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

PRELIMINARY AND INCOMPLETE

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Abstract

The measurement of systemic risk is at the forefront of economists and policymakers concerns in the wake of the 2008 financial crisis. What exactly are we measuring and do any of the proposed measures perform well outside the context of the recent financial crisis? One way to address these questions is to take backtesting seriously and assess how useful the recently proposed measures are when applied to historical crises. Ideally, one would like to look at the pre-FDIC era for a broad enough sample of financial panics to confidently asses the robustness of systemic risk measures but pre-FDIC era balance sheet and bank stock price data were heretofore unavailable. We rectify this data shortcoming by employing a recently collected financial dataset spanning the 60 years before the introduction of deposit insurance. Our panel spans many of the most severe financial panics in US history. Overall we find CoVaR and SRisk to be remarkably useful in alerting regulators of systemically risky financial institutions.

*The views expressed in this article are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Chicago or the Board of Governors or Federal Reserve System.

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1 Introduction

Effective macro prudential supervision requires the identification and monitoring of systemically risky firms. Measuring systemic risk has therefore been at the forefront of economists and policymakers concerns in the wake of the 2008 financial crisis. This agenda prompted the creation of new agencies specifically designed to analyze and monitor systemic risk (e.g. the OFR in the US, the ESRB in Europe) and has motivated a large and growing literature devoted to the identification of systemically risky firms. The contributions to systemic risk measurement are already quite sizable but no consensus best practice/unifying approach has yet to emerged.[1] One reason for the large number of competing risk measures is the lack of financial crisis data. Ideally, one would discriminate between competing measures by looking at their relative performance across a broad sample of financial panics but there have been few financial upheavals during the post-WWII era when financial data is readily available. To confidently assess the robustness of each measure we require a sufficiently broad sample of financial panics to fully gauge the robustness of competing systemic risk measures.

Between the founding of the national banking system and the establishment of FDIC insurance, the United States witnessed many financial panics similar in magnitude to the 2008 crisis. At first glance, the pre-FDIC era would appear to be an ideal laboratory for an evaluation of systemic risk measures. Alas, bank balance sheet and stock price data were heretofore unavailable. We rectify this data shortcoming by collecting a new dataset of bank balance sheets spanning the 60 years before the introduction of deposit insurance. We combine these new balance sheet data with a dataset containing the price and holding period returns of banks trading over-the-counter in New York City. Our combined stock and balance sheet panel spans several financial panics comparable to the 2008 crisis such as the panics of 1873 and 1884, the Barings Crisis of 1890, the subsequent panics of 1893 and 1896, the panic of 1907, and the real estate crash of 1921. These heretofore unknown data allow us to estimate and evaluate systemic risk measures across a large sample of financial crises.

The data available in the late 19th and early 20th century is not at par with todays standard practice. As a consequence, many of the currently used systemic risk measures require data which are not historically available. Our analysis is therefore confined to two of the popular systemic risk measures namely: CoVaR (Adrian and Brunnermeier (2011)) and SRisk (Brownlees and Engle (2012))CoVaR (Adrian and Brunnermeier (2011)) and SRisk (Brownlees and Engle (2012)) which can be computed using data available in our historical sample period.

Even after limiting our focus to CoVaR and SRisk we still face data limitations. For example, CoVaR and SRisk are typically computed with daily financial data, whereas our historical balance sheet and bank return data is collected at a 28-day frequency. Therefore, our paper also involves innovative econometric research

[1] For example, (Bisias, Flood, Lo, and Valavanis 2012) summarize thirty-one proposed measures of systemic risk. Brunnermeier and Oehmke (2012) and Hansen (2013) also survey and the recent literature on systemic risk measures.

so as to apply the recently developed methods to the historical data. In particular, we take advantage of the fact that the DJIA is available daily throughout much of our sample. We employ mixed frequency data (or MIDAS) techniques to resolve the mismatch of data sampling frequencies of individual bank stocks and DJIA market returns. A Component MIDAS model paired with a shrinkage estimation approach allows us to efficiently recover the return dynamics of the banks in the panel. The model is inspired by the recent mixed frequency volatility models of Ghysels, Santa-Clara, and Valkanov (2005) and Engle, Ghysels, and Sohn (2013).

Using these historic data, we evaluate the ability of the systemic risk measures to identify risky firms across a number of financial crises. Overall, pre-crisis measures of CoVaR and SRisk are remarkably useful in alerting regulators of systemically risky financial institutions. Specifically, financial crises tended to be preceded by aggregate deposit outflows disproportionately withdrawn from banks with high ex-ante systemic risk rankings. Moreover, when similarly large aggregate withdrawals occurred by were uniformly or disproportionately drawn from banks with low ex-ante systemic risk rankings crises did not occur.

Intuitively, a bank is systemically risky if its distress is likely to result in distress in many other banks. We formalize this intuition by modeling the hazard that a given banks deposit growth or stock return is below its 5th percentile as a function of other banks deposit growth or stock return being below their 5th percentile. We allow the hazard to vary with the ex-ante systemic risk ranking of other banks and find a strong monotonically relationship. When banks with high ex-ante systemic risk rankings suffer a tail event other banks are far more likely to also suffer a tail event as well.

The rest of the paper is organized as follows. Section 2 describes the historical data, section 3 presents the market-based measures of systemic risk we employ and the econometric methodology used to estimate systemic risk using sparse historical data, section 4 contains our preliminary empirical findings, and section 5 concludes.

2 History and Data

Our data is drawn from the reports of the New York Clearing House Association (NYCH) during what is commonly referred to as the national banking era - the period between the establishment of the national banking system and the adoption of FDIC insurance. The National Banking Acts (NBA) of 1863 and 1864 reorganized United States banking into a nationwide system of federally chartered banks. The NBA unified the national currency, established a federal regulator in the Office of the Comptroller of the Currency and, by providing regulatory incentives to pool excess reserves in central reserve cities, encouraged the development of a nationwide inter-bank money market centered in New York City. As a result many of the most systematically important banks in the United States were located in New York and members of the NYCH.

The New York Clearing House was a voluntary self-regulatory association of New York City banks which stored specie, facilitated exchange and clearing and monitored the liquidity of member institutions. National banking era bankers understood that asymmetric information about the health of an individual clearing house member could transform a run on a single member into a system-wide panic. The NYCH therefore attempted to minimize information asymmetries by requiring its member banks to publish weekly condensed balance sheet statements. These statements which appeared in the Saturday morning *New York Times*, *Wall Street Journal* and *Commercial and Financial Chronicle*, reported the average weekly and Friday closing values of each bank's loans, deposits, excess reserves, specie, legal tenders, circulation and clearings. NYCH statements were carefully scrutinized by investors and unexpected changes in leverage or liquidity could set off a stock market rally or decline.[2]

We use the weekly NYCH balance sheet statements to construct a panel of individual bank balance sheets sampled every 28 days between January 1866 and December 1925. The sample dates were chosen to correspond to the sample dates of another hand collected data set containing the stock price and cash flow information for every bank trading over the counter in New York City. The data was primarily collected from the New York Times and Wall Street Journal, but 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 Comptroller of the Currency. In some cases, missing data could not be located, as the New York Clearinghouse did not publish individual member information during periods of financial stress. As noted in (Gorton 1985), during banking panics, the clearinghouse organization pooled liabilities, uniting member banks under the Clearinghouse Committee. During these times the New York Clearinghouse only published aggregate balance sheet information.[3]

One hundred and forty-four individual banks and trusts appear in the NYCH statements between 1866 and 1925. After accounting for mergers and name changes, this number shrinks to 126. A time series plot of number of banks and trusts can be found in Figure 1. As seen in Figure 1, the New York Clearinghouse published information on about 60 members in 1865, a number that slowly moves down to nearly 40 members, including trusts, by the end of our sample.[4] Table **??** contains a list of the 126 banks and trusts for which data was collected and a brief description of the organization. In the analysis to follow, we focus on the NYCH Banks with both sufficient balance sheet and stock return data to estimate measures of systemic risk.

The bank balance sheet information is combined with a previously collected database of stock return information. The stock data consists of the price, shares outstanding, and dividends of bank stocks trading

[2]The New York Stock Exchange was open on Saturdays throughout our period of study.

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

[4]Trust companies were allowed to join the clearinghouse in 1911.

over-the-counter in New York City. The stock data was hand collected from the closing quotations published in the Commercial and Financial Chronicle. The price, share and dividend data allow us to compute the market value and 28-day holding period return for each bank stock trading between 1866 and 1925. Trusts and some NYCH member banks which were tightly held did not appear on the stock quotations list. Merging the balance sheet data to the equity returns data leaves us with a sample of 82 total banks that appear in on both lists. As shown in Figures 1 and 2, the number of banks tends to trend downward over time as the average size (in terms of capitalization) increased. Of note, is the jump in capitalization around 1900 after the passage of the Gold Standard Act of 1900.

3 Systemic Risk Measurement

Systemic risk measurement is a challenging problem and several competing approaches have been put forward in the literature. As emphasized by Bisias et al. (2012) who provide a thorough survey of systemic risk measures, it is unlikely that a single measure of systemic risk is able to characterize the dimensionality and complexity of the entire financial system. In this work, we focus on two market based measures of systemic risk: the CoVaR of Adrian and Brunnermeier (2011) and the SRISK of Acharya, Pedersen, Philippon, and Richardson (2010) and Brownlees and Engle (2012). An appealing feature of CoVaR and SRISK for our analysis is that these measures have only mild data requirements and that we are able to construct them using our dataset which, because of the historical nature of our analysis, has a number of constraints.

3.1 CoVaR and SRISK

CoVaR and SRISK associate systemic risk with the shortfall of financial system conditional on the realization of a systemic event. This is typically justified on the grounds that when financial system is under severe distress it will stop functioning properly and this in turn will have negative spillover effects on the real economy. There are important differences between the two approaches, in particular on the definition of the systemic event. CoVaR conditions on the distress of a single institution while SRISK conditions on the distress in the entire system.

Before introducing the definitions of CoVaR and SRISK used in this work we need to set appropriate notation. We are concerned in measuring systemic risk in a panel of n financial firms indexed $i = 1, ..., n$ over T periods $t = 1, ..., T$. We denote by $r_{i\,t}$ the compound return of bank i on period t and by $r_{m\,t}$ the corresponding value weighted compound return of the entire financial system over the same period. The computation of the indices also requires balance sheet information for the financial institutions in the panel. In what follows we denote by $\mathsf{W}_{i\,t}$ the market value of equity of firm i, by $\mathsf{D}_{i\,t}$ its book value of debt and by $\mathsf{A}_{i\,t} = \mathsf{W}_{i\,t} + \mathsf{D}_{i\,t}$ the its (market) value of assets.

Adrian and Brunnermeier (2011) define the CoVaR of firm i as the Value–at–Risk of the entire financial system conditional on institution i being distress, that is

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

where the distress of firm i is defined as the return of firm i being at its Value–at–Risk $\mathsf{VaR}^{q}_{i\,t}$. Adrian and Brunnermeier (2011) propose to measure the systemic risk contribution of firm i on the basis of the Δ CoVaR, which is defined as the difference between the CoVaRs of firm i conditional on its returns being at the Value–at–Risk and at the median, that is,

$$\Delta\mathsf{CoVaRadj}_{i\,t} = \mathsf{CoVaRadj}^{p,q}_{i\,t} - \mathsf{CoVaRadj}^{p,0.50}_{i\,t}\,. \tag{3.1}$$

Importantly, note that we depart here from the Adrian and Brunnermeier (2011) convention and call the systemic risk measure in (3.1) Adjusted Δ CoVaR. We use this nomenclature to emphasize that this Δ CoVaR measure does not take into account the size of the institution into account (hence is adjusted to its size). We also define a Dollar version of Δ CoVaR that takes the size of firm i into account, as in Adrian and Brunnermeier (2011). More precisely we define the Dollar Δ CoVaR as

$$\Delta\mathsf{CoVaR}_{i\,t} = W_{i\,t-1}\Delta\mathsf{CoVaRAdj}_{i\,t}\,.$$

In our application the confidence level p of the CoVaR is set to to 1%.

SRISK (Acharya, Pedersen, Philippon, and Richardson (2010), Brownlees and Engle (2012)) associates the systemic risk contribution of firm i with its expected capital shortfall conditional on a severe market downturn. Following Brownlees and Engle (2012), we define the capital buffer of firm i as the difference between the market value of equity minus a prudential fraction k of the market value of assets, that is $\mathsf{W}_{i\,t} - k\mathsf{A}_{i\,t}$. The parameter k is the prudential capital fraction, that is the percentage of total assets the firm holds as reserves because of regulation or prudential management. When the capital buffer is negative then the firm experiences a capital shortfall. Thus, we define the capital shortfall as the negative capital buffer

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

Acharya, Pedersen, Philippon, and Richardson (2010) argue that capital shortfalls are systemic when they occur when the system is in distress. This motivates to measure systemic risk using the conditional expectation of the capital shortfall conditional on a systemic event. Let the systemic event be $\{r_{m\,t} < C\}$

where C denotes the threshold loss for a systemic event. Then the SRISK index is defined as

$$\begin{aligned}\mathsf{SRISK}_{i\,t} &= \mathrm{E}_t(\mathsf{CS}_{i\,t}|r_{m\,t} < C)\ , \\ &= k\,\mathrm{E}_t(\mathsf{D}_{i\,t}|r_{m\,t} < C) - (1-k)\,\mathrm{E}_t(\mathsf{W}_{i\,t}|r_{m\,t} < C)\ , \\ &= k\,\mathsf{D}_{i\,t} - (1-k)\,\mathsf{W}_{i\,t}(1+\mathsf{MES}_{i\,t})\ , \end{aligned} \tag{3.2}$$

where $\mathsf{MES}_{i\,t}$ is the so called Marginal Expected Shortfall, the expectation of the firm equity return conditional on the systemic event, that is

$$\mathsf{MES}_{i\,t} = \mathrm{E}_t(r_{i\,t}|r_{m\,t} < C)\ .$$

Notice that the last equality of (3.2) follows from assuming that in the case of a systemic event debt cannot be renegotiated hence $\mathrm{E}_t(\mathsf{D}_{i\,t}|r_{m\,t} < C) = \mathsf{D}_{i\,t}$. Also, formula in equation (3.2) contains an approximation error due to the fact that we are using compound rather than arithmetic returns. We also introduce a size adjusted version of the SRISK index

$$\mathsf{SRISKAdj}_{i\,t} = k\,\mathsf{LVG}_{i\,t} - (1-k)\,\mathsf{MES}_{i\,t} - 1\ ,$$

where $\mathsf{LVG}_{i\,t}$ denotes the leverage ratio $(\mathsf{D}_{i\,t} + \mathsf{W}_{i\,t})/\mathsf{W}_{i\,t}$. In this work we set the prudential fraction parameter k to 10% and the systemic loss threshold C to -20%.

It is is also useful to introduce appropriate CoVaR and SRISK aggregates to measure the overall degree of systemic risk in the financial system. We define aggregate and average CoVaR respectively as

$$\Delta\mathsf{CoVaR}_t = \sum_{i=1}^{n} \Delta\mathsf{CoVaR}_{i\,t}$$

and

$$\Delta\overline{\mathsf{CoVaR}}_t = \frac{\sum_{i=1}^{n} \Delta\mathsf{CoVaR}_{i\,t}}{\sum_{i=1}^{n} W_{i\,t-1}}.$$

We define Aggregate and Average SRISK anagolously as

$$\mathsf{SRISK}_t = \sum_{i=1}^{n} \mathsf{SRISK}_{i\,t}$$

and

$$\overline{\mathsf{SRISK}}_t = \frac{\sum_{i=1}^{n} \mathsf{SRISK}_{i\,t}}{\sum_{i=1}^{n} W_{i\,t-1}}.$$

We define both the aggregate and average systemic risk indices since the financial sector has been evolving drastically in our sample period. Thus inspecting both the aggregate and average CoVaR or SRISK indices allows us assess if, for instance, an increase in systemic risk is due to an increase of risk or to the growth of the size of the financial sector.

3.2 Econometric Specification

The computation of CoVaR and SRISK requires to estimate indices synthetizing the dependence between the market and banks' returns. To this extent, for each financial institution we introduce a dynamic bivariate model which allows for time–varying volatility and correlation, that is

$$r_t = \left[\begin{array}{c} r_{m\,t} \\ r_{i\,t} \end{array} \right] \Bigg| \mathcal{F}_{t-1} \sim \mathcal{N}(0, \mathbf{H}_t)$$

where $\mathbf{H}_t$ denotes time time–varying covariance matrix.

Modeling time–varying covariance matrices is challenging in general - and in particular with the sparse data we have. In order to remain frugal in terms of parametric specification, we resort to a distributed lag covariance estimator inspired by MIDAS models - namely use single-parameter Beta polynomial (see e.g. Ghysels, Sinko, and Valkanov (2007) and). To be more precise, the covariance at time t is modeled as

$$\mathbf{H}_t = \sum_{j=1}^{12} w_j(\phi) r_{t-j} r'_{t-j} \tag{3.3}$$

where $w_l(\phi)$ is the MIDAS Beta polynomial weight $B(1, \phi)$. It is worth noting that Colacito, Engle, and Ghysels (2011) show this yields positive semi-definite H_t. In the left panel of Figure 3 we plot the weighting schemes for various values of ϕ, ranging from 1 to 6, with the former yielding a flat or equal weighting scheme. The higher the value of ϕ the steeper the decline in the weights, i.e. putting more weight on the most recent observations. In particular we note from the left panel that for $\phi = 6$: lag 1 has weight ≈ 0.5 The MIDAS-type weighting coefficient ϕ is estimated by maximizing the quasi likelihood function of each bivariate system. We estimate the optimal ϕ using a 5–year rolling recursive estimation scheme. The right panel displays the sample path of estimated $\hat{\phi}$ obtained from 5-year rolling samples of data throughout history. The shaded vertical lines are the financial crises during our sample. We note that memory is short-lived during financial crisis, since $\hat{\phi}$ peaks around the time of stress in the banking sector.

We use this approach to extract time varying market volatility $\sigma_{m\,t}$, bank volatility $\sigma_{i\,t}$, and market/bank correlation $\rho_{i\,t}$. Note that all time varying moments used in the subsequent analysis are computed using past information only and therefore do not have any look ahead bias. In Figure 4 we report the estimates using the covariance specification appearing in equation (3.3), more specifically the individual volatility estimates and the correlations. The left panel pertains to the volatilities. The shaded area covers the interquartile cross-sectional range of volatility estimates throughout the sample. The right panel contains the estimated correlations. Volatility often peaks around bank panics, although not exclusively. For example we observe some interesting volatility behavior around the turn of the 19^{th} and 20^{th} century. These estimates will be the input to the systemic risk measures defined in the previous subsection.

4 Empirical Findings

The pre-FDIC era provides us with a number of financial panics to investigate the ability of the systemic risk measures to identify risky banks. We find that most panics are preceded by a deterioration of the balance sheets of systemically important banks. Specifically, most pre-FDIC panics were preceded by deposit withdrawals disproportionately drawn from the banks with the highest ex-ante systemic risk rankings. To illustrate this fact we employ our balance sheet data to construct an entry-corrected index of aggregate deposits. We use the deposit index to date episodes of major withdrawals from clearinghouse banks and compute the cross-sectional rank correlations between individual bank deposit growth and ex-ante systemic risk ranking.

4.1 Deposit Index

We use the balance sheet reports to construct a measure of bank funding stress. The most natural measure of funding stress is the flow of deposits into and out of New York Clearinghouse banks. Define $\mathsf{DepGrowth}_t$ as the percentage change in deposits from time $\mathsf{t}-1$ to time t.

$$\mathsf{DepGrowth}_t = \frac{NYCHAggregateDeposits_t}{NYCHAggregateDeposits_{t-1}}.$$

We construct a time series of $\mathsf{DepGrowth}_t$ sampled every fourth Friday between Jan 1866 and December 1925. The series is corrected for entry and exit by computing the growth rate between time t and $\mathsf{t}+1$ using all banks in existence at both dates. The index therefore reflects the change in deposits of surviving banks and does not mechanically fall when a bank fails and exits the clearing house or mechanically increase when a new bank is chartered.

The 28-day sampling frequency was selected to correspond with dates for which one of the authors has previously collected the price, shares outstanding and dividends of New York banks. The stock data was hand collected from the over-the-counter bid and ask quotations published in the Commercial and Financial Chronicle.

4.2 The Pre-FDIC Banking Panics

In order to examine the ability of systemic risk measures to predict financial panics we require a consensus of exactly when financial panics occurred. This may seem like a trivial matter, but pre-FDIC bank deposits were extremely volatile and no consensus list of panics has emerged.[5] Although there are a number of episodes of large deposit withdrawals and financial stress that only a minority code as financial panics each of these authors agree that major panics occurred in 1873, 1884, 1890, 1893, and 1907. For each of these consensus panics we ask whether a hypothetical regulator armed with systemic risk rankings would have been able to detect danger before the panic occurred. In most cases we observe that panics were preceded by deposit withdrawals concentrated in the banks that ex-ante systemic risk measures deemed most systemic.

4.2.1 The Panic of 1873

The post-Civil War railroad boom went bust in September 1873. In particular, The financial panic of 1873 was set off by the bankruptcy of the bank of Jay Cooke and Company, which was deeply involved in the financing of the second transcontinental railroad. The panic was preceded by a sharp 11.25 percent decline in aggregate deposits between our sample dates of Aug 9^{th} and September 6^{th} 1873. Deposits were disproportionately withdrawn from banks that were the most systemically risky according to Aug 9^{th} CoVar and Srisk rankings. The 1^{st} and 3^{rd} riskiest banks suffered declines of 20 percent and 24 percent respectively which rank in the 1^{st} and 2^{nd} percentile of one-month deposit declines in our sample. These banks were not alone. Many of the riskiest banks ranked suffered disproportionately large declines in deposits. Table 1 reports the behavior of aggregate deposits around the panic of 1873 and the rank correlations between ex-ante systemic risk rankings and subsequent deposit growth. Large withdrawals from the riskiest banks in the month before the panic are reflected in the large significant negative correlation between deposit growth rates before the panic and ex-ante systemic risk rankings.

4.2.2 The Panic of 1884

The panic of 1884 occurred in late May 1884 and was preceeded by another railroad-related downturn. The panic was preceded by a relatively mild 6.4 percent decline in the aggregate deposit index over the 56-day sample period preceding the panic. But this decline was once again concentrated in banks with the highest pre-panic systemic risk rankings. While the aggregate deposit index declined a mere 6 percent, the bank with the riskiest delta CoVar ranking on March 7^{th} 1884 lost 11 percent of its deposits between March 7^{th} and May 2^{nd} and the 2^{nd} through 4^{th} riskiest banks suffered 28, 22 and 17 percent deposit declines respectively! Table 2 reports the behavior of aggregate deposits around the panic of 1884 and the rank correlations between ex-ante systemic risk rankings and subsequent deposit growth. Like the panic of 1873 the rank correlation between deposit growth in the months before the panic and ex-ante systemic risk rankings are negative and significant. Although few deposits left the NYCH on average the riskiest banks suffered large deposit outflows in the months before the panic.

[5] Kemmerer (1910), Sprague (1910), DeLong and Lawrence (1986), Gorton (1988), Bordo and Wheelock (1988), Wicker (2000), and Jalil (2015) have each examined the data and attempted to date pre-FDIC banking panics.

4.2.3 The Panic of 1890

Unlike the panics of 1873 and 1884 the panic of 1890 was a European panic that spread to the United States as foreign banks withdrew deposits in the wake of the Barings Crisis in London. The Panic culminated with the issuance of clearing house certificates in late November 1890. The months preceding the panic were characterized by slow deposit outflows rather than sharp declines. The aggregate index only declined 5 percent in the 112 days before the panic and the declines were relatively uniform with respect to the ex-ante delta CoVar and Srisk rankings.

4.2.4 The Panic of 1893

The panic of 1893 was a culmination of the stress introduced into financial markets and the overall economy by the Barings Crisis a few years earlier. Of note, the Panic of 1893 was by some measures the most severe panic of the pre-FDIC national banking era. The panic was preceded by a large decline in aggregate clearing house deposits. The aggregate deposit index declined 15 percent in the 140 days preceding the panic. Like the panics of 1873 and 1884 this decline was concentrated in the banks with the highest ex-ante systemic risk rankings. The bank with the riskiest delta CoVar on Feb 3rd 1893 suffered a 25 percent decline in deposits in the 140 days before the panic while the 4^{th} and 5^{th} riskiest banks each lost about 22 percent of their deposits. Table 4 reports the behavior of aggregate deposits around the panic of 1893 and the rank correlations between ex-ante systemic risk rankings and subsequent deposit growth. Across all systemic risk rankings the rank correlation between pre-panic deposit growth and ex-ante systemic risk ranking is negative and significant.

4.2.5 The Panic of 1907

The panic of 1907 is unlike any other panic in our sample. After a period of financial stress earlier in the year, a failed attempt to corner the copper market led to a run on Knickerbocker Trust and an overall crisis of confidence for the financial trust sector. Although the aggregate deposit index declined 9 percent in the 112 days before the panic there was no negative cross-sectional rank correlation between pre-panic deposit growth and the ex-ante systemic risk measures. The 6^{th} riskiest bank did suffer a devastating 59 percent decline in deposits over this period but 8 of the remaining 10 riskiest banks either enjoyed deposit inflows during this period of suffered less outflow than the aggregate index. Of course this panic was centered in the shadow banking sector of the era Trust companies. As depositors ran to withdraw money from trusts they deposited these funds into 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.

4.3 Dogs That Don′t Bark and Deposit Declines that Don′t Result in Panics

The deposit index and systemic risk measures appear to be a useful tools for forecasting the pre-FDIC consensus financial panics. An historical regulator armed with CoVar and Srisk measures of systemic risk would have been alerted to 3 of the 5 panics with a simple rule such as beware deposit outflows disproportionally drawn from the most systemically risky banks. A measure that flashes danger before 60

Nonetheless, some words of caution are in order. Pre-FDIC deposits were notoriously volatile and weve said nothing about the distribution of deposit withdrawals in the deposit declines that did not lead to panics. If all (or a majority) of deposit declines are disproportionately drawn from the riskiest banks the advice to beware deposit outflows disproportionally drawn from the most systemically risky banks is likely to successfully predict the panics but also deliver a number of false positives. To investigate the utility of the systemic risk measures we look at the ten largest declines in the deposit index that do not coincide with one of the consensus panics. Some of these deposit declines are associated with financial stress denoted as a panic by one or more of the previously cited papers and many are large declines in deposits that nonetheless uncorrelated with financial stress.

Table 6 reports the dates of major declines in the deposit index, the cross-sectional correlation of deposit growth rates and ex-ante measures of systemic risk and the proportion of papers that code this episode as a financial panic. The most striking fact about the deposit declines in Table 6 is their magnitude. The ten largest declines not associated with a consensus panic ranged from 16.7

What would a hypothetical regulator armed with the systemic risk measures have thought about these large declines? Would a rule like beware deposit outflows disproportionally drawn from the most systemically risky banks have triggered false positives? A look at Table 6 tells us that of the six deposit declines that all authors coded as non-panic only one (July-Oct 1881) exhibited a significantly negative rank correlation between deposit growth and a systemic risk measure. A regulator who worried about large deposit withdrawals disproportionally drawn from the systemically risky banks would not have been concerned with the majority of these withdrawal episodes.

Of the four deposit declines that coincide with a minority of authors coding the decline as a panic each has a significant negative correlation between deposit growth and at least one of the ex-ante CoVar or Srisk systemic risk measures. The regulator that worried about disproportional withdrawals from the banks that rank high ex-ante in CoVar or Srisk would have anticipated a financial panic in each of the episodes that at least one paper codes as a panic and would have concluded that despite the large deposit outflows there was no reason to be alarmed in five of the six episodes where every author concludes there was no panic!

4.4 Discrete time hazard models of tail events

Intuitively, a bank is systemically risky if its distress is likely to result in distress in many other banks. We formalize this intuition by modeling the hazard that a given banks deposit growth or stock return is below its 5th percentile as a function of other banks deposit growth or stock return being below their 5th percentile. A word of caution is in order. Even if our systemic risk rankings contained no useful information about the relative systemic importance of each bank, it would not be surprising to find that knowledge about a tail event at one bank predicts simultaneous tail events at other banks. Our sample of banks are all drawn from the same industry and location and are surely subject to common shocks. On the other hand, if our systemic risk rankings do carry useful information about the relative systemic importance of each bank we would expect a tail event at a bank with a relatively high systemic risk ranking to have a disproportionately large effect on the hazard of tail events at other banks. We adopt a specification that reflects this idea by allowing the hazard to vary with the ex-ante systemic risk ranking of other banks.

We observe a panel of bank stock returns and deposit growth rates. Define the stock return (deposit growth) tail dummy as:

- d_{it} = 1 if bank is time t stock return (deposit growth) is below the 5^{th} percentile of observed bank i stock returns (deposit growth)
- d_{it} = 0 otherwise

We wish to model the hazard that d_{it} = 1. We start with the assumption that the data are generated via a continuous time process with a proportional hazard

$$h(t, X_{it}) = h_0(t) \exp (X_{it}\beta) \tag{4.4}$$

where $h_0(t) = \gamma\rho t^{(\rho-1)}$ is a baseline Weibull hazard (where t is the time elapsed since the last tail event) and X_{it} are bank-specific covariates which shift the hazard relative to baseline hazard model. The Weibull specification allows for duration dependence in the baseline hazard. If $\rho > 1$, the baseline hazard increases with the time since last tail event; if $\rho < 1$, the baseline hazard decreases with time since last tail event; and if ρ = 1, the baseline hazard becomes the exponential model with constant hazard. In all of our specifications we cannot reject no duration dependence (ρ = 1) and only report the results for the constant baseline hazard below.

When the data are generated by (4.4), Prentice and Gloeckler (1978) derive the discrete time hazard with time-varying covariates. The probability that bank i suffers a tail event at time t, denoted P_{it} :

$$P_{it} = 1 - \exp\{-(h_0(t) \exp (X_{it}\beta))\} \tag{4.5}$$

Given I banks, the log likelihood is defined as:

$$\ln L = \sum_{i=1}^{I} \{ \sum_{t=1}^{T_i} D_{it} \ln \left(\frac{P_{it}}{1 - P_{it}} \right) + \sum_{t=1}^{T_i} \ln (1 - P_{it}) \}$$

where T_i is the number of time series observations for bank i. We estimate the parameter vector β via MLE. We adopt a specification that reflects the hypothesis that a tail event in a systemically important bank should have a disproportionate impact on the hazard that other banks suffer a tail event. Specifically, we estimate via maximum likelihood with six variables in X_{it} :

1. # of banks 1-5 in tail = number of banks with top 5 Systemic Risk Measure (SRM) at time $t - 1$ that have a tail dummy = 1 at time t

2. # of banks 6-10 in tail = number of banks with a SRM ranked 6 through 10 at time $t - 1$ that have a a tail dummy = 1 at time t

3. # of banks 11-15 in tail = number of banks with a SRM ranked 11 through 15 at time $t - 1$ that have a tail dummy = 1 at time t

4. # of banks 16+ in tail = number of banks with a SRM ranked 16 or above at time $t - 1$ that ha a tail dummy = 1 at time t

5. LVG$_{i\,t-1}$: Leverage Ratio $D_{i\,t-1}/W_{i\,t-1}$

6. Liq$_{i\,t-1}$: Liquidity Ratio (legal tender liquid assets relative to deposits for bank i at time $t - 1$)

The first four variables are counts of banks (other than bank i) that have tail events at time t grouped according to their systemic risk measure (SRM) at time t - 1. This specification allows the hazard of bank i to vary with the ex-ante SRM of other banks suffering tail events. If ex-ante systemic risk rankings carry no information about the relative likelihood that a tail event in one bank effects the hazard of tail events in other banks we would expect the coefficients on each group of banks to be equal. On the other hand, if tail events in banks with high relative systemic risk rankings are more likely to cause tail events in other banks we would expect the hazard model coefficients to monotonically decline as we moved down the systemic risk groupings in X.

The hazard model coefficients are reported in Table 7. There is considerable evidence that the systemic risk rankings contain valuable information about the likelihood that a tail event in a given bank is likely to coincide with tail events in other banks. For both stock returns and deposit growth there is a strong monotonically decreasing relationship between the fitted hazard and the systemic risk grouping of banks suffering tail events. Regardless of systemic risk measure, a tail event in a bank with an ex-ante Top 5 or Top 10 systemic risk ranking results in a much larger increase in the hazard than tail events in banks ranked outside the Top 10. In fact, with only one exception (rankings based on SRISKadj), the relationship between ex-ante systemic risk rankings and hazard is monotonically decreasing as one moves from the Top5 to Top6-10, Top11-15 and 16+ groupings. The estimated hazard model coefficients are consistent with the hypothesis that distress at a bank with high ex-ante systemic risk is likely to result in distress in other banks.

5 Conclusion

The financial crisis of 2008 inspired a large body of research with the aim of identifying systemically important financial institutions. Importantly, much of the resultant measures of systemic risk, both market- and fundamental-based, provide valuable information on the run-up in risks prior to the recent financial crisis. That said, a financial crisis occurs roughly every 20 years. And, as a result it is extremely important to examine the usefulness of measures of systemic risk outside of recent episodes and not wait for the next period of financial stress to assess the efficacy of these measures. Consequently, we examine the pre-FDIC panics of the United States and find both CoVar and Srisk to be remarkably useful in alerting regulators to financial conditions likely to result in financial crisis. 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 these fleeing deposit were disproportionately withdrawn from banks that had high ex-ante CoVar or Srisk rankings, financial panics were likely to follow. On the other hand, large deposit outflows that were uniformly spread among all clearing house members or concentrated in banks that had low ex-ante systemic risk rankings were unlikely to lead to panics. 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.

We formalize systemic risk spill-overs by modeling the hazard that a given banks deposit growth or stock return is below its 5th percentile as a function of other banks deposit growth or stock return being below their 5th percentile. The hazard model estimates reveal there is considerable evidence that the systemic risk rankings contain valuable information about the likelihood that a tail event in a given bank is likely to coincide with tail events in other banks. The estimated hazard model coefficients are consistent with the hypothesis that distress at a bank with high ex-ante systemic risk is likely to result in distress in other banks.

PRELIMINARY AND INCOMPLETE: MORE TO COME(GREAT DEPRESSION PANICS)

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Figure 1: Count of Banks and Trusts

The blue and red-dashed lines in the figure display the total count of both banks and trusts that were members of the New York Clearninghouse. Investment trusts entered the sample in 1911, although it can be seen that one member organization was both a bank and trust prior to 1911.

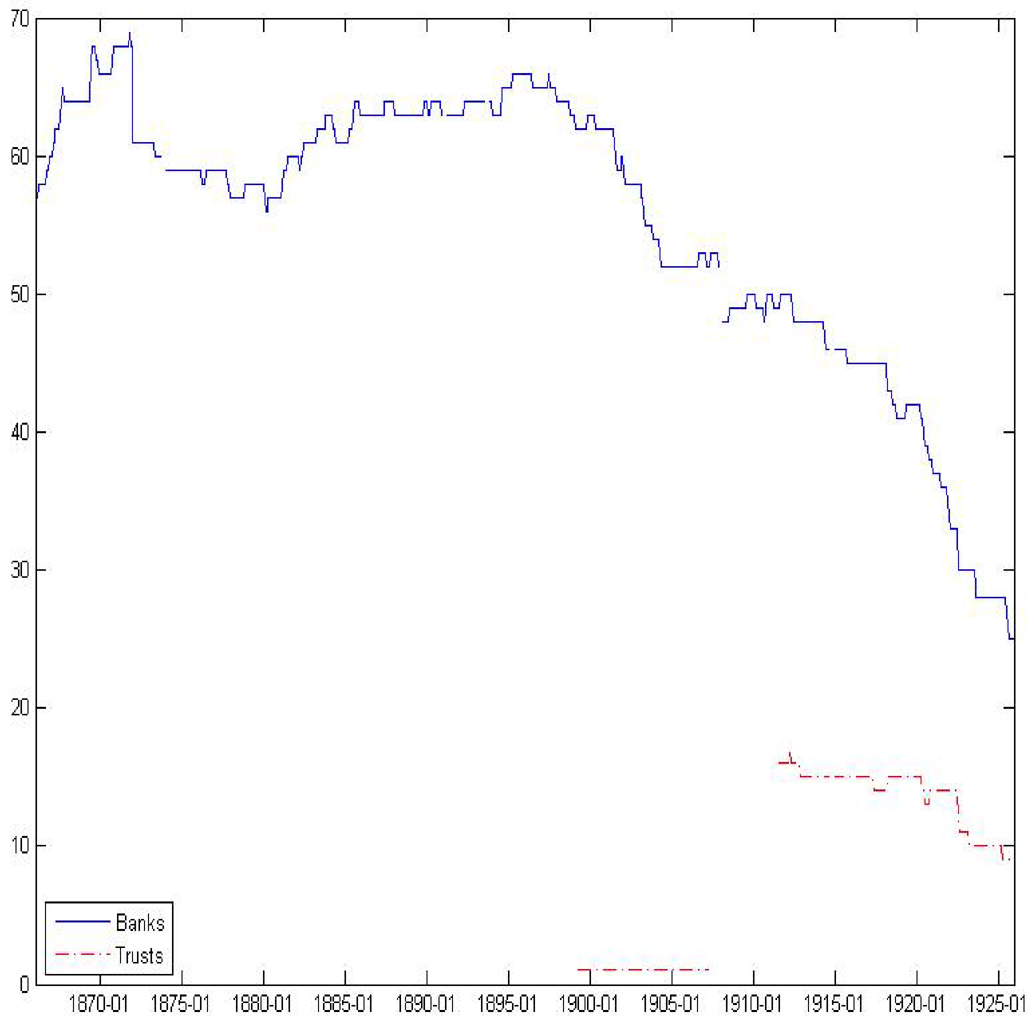

Figure 2: Aggregate Capital
The blue line in the figure is the aggegate nominal captial stock for New York Clearinghouse member banks.

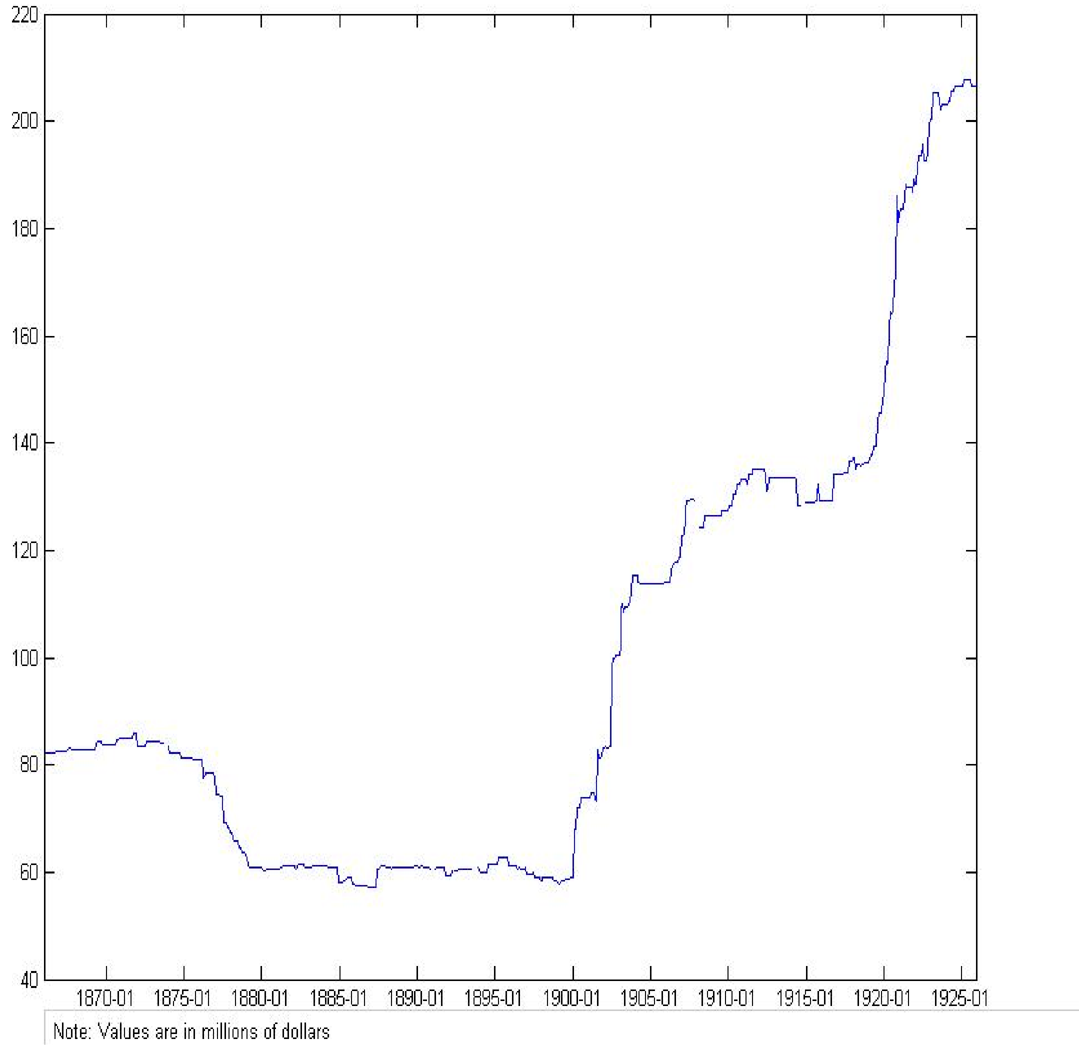

Figure 3: Econometric Specification of Conditional Second Moments of Individual Bank and Market returns

The left panel figure shows the $B(1, \phi)$ Weighting MIDAS-type weighting for ϕ= $1, 2, \ldots, , 6$. The higher ϕ the higher the importance of more recent observations, with $\phi = 1$ corresponding to equal weights. The right panel displays the sample path of estimated $\hat{\phi}$ obtained from 5-year rolling samples of data throughout history. The shaded vertical lines are the financial crises during our sample.

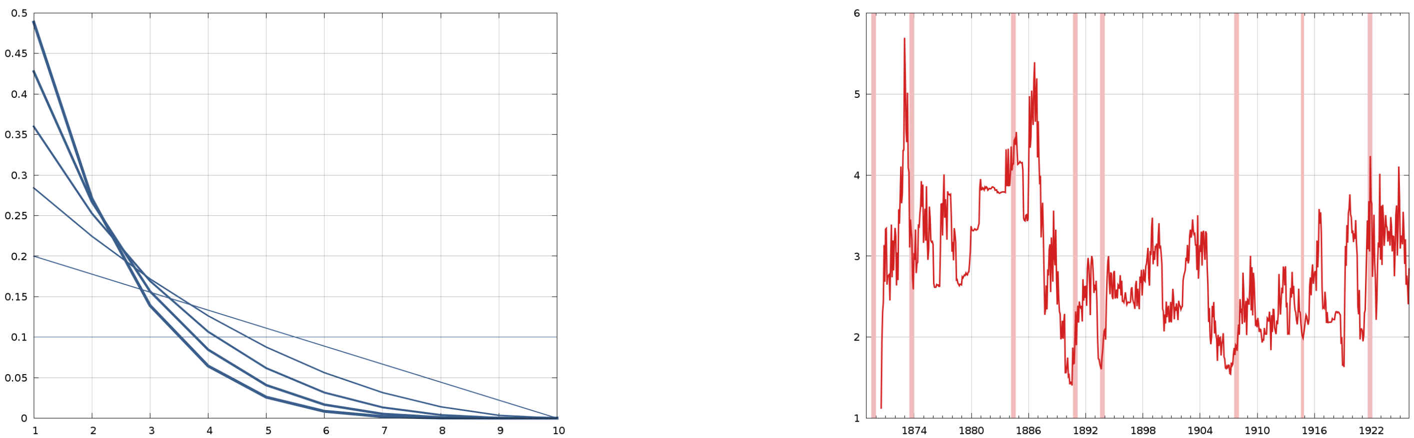

Figure 4: Estimated volatility and correlation for individual financial institutions

The figure shows the estimates using the covariance specification appearing in equation (3.3), more specifically the individual volatility estimates and the correlations. The left panel pertains to the volatilities. The shaded area covers the interquartile cross-sectional range of volatility estimates throughout the sample. The estimation is based on 5-year rolling sample window. The right panel contains the estimated correlations.

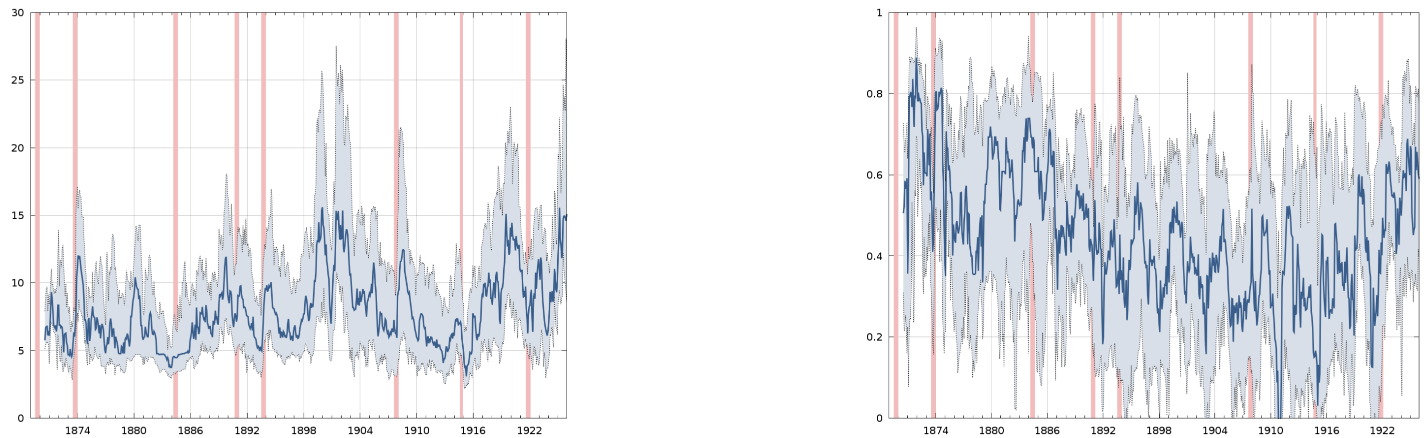

Figure 5: Average CoVaR and SRisk

The red and black lines are the average delta CoVar and average SRisk measures as estimated from 1970 to 1925. The red bars reflect financial crises.

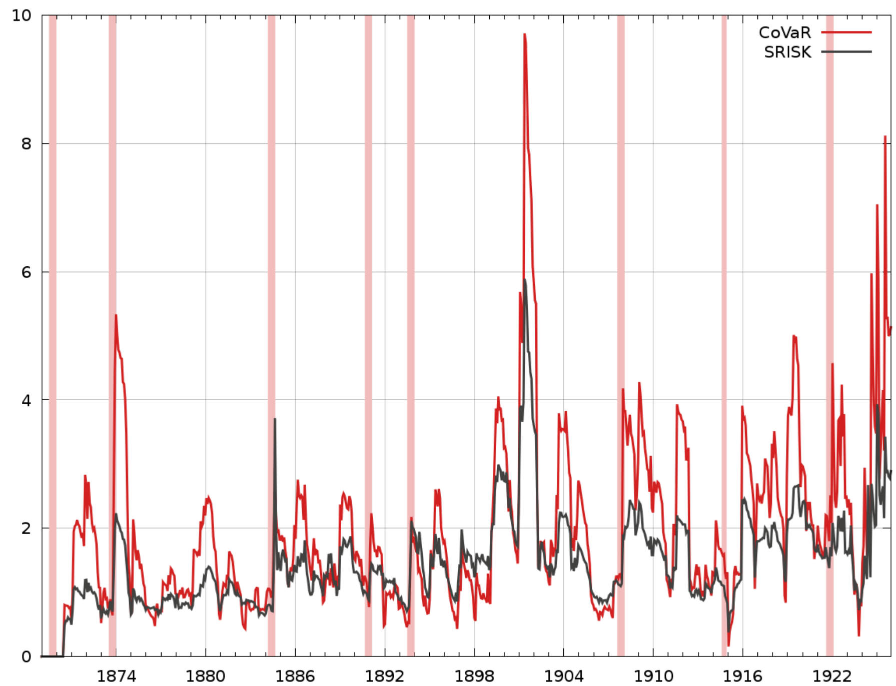

Table 1: Panic of 1873: Deposits and Systemic Risk: Rankings and Correlations

Panel A reports deposit index (column header Deposit Index) during the panic of 1873 and the reporting of Clearinghouse data (column header CH Data). Panel B reports the cross-sectional rank correlation between ex-ante systemic risk measures and deposit changes for individual financial institutions. The dates to compute the deposit growth (column header Dep growth) reports the dates over which the deposit changes are computed, whereas the systemic risk measure date appears in the column with the header SRM.

Panel A: Deposits in the Banking Sector

Obs #	Date	Deposit Index	CH Data	Obs #	Date	Deposit Index	CH Data
92	12-28-72	100.00	Yes	100	08-09-73	119.66	Yes
93	01-25-73	106.75	Yes	101	09-06-73	106.20	Yes
94	02-22-73	103.21	Yes	102	10-04-73	93.54	no
95	03-22-73	98.61	Yes	103	11-01-73		no
96	04-19-73	95.67	Yes	104	11-29-73		no
97	05-17-73	104.88	Yes	105	12-27-73	95.73	Yes
98	06-14-73	108.85	Yes	106	01-24-74	116.86	Yes
99	07-12-73	120.35	Yes	107	02-21-74	121.57	Yes

Panel B: Cross-sectional Correlations

Dep growth dates		SRM date	Δ CoVar		Δ CoVaradj		Srisk		Sriskadj	
			rho	p-val	rho	p-val	rho	p-val	rho	p-val
99	101	99	-0.56	0.01	0.06	0.78	-0.45	0.03	-0.16	0.44
100	101	100	-0.50	0.01	0.16	0.45	-0.46	0.03	0.16	0.45
99	105	99	0.05	0.82	-0.15	0.48	-0.06	0.80	-0.05	0.83
100	105	100	-0.02	0.92	-0.16	0.44	0.02	0.94	-0.10	0.62

Table 2: Panic of 1884: Deposits and Systemic Risk: Rankings and Correlations

Panel A reports deposit index (column header Deposit Index) during the panic of 1884 and the reporting of Clearinghouse data (column header CH Data). Panel B reports the cross-sectional rank correlation between ex-ante systemic risk measures and deposit changes for individual financial institutions. The dates to compute the deposit growth (column header Dep growth) reports the dates over which the deposit changes are computed, whereas the systemic risk measure date appears in the column with the header SRM.

Panel A: Deposits in the Banking Sector

Obs #	Date	Deposit Index	CH Data	Obs #	Date	Deposit Index	CH Data
235	12-15-83	100	Yes	240	05-02-84	105.58	Yes
236	01-11-84	105.28	Yes	241	05-30-84	92.15	Yes
237	02-08-84	113.10	Yes	242	06-27-84	91.34	Yes
238	03-07-84	112.77	Yes	243	07-25-84	98.36	Yes
239	04-04-84	107.65	Yes	244	08-22-84	98.64	Yes

Panel B: Cross-sectional Correlations

Dep growth dates		SRM date	Δ CoVar		Δ CoVaradj		Srisk		Sriskadj	
			rho	p-val	rho	p-val	rho	p-val	rho	p-val
237	240	237	-0.32	0.13	0.15	0.45	-0.26	0.20	0.40	0.03
238	240	238	-0.41	0.05	0.01	0.95	-0.48	0.01	0.11	0.57
239	240	239	-0.29	0.17	0.02	0.91	0.43	0.02	-0.05	0.80
238	242	238	0.26	0.24	0.03	0.89	-0.04	0.83	-0.32	0.09

Table 3: Panic of 1890: Deposits and Systemic Risk: Rankings and Correlations

Panel A reports deposit index (column header Deposit Index) during the panic of 1890 and the reporting of Clearinghouse data (column header CH Data). Panel B reports the cross-sectional rank correlation between ex-ante systemic risk measures and deposit changes for individual financial institutions. The dates to compute the deposit growth (column header Dep growth) reports the dates over which the deposit changes are computed, whereas the systemic risk measure date appears in the column with the header SRM.

Panel A: Deposits in the Banking Sector

Obs #	Date	Deposit Index	CH Data	Obs #	Date	Deposit Index	CH Data
321	07-25-90	100	Yes	326	12-12-90	91.32	No
322	08-22-90	94.04	Yes	327	01-09-91	94.56	No
323	09-19-90	95.35	Yes	328	02-06-91	100.86	No
324	10-17-90	98.67	Yes	329	03-06-91	99.92	Yes
325	11-14-90	95.02	Yes	330	04-03-91	100.36	Yes

Panel B: Cross-sectional Correlations

Dep growth dates		SRM date	Δ CoVar		Δ CoVaradj		Srisk		Sriskadj	
			rho	p-val	rho	p-val	rho	p-val	rho	p-val
321	325	321	-0.10	0.53	-0.20	0.18	-0.10	0.49	-0.16	0.28
324	325	324	-0.11	0.45	-0.38	0.01	-0.15	0.31	-0.33	0.02
321	329	321	0.49	0.00	0.01	0.92	0.43	0.00	-0.08	0.59

Table 4: Panic of 1893: Deposits and Systemic Risk: Rankings and Correlations

Panel A reports deposit index (column header Deposit Index) during the panic of 1893 and the reporting of Clearinghouse data (column header CH Data). Panel B reports the cross-sectional rank correlation between ex-ante systemic risk measures and deposit changes for individual financial institutions. The dates to compute the deposit growth (column header Dep growth) reports the dates over which the deposit changes are computed, whereas the systemic risk measure date appears in the column with the header SRM.

Panel A: Deposits in the Banking Sector

Obs #	Date	Deposit Index	CH Data	Obs #	Date	Deposit Index	CH Data
352	12-09-92	100	Yes	359	06-23-93	92.48	Yes
353	01-06-93	101.24	Yes	360	07-21-93	90.72	No
354	02-03-93	109.37	Yes	361	08-18-93	86.03	No
355	03-03-93	102.02	Yes	362	09-15-93	87.65	No
356	03-31-93	96.82	Yes	363	10-13-93	95.90	No
357	04-28-93	95.29	Yes	364	11-10-93	105.88	Yes
358	05-26-93	96.69	Yes				

Panel B: Cross-sectional Correlations

Dep growth dates		SRM date	Δ CoVar rho	Δ CoVar p-val	Δ CoVaradj rho	Δ CoVaradj p-val	Srisk rho	Srisk p-val	Sriskadj rho	Sriskadj p-val
354	359	354	-0.38	0.01	-0.35	0.01	-0.45	0.00	-0.33	0.01
358	359	358	-0.07	0.64	-0.01	0.91	-0.10	0.46	-0.01	0.94

Table 5: Panic of 1907: Deposits and Systemic Risk: Rankings and Correlations

Panel A reports deposit index (column header Deposit Index) during the panic of 1907 and the reporting of Clearinghouse data (column header CH Data). Panel B reports the cross-sectional rank correlation between ex-ante systemic risk measures and deposit changes for individual financial institutions. The dates to compute the deposit growth (column header Dep growth) reports the dates over which the deposit changes are computed, whereas the systemic risk measure date appears in the column with the header SRM.

Panel A: Deposits in the Banking Sector

Obs #	Date	Deposit Index	CH Data	Obs #	Date	Deposit Index	CH Data
541	06-07-07	100	Yes	546	10-25-07	91.80	Yes
542	07-05-07	100.68	Yes	547	11-22-07	96.82	No
543	08-02-07	98.22	Yes	548	12-20-07	95.00	No
544	08-30-07	93.52	Yes	549	01-17-08	97.75	No
545	09-27-07	94.28	Yes	550	02-14-08	101.53	Yes

Panel B: Cross-sectional Correlations

Dep growth dates		SRM date	Δ CoVar		Δ CoVaradj		Srisk		Sriskadj	
			rho	p-val	rho	p-val	rho	p-val	rho	p-val
542	546	542	0.33	0.04	0.05	0.73	0.20	0.21	-0.15	0.31
543	546	543	0.26	0.10	0.03	0.84	0.12	0.43	-0.13	0.39
545	546	545	0.40	0.01	0.01	0.97	0.34	0.02	-0.01	0.95
542	550	542	0.44	0.00	0.07	0.63	0.29	0.06	-0.22	0.14

Table 6: Deposit Declines During Non-Crises Periods

This table reports the dates of major declines in the deposit index, the cross-sectional correlation of deposit growth rates, measures of systemic risk, and the proportion of academic papers would ascrbe each episode as a financial panic.

Start Date	End Date	Deposit Decline		Covar	Covaradj	Srisk	Sriskadj	Financial Crisis?	% of papers that date decline as panic
07-16-70	10-08-70	-0.208	corr:	0.1374	0.0714	0.2967	0.0934	NO	0
			p-val	0.6560	0.8206	0.3247	0.7646		
09-09-71	11-04-71	-0.167	corr:	-0.1059	-0.0361	0.0609	0.0526	NO	0
			p-val	0.6968	0.8888	0.8114	0.8370		
07-15-71	11-04-71	-0.194	corr:	-0.1412	0.0175	-0.1476	-0.0402	NO	0
			p-val	0.6015	0.9475	0.5578	0.8758		
07-13-72	10-05-72	-0.236	corr:	-0.0085	0.1959	-0.0875	0.0570	NO	0
			p-val	0.9719	0.3805	0.6979	0.8012		
07-10-75	12-25-75	-0.208	corr:	0.2342	0.2186	0.2985	0.1899	NO	0
			p-val	0.2484	0.2721	0.1385	0.3413		
07-30-81	10-22-81	-0.174	corr:	-0.2652	-0.1817	-0.4923	-0.3842	NO	0
			p-val	0.2096	0.3531	0.0134	0.0444		
08-16-95	03-27-96	-0.167	corr:	-0.3246	-0.1612	-0.4152	-0.1987	Maybe	14.29
			p-val	0.0249	0.2303	0.0024	0.1381		
04-21-99	12-29-99	-0.196	corr:	-0.1858	-0.1412	-0.2796	-0.2514	Maybe	42.86
			p-val	0.1912	0.3029	0.0430	0.0643		
08-04-05	12-22-05	-0.177	corr:	-0.7047	-0.366	-0.6354	-0.2034	Maybe	28.57
			p-val	0.0000	0.0109	0.0000	0.1651		
08-06-09	12-24-09	-0.182	corr:	-0.5539	-0.3017	-0.5202	-0.1893	Maybe	16.67
			p-val	0.0001	0.0444	0.0004	0.2122		

Table 7: Hazard of Individual Bank Extreme Stock Market Decline

This table reports the MLE estimates for the discrete time hazard with time-varying covariates appearing in (4.5). The covariates X_{it} are: (a) # of banks 1-5 in tail = number of banks with top 5 Systemic Risk Measure (SRM) at time $t-1$ that have a tail dummy = 1 at time t, (b) # of banks 6-10 in tail = number of banks with a SRM ranked 6 through 10 at time $t-1$ that have a a tail dummy = 1 at time t, (c) # of banks 11-15 in tail = number of banks with a SRM ranked 11 through 15 at time $t-1$ that have a tail dummy = 1 at time t, (d) # of banks 16+ in tail = number of banks with a SRM ranked 16 or above at time $t-1$ that ha a tail dummy = 1 at time t, (e) LVG$_{i\,t-1}$: Leverage Ratio $D_{i\,t-1}/W_{i\,t-1}$, (f) Liq$_{i\,t-1}$: Liquidity Ratio (legal tender liquid assets relative to deposits for bank i at time $t-1$)

Covariates	ΔCoVaR	ΔCoVaRadj	SRISK	SRISKadj
Constant	-3.31^{***}	-3.33^{***}	-3.34^{***}	-3.35^{***}
# of banks 1-5 in tail	0.29^{***}	0.32^{***}	0.25^{***}	0.27^{***}
# of banks 6-10 in tail	0.22^{***}	0.24^{***}	0.25^{***}	0.19^{***}
# of banks 11-15 in tail	0.20^{***}	0.21^{***}	0.24^{***}	0.21^{***}
# of banks 16+ in tail	0.13^{***}	0.12^{***}	0.11^{***}	0.14^{***}
LVG$_{i\,t-1}$	-0.00	-0.00	-0.00	-0.00
Liq$_{i\,t-1}$	-0.34	-0.28	-0.17	-0.25
Goodness of fit	0.63	0.63	0.63	0.63
N	21209	22597	22212	22591

Table 8: Hazard of Individual Bank Runs

This table reports the MLE estimates for the discrete time hazard with time-varying covariates appearing in (4.5). The covariates X_{it} are: (a) # of banks 1-5 in tail = number of banks with top 5 Systemic Risk Measure (SRM) at time $t-1$ that have a tail dummy = 1 at time t, (b) # of banks 6-10 in tail = number of banks with a SRM ranked 6 through 10 at time $t-1$ that have a a tail dummy = 1 at time t, (c) # of banks 11-15 in tail = number of banks with a SRM ranked 11 through 15 at time $t-1$ that have a tail dummy = 1 at time t, (d) # of banks 16+ in tail = number of banks with a SRM ranked 16 or above at time $t-1$ that ha a tail dummy = 1 at time t, (e) LVG$_{i\,t-1}$: Leverage Ratio $D_{i\,t-1}/W_{i\,t-1}$, (f) Liq$_{i\,t-1}$: Liquidity Ratio (legal tender liquid assets relative to deposits for bank i at time $t-1$)

Covariates	ΔCoVaR	ΔCoVaRadj	SRISK	SRISKadj
Constant	-3.35^{***}	-3.40^{***}	-3.35^{***}	-3.38^{***}
# of banks 1-5 in tail	0.36^{***}	0.30^{***}	0.36^{***}	0.25^{***}
# of banks 6-10 in tail	0.32^{***}	0.28^{***}	0.28^{***}	0.31^{***}
# of banks 11-15 in tail	0.28^{***}	0.27^{***}	0.24^{***}	0.23^{***}
# of banks 16+ in tail	0.15^{***}	0.16^{***}	0.15^{***}	0.16^{***}
LVG$_{i\,t-1}$	-0.11^{***}	-0.12^{***}	-0.11^{***}	-0.12^{***}
Liq$_{i\,t-1}$	1.16^{***}	1.41^{***}	1.24^{***}	1.40^{***}
Goodness of fit	0.68	0.68	0.68	0.68
N	24782	26427	25983	26427