be systemically important.

¹³The Clearinghouse ceased publishing information on loans, legal, and reserves at the beginning of 1928. 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.

¹⁴Table OA.1 in the Online Appendix 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, Chase and Citibank). The large majority of banks listed have disappeared, merged or were acquired by other banks or financial institutions. It is important to note that, due to their historical nature, 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.

¹⁵For example, Bank of America's acquisition of Merrill Lynch likely forestalled Merrill's collapse in 2007.

in the country as a whole. This is due, in part, to the Gold Standard Act of 1900 ((Rousseau 2011)) and the emergence of the Federal Reserve as a competing institution for membership in the New York Clearinghouse.

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.¹⁶ 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 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.¹⁷

3 The Behavior of Deposits and Systemic Risk around Panic Events

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 (2000a), 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, 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 1 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.¹⁸

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

¹⁶The 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.

¹⁷Our 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.

¹⁸In the Online Appendix section OA.3 we summarize the historical details for each of these eight major financial crises.

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.

3.1 The Pre–FDIC Panics

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 2 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 one period 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. $\Delta\text{CoVaR}_{it}^{\%}$ and $\text{SRISK}_{it}^{\%}$. For comparison purposes, the table also reports the value and rank obtained from leverage, size, volatility, beta and VaR. In what follows we provide some detailed comments regarding 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 2, 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.¹⁹

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.²⁰ Likewise, the Metropolitan bank holds a relatively elevated position in terms of CoVaR and was extensively written about as being highly exposed to the railroad sector, as its president and the bank were heavily involved in railroad speculation.²¹

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 2 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 2. 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

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

²⁰See New York Times, June 19, 1884.

²¹The 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.

suffered larger bank runs.²² 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.²³ 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 Bank of Commerce, ranked first in both deposit losses and SRISK, and ranked third in CoVaR in Table 2, was highly exposed to Knickerbocker Trust and had been extending credit to the Trust company up until the start of the crisis (see Moen and Tallman (1990)).

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 2, 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.²⁴ Importantly, National City was ranked first in terms of both CoVaR and SRISK prior to the crisis and seen in Figure 5.

²²See New York Times, June 15, 1893.

²³The crisis originated in what was essentially the shadow banking system. Recall that we excluded trust companies from our sample.

²⁴See New York Times, June 12 and August 1, 1914.

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 not to be defined as a panic in previous research. Indeed, overall deposit losses for Clearinhouse banks were only two percent. That said, several banks, such as First National Bank, lost roughly a quarter of a substantial amount of deposits at the time and were ranked highly for our measures of systemic risk.²⁵

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 (see Richardson (2007)). Starting in August of 1931, 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 Table 2, there 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.

3.2 Aggregate measures around the Pre–FDIC Panics

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 1. Figure 2 displays aggregate deposits in a two year window containing each of the panics. The vertical shaded areas are the panics listed in Table 1. 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

²⁵It could be argued that the inclusion of the panic of 1921 is somewhat arbitrary. In the literature 1921 is excluded from many panic and crisis accounts, in part, due to most studies ending their chronology in 1914. It is important to note the overall effects of the panic of 1921 on the financial sector were diffuse and short lived. This was in part due to the reaction of the Federal Reserve. To be sure, in 1921 the Comptroller of the Currency reported that overall bank deposits declined by 7 percent and interbank borrowing declined by 22 percent. By these metrics 1921 should be considered a banking panic.

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.

We plot in Figure 3 the aggregate bank index – obtained from our sample of individual bank returns – and the Cowles Index for the New York Stock Exchange around panic events.²⁶ We note that our aggregate bank index features larger declines in comparison to the Cowles index, with the Great Depression.²⁷ This is not surprising since our aggregate bank index concentrates on the financial sector which is the focal point of the panics. Also worth noting is that the declines in the bank index often occur well ahead of the shaded areas, i.e. ahead of the panics. This gives credence to the use of CoVaR and SRISK which rely on the market's assessment of impending crises.

Moving on to Figure 4, we report the times series plots of aggregate CoVaR and SRISK, denoted respectively $\Delta\overline{\text{CoVaR}}_t$ and $\overline{\text{SRISK}}_t$, 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, $\Delta\overline{\text{CoVaR}}_t$ and $\overline{\text{SRISK}}_t$ 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 $\Delta\overline{\text{CoVaR}}_t$ and $\overline{\text{SRISK}}_t$, 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 4 for both $\Delta\overline{\text{CoVaR}}_t$ and $\overline{\text{SRISK}}_t$, 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 5 presents a decomposition of the aggregate CoVaR and SRISK series. The figure splits the time series and presents the SRISK and CoVaR for each

²⁶See <https://som.yale.edu/faculty-research/our-centers-initiatives/international-center-finance/data/historical-cowles> for more information.

²⁷The flat lines during the 1914 crisis were due to the closing of financial markets caused by the outbreak of WWI.

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 4. Moreover, the decomposition provides evidence that 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 5 in the next section.

4 The SIFI Ranking Challenge

In this section we assess whether individual bank CoVaR and SRISK help identifying systemically important financial institutions ahead of a panic. 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 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' value, i.e. deposits, will decline. Consequently, the largest declines in deposits are associated with banks for which depositors ascribe a high likelihood of failure.²⁸ Deposit declines during panic events are, however, hard to measure for at least three reasons. First, when the deposit 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 were already 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 from the beginning until the end of the panic as a sensible proxy of the distress. To make this figure easier to read across different panic events, we standardize the maximum deposit loss by the sum of the max deposit

²⁸It 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.

contraction in each panic event. We will denote this as ΔDep_{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. $\Delta\text{CoVaR}_{it}^{\%}$ and $\text{SRISK}_{it}^{\%}$, but to simplify notation we simply refer to them as CoVaR and SRISK.

4.1 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.²⁹ The use of panel regression analysis serves two purposes: (1) it simplifies reporting the empirical findings and (2) the pooling across crisis strengthens the evidence. The regressors exclusively pertain to observations prior to the crises. More specifically, we consider the following specification:

$$\Delta\text{Dep}_{it} = \beta \text{SRM}_{it-l} + \sum_{k=1}^p \gamma_k x_{k\ it-l} + \eta_i + \nu_t + u_{it} \quad (8)$$

where the dependent variable ΔDep_i is the maximum deposit contraction of institution i from the beginning of a 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 (8) are computed 1-month-ahead, 3-months-ahead and 6-months-ahead in order to assess how predictability is affected by the horizon. Hence, the lags in the above equation are either $l = 1, 3$ or 6 , whereas t stands for the time stamp associated with the start of each panic. 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.

Two important issues regarding the regressors SRM_i require further elaboration. First, for the three horizons, $l = 1, 3$ or 6 , we compute CoVaR and SRISK using only data aligned with the information set available at

²⁹In the Online Appendix section we report empirical results for each individual panic, whereas in the main body of the paper we pool all panic events in our sample and estimate a panel specification to assess whether CoVaR and SRISK provide significant signals across all events.

the time of prediction. This means that the 5-year estimation window for the parameter estimates used to construct the systemic risk measures ends respectively 1-month, 3-months and 6-months prior to the onset of a panic. Second, the SRM_i are generated regressors due to the estimation error. In the simple case where the latter is uncorrelated with the dependent variable and the control variables we expect a downward bias in the estimation of β and inflated standard error estimates. Hence, we expect the inference to be conservative.³⁰

Table 3 reports the estimation results of the model in equation (8) 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.

³⁰Note that we do expect some correlation between SRM_i and control variables pertaining to the *same* panic. The virtue of pooled panel regressions is that control variables across all panics are used as instruments, and this in turn dilutes the correlation over the entire sample used in estimation. In the Online Appendix Table OA.3 we report estimates of individual crises. These estimates are therefore more prone to generated regressor bias. Another virtue of the panel regressions is that the crisis events are far apart in time, and therefore autocorrelation in the errors should not be a major concern. Moreover, since all variables are normalized, the potential of heteroskedasticity is also accounted for.

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 3). It is worth noting that neither leverage nor size are significant. Only volatility and VaR are consistently significant across all horizons.

We also synthesize the degree of accordance in each panic between the rankings of ex-post deposit losses and ex-ante risk measures in the Online Appendix Table OA.4 where we report rank correlations for each panic event in our sample and for different horizons equal to 1, 3 and 6 months. 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. 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, while size performs well and is at par with CoVaR and/or SRISK in terms of rank correlations.

It is also of interest to gather how different the rankings are across the various measures. To this extent, in the Online Appendix Table OA.5 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. We find 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.

4.2 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?³¹ For expansions and contractions we take respectively the periods

³¹To 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-

corresponding to the eight largest deposit increases and the eight non-panic biggest declines and run again panel regressions of the type in equation (8). All the regressors are the same, except that we replace the panic fixed effect by expansion and contraction fixed effects covering each of the six selected episodes.

Table 4 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 flag 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 OA.6 in the Online Appendix) show results that are roughly in line with the finding during panics (Table OA.4 in Online Appendix), namely CoVaR and SRISK are significantly correlated with deposit contractions for the vast majority of contraction events.

Table 5 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 OA.7 in the Online Appendix) show that CoVaR and SRISK are typically not significantly correlated with deposit increases.

4.3 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

$$CS_i = \alpha_0 + \alpha_1 SRISK_i + u_i ,$$

where CS_i is the realized capital shortage suffered by bank i at the last period of the panic window computed according to equation (5) and $SRISK_i$ denotes the SRISK of firm i measured in dollars. The capital shortage

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.

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 6. 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.³²

5 The Financial Crisis Prediction Challenge

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.

³²We 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.

5.1 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,

$$\Delta\overline{\text{Dep}}_{t+h} = \alpha_0 + \sum_{l=1}^3 \alpha_l \Delta\overline{\text{Dep}}_{t-l} + \sum_{l=1}^3 \beta_l \Delta\overline{\text{SRM}}_{t-l} + \sum_{k=1}^p \sum_{l=1}^3 \gamma_{kl} x_{k,t-l} + u_{t+h}, \quad (9)$$

where $\Delta\overline{\text{Dep}}_t$ is the forward-looking 6-month change in aggregate deposits starting with month t until $t+6$, $\Delta\overline{\text{SRM}}_t$ is the monthly change in 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. We run this regression for different horizons h for 1 and 3 months ahead, hence predicting changes from $t+1$ to $t+7$ and $t+3$ to $t+9$ respectively using $t-1$ information.³³

The results appear in Table 7 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.

In the Online Appendix Table OA.8 we report the time series correlations between the various aggregate risk measures and aggregate deposit losses and Table OA.9 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.

Overall, these findings are consistent with Fahlenbrach, Prilmeier, and Stulz (2012), Baron and Xiong

³³We carry out inference using robust Newey-West standard errors. 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.

(2017), and Krishnamurthy and Muir (2017) which show that equity and bond markets are bad at predicting banking crises in advance, and that crises mostly come as surprises to markets.

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

We repeat the time series regressions appearing in equation (9) for the expansions and recession samples described in section 4.2. The results appear in Tables 8 (Deposit Loss Regressions Around NBER Contractions) and 9 (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 SIFI's 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 SIFI's. 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 than it today? These are a number of research topics we leave for future research.

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Table 1: 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. In the Online Appendix section OA.3 we summarize the historical details for each of these eight major financial crises.

Table 2: 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	Value	Rank
1873 (-27%)	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	
	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 (-17%)	Metropolitan	-11.79	2.62	3	1.90	17	1.82	46	15.34	5	2.38	41	1.04	16	1.67	30	
	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 (-12%)	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	
	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 (-11%)	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	
	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 (-14%)	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
	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 (-32%)	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
	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 (-2%)	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
	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 (-21%)	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
	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 $\Delta\text{CoVaR}_{it}^{\%}$ and $\text{SRISK}_{it}^{\%}$ one period 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 3: BANK DEPOSIT LOSS PANEL REGRESSIONS AROUND PANIC EVENTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Horizon	1									
CoVaR	-0.036*** (0.010)	-0.023* (0.015)			-0.013 (0.012)	-0.008 (0.015)			-0.022** (0.012)	-0.012 (0.015)
SRISK			-0.608*** (0.068)	-0.564*** (0.070)			-0.562*** (0.079)	-0.565*** (0.083)		
Lev					-0.290** (0.132)	-0.380*** (0.154)	-0.063 (0.125)	-0.046 (0.150)	-0.235** (0.131)	-0.286** (0.150)
Siz					-1.014*** (0.294)	-1.343*** (0.420)	-0.468** (0.267)	-0.318 (0.401)	-0.982*** (0.297)	-1.082*** (0.407)
Vol					0.157* (0.114)	0.177* (0.125)	0.189** (0.104)	0.200** (0.114)	-0.028 (0.083)	0.005 (0.100)
Beta					-0.064 (0.217)	-0.019 (0.230)	0.289* (0.205)	0.256 (0.215)	-0.164 (0.215)	-0.171 (0.222)
VaR					-0.272*** (0.116)	-0.297** (0.131)	-0.238*** (0.101)	-0.185* (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*** (0.014)	-0.035** (0.020)			-0.021 (0.017)	-0.012 (0.021)			-0.034** (0.016)	-0.020 (0.021)
SRISK			-0.753*** (0.067)	-0.715*** (0.069)			-0.719*** (0.077)	-0.729*** (0.081)		
Lev					-0.447*** (0.127)	-0.561*** (0.145)	-0.182* (0.113)	-0.163 (0.134)	-0.388*** (0.127)	-0.459*** (0.142)
Siz					-0.925*** (0.296)	-1.374*** (0.418)	-0.220 (0.249)	-0.006 (0.378)	-0.888*** (0.299)	-1.075*** (0.408)
Vol					0.192** (0.114)	0.218** (0.125)	0.220** (0.099)	0.238** (0.107)	-0.011 (0.085)	0.018 (0.101)
Beta					-0.006 (0.213)	0.053 (0.224)	0.395** (0.188)	0.358** (0.197)	-0.132 (0.210)	-0.139 (0.215)
VaR					-0.297*** (0.113)	-0.342*** (0.127)	-0.257*** (0.094)	-0.209** (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*** (0.014)	-0.044** (0.021)			-0.025* (0.017)	-0.021 (0.022)			-0.038** (0.017)	-0.028* (0.022)
SRISK			-0.566*** (0.064)	-0.527*** (0.066)			-0.513*** (0.072)	-0.510*** (0.075)		
Lev					-0.305*** (0.123)	-0.392*** (0.144)	-0.102 (0.115)	-0.121 (0.138)	-0.245** (0.122)	-0.314** (0.141)
Siz					-0.919*** (0.301)	-1.227*** (0.418)	-0.499** (0.262)	-0.429 (0.387)	-0.881*** (0.304)	-1.036*** (0.414)
Vol					0.192** (0.116)	0.190* (0.126)	0.217** (0.106)	0.233** (0.114)	-0.002 (0.086)	0.010 (0.101)
Beta					-0.099 (0.220)	-0.101 (0.228)	0.239 (0.206)	0.213 (0.214)	-0.182 (0.220)	-0.213 (0.225)
VaR					-0.281*** (0.114)	-0.287*** (0.122)	-0.260*** (0.100)	-0.225** (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 (8) pooling all panic events and regressing ΔDep_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 regressors are computed using the data available 1, 3, and 6 months-ahead of the beginning of the panic event.

Table 4: BANK DEPOSITS LOSS REGRESSIONS AROUND NBER CONTRACTIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon	1							
CoVaR	-0.029*** (0.006)	-0.029*** (0.006)			-0.030*** (0.009)	-0.031*** (0.009)		
SRISK			-0.353*** (0.114)	-0.354*** (0.115)			-0.217* (0.133)	-0.213* (0.135)
Lev					0.051 (0.112)	0.042 (0.116)	0.084 (0.115)	0.079 (0.119)
Siz					-0.554** (0.323)	-0.557** (0.326)	-0.546* (0.336)	-0.551* (0.340)
Vol					0.062* (0.047)	0.070* (0.052)	0.030 (0.048)	0.032 (0.053)
Beta					-0.454 (0.397)	-0.505 (0.405)	-0.162 (0.443)	-0.193 (0.453)
VaR					-0.744* (0.552)	-0.836* (0.612)	-0.594 (0.575)	-0.620 (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*** (0.007)	-0.033*** (0.007)			-0.029*** (0.010)	-0.030*** (0.010)		
SRISK			-0.472*** (0.120)	-0.472*** (0.121)			-0.315** (0.142)	-0.309** (0.143)
Lev					0.003 (0.105)	-0.006 (0.108)	0.049 (0.106)	0.046 (0.109)
Siz					-0.552** (0.325)	-0.550** (0.327)	-0.492* (0.335)	-0.498* (0.338)
Vol					0.049* (0.035)	0.057* (0.039)	0.031 (0.036)	0.037 (0.040)
Beta					-0.451 (0.427)	-0.518 (0.436)	-0.037 (0.469)	-0.084 (0.481)
VaR					-0.761* (0.501)	-0.886* (0.557)	-0.741* (0.510)	-0.836* (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*** (0.007)	-0.031*** (0.007)			-0.024** (0.011)	-0.024** (0.011)		
SRISK			-0.362*** (0.119)	-0.362*** (0.120)			-0.175 (0.138)	-0.171 (0.140)
Lev					0.039 (0.105)	0.029 (0.108)	0.073 (0.106)	0.066 (0.109)
Siz					-0.528* (0.328)	-0.517* (0.330)	-0.492* (0.336)	-0.487* (0.339)
Vol					0.025 (0.024)	0.028 (0.025)	0.017 (0.024)	0.019 (0.025)
Beta					-0.400 (0.433)	-0.448 (0.442)	-0.149 (0.477)	-0.190 (0.489)
VaR					-0.528* (0.360)	-0.572* (0.380)	-0.655** (0.356)	-0.695** (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 (8) pooling all contraction events and regressing ΔDep_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 $\Delta CoVaR$ 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 regressors are computed using the data available 1, 3, and 6 months-ahead of the beginning of the panic event.

Table 5: BANK DEPOSITS LOSS REGRESSIONS AROUND NBER EXPANSIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon	1							
CoVaR	-0.133 (0.206)	-0.132 (0.236)			-0.201 (0.264)	-0.129 (0.275)		
SRISK			0.015 (0.182)	0.036 (0.193)			-0.111 (0.224)	-0.072 (0.229)
Lev					0.674** (0.408)	0.650* (0.420)	0.791** (0.413)	0.726** (0.427)
Siz					1.455 (1.200)	1.827* (1.389)	1.253 (1.163)	1.714 (1.355)
Vol					-0.908* (0.647)	-0.739 (1.846)	-0.970* (0.686)	-0.722 (1.863)
Beta					-0.470 (0.828)	-0.599 (0.843)	-0.301 (0.872)	-0.497 (0.894)
VaR					-0.264 (1.492)	-4.301 (3.858)	-0.337 (1.493)	-4.600 (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 (0.271)	-0.003 (0.295)			-0.024 (0.326)	0.057 (0.333)		
SRISK			0.074 (0.147)	0.088 (0.154)			-0.010 (0.165)	0.002 (0.168)
Lev					0.690** (0.403)	0.705** (0.427)	0.704** (0.395)	0.682* (0.424)
Siz					1.366 (1.180)	2.156* (1.434)	1.351 (1.130)	2.231* (1.387)
Vol					-1.640* (1.192)	-0.729 (2.288)	-1.651* (1.216)	-0.747 (2.286)
Beta					-0.278 (0.813)	-0.516 (0.829)	-0.263 (0.840)	-0.518 (0.859)
VaR					0.408 (1.599)	-4.285 (3.866)	0.397 (1.592)	-4.145 (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 (0.245)	-0.127 (0.266)			-0.207 (0.308)	-0.214 (0.319)		
SRISK			0.155 (0.169)	0.185 (0.178)			0.076 (0.190)	0.090 (0.201)
Lev					0.663** (0.376)	0.609* (0.441)	0.732** (0.356)	0.679* (0.419)
Siz					2.590** (1.402)	2.616** (1.498)	1.992* (1.329)	2.046* (1.431)
Vol					-2.589** (1.260)	-2.916 (3.206)	-2.380** (1.289)	-2.344 (3.164)
Beta					-0.731 (0.896)	-0.916 (0.975)	-0.787 (0.927)	-1.014 (1.013)
VaR					1.442 (1.593)	-1.493 (5.620)	1.346 (1.596)	-1.836 (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 (8) pooling all expansion events and regressing ΔDep_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 regressors are computed using the data available 1, 3, and 6 months-ahead of the beginning of the panic event.

Table 6: PREDICTED VS ACTUAL CAPITAL SHORTAGES AROUND PANIC EVENTS

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

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 $CS_i = \alpha_0 + \alpha_1 SRISK_i + u_i$, 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 7: AGGREGATE DEPOSIT LOSS REGRESSIONS AROUND PANIC EVENTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon	1				3			
DG _t	0.925*** (0.051)	0.924*** (0.062)	0.942*** (0.053)	0.946*** (0.060)	0.717*** (0.074)	0.728*** (0.067)	0.766*** (0.075)	0.794*** (0.072)
DG _{t-1}	0.060** (0.028)	-0.168*** (0.053)	0.052* (0.027)	-0.303*** (0.059)	0.026 (0.044)	-0.124** (0.058)	-0.015 (0.046)	-0.118 (0.091)
DG _{t-2}	-0.001 (0.064)	-0.004 (0.075)	0.035 (0.064)	0.028 (0.077)	0.025 (0.060)	0.028 (0.061)	0.026 (0.071)	0.006 (0.067)
CoVaR _t	-0.039 (0.028)		-0.035 (0.030)		-0.022 (0.040)		-0.071 (0.051)	
CoVaR _{t-1}	-0.119*** (0.042)		-0.116*** (0.044)		-0.338*** (0.064)		-0.371*** (0.058)	
CoVaR _{t-2}	0.006 (0.029)		-0.023 (0.025)		0.102** (0.050)		0.015 (0.053)	
SRISK _t		-0.039 (0.046)		-0.091 (0.073)		0.007 (0.044)		0.077 (0.085)
SRISK _{t-1}		-0.074* (0.041)		-0.060 (0.045)		-0.327*** (0.070)		-0.372*** (0.068)
SRISK _{t-2}		-0.009 (0.031)		0.026 (0.054)		0.024 (0.059)		0.067 (0.095)
Lev _t			-0.023 (0.025)	0.026 (0.054)			0.015 (0.053)	0.067 (0.095)
Lev _{t-1}			-0.164*** (0.017)	-0.065** (0.026)			-0.135*** (0.025)	-0.096*** (0.034)
Lev _{t-2}			-1.848 (1.124)	-9.999*** (2.023)			-0.181 (1.600)	-3.606 (2.879)
Siz _t			0.031 (0.056)	0.003 (0.046)			0.084 (0.177)	0.070 (0.180)
Siz _{t-1}			-0.003 (0.051)	-0.014 (0.049)			-0.085 (0.113)	-0.069 (0.110)
Siz _{t-2}			-0.029 (0.067)	0.038 (0.065)			0.084 (0.157)	0.068 (0.158)
Vol _t			-0.031** (0.015)	-0.003 (0.022)			0.006 (0.024)	-0.016 (0.032)
Vol _{t-1}			-0.353 (1.607)	-3.040 (2.224)			1.668 (1.468)	3.875 (2.512)
Vol _{t-2}			0.084 (0.056)	0.106*** (0.040)			0.020 (0.094)	0.031 (0.086)
Beta _t			-0.034 (0.051)	-0.047 (0.041)			-0.024 (0.082)	-0.006 (0.078)
Beta _{t-1}			-0.081 (0.072)	-0.099 (0.064)			0.126 (0.114)	0.056 (0.105)
Beta _{t-2}			0.009 (0.016)	-0.010 (0.019)			0.029 (0.022)	0.007 (0.030)
VaR _t			0.256 (1.166)	1.812 (1.486)			2.617 (2.054)	4.788* (2.565)
VaR _{t-1}			-0.102 (0.105)	-0.041 (0.112)			-0.085 (0.103)	-0.077 (0.105)
VaR _{t-2}			0.065 (0.070)	0.034 (0.069)			0.008 (0.102)	0.004 (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 (9) projecting $\Delta \overline{\text{Dep}}_t$, is the monthly change in aggregate deposits onto its own lags as well as lags of $\Delta \overline{\text{SRM}}_t$, the monthly change in 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 8: AGGREGATE DEPOSIT LOSS REGRESSIONS AROUND NBER CONTRACTIONS

Horizon	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1				3			
DG _t	1.009*** (0.055)	1.012*** (0.065)	1.017*** (0.054)	1.005*** (0.064)	0.902*** (0.086)	0.917*** (0.087)	0.948*** (0.100)	0.992*** (0.101)
DG _{t-1}	-0.010 (0.033)	-0.098** (0.046)	-0.041 (0.044)	-0.231*** (0.088)	0.003 (0.054)	-0.069 (0.045)	-0.113 (0.077)	-0.167* (0.092)
DG _{t-2}	-0.013 (0.072)	-0.018 (0.086)	0.044 (0.075)	0.055 (0.086)	0.020 (0.072)	0.019 (0.071)	0.036 (0.089)	0.015 (0.080)
CoVaR _t	0.014 (0.032)		-0.030 (0.034)		0.044 (0.042)		-0.036 (0.060)	
CoVaR _{t-1}	-0.142*** (0.045)		-0.144*** (0.046)		-0.405*** (0.065)		-0.439*** (0.059)	
CoVaR _{t-2}	0.000 (0.032)		-0.024 (0.028)		0.100* (0.058)		-0.024 (0.062)	
SRISK _t		0.002 (0.041)		-0.102 (0.086)		0.027 (0.044)		0.102 (0.076)
SRISK _{t-1}		-0.118** (0.050)		-0.107** (0.047)		-0.414*** (0.066)		-0.457*** (0.067)
SRISK _{t-2}		-0.018 (0.034)		0.018 (0.059)		0.034 (0.051)		0.120 (0.102)
Lev _t			-0.024 (0.028)	0.018 (0.059)			-0.024 (0.062)	0.120 (0.102)
Lev _{t-1}			-0.134*** (0.013)	-0.079*** (0.024)			-0.108*** (0.020)	-0.066** (0.029)
Lev _{t-2}			-2.147* (1.105)	-7.337*** (2.311)			-0.985 (1.328)	-4.916* (2.900)
Siz _t			0.085 (0.097)	0.038 (0.103)			0.192 (0.149)	0.095 (0.147)
Siz _{t-1}			-0.026 (0.114)	0.016 (0.102)			0.105 (0.236)	0.164 (0.227)
Siz _{t-2}			-0.017 (0.088)	-0.022 (0.057)			0.220 (0.173)	0.127 (0.127)
Vol _t			-0.013 (0.011)	0.009 (0.019)			0.021 (0.023)	0.004 (0.028)
Vol _{t-1}			-0.006 (1.054)	-2.577 (2.127)			2.055 (1.645)	4.467 (2.777)
Vol _{t-2}			-0.015 (0.081)	-0.016 (0.078)			-0.095 (0.121)	-0.069 (0.114)
Beta _t			0.145* (0.077)	0.109 (0.081)			0.341** (0.158)	0.304* (0.157)
Beta _{t-1}			0.037 (0.080)	0.044 (0.064)			0.212 (0.150)	0.170 (0.127)
Beta _{t-2}			0.020 (0.013)	0.011 (0.016)			0.047** (0.023)	0.021 (0.028)
VaR _t			0.877 (0.967)	1.983 (1.491)			2.265 (1.526)	5.584** (2.318)
VaR _{t-1}			-0.081 (0.097)	-0.022 (0.104)			0.033 (0.162)	0.071 (0.180)
VaR _{t-2}			0.006 (0.091)	-0.003 (0.090)			0.136 (0.173)	0.147 (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

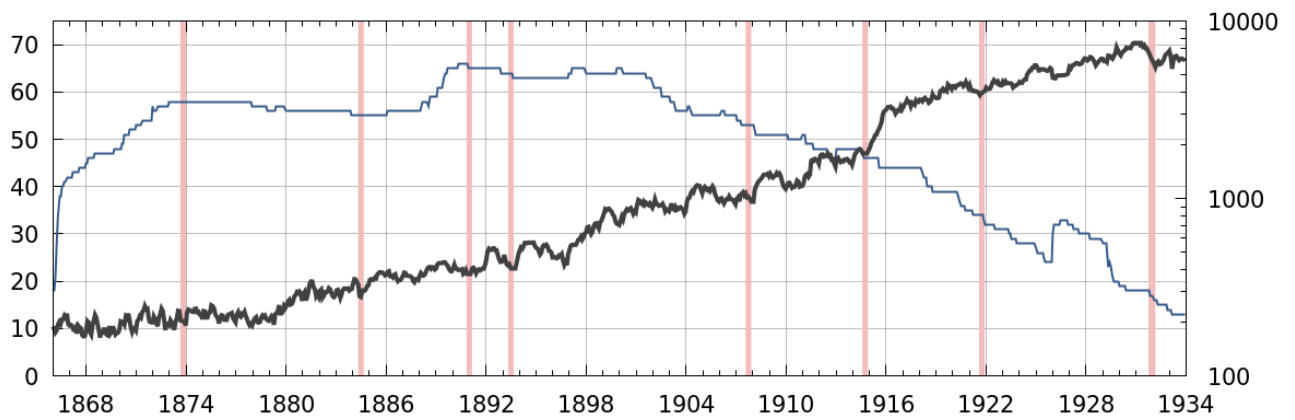
The entries pertain to the time series regressions appearing in equation (9) projecting $\Delta \overline{\text{Dep}}_t$, is the monthly change in aggregate deposits onto its own lags as well as lags of $\Delta \overline{\text{SRM}}_t$, the monthly change in the aggregate systemic risk measures (either 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 9: AGGREGATE DEPOSIT LOSS REGRESSIONS AROUND NBER EXPANSIONS

Horizon	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1				3			
DG _t	1.008*** (0.072)	1.048*** (0.084)	1.021*** (0.081)	1.027*** (0.083)	0.688*** (0.138)	0.734*** (0.160)	0.698*** (0.159)	0.713*** (0.169)
DG _{t-1}	-0.010 (0.034)	-0.279*** (0.050)	-0.013 (0.035)	-0.306** (0.126)	-0.028 (0.063)	-0.219*** (0.057)	-0.069 (0.067)	-0.106 (0.119)
DG _{t-2}	-0.159*** (0.054)	-0.168*** (0.061)	-0.165*** (0.061)	-0.160*** (0.060)	-0.044 (0.083)	-0.038 (0.096)	-0.032 (0.096)	-0.027 (0.099)
CoVaR _t	-0.063** (0.032)		-0.056* (0.029)		0.047 (0.053)		0.041 (0.052)	
CoVaR _{t-1}	-0.015 (0.044)		0.067* (0.040)		-0.141 (0.091)		-0.075 (0.104)	
CoVaR _{t-2}	0.052 (0.036)		-0.009 (0.036)		0.149** (0.059)		0.052 (0.057)	
SRISK _t		-0.003 (0.028)		0.019 (0.040)		0.065 (0.062)		0.143 (0.087)
SRISK _{t-1}		0.006 (0.045)		0.071* (0.041)		-0.172 (0.112)		-0.102 (0.116)
SRISK _{t-2}		-0.022 (0.030)		0.008 (0.065)		0.098* (0.058)		0.176** (0.084)
Lev _t			-0.009 (0.036)	0.008 (0.065)			0.052 (0.057)	0.176** (0.084)
Lev _{t-1}			-0.172*** (0.018)	-0.071* (0.042)			-0.185*** (0.025)	-0.146*** (0.048)
Lev _{t-2}			-3.748 (3.026)	-10.481** (4.483)			-5.784 (3.930)	-7.125 (5.235)
Siz _t			0.077 (0.091)	0.038 (0.091)			-0.022 (0.144)	-0.062 (0.151)
Siz _{t-1}			0.007 (0.062)	0.033 (0.054)			0.031 (0.114)	0.076 (0.120)
Siz _{t-2}			-0.077 (0.066)	-0.049 (0.055)			0.124 (0.128)	0.090 (0.122)
Vol _t			-0.013 (0.016)	-0.022 (0.017)			-0.008 (0.034)	-0.051 (0.036)
Vol _{t-1}			-0.677 (1.141)	0.402 (1.638)			-1.036 (2.071)	2.229 (3.109)
Vol _{t-2}			0.032 (0.068)	-0.002 (0.066)			-0.045 (0.105)	-0.063 (0.104)
Beta _t			0.006 (0.049)	0.021 (0.045)			0.014 (0.096)	0.000 (0.091)
Beta _{t-1}			0.001 (0.077)	-0.002 (0.071)			0.143 (0.151)	0.190 (0.150)
Beta _{t-2}			-0.028 (0.019)	-0.035 (0.029)			-0.003 (0.041)	-0.059 (0.049)
VaR _t			-1.956 (1.242)	-0.840 (2.327)			-3.917 (2.707)	-0.207 (2.924)
VaR _{t-1}			-0.095 (0.073)	-0.074 (0.078)			0.027 (0.143)	0.080 (0.147)
VaR _{t-2}			0.051 (0.047)	0.035 (0.051)			-0.038 (0.117)	-0.095 (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

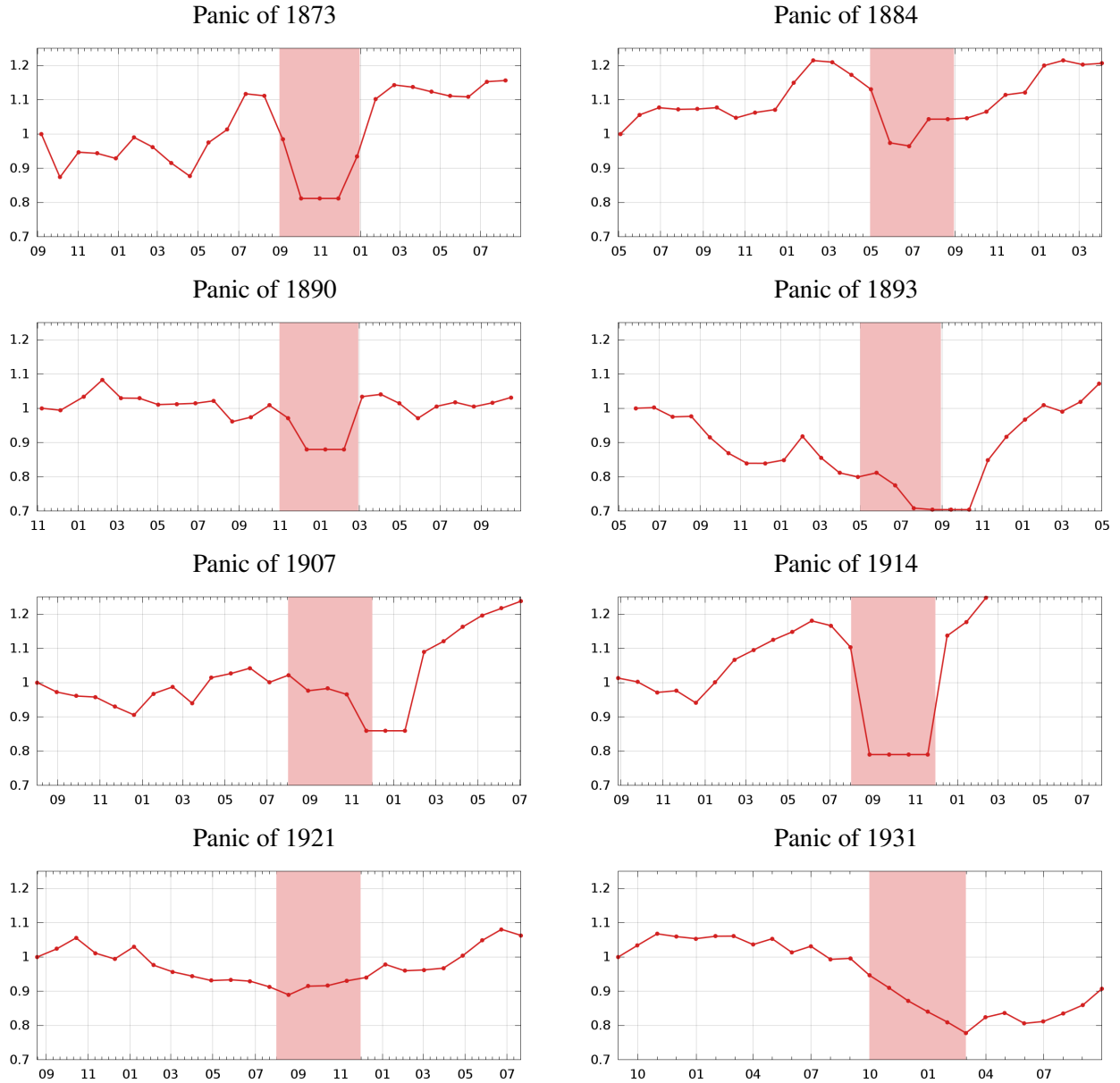
The entries pertain to the time series regressions appearing in equation (9) projecting $\Delta \overline{\text{Dep}}_t$, is the monthly change in aggregate deposits onto its own lags as well as lags of $\Delta \overline{\text{SRM}}_t$, the monthly change in the aggregate systemic risk measures (either 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 AND AGGREGATE DEPOSITS



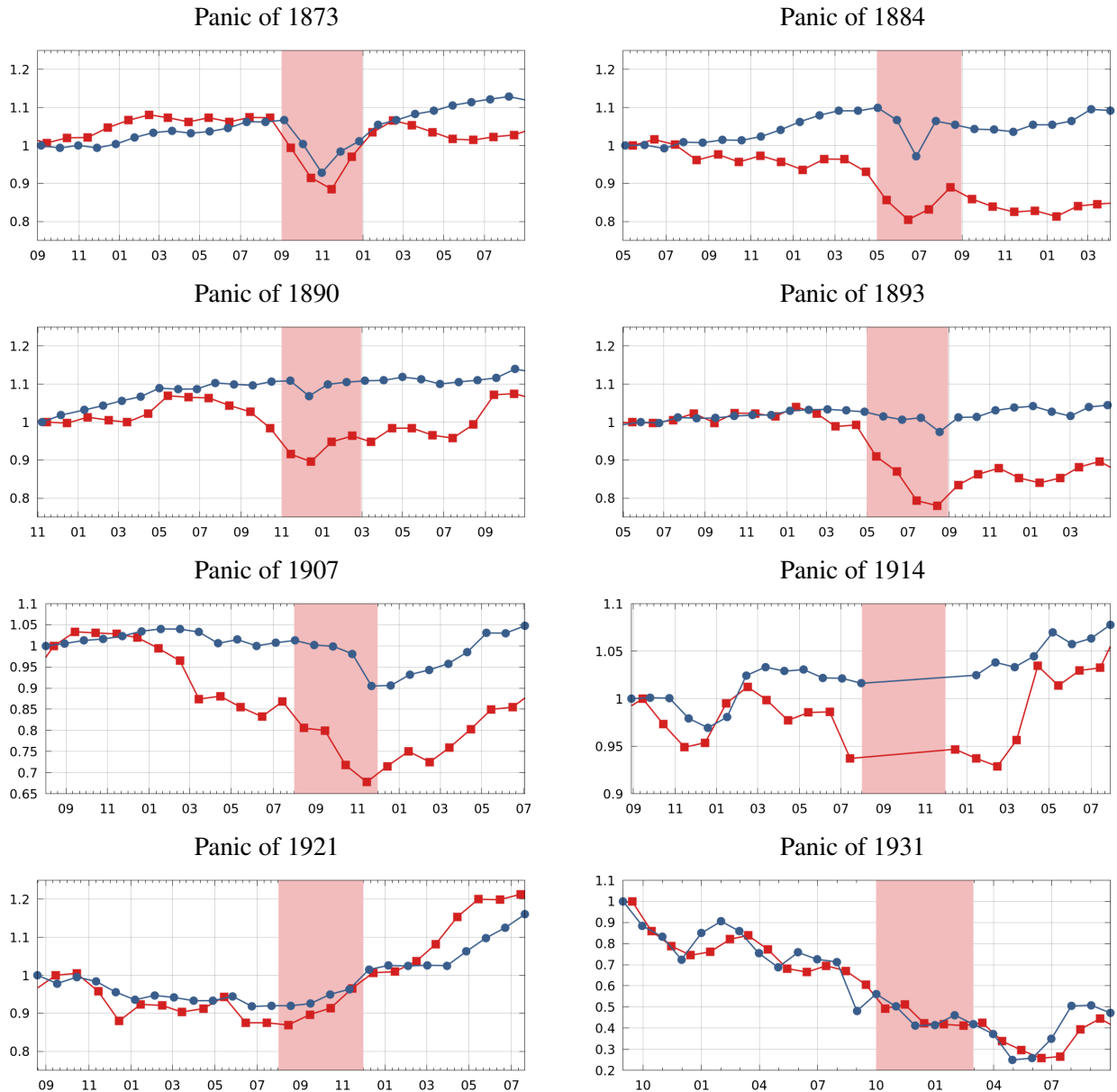
Our historical dataset comprises balance sheet and market information for a panel of New York banks and trusts from January 1866 to December 1933. The thin blue line in the figure reports the time series of the number of banks in the panel throughout the sample period. The thick black line presents the aggregate deposits. The red vertical shaded area represent the panic periods described in Table 1

Figure 2: AGGREGATE DEPOSITS AROUND PANIC EVENTS



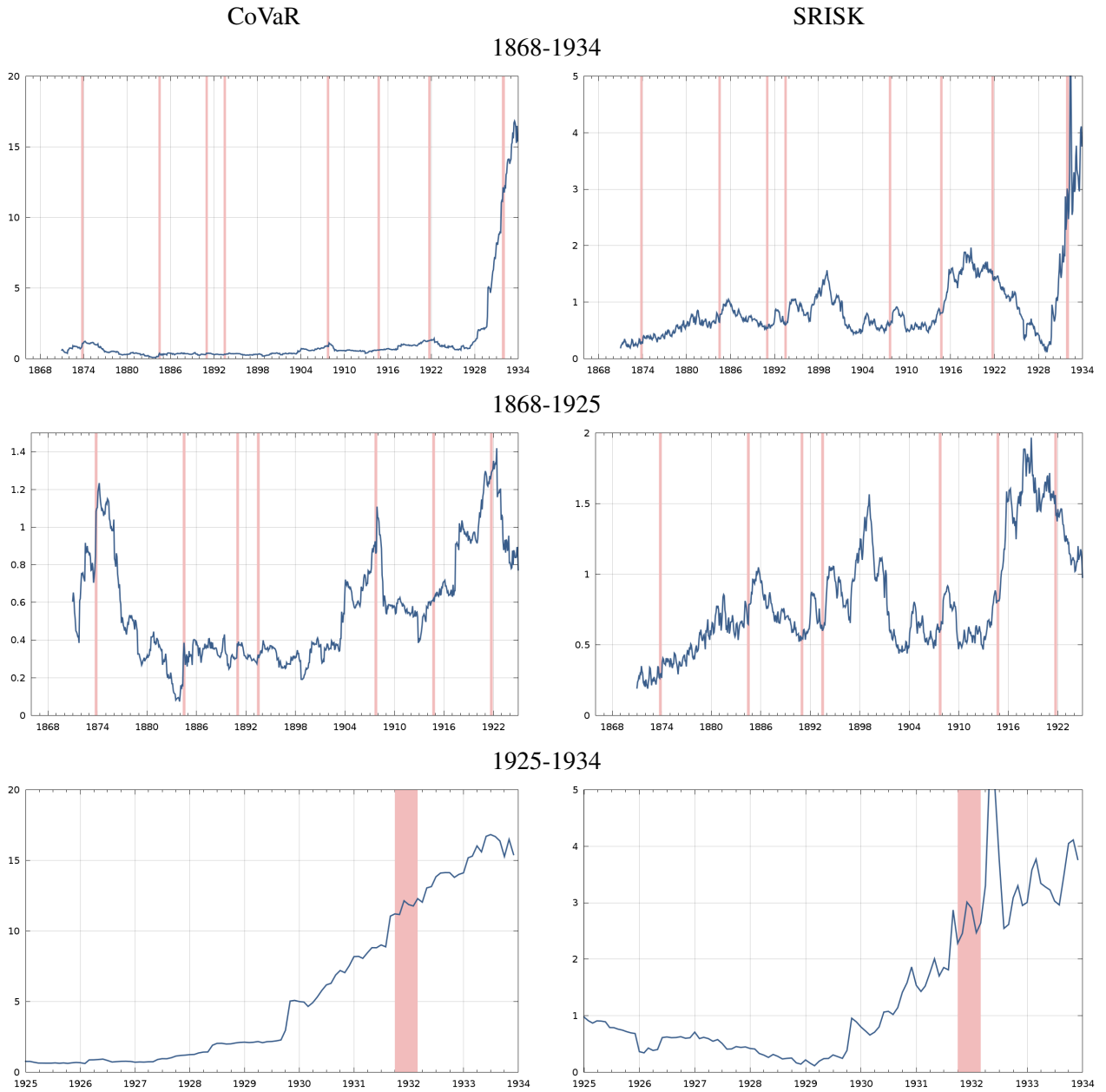
Plots of aggregate deposits in a two year window containing each of the panics. The vertical shaded areas are the panics as listed in Table 1.

Figure 3: AGGREGATE BANK INDEX AND COWLES INDEX AROUND PANIC EVENTS



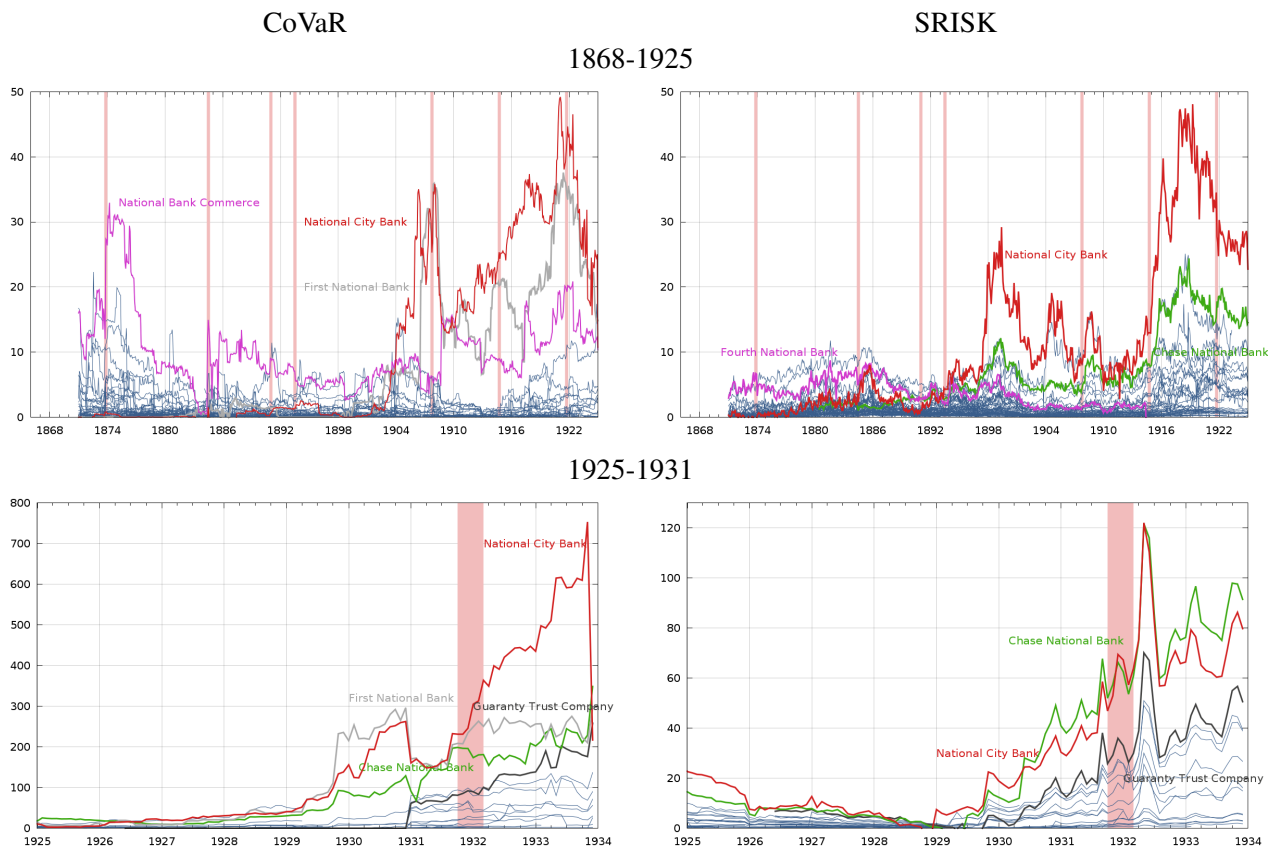
Aggregate bank index (square) and Cowles index (circle). The vertical shaded areas are the panics as listed in Table 1.

Figure 4: 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 1.

Figure 5: DECOMPOSITION OF SYSTEMIC RISK



Note: The red vertical shaded area represent the panic periods described in table 1.