Central Bank Policy and the Concentration of Risk: Empirical Estimates

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Abstract

Before the 2008 crisis, the cross-sectional skewness of banks' leverage went up and macro risk concentrated in the balance sheets of large banks. Using a model of profit-maximizing banks with heterogeneous Value-at-Risk constraints, we extract the distribution of banks' risk-taking parameters from balance sheet data. The time series of these estimates allow us to understand systemic risk and its concentration in the banking sector over time. Counterfactual exercises show that (1) monetary policymakers confront the trade-off between stimulating the economy and financial stability, and (2) macroprudential policies can be effective tools to increase financial stability.

JEL Codes: E44, E52, E58, G21, G28.
Keywords: Bank regulation, Financial cycle, Leverage, Monetary policy, Risk-taking, Systemic risk.

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1. Introduction

Financial crises are a recurring phenomenon in economic history. Their consequences on growth and investment can be severe and protracted, as the Great Financial Crisis of 2008 so clearly illustrated. Eichengreen and Portes (1987) write that "much as the study of disease is one of the most effective ways to learn about human biology, the study of financial crises provides one of the most revealing perspectives on the functioning of monetary economies." There is now substantial evidence showing that credit expansions can end in crashes materializing in banking crises and recessions, (e.g., Borio and Lowe, 2002; Mian and Sufi, 2009; Schularick and Taylor, 2012; Fouliard, Howell and Rey, 2020). However, the mechanism and characteristics of credit expansions as well as their root causes remain largely elusive. Making progress on those fronts is key for policymakers in charge of macroprudential policies.

In this paper, we start from three facts important facts. First, there is substantial heterogeneity in risk-taking across financial intermediaries, particularly during credit booms, and some large actors are particularly reckless. Leverage increases on average in the financial system during booms, but some banks gain market share rapidly. Wilmarth (2014) for the US before 2008, Englund (2016) for Sweden before 1992, Santos (2017) and Hellwig (2018) for Spain and Germany respectively before 2008 all show in their case studies on crises that a subset of large actors took excessive amounts of macro risk before the crash. For example, Deutsche Bank leveraged up to quadruple the size of its balance sheet from about €0.5 trillion in early 1990s to about €2 trillion in 2008 as a return of equity (RoE) of 25% was regularly targeted by the bank CEO. Second, as explained in Adrian and Shin (2010); Adrian and Boyarchenko (2012); Stulz (2016), banks and other financial institutions make extensive use of value-at-risk (VaR) measures to manage their risk. Firms estimate the probability of making losses that could put them in financial distress or default. A certain amount of losses that is exceeded with a probability p over one month gives the VaR over one month at

the probability level p. The use of VaR is ubiquitous in the financial sector. Third, there is great variation across financial intermediaries regarding how VaR are calculated and how internal risk models of banks are evaluated. A *prima facie* example of that variation is the exercise performed by the Basel Committee on Banking Supervision, who undertook a review of the consistency of risk weights used by a sample of banks (Basel Committee on Banking Supervision, 2013). Those risk weights, for a given portfolio, depend on internal risk models of the different institutions. When given a diversified test portfolio, the surveyed banks, who knew they were answering their regulators, produced a wide range of results in terms of modeled VaR and gave answers ranging from 13 million to 33 million euros in terms of capital requirement with a median of about 18 million. These differences in VaR modeling may be reflecting corporate culture (risk appetite of the boards as discussed by Stulz, 2016) or different interactions between banks and their national supervisors, some being much more prescriptive than others. The tightness of VaR constraints varies substantially across institutions.

In this paper, we zoom on this heterogeneity in risk-taking by analyzing the evolution of the cross-sectional composition of the balance sheets of financial intermediaries. We estimate the distribution of their VaR constraint parameters and show how they change over time as macroeconomic conditions and regulations fluctuate. We show that the time variation and the shape of the estimated distributions of the VaR parameters are very good predictors of bank performance and carry important information on systemic risk. Importantly, we find that it is crucial to consider the heterogeneity across different financial intermediaries as the larger share of time variation in our measure comes from the cross-section. Simply looking at changes in aggregate leverage in the system would therefore miss an essential part of the story. As an aside, our measure outperforms those based on asset prices when predicting aggregate risk. In spirit, our systemic risk indicator is related to Baron and Xiong (2017) who link bank credit expansion to negative predicted excess returns of the bank equity index in the next three years, but we estimate structural parameters at the bank level rather than
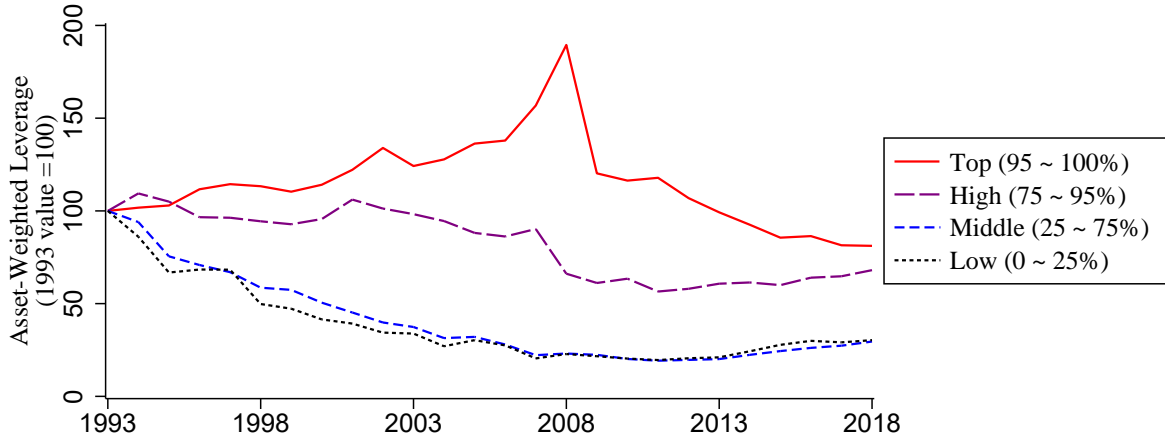
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Figure 1: Evolution of leverage by quantiles: The figure plots the average of the asset weighted leverage by quantiles. Values were rebased to 100 for the starting year 1993, to highlight the stark difference in dynamics. See Table A1 for unweighted leverage by qunatiles.

outcome variables at the country level.

Figure 1 presents the time series of asset-weighted leverage for quantiles of a broad cross-section of financial intermediaries worldwide. There is clearly substantial heterogeneity in the cross-sectional dynamics of asset-weighted leverage. In the build-up to the 2008 crisis, the intermediaries that were already the most leveraged were the ones that increased asset-weighted leverage the most, while the middle and lower quantiles tended to decrease their asset-weighted leverage during this period. This indicates that the rise in asset-weighted leverage pre-crisis was driven primarily by large, highly levered intermediaries and not by small ones with little macroeconomic importance.

Simply looking at changes in leverage to assess systemic risk could however be misleading as the implications for financial stability can be very different depending on the main driver behind such changes. In the words of Gorton and Ordoñez (2019), there are good booms and bad booms. For example, if changes in growth and investment opportunities are driving leverage, that might have very different implications from a case where leverage is being driven by a rise in the supply of credit by intermediaries due to low cost of funds or a rise in risk appetite. By using a structural model, we can make progress on those issues. Coimbra

and Rey (2020) develop a full general equilibrium model of good booms and bad booms and of the risk-taking channel of monetary policy.

Our empirical strategy relies on two assumptions: i) leveraged financial intermediaries maximize profits under their specific VaR constraints, and ii) the VaR parameters follow a time-varying Beta distribution. We use a maximum likelihood approach applied to Compustat Fundamentals Annual data from 1993 to 2018 to estimate the distribution of VaR parameters from leverage data. The estimated risk-taking behavior closely relates to observed intermediaries' distress and to both market and book returns, providing external validity to our estimates.

We then use the results to understand how changes in the distribution of risk-taking affect financial instability. Aggregate systemic risk — the probability of a systemic crisis occurring — can be measured by the asset-weighted mean of VaR parameters. An individual intermediary's contribution to our systemic risk measure is then a combination of its size and balance sheet risk. Our measure indicates that systemic risk is very concentrated, with the top 5% intermediaries contributing to about 79% of the total value on average and also driving most of the variation over time. Also, we find strong evidence that it is crucial to account for heterogeneity in macro-finance research. A measure consisting of a representative intermediary with average leverage would only explain around 22% of the systemic risk measure.

We find that systemic risk increased between 2000 and 2008 as liquidity was abundant in the global economy and regulatory policies were loose. It decreased after the financial crisis when banking regulations were gradually tightened. According to our structural interpretation, changes in the distribution of risk-taking pre-crisis were driven by a fall in the cost of funds (due in part to the abundance of world savings and loose monetary policy) and to weak bank and financial markets regulation. We perform two counterfactual exercises; one where we consider what would have happened with higher costs of funds; and another one without changes in the regulatory environment post-crisis. The recent decline of systemic

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risk measures stems from changes in the post-global financial crisis's regulatory environment. Monetary policy faces a trade-off between stimulating the economy (low interest rate, low cost of funds) and financial stability. Low interest rates generate incentives for intermediaries to borrow, which increases systemic risk, but also may be necessary from the point of view of economic activity. These results suggest that macroprudential policy can serve as a useful complement to monetary policy.[1].

The paper is organized as follows: Section 2 presents a framework and estimation strategy for investigating heterogeneity in risk-taking behavior. Section 3 documents the estimation results and validation of our framework. Section 4 provides evidence on systematic relationships among risk-taking behavior, bank performance, and financial crisis. Section 5 analyzes systemic risk. In Section 6, we explore different counterfactuals in order to better understand the role of monetary policy and regulatory policy changes. Section 7 concludes.

2.   A Framework with Heterogeneity in Risk-Taking

2.1.   Model

This section presents our empirical framework to analyze the heterogeneous risk-taking behavior of financial intermediaries. Consider a financial sector composed of a continuum of financial intermediaries in a competitive environment. An intermediary i is a risk-neutral agent that maximizes its profit subject to a Value-at-Risk (VaR) constraint. This constraint imposes that intermediary i chooses an investment strategy such that the probability its return on equity is negative is smaller than an intermediary-specific parameter $\alpha_{i,t}$. A large $\alpha_{i,t}$ will therefore denote a high risk tolerance while a low $\alpha_{i,t}$ will characterize a more conservative bank. Specifically, the VaR constraint can be written as:

$$\Pr(\pi_{i,t+1} < \omega_{i,t}) \leq \alpha_{i,t}. \tag{1}$$

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[1]See Coimbra and Rey (2020); Caballero and Simsek (2020) for theoretical discussions about these issues.

This condition imposes that intermediary i invests in such a way that the probability of distress – negative returns on equity – must be no greater than an intermediary-specific threshold parameter $\alpha_{i,t}$. Negative returns on equity occur when its cash flow $\pi_{i,t+1}$ is smaller than starting equity $\omega_{i,t}$. We assume that the idiosyncratic return of assets $r^a_{i,t+1}$ is an independent and identically distributed random variable Z_{t+1}. The conditional mean and variance of $\ln Z_{t+1}$ are $\mu_{Z,t}$ and $\sigma^2_{Z,t}$, respectively. The deposit (debt) $d_{i,t}$ is contracted at the costs of funds (interest rate) r^d_t. The cash flow, thus, is $\pi_{i,t+1} = \omega_{i,t} + r^a_{i,t+1}a_{i,t} - r^d_t d_{i,t}$ where $a_{i,t}$ are total assets. For a participating intermediary i, the VaR constraint binds because of risk neutrality[2]. For convenience, introduce $Z^e_{t+1} = \exp(\mu_{Z,t})$. After some straightforward algebra, we obtain the following equation that links the leverage $\lambda_{i,t}$, defined as assets divided by equity, to the threshold $\alpha_{i,t}$

$$\lambda_{i,t} \equiv \frac{a_{i,t}}{\omega_{i,t}} = \frac{r^d_t}{r^d_t - Z^e_{t+1}Q_t(\alpha_{i,t})}, \tag{2}$$

where we define $Q_t(\cdot)$ by the quantile function (inverse cumulative distribution function) of Z_{t+1}/Z^e_{t+1}. The mapping between leverage and the parameter $\alpha_{i,t}$ varies systemically with macroeconomic fundamentals: expected asset returns, interest rate, and uncertainty.

Equation (2) allows us to use the leverage of financial intermediaries observed in the data and the VaR constraint to infer risk-taking and fundamental macroeconomic parameters. The equation can be rewritten in terms of the debt-to-asset ratio $\psi_{i,t}$ which can be conveniently expressed as follows.[3]

$$\psi_{i,t} \equiv 1 - \frac{1}{\lambda_{i,t}} = \zeta_t Q_t(\alpha_{i,t}), \tag{3}$$

where $\zeta_t = Z^e_{t+1}/r^d_t$ is the ratio of the expected returns of assets to the cost of funds. ζ_t and

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[2]In Coimbra and Rey (2020), intermediaries endogenously choose whether to participate or not in the market for risky projects. They also choose how much to leverage based on macroeconomic conditions and their characteristics. Non participating intermediaries invest in a safe storage technology.

[3]Since the debt-to-asset ratio is bounded between 0 and 1, its moments always exist. However, leverage can be theoretically infinite. Its upper tail is fat, thus some moments do not exist.

$Q_t(\cdot)$ embeds some macroeconomic variables such as the expected volatility of returns. $Q_t(\cdot)$ falls *ceteris paribus* when volatility rises so that a bank needs to decrease leverage if it wants to keep constant its level of risk-taking. Coimbra and Rey (2020) show that VaR constraints get looser when the cost of funds is low (high ζ_t), and volatility is low (low $\sigma_{Z,t}^2$), and that such conditions enable the more risk-tolerant intermediaries to leverage up massively. When interest rates are low or when the volatility of returns is low, the probability of distress is lower, ceteris paribus. In that region, increases in leverage translate into small increases in the probability of distress, which implies that intermediaries can increase leverage by sizable amounts until they hit the VaR constraint. Similarly, for looser VaR constraints, leverage can be increased a lot before the constraint is hit. Thus, the most risk-taking intermediaries' leverage will respond more to changes in the cost of funds. This heterogeneity of leverage to changes in the cost of funds means a more skewed cross-sectional distribution of leverage as interest rates fall. This generates a composition effect, where the proportion of assets being held by the more risk-taking intermediary rises. Since the intensive margin effect is more significant with low interest, it follows that this composition effect is particularly strong at low interest rates.

2.2. Estimation Strategy

To make use of the structure of our model, we make two parametric assumptions, which are very general. We first assume that $\ln Z_{t+1}$ follows a logistic distribution with parameters $(\mu_{Z,t}, \sigma_{Z,t}^*)$. Its mean and standard deviation are thus $\mu_{Z,t}$ and $\sigma_{Z,t} = \pi \sigma_{Z,t}^*/\sqrt{3}$, respectively. Z_{t+1}/Z_{t+1}^e therefore follows the log-logistic distribution with parameters $(0, \sigma_{Z,t}^*)$, and the quantile function Q_t is given by $Q_t(p) = [p/(1-p)]^{\sigma_{Z,t}^*}$. Second, we assume that the cross-sectional distribution of risk-taking ability (VaR threshold) follows a Beta distribution: $\alpha_{i,t}/\alpha_t^{\mathrm{ub}} \sim \mathrm{Beta}(\phi_{L,t}, \phi_{R,t})$ on $(0,1)$ where $\alpha_t^{\mathrm{ub}} \leq 1$ is the upper bound of $\alpha_{i,t}$ for period t. Beta distributions are widely used in statistical models of bounded random variables due to their flexibility. Note that α_t^{ub} is the upper bound of the support of $\alpha_{i,t}$ at t so will in general

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be larger than the (finite) sample maximum. $\phi_{L,t}$ and $\phi_{R,t}$ are shape parameters for the left and right tails, respectively.[4] The shape of the right tail parametarizes the concentration of risk on the balance sheet of the most risk-taking intermediaries. This is a particularly important parameter as the larger the mass of high risk intermediaries, the less financially stable the economy.

Given our parametric assumptions, the debt-to-asset ratio follows the McDonald and Xu (1995)'s five parameters generalized beta distribution with $\mathbf{\Phi}_t = \{\phi_{p,t}, \phi_{s,t}, \phi_{c,t}, \phi_{L,t}, \phi_{R,t}\}$, where $\{\phi_{p,t}, \phi_{s,t}, \phi_{c,t}, \phi_{L,t}, \phi_{R,t}\} = \{1/\sigma_{Z,t}^*, \zeta_t(\alpha_t^{\mathrm{ub}})^{\sigma_{Z,t}^*}, \alpha_t^{\mathrm{ub}}, \phi_{L,t}, \phi_{R,t}\}$.[5] The generalized beta distribution nests many distributions used in economics and finance, for example, the Burr, gamma, beta, log normal, Weibull, log-logistic, Pareto, uniform, and exponential distributions. Therefore, despite our parametric assumptions, the shape of the distribution of $\alpha_{i,t}$ is relatively unrestricted and is mostly determined by the underlying data itself. The probability density function (pdf) is

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\mathrm{pdf}_\psi\left(x|\mathbf{\Phi}_t\right) = \frac{\phi_{p,t} x^{\phi_{p,t}\phi_{L,t}-1} \left[1 - (1-\phi_{c,t})\left(x/\phi_{s,t}\right)^{\phi_{p,t}}\right]^{\phi_{R,t}-1}}{(\phi_{s,t})^{\phi_{p,t}\phi_{L,t}} \, \mathrm{B}\left(\phi_{L,t}, \phi_{R,t}\right)\left[1 + \phi_{c,t}\left(x/\phi_{s,t}\right)^{\phi_{p,t}}\right]^{\phi_{L,t}+\phi_{R,t}}}
\tag{4}
$$

on $\left(0, \phi_{s,t}/\left(1-\phi_{c,t}\right)^{1/\phi_{p,t}}\right)$. From our structural model, it follows that the power $\phi_{p,t}$ and scale parameters $\phi_{s,t}$ are positive and we include that restriction in the estimation. The parameter $\phi_{c,t}$ determines the class of distribution: values $\phi_{c,t} \to 0$ and $\phi_{c,t} \to 1$ imply beta distributions of the first and second kind, respectively. $\phi_{L,t}$ and $\phi_{R,t}$ are the left and right tail shape parameters, respectively. The tails of the risk-taking distribution determine the tails of the debt-to-asset ratio distribution. This property allows us to recover the risk-taking

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[4]The probability density function (PDF) is $x^{\phi_{L,t}-1}(1-x)^{\phi_{R,t}-1}/\mathrm{B}(\phi_{L,t}, \phi_{R,t})$ on $(0,1)$, where $\mathrm{B}(y,z) = \int_0^1 w^{y-1}(1-w)^{z-1}dw$ is the (complete) beta function.

[5]We are interested in a random variable on a non-negative support. Thus, we assume that $\phi_{p,t}$ and $\phi_{s,t}$ are positive. However, the original five parameter generalized beta distribution does not restrict $\phi_{p,t}$ and $\phi_{s,t}$, and it can have a negative support. See McDonald and Xu (1995) for details of the five parameter generalized beta distribution. Also, see McDonald (1984); Cummins et al. (1990); McDonald and Xu (1995,?); Parker (1999); Cowell and Flachaire (2015); Kakamu and Nishino (2019); Higbee and McDonald (2021) for applications of the generalized beta distribution.

distribution ($\alpha_{i,t}$) by parametric estimations from the observed debt-to-asset ratios ($\psi_{i,t}$).

Rather than assuming a particular time series-structure for the parameters, we estimate $\mathbf{\Phi}_t$ each year using a weighted maximum likelihood (ML) method:

$$\hat{\mathbf{\Phi}}_t = \arg\max_{\mathbf{\Phi}_t} \quad \sum_i w_{i,t} \times \ln \mathrm{pdf}_\psi \left(\psi_{i,t} | \mathbf{\Phi}_t \right) \quad \text{on} \quad (0, \psi_t^{\mathrm{ub}})$$

$$\text{subject to} \quad \phi_{p,t}, \phi_{s,t}, \phi_{L,t}, \phi_{R,t} > 0, \ \phi_{s,t} < 2, \ \phi_{c,t} = 1 - \left(\phi_{s,t}/\psi_t^{\mathrm{ub}} \right)^{\phi_{p,t}}, \text{ and } \psi_t^{\mathrm{ub}} = 1.$$

The log-likelihood function is weighted by log size (measured by assets) so that we take into account that larger intermediaries are economically more important than smaller ones.[6]

We restrict the parameter space so that the distribution is defined only when $\phi_{L,t}$, $\phi_{R,t}$, and $\phi_{s,t}$ are positive as in standard generalized Beta distributions. Since α_t^{ub} should be less than one, we obtain $\phi_{s,t} < \zeta_t$, where ζ_t defined in equation (3) is the *spread*, i.e. the ratio of expected returns on assets over the cost of funds. Thus, setting the upper bound on ζ_t to two (which implies $\phi_{s,t} < 2$, is equivalent to setting an upper bound on the margin of above one hundred percentage points, which is again quite unrestrictive. The restriction on $\phi_{c,t}$ derives from the support of distribution: $\psi_t^{\mathrm{ub}} = \phi_{s,t}/(1 - \phi_{c,t})^{1/\phi_{p,t}}$. We fix the upper bound of the debt-to-asset ratio at one because the maximum debt-to-asset ratio we observe during any year is almost one.

Before applying the ML procedure to the balance sheet data, we drop intermediaries with leverage in the bottom ten percent of our sample over the whole period[7]. Our specification relies on the model-derived binding VaR constraint faced by endogenously-levered financial intermediaries in the previous section. However, some intermediaries' VaR constraints might not be binding: in the structural model of Coimbra and Rey (2020) there is a cutoff value of the VaR threshold, below which an intermediary j will choose not to leverage up to its constraint.[8] For those intermediaries, the VaR constraint does not bind, and our empirical

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[6]We also performed an unweighted estimation. All the main results are robust.

[7]We also performed robustness checks with the bottom 5 percent

[8]The cutoff systemically varies with economic conditions. Thus we drop the bottom five or ten percent of our whole period sample, not each year.
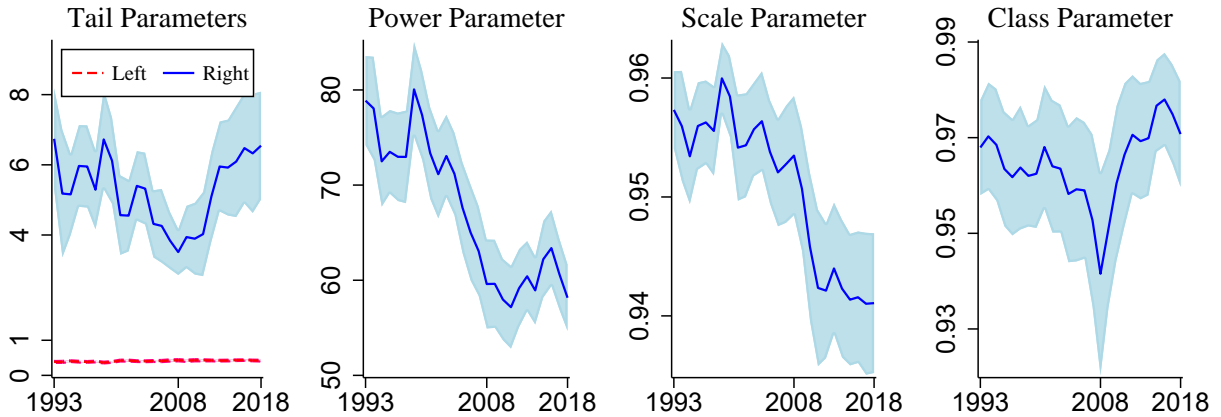
Figure 2: Estimated Parameters: The figure plots the MLE results of the distribution of the debt-to-asset ratio $\psi_{i,t}$. In all figures, the shades are 95% intervals with robust standard errors. In the first figure, the blue solid and red dashed lines report estimates of the right- and left-tail parameters. The second figure reports the estimated power parameter. The third and fourth figures report the estimated scale and class parameters.

strategy is not suitable for the estimation. We, therefore, drop the low leverage (debt-to-asset ratio) intermediaries in the estimation stage. However, after the ML estimation, the construction of our systemic risk measure and counterfactual analysis use the entire sample.

3.   Heterogeneous Intermediaries and Their Distribution

This section applies the ML procedure to the balance sheet data of financial intermediaries. Compustat Fundamentals Annual data from 1993 to 2018 yields a yearly sample with 584 observations on average and with observation counts ranging from 448 to 521.[9] We also impose certain filtering criteria such as, for example, excluding observations with negative equity or negative assets. Appendix A provides more details on the sample used.

Figure 2 describes estimates of the generalized beta distribution and their variation over time.[10]   There is important time variation in the right tail parameter, as well as in the

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[9]We report summary statistics in Figures A2 – A4. Table A1's Panel A also provides information on the identity, leverage and balance sheet size of the 20 largest intermediaries in 2008 and their respective values for 2006 and 2010.

[10]See Table A2 in Appendix B for some summary statistics of the estimates.
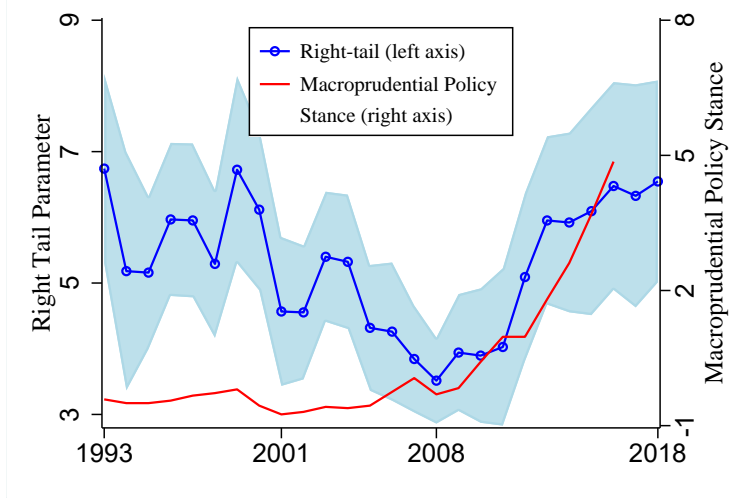
Figure 3: Right-tail Parameter and Macroprudential Policy Stance: The figure plots estimated $\phi_{R,t}$ from the estimation results (blue line with circles) with 95% intervals (light blue shades) and average macroprudential policy stance of advanced countries (red line) measured by Forbes (2021).

power and scale parameters. We discuss their economic implications below. In Appendix B, Figure A5 shows our estimated distribution of debt-to-asset ratios for each year. Overall the fit seems quite good, which shows the benefit of using a highly flexible and general class of distributions for our estimation.

Once we have estimated the distribution parameters, we can use observed leverage to recover the implied risk-taking of each intermediary i using equation (2):

$$\hat{\alpha}_{i,t} = \alpha(\lambda_{i,t}|\hat{\Phi}_t) = \frac{\hat{\phi}_{c,t}\left(1 - 1/\lambda_{i,t}\right)^{\hat{\phi}_{p,t}}}{(\hat{\phi}_{s,t})^{\hat{\phi}_{p,t}} + \hat{\phi}_{ct}\left(1 - 1/\lambda_{i,t}\right)^{\hat{\phi}_{p,t}}}, \tag{5}$$

where the function $\alpha(\lambda_{i,t}|\hat{\Phi}_t)$ is independent of the left and right tail parameters $\hat{\phi}_{L,t}$ and $\hat{\phi}_{R,t}$, respectively. Conditional on the estimated parameters in equation (5), concentration in risk-taking emerges from the concentration in leverage. Of course, all parameter estimates are dependent on the entire sample distribution for each year.

In Figure 2, we observe that $\phi_{L,t}$ is smaller than one, while $\phi_{R,t}$ is greater than one for all periods. These results imply that the density of $\alpha_{i,t}$ is strictly decreasing, as Figure 4

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shows. We find that the risk-taking of financial intermediaries is right (i.e., positively) skewed. Dynamically, the left tail parameter is quite stable over time, while there is significant variation in the right tail. Before the financial crisis, the right tail parameter decreased, implying a thicker right tail in the risk-taking distribution. A low right tail parameter implies more intermediaries taking high risks.[11] As we can infer from the relationship between leverage and $\alpha_{i,t}$, the distribution of leverage also has a thicker right tail, and we can observe a significant growth in risk-taking (higher $\alpha_{i,t}$) in the run-up to the crisis (Figure 4). In recent years, this trend has reversed, and the right tail parameter has risen. This recent trend likely results from significant changes in banking regulation imposed by the Basel III Accord as shown in Figure 3. As can be seen from the measure of macroprudential policy stance of Forbes (2021)[12], macroprudential policies were largely nonexistent in advanced economies before 2009. In that environment where the dominant supervision doctrine was one of "laissez-faire", banks were stretching regulatory frameworks to their limits. Some of them were increasing their leverage massively without any corresponding increase in their value-at-risk: leverage was going up over time while estimated risk-weighted capital stayed constant. This period of lax regulation and laissez-faire is captured by a decrease in the right tail parameter between 1999 and 2008. After the crisis, macroprudential regulations were gradually tightened in all advanced economies, supervisors became much more active, and our right tail parameter went back up.

Central to our estimation strategy are the intermediaries' VaR constraints, which are hard to get directly from the data[13]. Fitting the implied moments of risk-taking $\alpha_{i,t}$ and uncertainty (volatility) $\sigma_{Z,t}$, however, can serve as an indirect test of our empirical framework. We perform a number of external validation checks of our estimates. Figure 4 shows the

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[11]In Table A2 we can also observe that the period of 2000-2008 was characterized by a low right tail parameter when compared to both the preceding period (1993-2000) and the post-crisis period of 2009-2018.

[12]We are very grateful to Kristin Forbes for sharing her data and calculations of the macroprudential policy stance.

[13]Some large banks report some of their VaRs. However, they do not cover their entire balance sheet; because they depend on internal risk models for specific portfolios, they do not represent the aggregate risk-taking behavior of intermediaries, which is our parameter of interest.
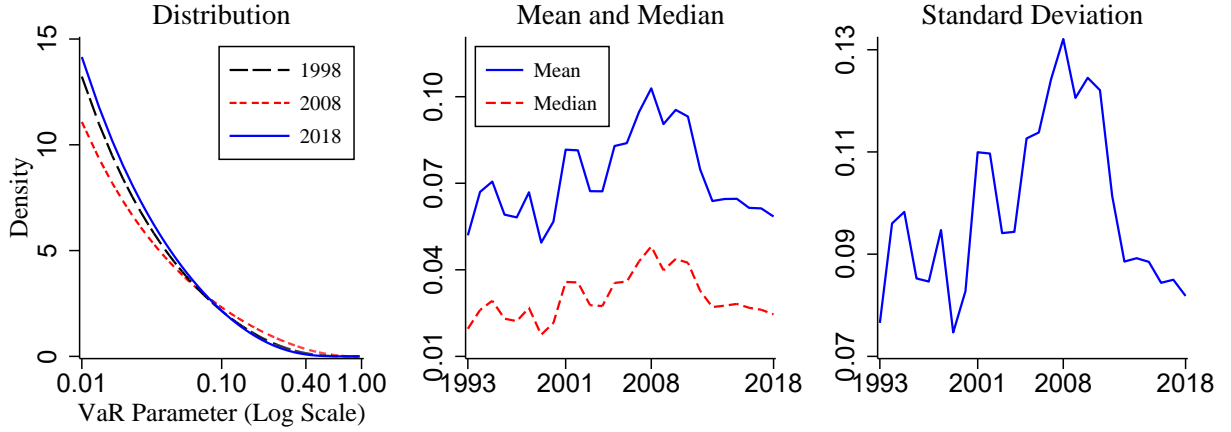
Figure 4: Estimated Distribution of Risk-Taking Behavior, $\alpha_{i,t}$: The figure plots the estimated distribution of $\alpha_{i,t} \sim \phi_{c,t} \times \text{Beta}(\phi_{L,t}, \phi_{R,t})$ on $(0, \phi_{c,t})$. In the first figure, the black long and red short dashed and blue solid lines are the estimated distribution based on parameter estimates for the years 1998, 2008, and 2018, respectively. In the second figure, the blue solid and red dashed lines report the mean and median, respectively. The third figure plots the standard deviation. The statistics are calculated from the estimated distributions as follows. The mean, median, standard deviations of the distribution $\alpha_{i,t}$ are $\phi_{c,t}\phi_{L,t}/(\phi_{L,t} + \phi_{R,t})$ and $\phi_{c,t}I_{1/2}^{-1}(\phi_{L,t}, \phi_{R,t})$, and $\phi_{c,t}\sqrt{\phi_{L,t}\phi_{R,t}}/[(\phi_{L,t} + \phi_{R,t})\sqrt{\phi_{L,t} + \phi_{R,t} + 1}]$, respectively, in which $I_p(\phi_{L,t}, \phi_{R,t})$ is the regularized incomplete beta function.

estimated distribution of risk-taking behavior and some cross-sectional statistics over time. In the figure, the mean and median plots are inversely U-shaped. The peak of intermediaries' risk-taking, on average, is around the financial crisis, with a sustained rise between 1999 and 2008. This pattern corresponds to the U-shape of right-tail parameters over time in Figure 2. That pattern implies that the right tail movements mainly drive the distribution changes over time. In Figure 4, one can see that the right tail around 2008 is fatter than that of 2018 or 2013. Interestingly, we also see that the dispersion of risk-taking parameters is increasing markedly before the crisis. This fits very well with the papers cited in the introduction which emphasize a race for a market share of the most reckless financial intermediaries during boom times, while the most conservative ones hold back. Understanding the time variations in the distribution of risk-taking parameters is important because they are systemically related to financial instability in the macroeconomy.
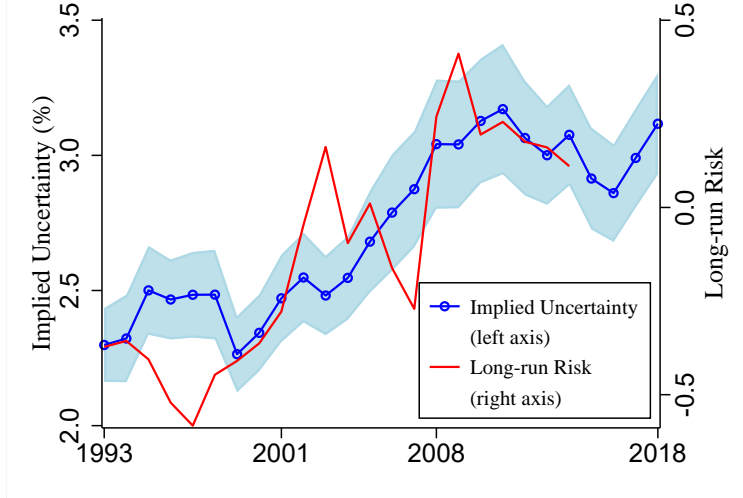
Figure 5: Uncertainty: The figure plots implied uncertainty (%) $100 \times \sigma_{Z,t} = 100 \times \pi/(\phi_{p,t}\sqrt{3})$ from the estimation results (blue line with circles) with 95% intervals (light blue shades) and long-run risk measure (red line) as an uncertainty measure. The long-run risk measure comes from Schorfheide, Song and Yaron (2018)'s structural model estimation.

To check our model's validity, we also look at whether the secular trends in our implied uncertainty measure are consistent with traditional measures in the literature. Figure 5 illustrates estimates for uncertainty in asset returns derived from our structural model as $\sigma_{Z,t} = \pi/(\phi_{p,t}\sqrt{3})$. We find an increasing secular trend of implied uncertainty, up to the financial crisis, with a slight reversion in its aftermath. Even though we do not use any standard macro variables and extract information only from the cross-sectional moments of leverage alongside our structural model, the implied uncertainty of the economy shows a similar pattern to the macroeconomic risk of long-term economic growth estimated by Schorfheide, Song and Yaron (2018): i.e., the volatility of the persistent component in the long-run risk model. Comin and Philippon (2005); Kehrig (2015); Bloom et al. (2018); Farhi and Gourio (2018); Schorfheide, Song and Yaron (2018) document similar patterns of rising volatility or uncertainty in macro and macro-finance.[14]

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[14]More precisely, our implied uncertainty changes are consistent with 1) Farhi and Gourio (2018)'s risk component of the spread between the marginal product of capital and the risk-free rates, 2) Schorfheide, Song and Yaron (2018)'s estimate of long-run risk components, 3) Comin and Philippon (2005); Kehrig (2015); Bloom et al. (2018) document a similar pattern of (respectively) rising volatility, dispersion and uncertainty in macro.

Table 1: Risk-Taking Behavior: Distress or Defaulted Banks during 2007 − 2009

		Full Sample	Default	Distress Benchmark	Distress Alternative
	Statistics				
VaR parameter	Mean	0.125	0.462	0.152	0.310
	Upper quantile (P75)	0.135	0.730	0.197	0.547
	Median (P50)	0.043	0.547	0.045	0.245
	Lower quantile (P25)	0.009	0.195	0.010	0.010
	Observations	1326	11	427	55

4. Risk-Taking and Economic Performance

4.1. Risk-Taking Behavior and Financial Distress

To provide external validation of our estimates, we now study the link between estimated VaR parameters and outcomes. The VaR parameter should have a strong link with the intermediary's risk-taking and, therefore, its economic performance. More precisely, the estimated VaR parameter should strongly predict the (ex-post) default or distress of individual financial intermediaries. We check whether our measure predicts bank outcomes, *despite not using any specific information about those in our estimation procedure.*

As equation (5) highlights, the VaR parameter is the probability that returns on equity are negative. A negative RoE may lead to default, liquidation, delisting, and/or being acquired. We construct a default dummy $Default_{i,t}$ using a strict definition of default[15]. We also construct a distress event dummy $Distress_{i,t}$ using combinations of the following events: (1) income is non-positive, (2) equity becomes non-positive, and (3) existed in the previous period but is no longer available in the current period. The benchmark distress dummy $Distress_{i,t}$ has value one if (1), (2), or (3) occurs at time $t + 1$, and 0 otherwise. As an alternative, we also consider (2) and (3) for a more narrowly defined distress event.[16] Table 1

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[15]When *Research Company Reason for Deletion* ($dlrsn_i$) is identified as 02 (Bankruptcy) or 03 (Liquidation). This definition is, however, very limited because of missing labels in the data. In our sample, only 0.1% of banks are identified explicitly as bankrupt or liquidated, which is significantly lower than what can be inferred from FDIC data.

[16]More precisely, in the benchmark, $Distress_{i,t} = 1$ when the following cases occur: (1) Income is non-positive: $ib_{i,t+1} \leq 0$, (2) Research Company Deletion Date is non-empty $dldte_i \neq \cdot$, and t is the last period

Table 2: Risk-Taking Behavior and Bank Distress

	Distress Dummy: $Distress_{i,t}$							
	Benchmark Broad Definition				Alternative Narrow Definition			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VaR parameter	0.09**	0.23***	0.13**	0.19***	0.04	0.16***	0.11**	0.15***
	(0.03)	(0.01)	(0.05)	(0.01)	(0.04)	(0.02)	(0.05)	(0.02)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year-Bank Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Year-Country FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	7417	7164	7362	7109	7417	7164	7362	7109
R-squared	0.11	0.16	0.28	0.31	0.02	0.04	0.21	0.22

Note: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors (in parentheses) are clustered at the country-bank type level. Singleton observations are dropped in all regressions. The estimation is based on equation (6). We use a logistic estimation. The dependent variable is the one-year ahead distress dummy. Other controls are dividend yield, book to market ratio, and asset size in logs.

shows some summary statistics for quantiles values of the estimated VaR parameter around the global financial crisis. We observe that the subset of banks that defaulted or were in distress indeed have significantly larger estimated risk-taking parameters than the population and that this difference is larger, the stricter the definition is. This comforts us in the view that our estimated distributions capture risk-taking meaningfully.

For an investigation of the statistical relation between VaR parameters and realized distress events[17], we estimate the following logistic regression equation:

$$Distress_{i,t} = b_0 + b_1\alpha_{i,t} + (\ln \mathbf{x}_{i,t})^{\mathrm{T}}\mathbf{b} + \delta_{i,t} + \varepsilon_{i,t}, \tag{6}$$

The bank corporate trait vector is denoted by $\mathbf{x}_{i,t}$ and includes dividend yield, book to market ratio, and asset size. Note that our regressions also include various fixed effects denoted broadly by $\delta_{i,t}$. We include a bank, bank type, country, and/or year fixed effects.[18]

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of i's observations, (3) Assets $\mathtt{at}_{i,t+1}$ are not greater than total liabilities $\mathtt{lt}_{i,t+1}$, (4) Negative Stockholders' Equity — Total is non-positive: $\mathtt{seq}_{i,t+1} \leq 0$, (5) Negative Common/Ordinary Equity — Total is non-positive: $\mathtt{ceq}_{i,t+1} \leq 0$, or (6) Common Equity — Tangible is non-positive: $\mathtt{ceqt}_{i,t+1} \leq 0$. The alternative distress dummy $Distress_{i,t}^{alt} = 1$ when at least one of (2) – (4) or (5) occurs.

[17]There are not enough default observations to run a regression.

[18]We use the North American Industry Classification System (NAICS) 4 digit code for bank type.
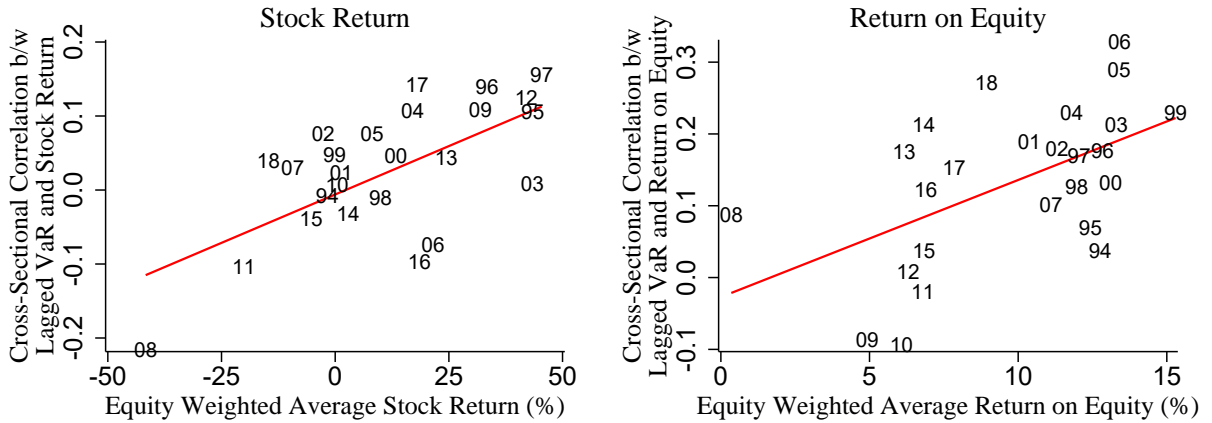
Figure 6: Risk-Taking Behavior and Bank Performance: The figures plot each year cross-sectional correlation between a bank's lagged risk-taking measure ($\alpha_{i,t}$) and its performance measure (the y-axis) and each period average performance of banks weighted by the equity (the x-axis). Bank performance is measured by stock returns (left) and return on equity (right). See Figure A6 for the corresponding figure with return on asset.

These fixed effects allow us to control for (i) any time-invariant firm-specific, sub-sector, and cross-country differences that might affect the distress and (ii) time-varying characteristics that influence the distress.

Table 2 provides statistically significant evidence on the positive association of our risk-taking measure (VaR parameter) with ex-post bank distress. Our VaR parameter is consistently positively associated with a higher probability of distress for all our specifications. We now look at whether the pattern of stock returns is also consistent with our structural model.

4.2. Risk-Taking Behavior and Stock Returns

Conventional theory suggests that high risk-taking intermediaries' ex-post returns should be larger in good times, but that their losses should be larger in bad times (see Miranda-Agrippino and Rey (2020)). We now use the estimated risk-taking behavior in the previous section to predict stock returns during good and bad times in order to provide further evidence on the external validity of our estimates.

Figure 6 highlights that the cross-sectional correlation between the lagged VaR parameter and bank performance (measured by stock returns or return on equity) fluctuates over time. The relationship between intermediary risk-taking and performance depends on the banking sector's aggregate performance. When the banking sector performs well, high risk-taking intermediaries earn more than others, thus profiting from their aggressive approach. The cross-sectional correlation between lagged VaR and returns is then positive. However, when returns are negative, they also make the largest losses, and the correlation turns negative.

To examine whether bank's risk-taking behavior matters for stock returns more formally, we use the following panel regression:

$$r_{i,t+1}^{\text{excess}} = b_0 + b_1 \ln \alpha_{i,t} + (\ln \mathbf{x}_{i,t})^{\text{T}} \mathbf{b} + \delta_{i,t} + \varepsilon_{i,t}, \tag{7}$$

which predicts one-year forward excess stock return (%) $r_{i,t+1}^{\text{excess}}$ defined by a bank i's stock returns $r_{i,t+1}^{\text{stock}}$ minus the equity-weighted average stock return $\bar{r}_{t+1}^{\text{stock}}$, conditional on the risk-taking behavior (VaR parameter $\alpha_{i,t}$) in logs, other controls and fixed effects. The bank corporate trait vector is denoted by $\mathbf{x}_{i,t}$ and includes dividend yield, book to market ratio, and asset size. Our regression also includes various fixed effects denoted by $\delta_{i,t}$. We include a bank, year-bank type, and/or year-country fixed effects.[19] These fixed effects allow us to control (i) any time-invariant financial intermediaries' characteristics that generate a firm-specific trend in stock returns, (ii) any time-varying and time-invariant sub-sector differences that might affect stock returns, and (iii) time-varying and time-invariant country characteristics that influence the stock market performances.

In Table 3, we present the results of the panel regression model specified in equation (7) using three different samples.[20] Columns (1), (4), and (7) correspond to results associated with the entire sample. Intermediary market returns increase when they take more risk.

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[19]The North American Industry Classification System (NAICS) 4 digit code classifies our bank type.

[20]Table A3 reports additional estimation results. We split the sample between "bull" and "bear" periods based on the equity-weighted average of market returns $\bar{r}_{t+1}^{\text{stock}}$. The bull and bear markets are $\bar{r}_{t+1}^{\text{stock}} > 0$ and ≤ 0, respectively.

Table 3: Risk-Taking Behavior and Stock Returns

	One Year Ahead Excess Stock Returns: $r^{\text{excess}}_{i,t+1} = r^{\text{stock}}_{i,t+1} - \bar{r}^{\text{stock}}_{t+1}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	All	Positive	Negative	All	Positive	Negative	All	Positive	Negative
VaR parameter (log)	0.71***	1.23***	-0.23**	1.64***	2.03***	-0.49***	1.64***	1.96***	-0.55***
	(0.20)	(0.21)	(0.09)	(0.26)	(0.09)	(0.12)	(0.26)	(0.03)	(0.04)
Other Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Year-Bank Type FE	No	No	No	No	No	No	Yes	Yes	Yes
Year-Country FE	No	No	No	No	No	No	Yes	Yes	Yes
Observations	8260	5421	2692	6986	4554	2304	6986	4376	2177
R-squared	0.24	0.38	0.70	0.36	0.50	0.73	0.36	0.56	0.75

Note: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors (in parentheses) are clustered at the country-bank type level. Singleton observations are dropped in all regressions. The estimation is based on equation (7). The dependent variable is the excess stock return. Other controls are dividend yield, book to market ratio, and asset size in logs. Columns (2), (5), and (8) only include intermediaries with positive excess market returns. Columns (3), (6), and (9) only include intermediaries with negative excess market returns.

When an intermediary's VaR threshold parameter increases one basis point, its stock return increases between 0.71% and 1.64%. Risk-taking is, on average, compensated by larger returns, as expected. We also consider the following two subsamples. In Columns (2), (5), and (8), we first include intermediaries with positive excess market returns. Second, Columns (3), (6), and (9) contain intermediaries with negative excess market returns. When intermediaries succeed, their market returns are increasing in risk-taking. However, their returns are decreasing in risk-taking when they fail.

Figure 6 provides descriptive evidence supporting the prediction that high risk-taking financial intermediaries lose more than others if bad states occur. In Table 4, we test this hypothesis by interacting the estimated risk-taking behavior $\ln \alpha_{i,t}$ with dummies indicating financial crises at $t+1$ in regression equation (7). As expected, the estimated coefficients of the interaction term are significantly negative. Risk-taking predicts excess returns but also larger volatility of returns and their pattern over the business cycle. All this is consistent with the conventional view of risk-taking and returns. Note that even though we did not use any information on returns or additional business cycle variables to estimate α_i, our measures

Table 4: Risk-Taking Behavior and Stock Returns during Crises

	One Year Ahead Excess Stock Returns: $r_{i,t+1}^{\text{excess}} = r_{i,t+1}^{\text{stock}} - \bar{r}_{t+1}^{\text{stock}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
VaR parameter (log)	0.75***	1.84***	1.56***	0.79***	1.80***	1.52***
	(0.07)	(0.29)	(0.02)	(0.07)	(0.28)	(0.02)
VaR parameter (log) × Crisis Dummy (One-Year Ahead)						
Global Financial Crisis (2008)	-4.49***	-3.24***	-2.74***			
	(0.34)	(0.49)	(0.02)			
Global Financial Crisis (2008)				-3.69***	-2.05***	-1.69***
and Sovereign Debt Crisis (2011)				(0.28)	(0.44)	(0.02)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
Year-Bank Type FE	No	No	Yes	No	No	Yes
Year-Country FE	No	No	Yes	No	No	Yes
Observations	7042	6986	6736	7042	6986	6736
R-squared	0.03	0.36	0.47	0.03	0.36	0.46

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors (in parentheses) are clustered at country-bank type level. Singleton observations are dropped in all regressions. The estimation is based on equation (7). The dependent variable is the excess stock return. Other controls are dividend yield, book to market ratio, and asset size in logs.

predict patterns consistent with our structural interpretation based on risk-taking.

5. Systemic Risk and Concentration of Risk

In this section, we use our structural measures of risk-taking to generate a simple aggregate measure that is indicative of risk in the financial sector as a whole. We depart from our individual measures of risk-taking, and although we could in practice use information from the entire set of moments of the distribution, we take a simple approach and provide a scalar index of systemic risk. To do so, we simply weigh the risk-taking parameter of each intermediary by its balance sheet size. Intuitively this corresponds to the ex-ante probability that a certain proportion of assets are in the hands of distressed intermediaries.

Using equation (5), observed leverage $\lambda_{i,t}$ and the set of estimated parameters $\hat{\Psi}_t$, we can recover the implied empirical distribution of $\hat{\alpha}_{i,t}$ and calculate measures of systemic risk such as $\overline{\alpha}_t^{AW}$, the asset-weighted mean of VaR parameters. We can of course also recover
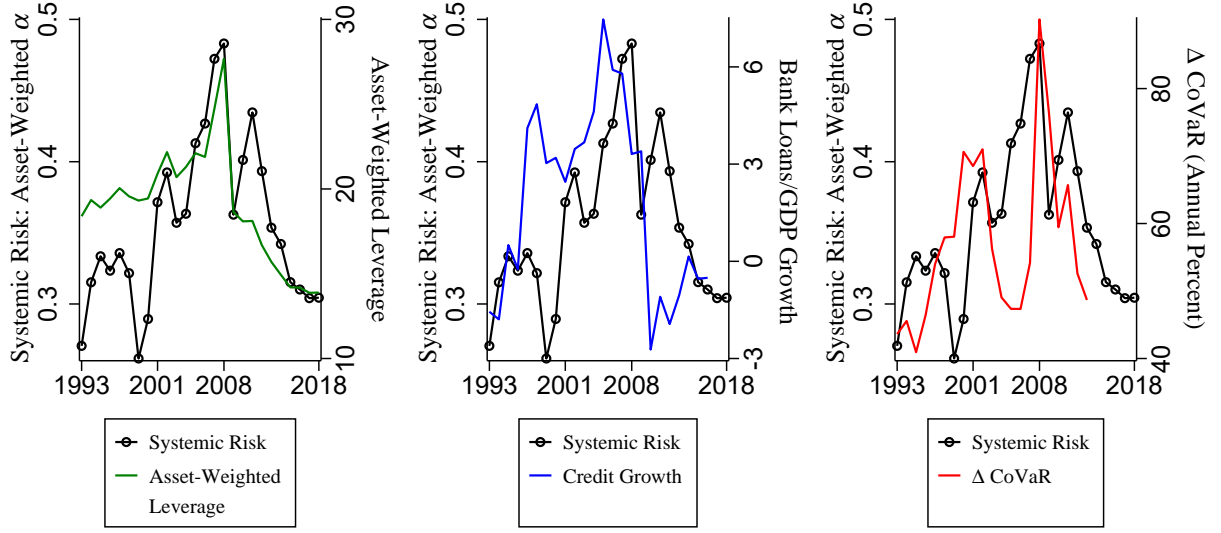
Figure 7: Evolution of Systemic Risk over Time, $\overline{\alpha}_t^{AW}$: The figures plot the systemic risk measured by the estimated asset-weighted VaR parameter (black circled lines) and alternative measures (solid lines) from previous studies. In the left figure, the green line (right y-axis) is the asset-weighted leverage in our sample. In the middle figure, the blue line (right y-axis) is the bank credit measured by the sum of the country's total loans to the non-financial private sector divided by the sum of each country's GDP (nominal, USD). Then, we calculate the growth rates. The data are from the Jorda-Schularick-Taylor Macrohistory Database. In the right figure, the red line (right y-axis) is ΔCoVaR, the change in the value-at-risk of the financial system conditional on an institution being under distress relative to its median state, from Adrian and Brunnermeier (2016). We calculate the annual ΔCoVaR by adding their quarterly ΔCoVaR (estimated using data 1971 – 2013) each year.

the unweighted averages $\overline{\alpha}_t^U$, although we believe it is important to weigh the risk-taking parameter by the economic size of the respective intermediary. Specifically:

$$\overline{\alpha}_t^{AW} \equiv \sum_{i=1}^{N_t} \left(\frac{a_{i,t}}{\sum_{j=1}^{N_t} a_{j,t}} \right) \hat{\alpha}_{i,t} \quad \text{and} \quad \overline{\alpha}_t^U \equiv \frac{1}{N_t} \sum_{i=1}^{N_t} \hat{\alpha}_{i,t},$$

where N_t is the number of financial intermediaries and $a_{i,t}$ the balance sheet size of intermediary i at time t.

Our benchmark measure of systemic risk is the asset-weighted mean of risk-taking $\overline{\alpha}_t^{AW}$, which takes into account the size of each intermediary in the macroeconomy. For example, an economy with one safe and one very risky intermediary will not have the same amount of macroeconomic risk if the risky bank only holds 5% of assets or holds 95% of the assets. A nice

feature of our framework is that we have a direct mapping between the underlying parameters of our VaR framework and different relevant definitions of systemic risk such as "ex-ante probability that a certain percentage of assets are in the hands of distressed intermediaries" or "ex-ante probability that the entire leverage sector (or x% of it) is distressed".

In Figure 7, we present the time series of the asset-weighted mean of estimated risk-taking $\overline{\alpha}_t^{AW}$ which is the asset-weighted (ex-ante) probability of distress (VaR parameter) of the entire sample of intermediaries. We compare it in each panel to an alternative measure of systemic risk taken from the literature. We estimate $\overline{\alpha}_t^{AW}$ from the Compustat Fundamentals Annual data using the methodology described above. As is clear from the figure, our estimates suggest a significant increase in systemic risk between 2000 and 2008 as liquidity conditions in the global economy were loose and regulation were lax, and a significant decline after 2008 and as banking regulations tightened. In the next section, we provide counterfactual exercises in which we explore further these different factors.

Figure 7 also compares our measure to 3 different alternatives. In the left panel, we compare it to a simple asset-weighted mean of leverage. This illustrates the usefulness of the structural model, as asset-weighted leverage completely misses the increased systemic risk during the European sovereign debt crisis and seems to be relatively flat almost until 2008 when the crisis actually hits. This delayed rise is also there to an even greater extent with the ΔCoVaR measure, which dramatically rises in 2008 but gave no early warning signs to a policymaker observing the measure in the preceding years. This is a common problem with price-based measures: when they predict a crisis, it is too late. Credit growth (middle panel) seems to exhibit the most similar pattern to our measure, but it would also miss the European sovereign debt crisis and peak a couple of years before the crisis.

In order to explore further the role of heterogeneity in risk-taking across intermediaries we decompose our systemic risk measure $\overline{\alpha}_t^{AW}$ into a representative average component and an heterogeneous component. Using the definition of leverage, we express assets as $a_{i,t} = \lambda_{i,t}\omega_{i,t}$,
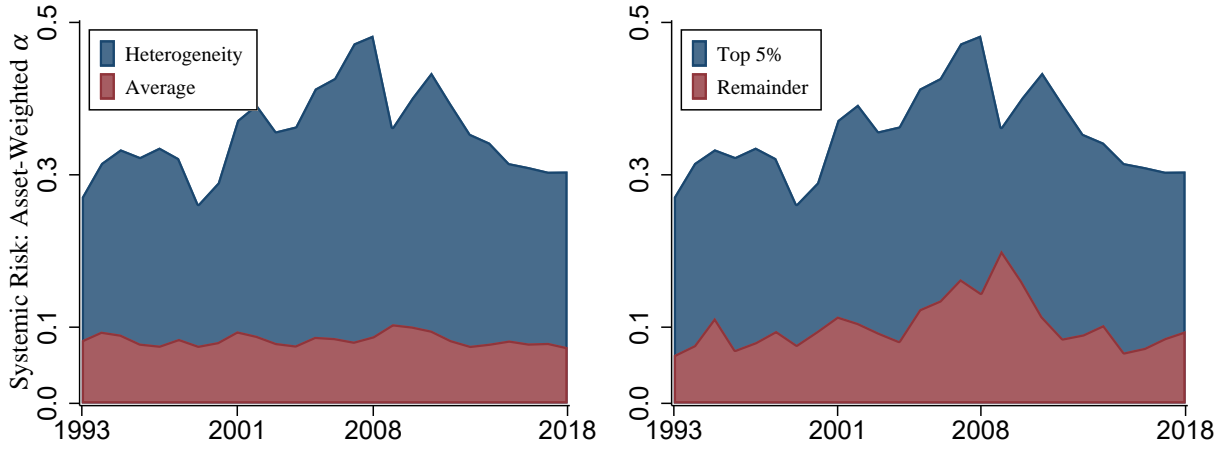
Figure 8: Heterogeneity and Concentration of Systemic Risk: The first figure plots the decomposition of systemic risk into the contributions of heterogeneity (blue) and average (red) components. The second figure plots the contributions of top 5% quantiles of the financial intermediaries' risk-taking behavior, $\alpha_{i,t}$, (blue) and the remainder (red).

and decompose the measure of systemic risk $\overline{\alpha}_t^{AW}$ around a reference point $\overline{\alpha}_t$ as follows:

$$\overline{\alpha}_t^{AW} = \underbrace{\overline{\alpha}_t \lambda(\overline{\alpha}_t|\hat{\Phi}_t) \left(\frac{\sum_{j=1}^{N_t} \omega_{i,t}}{\sum_{j=1}^{N_t} a_{j,t}} \right)}_{\text{average component}} + \underbrace{\sum_{i=1}^{N_t} \left[\hat{\alpha}_{i,t}\lambda_{i,t} - \overline{\alpha}_t \lambda(\overline{\alpha}_t|\hat{\Phi}_t) \right] \left(\frac{\omega_{i,t}}{\sum_{j=1}^{N_t} a_{j,t}} \right)}_{\text{heterogeneity component}}, \qquad (8)$$

where $\lambda(\alpha|\Phi_t) = \left\{ 1 - \phi_{s,t}(\phi_{c,t})^{-1/\phi_{p,t}}[\alpha/(1-\alpha)]^{1/\phi_{p,t}} \right\}^{-1}$ is derived from equation (5). The average component takes the unweighted average of intermediaries' risk-taking behavior $\overline{\alpha}_t = \overline{\alpha}_t^U$ as its reference point.[21] Here, the first and second components represent the contribution of average and heterogeneous financial intermediaries, respectively. Intuitively, the average component considers the risk-taking of a representative intermediary with mean risk-taking, while the heterogeneity component is the sum of the additional contributions arising from the deviations of each intermediary from the representative agent's behavior.

Figure 8 highlights the importance of heterogeneous financial intermediaries in macro-finance research. The first panel of Figure 8 shows that the average component plays a limited

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[21]Alternatively, we can decompose the systemic risk measure as $\overline{\alpha}_t^{AW} = \overline{\alpha}_t + \sum_{i=1}^{N_t}(\hat{\alpha}_{i,t} - \overline{\alpha}_t)[a_{i,t}/(\sum_{j=1}^{N_t} a_{j,t})]$, which does not yield significant difference from our decomposition in equation (8).

role in the fluctuations of our systemic risk measure, though it accounts for about 28.6% of the measure on average.[22]. However, the heterogeneous component drives the vast majority of the dynamics and peaks exactly around the crisis, while the average component peak would happen post-crisis and even seems to fall slightly in the run-up to the crisis. The correlation coefficients of the systemic risk measure with the average and heterogeneous terms are 0.390 and 0.991, respectively. Considering heterogeneity is therefore extremely important, not only in the estimation procedure but also for the dynamics and level of the systemic risk measure.

The right panel of Figure 8 illustrates the concentration of risk and its changes over time, showing the time series of systemic risk for the top 5% quantile of risk-taking behavior, $\alpha_{i,t}$. The top 5% of intermediaries contribute to 71.0% of systemic risk over the sample.[23] Moreover, high quantiles are positively correlated with the aggregate systemic risk measure. The correlation coefficient between aggregate systemic risk and contributions of the top 5% is 0.817. The peak of the contribution of the lower 95% occurs in the aftermath of the crisis, while the top 5% peaks in 2008. In Panel B of Table A1 we list the 20 institutions with the largest asset-weighted α in 2008 and their respective values in 2006 and 2010. These intermediaries, whether investment banks or universal banks, were highly levered and featured very large balance sheets before the crisis. This highlights the disturbing fact that several systemically important banks were engaging in significant risk-taking before the crisis.

It is clear that risk-taking does not rise and fall across the board, but that there are important cross-sectional patterns that would be missed by simply looking at averages or aggregate variables. Modeling and tracking heterogeneity in the financial sector is important as financial instability often arises from large, high risk-taking intermediaries.

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[22]The maximum and minimum share of the average component are 24.7 and 33.7%, respectively.

[23]The maximum and minimum share of the top 5% quantile contribution are 44.6 and 78.8%, respectively.

6. Counterfactual Analysis: Central Bank Policy

This section presents two counterfactual exercises that provide insight into the impact of banking regulation and monetary policy (cost of funds) on financial instability and their contribution to our systemic risk measure dynamics.

In the first, we perform a counterfactual exercise on the tightness of financial regulation by fixing the right tail parameter $\phi_{R,t}$ of our risk-taking distribution.[24] Since regulatory policy imposes limits to the risk-taking of intermediaries, it is natural to model changes in regulatory policy by changes in the right tail parameter as it describes the behavior of the riskiest players. A cap on leverage, for example, would affect the right tail parameter. We estimate the extent to which increases in regulatory tightness affect the degree of systemic risk. For our second exercise, we calculate counterfactual systemic risk measures by changing the value of the ratio of expected returns on assets to the costs of funds ζ_t.[25] In Coimbra and Rey (2020), an expansionary monetary policy (low policy rate) directly lowers the cost of funds but also compresses spreads through its impact on asset prices. Thus, our second counterfactual exercise allows us to investigate the contribution of monetary policy to the evolution of systemic risk.

The counterfactual systemic risk measures are straightforward to calculate:

- **Step 0**: Set the counterfactual parameter: $\tilde{\Phi}_t$.[26]

- **Step 1**: Recover the the risk-taking behavior (VaR parameter) from the estimates of

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[24]As an alternative exercise, we could also fix both the left and right tail parameters. Because variations in the left tail shape are small, this exercise would yield close to our benchmark counterfactual analysis with the fixed right tail. Our counterfactual results with fixed $\phi_{R,t}$ and fixed ($\phi_{L,t}$, $\phi_{R,t}$) are indistinguishable. Given our interpretation of regulation compressing the top tier of risk-taking, it seems natural to conduct our counterfactual analysis on $\phi_{L,t}$.

[25]The estimated ratio of expected asset returns to funding costs consists of three estimates: $\hat{\zeta}_t = \hat{\phi}_{s,t}(\hat{\phi}_{c,t})^{-1/\hat{\phi}_{p,t}}$. Note that $\hat{\phi}_{c,t}$ and $-1/\hat{\phi}_{p,t}$ are close to one and zero, respectively: 0.99 and -0.01 on average between 1993 and 2018. Thus, $\hat{\phi}_{s,t}$ is the main driver of changes in $\hat{\zeta}_t$ over time. The power parameter $\phi_{p,t}$ is the mirror image of uncertainty: $\sigma_{Z,t} = \pi/(\phi_{p,t}\sqrt{3})$. The scale parameter $\phi_{s,t}$ is the upper bound of risk-taking behavior: $\alpha_t^{\text{ub}} = \phi_{s,t}$. We set the scale parameter for the counterfactual exercise to be $\tilde{\phi}_{s,t} = \tilde{\zeta}(\hat{\phi}_{c,t})^{1/\hat{\phi}_{p,t}}$ for given $\tilde{\zeta}$ and estimated $\hat{\phi}_{p,t}$ and $\hat{\phi}_{c,t}$.

[26]For example, we consider $\hat{\Phi}_t$ and $\tilde{\Phi}_t = \{\hat{\phi}_{p,t}, \hat{\phi}_{s,t}, \hat{\phi}_{c,t}, \hat{\phi}_{L,t}, \hat{\phi}_{R,2008}\}$ to analyze impact of bank regulation on systemic risk after the global financial crisis.
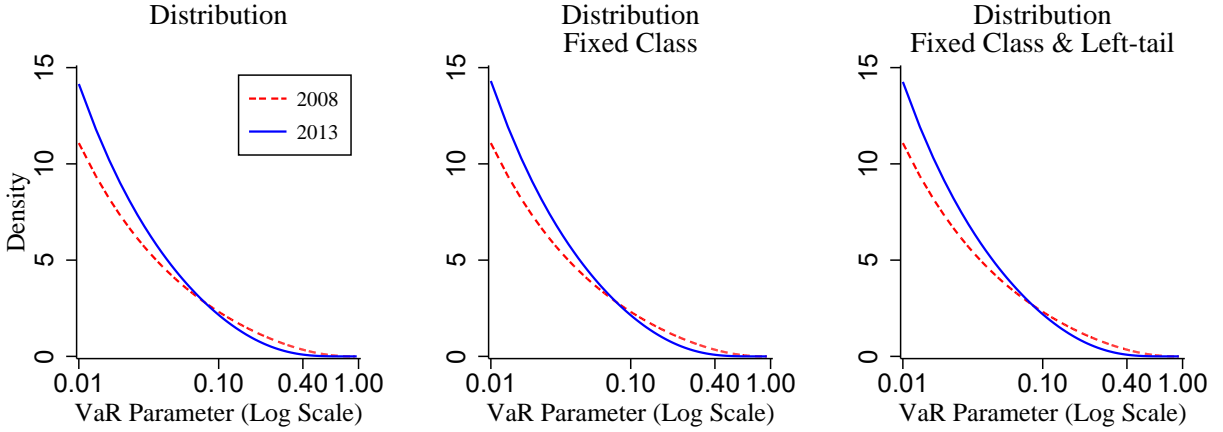
Figure 9: Distribution of Risk-Taking Behavior: The figure plots the estimated distribution of $\alpha_{i,t} \sim \phi_{c,t} \times \text{Beta}(\phi_{L,t}, \phi_{R,t})$ on $(0, \phi_{c,t})$. We fix the class parameter as $\phi_{c,2008}$ in the second figure. The third figure is done with the fixed class and left tail parameters as $\phi_{c,2008}$ and $\phi_{L,2008}$.

the distribution and leverage data: $\hat{\alpha}_{i,t} = \alpha(\lambda_{i,t}|\hat{\Phi}_t)$.

- **Step 2**: Use the complementary distribution function (tail distribution function) denoted by $\text{ccdf}_\alpha(\cdot|\Phi_t)$ and its inverse function to calculate the implied counterfactual risk-taking behavior: $\tilde{\alpha}_{i,t} = \text{ccdf}_\alpha^{-1}[\text{ccdf}_\alpha(\hat{\alpha}_{i,t}|\hat{\Phi}_t)|\tilde{\Phi}_t]$.

- **Step 3**: Calculate the implied counterfactual leverage using $\tilde{\alpha}_t^i$: $\tilde{\lambda}_{i,t} = \lambda(\tilde{\alpha}_{i,t}|\tilde{\Phi}_t)$. [27]

- **Step 4**: Calculate the implied counterfactual assets using the observed equity and the implied leverage: $\tilde{a}_{i,t} = \omega_{i,t}\tilde{\lambda}_{i,t}$.

- **Step 5**: Calculate weighted and unweighted averages of $\tilde{\alpha}_{i,t}$. The weights are based on the counterfactual asset size $\tilde{a}_{i,t}$ and leverage $\tilde{\lambda}_{i,t}$, not the observed $a_{i,t}$ and $\lambda_{i,t}$ from the data.[28]

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[27]The leverage for given risk behavior is: $\lambda(\tilde{\alpha}|\tilde{\Phi}_t) = \left\{1 - \tilde{\phi}_{s,t}(\tilde{\phi}_{c,t})^{-1/\tilde{\phi}_{p,t}}[\tilde{\alpha}/(1-\tilde{\alpha})]^{1/\tilde{\phi}_{p,t}}\right\}^{-1}$. That is independent of the left and right tail parameters: $\tilde{\phi}_{L,t}$ and $\tilde{\phi}_{R,t}$. We set the maximum value of leverage to be 1000.

[28]In the case of $\tilde{\Phi}_t = \hat{\Phi}_t$, the procedure yields $\tilde{\alpha}_{i,t} = \hat{\alpha}_{i,t}$, $\tilde{a}_{i,t} = a_{i,t}$, and $\tilde{\lambda}_{i,t} = \lambda_{i,t}$ where assets $a_{i,t}$ and leverage $\lambda_{i,t}$ are observed from the data.
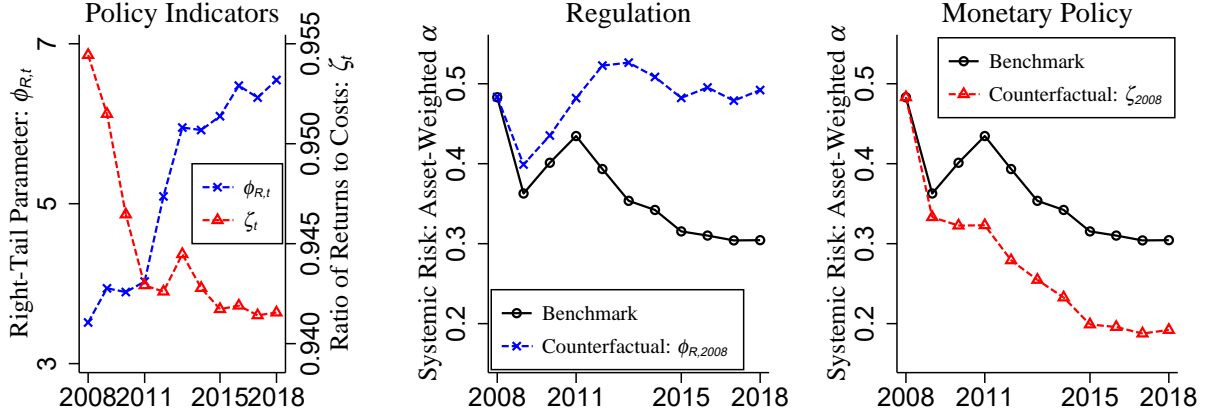
Figure 10: Counterfactual Analysis - Systemic Risk and Central Bank Policy: The first figure plots the estimated right tail parameter ($\hat{\phi}_{R,t}$) and the ratio of expected returns to costs ($\hat{\zeta}_t = \hat{\phi}_{s,t}(\hat{\phi}_{c,t})^{-1/\hat{\phi}_{p,t}}$). The second and third figures plot the estimated systemic risk measure (asset-weighted mean of risk-taking) and its counterfactual values. The solid black lines are implied from the data and the estimates. The blue dash line with crosses is implied with the fixed value of the right tail index of risk-taking behavior ($\tilde{\phi}_{R,t} = \hat{\phi}_{R,2008}$). The red dash line with triangles is implied with the fixed value of the ratio of the expected returns of asset to the cost of funds ($\tilde{\phi}_{s,t} = \hat{\zeta}_{2008}(\hat{\phi}_{c,t})^{1/\hat{\phi}_{p,t}}$).

Figure 10 reports the benchmark systemic risk measures (solid black line with circles) and their counterfactual counterparts. As the solid black line with circles in the middle and right panels shows, financial instability measured by systemic risk decreased after the financial crisis. On the left pane of Figure 10, we also show the evolution of the estimated $\phi_{R,t}$ and ζ_t in this period. The right tail parameter has trended upwards since the financial crisis, indicating less concentration at the top of the risk-taking distribution. This could be due to the tightening of the post-crisis regulatory environment, including the implementation of Basel III. The transition from 2008 to 2018 involves the right tail becoming steadily thinner. Figure 9 shows that the distributional changes are not due to changes in the class or left-tail parameter, as the middle and right panel distributions are extremely similar to the estimated ones in the left panel. Keeping the class or left tail parameters fixed at 2008 levels does not impact our systemic risk measure. Coming back to Figure 10, the spread ζ_t fell steadily in the years after the crisis and up to 2014. This indicates a loosening of funding conditions

27

during this period, at which point it stabilized and even rose slightly but remained at much lower levels than in 2008.

In the first counterfactual, we set the right tail parameter that governs risk behavior to remain after the crisis at our 2008 estimates. The question we ask is therefore: "what would have happened *ceteris paribus* to systemic risk if the precrisis lax regulatory policies had stayed the same post crisis?". The answer can readily be seen on the second panel of Figure 10 which reports the counterfactual systemic risk measure (in blue) next to the benchmark (in black). With a fixed right tail, systemic risk measures during 2011 and 2018 would be very similar to that of 2008 and, more generally, consistently above the benchmark. Without bank regulation, financial markets would struggle with instability which would remain near their 2008 peak. Financial stability improvements after the financial crisis were thus driven strongly by changes in the distribution tracked by the tail parameter and concerning high-risk intermediaries. Banking regulation constraining risk-taking in the right tail has been effective.

In the second counterfactual, we keep the *spread*, i.e., the ratio of expected returns on assets to costs of funds, equal to our 2008 estimates. The question we ask is therefore: "what would have happened *ceteris paribus* to systemic risk if the 2008 funding conditions had stayed the same instead of the very loose post 2009 monetary policy?".[29]

The right panel of Figure 10 shows the benchmark measure of systemic risk (in black) with the counterfactual measure reflecting tighter funding conditions (in red). The 2018 benchmark systemic risk measure is considerably larger than that of 2018 counterfactual. Without the expansionary monetary policy, financial markets would be more stable, as can be seen by the counterfactual systemic risk measure being consistently below the benchmark case. This illustrates the trade-off that monetary policy faces between stimulating the economy (low-interest rate) and financial stability. A fall in interest rates gives an incentive for intermediaries to take on more risk, which increases investment but also systemic risk. It is important to note that our counterfactual systemic risk measure drops below the sample

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[29]Table A7 report the counterfactual exercises with the highest and lowest level of the right tail parameter ($\phi_{R,t}$)/ the ratio of expected returns to costs (ζ_t) between 1993 and 2018.

minimum, which may not be desirable. Financial markets need a healthy degree of risk-taking to function normally. It is not only possible but likely that financial markets would have been too risk-averse with both tighter regulation and tighter funding conditions. It is important to note that we do not believe that the lower values of our measure are always better; rather, values approaching the higher end of the sample indicate that financial stability concerns should be taken seriously. These results point to the importance of regulating and monitoring high-risk financial intermediaries. They also advocate for a degree of complementarity between monetary policy and macroprudential policies.

7. Conclusion

Financial stability and systemic risk have become essential concerns for monetary authorities worldwide. Measuring and tracking the financial system's stability requires indicators that reflect the degree of risk-taking among intermediaries. Although simple observable measures like leverage or credit growth can already provide meaningful information, they do not always track balance sheet risk. Credit growth can be driven by many different causes, such as, for example, more substantial investment opportunities or a fall in the cost of funds. Given observed aggregate credit and leverage growth, the implications for financial stability might be very different depending on the main driving cause.

In this paper, we make use of bank-level leverage data and a structural model to extract a distribution of intermediary risk-taking parameters. We use a simple Value-at-Risk (VaR) framework in which intermediaries endogenously choose leverage based on macroeconomic conditions (cost of funds, expected returns, and their volatility) and their characteristics. By exploiting the cross-sectional dynamics of leverage in the data, we are able to distinguish between different types of leverage booms and their implications for systemic risk. This way, we are able to infer macroeconomic and financial conditions without the need of additional variables. We show that our structural estimate of uncertainty is consistent with measures of long-run risk and that our risk-taking measures help predict the probability of intermediary

distress/failure as well as its economic performance, including its cyclical and cross-sectional dynamics.

Using our estimates, we construct a simple measure of systemic risk by weighting bank-level risk-taking by its balance sheet size. This measure corresponds intuitively to the probability that a certain amount of assets are held by distressed investors. The measure rises significantly in the period before the financial crisis, peaks in 2008 and decreases going forward except before the euro area crisis. The weights serve an essential function because the measure reflects that growth in risk-taking among large intermediaries is more worrying than growth among smaller ones. They also allow us to highlight the importance of heterogeneity across financial intermediaries, as we can decompose the contribution to systemic risk of changes in average risk-taking and those arising from the heterogeneity around the mean. We show that heterogeneity within the financial sector plays a fundamental role in financial stability. The heterogeneous component drives most of the changes in our systemic risk measure. In contrast, the average component lags the crisis and is therefore not a good predictor by itself. Using a similar decomposition, we also show that changes in the systemic risk measure are driven mainly through banks in the top quantiles, particularly the top 5% contributing up to 71% of the variance in the recent decades.

Finally, we explore different counterfactuals in order to highlight the important complementarity between monetary policy and financial regulation. Our first exercise shows that if regulation had not compressed the concentration of risk at the top of the distribution after the crisis, then systemic risk would have been post-crisis at much higher levels due to loose funding conditions. The counterfactual measure of systemic risk would have been closer to the 2008 crisis peak throughout the 2010s. In the second exercise, we show that loose monetary conditions tended to increase systemic risk after 2009; but they did not increase systemic risk significantly because of tighter macroprudential regulation.

To conclude, this paper provides empirical estimates of risk-taking at the financial intermediary level. It then constructs a measure of systemic risk that uses the heterogeneity

in the cross-section of leverage to distinguish different types of leverage cycles. It can be used as an advance warning measure for macroprudential policies. Policy-makers can also use it to investigate the complementarity between monetary policy and macroprudential policies by constructing counterfactuals. First and foremost, it reveals the vital interplay between regulation and monetary policy, which determines financial stability.

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Appendix

A. Data Construction

We use annual bank (consolidated) balance sheet data from the Compustat Fundamentals Annual (North America, 1993 – 2018) databases via WRDS. Figures A2 – A4 in Appendix B present the number of observations and summary statistics of assets, equity, leverage, returns on assets and equity for the cleaned data by period.

We construct the database as follows. First, we keep the following observations.

- Consolidated: $\mathtt{consol} = \mathrm{C}$.

- USD currency: $\mathtt{curcd} = \mathrm{USD}$.

- Not old entity: bank name ($\mathtt{conm}$) is not tagged by OLD.

- No major mergers flag: Comparability status ($\mathtt{compst}$) does not equal to AB.

Then, we we exclude financial intermediaries with the following criteria.

- Leverage is smaller than one: $\mathtt{at}_{i,t}/(\mathtt{at}_{i,t} - \mathtt{lt}_{i,t}) \le 1$.

- Extreme leverage (above 200): $\mathtt{at}_{i,t}/(\mathtt{at}_{i,t} - \mathtt{lt}_{i,t}) \ge 200$.

- Non-positive assets — total: $\mathtt{at}_{i,t} \le 0$.

- Non-positive common/ordinary equity — total: $\mathtt{ceql}_{i,t} \le 0$.

- Non-positive common equity — tangible: $\mathtt{ceqt}_{i,t} \le 0$.

- Low assets (below 1 billion USD on average): $(1/T_i) \sum_t \mathtt{at}_{i,t} \le 1000$

- Low equity (below 1 million USD): $\mathtt{at}_{i,t} - \mathtt{lt}_{i,t} \le 1$

- High repurchase agreements ratio to assets (above 0.9) ($\mathtt{ceqt}_{i,t}/\mathtt{at}_{i,t} \ge 0.9$)

Lastly, for ML estimation, we calculate the bottom ten (or five) percentile of leverage based on the whole sample of database from 1993 and to 2018 (not each year). Then, we drop all observations below the bottom ten percentile in our MLE procedure. In measuring systemic risk and doing counterfactual exercises, we do not exclude the bottom percentile.

Then, we calculate variables as follows.

- Assets: `at`

- Liability: `lt`

- Equity: `at` − `lt`

- Leverage: `at`/(`at` − `lt`)

- RoA: `ib`/`at`

- RoE: `ib`/(`at` − `lt`)

To calculate annual stock returns, we collect monthly total returns (`trt1m`) from the Compustat Security Monthly (North America, 1992 – 2018). Then, we calculate stock returns in a fiscal year. We merge stock return data using `cusip` and `datadate`.

B.   Additional Figures and Tables
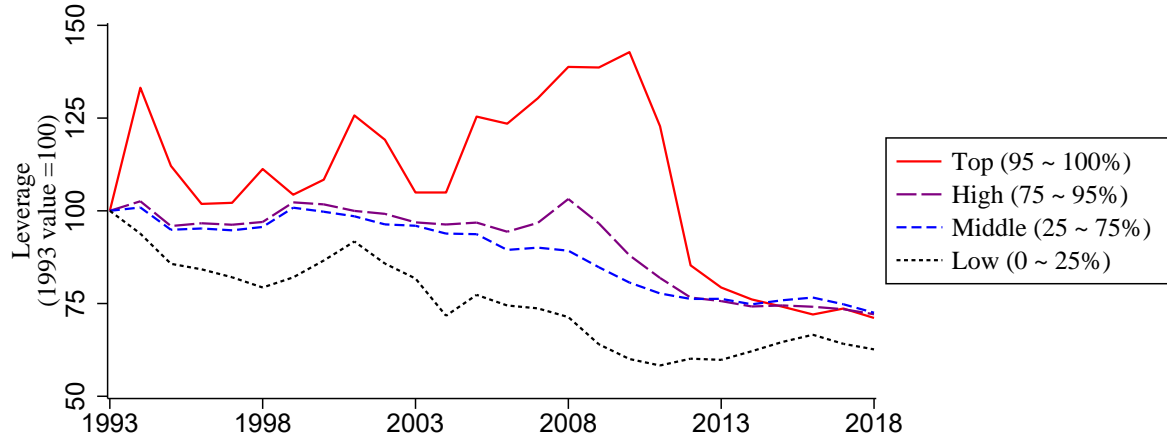
Figure A1: Evolution of unweighted leverage quantiles: The figure plots the average of the unweighted leverage's quantiles. Values were rebased to 100 for the starting year 1993, to highlight the stark difference in dynamics.
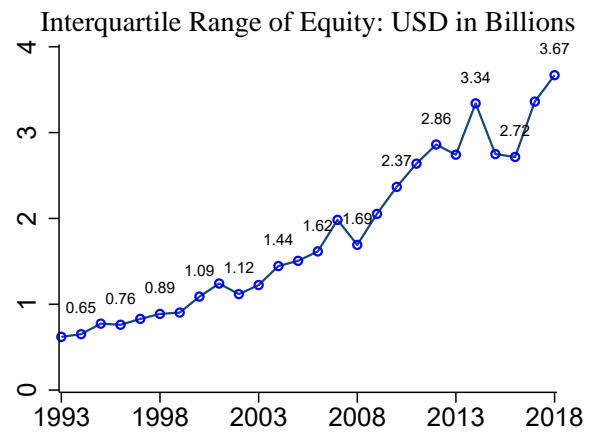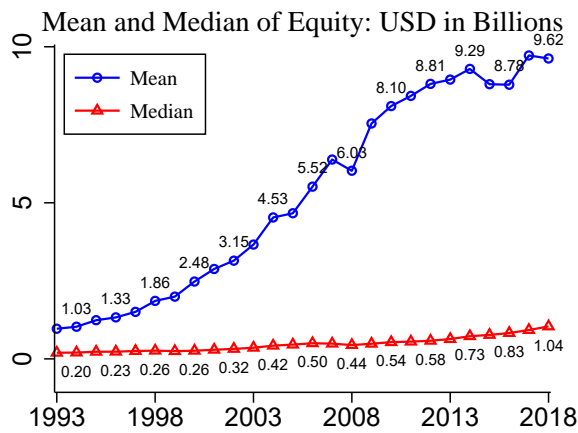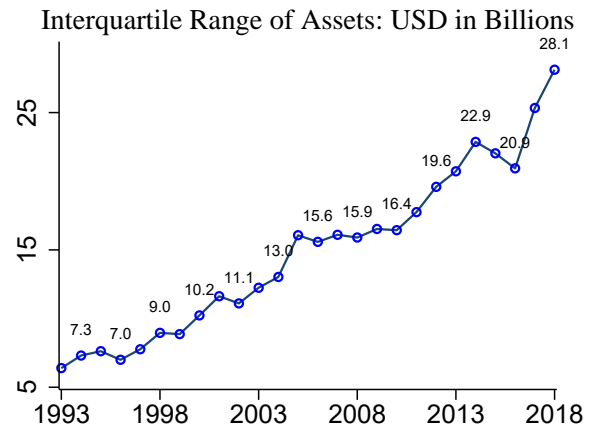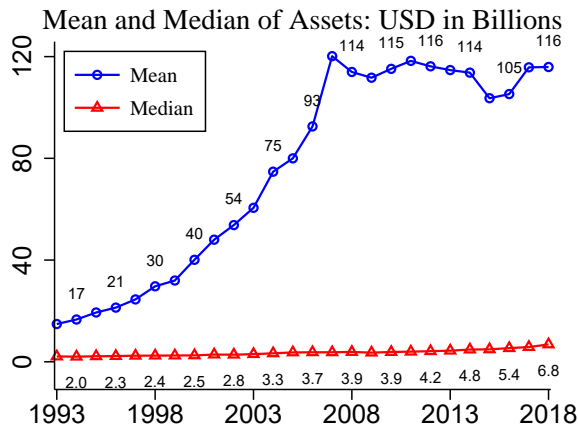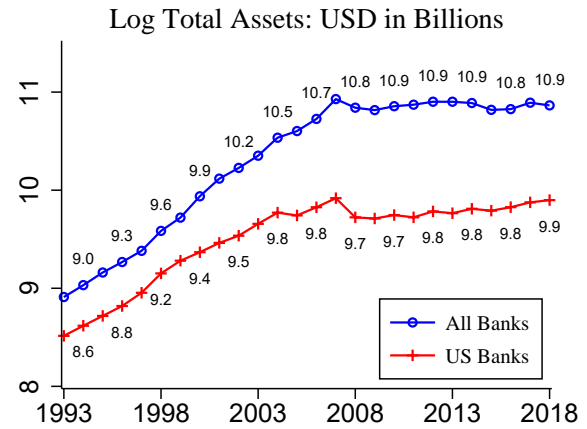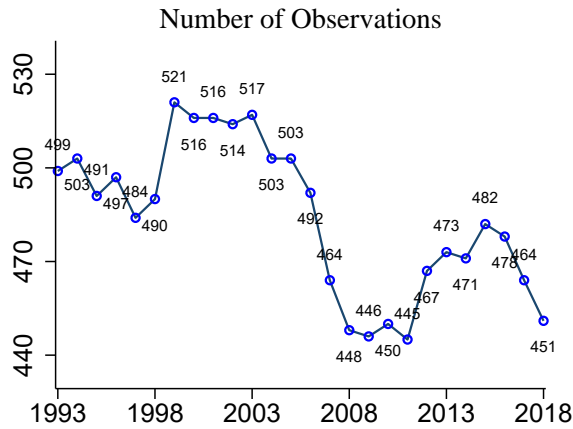
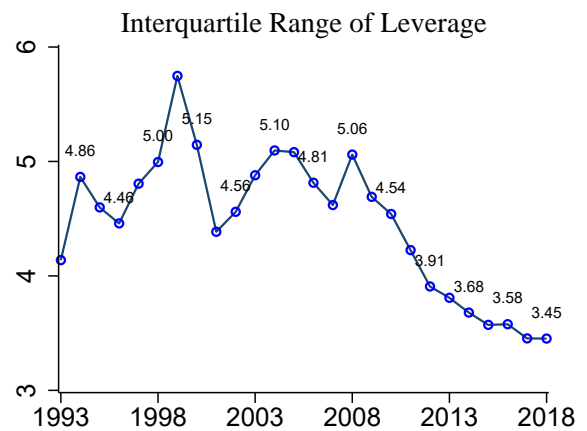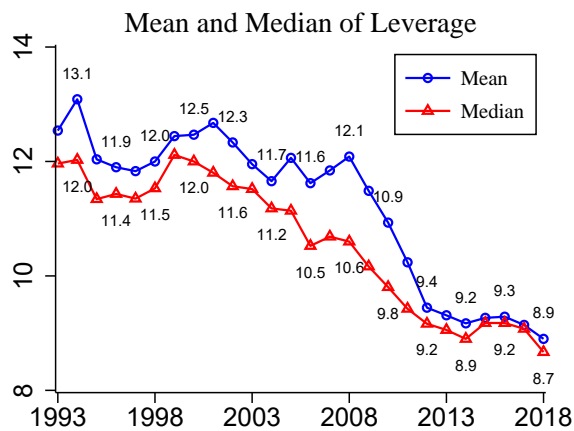**Figure A2: Summary Statistics I: Number of Observations, Assets, and Equity**
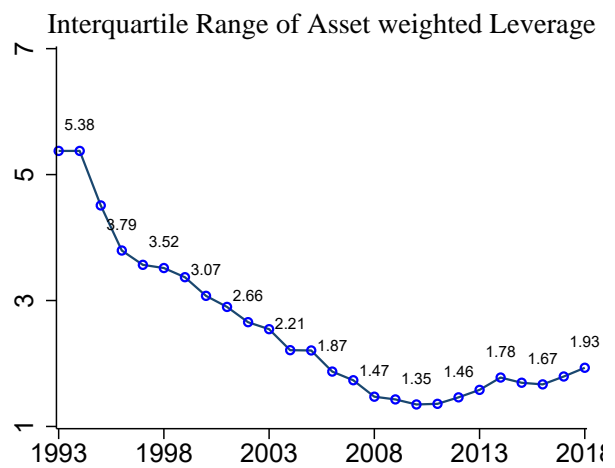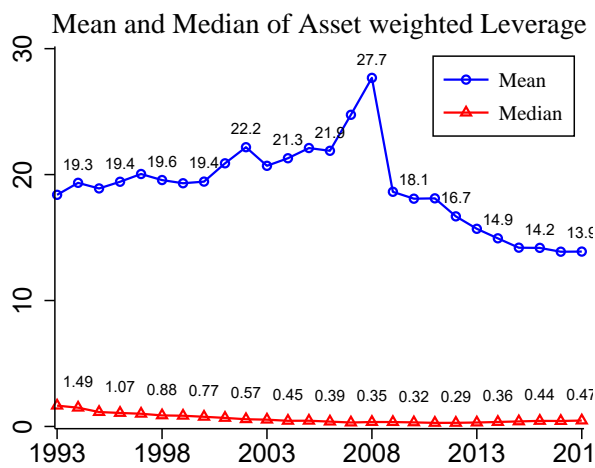
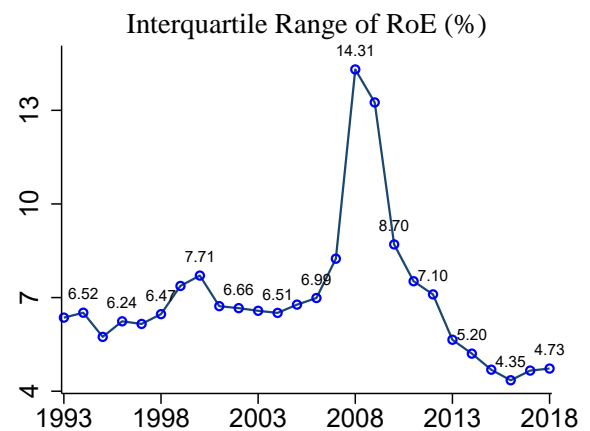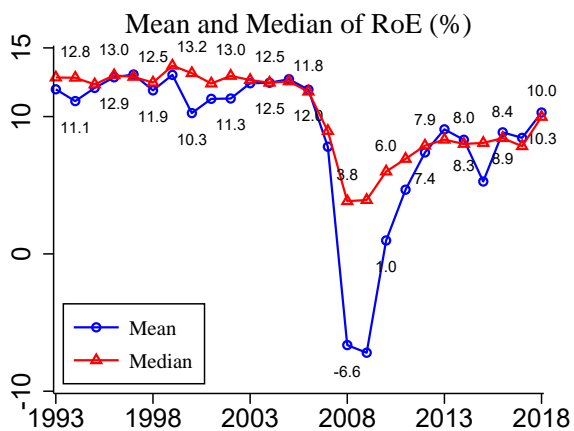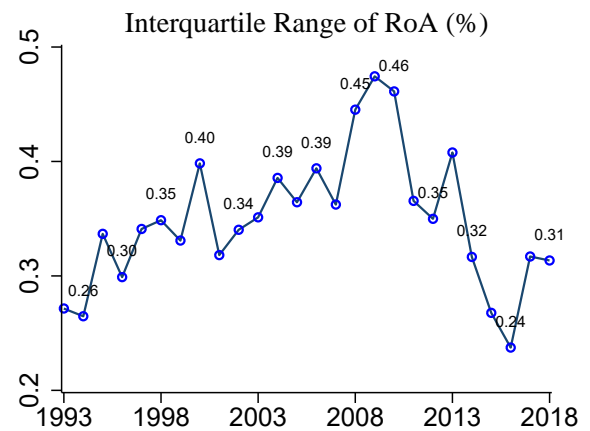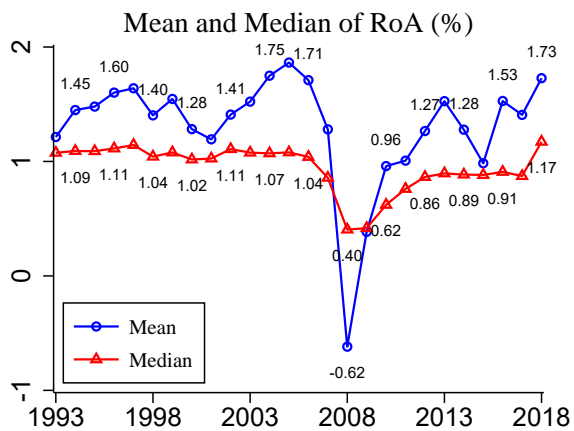**Figure A3: Summary Statistics II: Leverage and Asset-Weighted Leverage**

Figure A4: Summary Statistics III: Returns on Asset and Returns on Equity
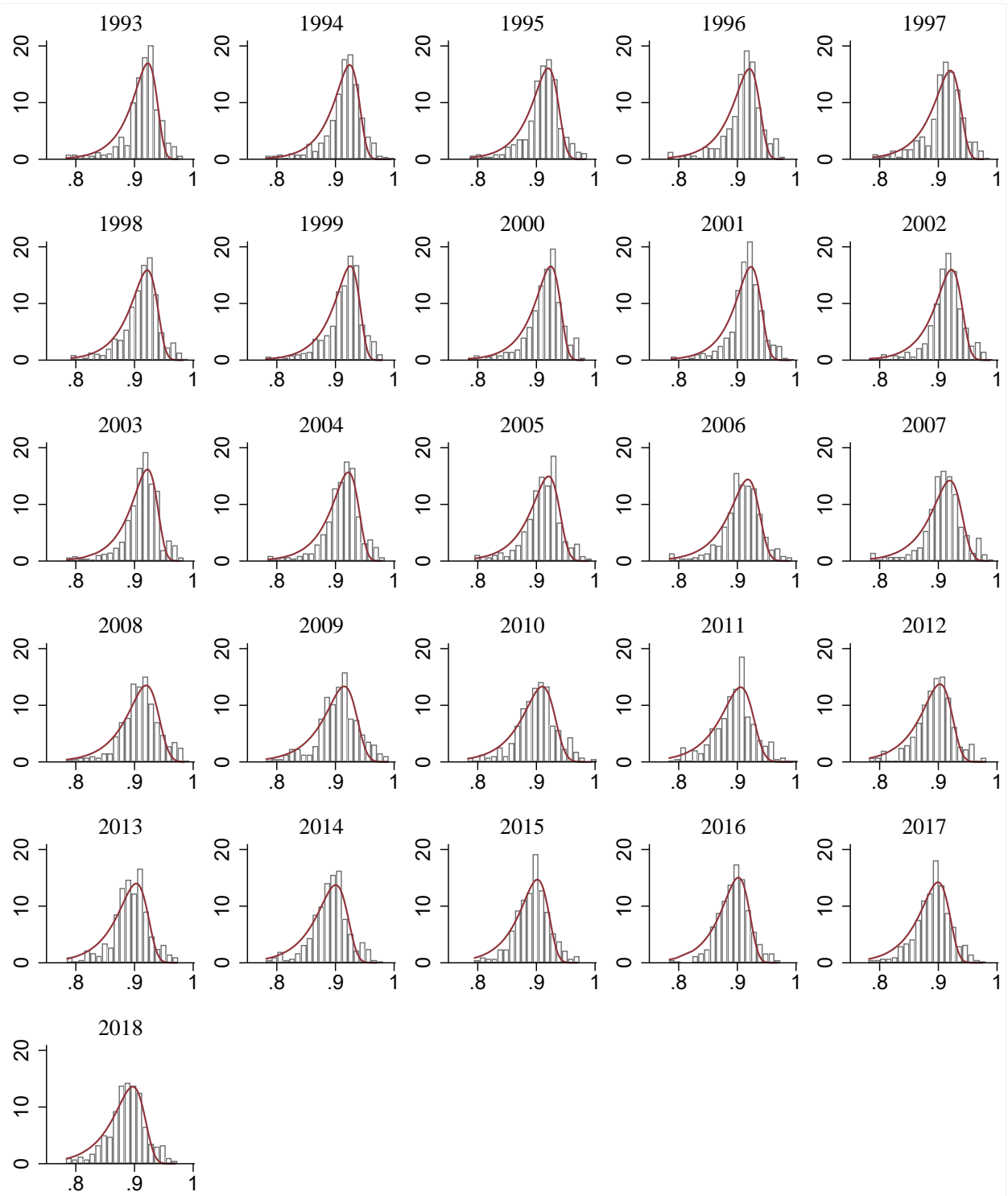
Figure A5: Estimated PDFs of Debt-to-Asset Ratio with Histograms: The red line plots the estimated probability density functions of debt-to-asset ratio with histograms (the width of bins to be 0.01). In this figure, we plot the debt-to-asset ratio by the bottom 10% (around 0.77).
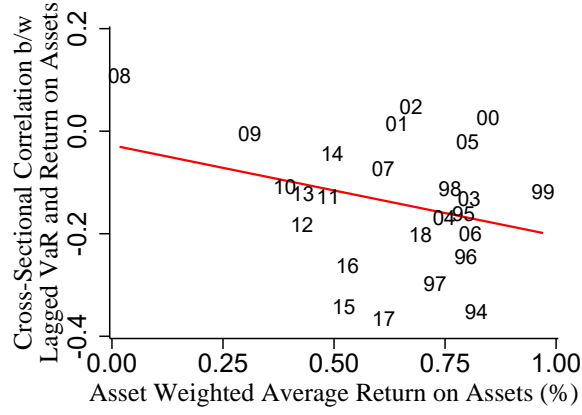
Figure A6: Risk-Taking Behavior and Return on Assets: The figures plot each year cross-sectional correlation between a bank's lagged risk-taking measure ($\alpha_{i,t}$) and its return on assets (the y-axis) and each period average return on assets of banks weighted by the assets (the x-axis).
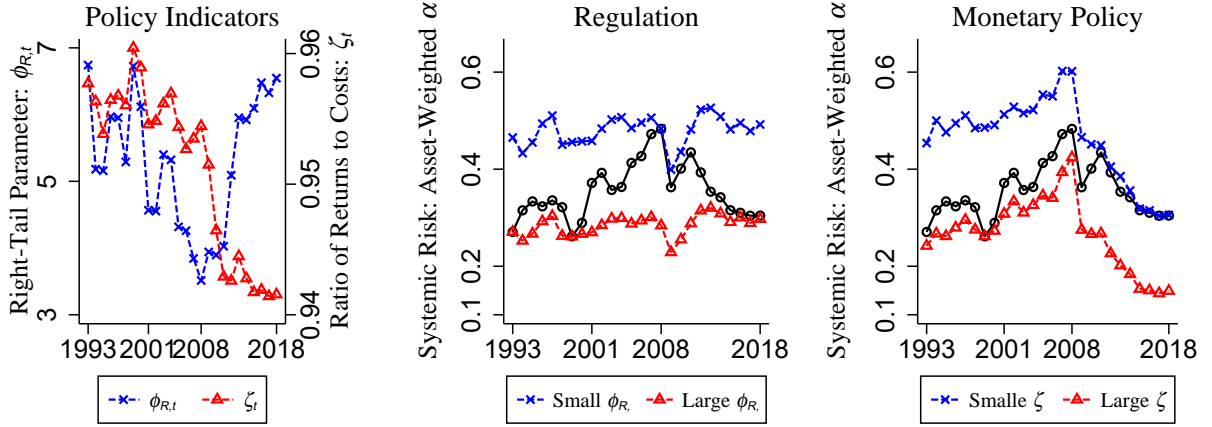

Figure A7: Systemic Risk and Counterfactuals: The figure plots estimated systemic risk measure (asset weighted mean of risk-taking) and its counterfactual values. The solid black lines with circles are implied from the data and the estimates. In the first figure, the blue dash lines with crosses and red dash lines with triangles are implied with the smallest (2008) and largest (1993) values of the estimated right tail index of risk-taking behavior ($\tilde{\phi}_{R,t}$), respectively. In the second figure, the blue and red dash lines are implied with the smallest (2017) and largest (1999) values of the estimated the ratio of the expected returns of capital to the costs of funds ($\tilde{\zeta}_t$), respectively.

Table A1: Lists of the Top 20 Largest and Most Risk-Taking Banks

Bank Name	Year: 2006			Year: 2008			Year: 2010		
	Rank	Size	Leverage	Rank	Size	Leverage	Rank	Size	Leverage
Panel A. Top 20 Largest Banks (Assets)									
NATWEST GROUP PLC	6	3.75	19.16	1	6.88	29.83	7	4.32	18.91
DEUTSCHE BANK AG	9	3.26	34.33	2	6.00	69.01	2	4.88	37.82
BARCLAYS PLC	2	4.29	36.39	3	5.88	43.30	5	4.42	23.93
BNP PARIBAS	3	4.17	26.27	4	5.66	35.20	1	5.11	23.34
HSBC HLDGS PLC	5	4.09	16.19	5	4.95	25.22	3	4.73	15.85
JPMORGAN CHASE & CO	11	2.97	11.67	6	4.26	13.03	8	4.08	12.02
MITSUBISHI UFJ FINANCIAL GRP	8	3.48	16.45	7	3.82	29.92	4	4.74	23.40
CITIGROUP INC	4	4.14	15.73	8	3.80	13.69	10	3.69	11.54
UBS GROUP AG	1	4.31	42.97	9	3.70	49.39	16	2.71	25.40
ING GROEP NV	7	3.55	29.75	10	3.63	46.03	12	3.19	26.37
BANK OF AMERICA CORP	10	3.20	10.79	11	3.56	10.27	6	4.37	9.92
SOCIETE GENERALE GROUP	14	2.77	28.62	12	3.08	27.64	15	2.90	22.21
MIZUHO FINANCIAL GROUP INC	13	2.80	22.29	13	3.02	36.48	9	3.75	24.28
BANCO SANTANDER SA	16	2.42	17.71	14	2.86	17.49	13	3.12	15.05
WELLS FARGO & CO	31	1.06	10.51	15	2.57	13.22	17	2.43	9.84
SUMITOMO MITSUI FINANCIAL GR	18	1.88	18.92	16	2.36	25.94	11	3.21	19.32
CREDIT SUISSE GROUP	17	2.26	21.32	17	2.15	24.78	18	2.13	23.99
GOLDMAN SACHS GROUP INC	21	1.84	20.67	18	1.73	13.40	19	1.76	11.65
BBVA	28	1.19	18.46	19	1.48	20.32	21	1.41	14.75
MERRILL LYNCH & CO INC	20	1.85	21.55	20	1.31	33.37	23	1.20	12.40
Column Average	12.2	2.97	21.99	10.5	3.63	28.88	11	3.41	19.10
Panel B. Top 20 Most Risk-Taking Banks (Asset-Weighted VaR Parameter)									
DEUTSCHE BANK AG	5	3.26	34.33	1	6.00	69.01	1	4.88	37.82
BARCLAYS PLC	2	4.29	36.39	2	5.88	43.30	4	4.42	23.93
NATWEST GROUP PLC	9	3.75	19.16	3	6.88	29.83	7	4.32	18.91
BNP PARIBAS	3	4.17	26.27	4	5.66	35.20	2	5.12	23.34
UBS GROUP AG	1	4.32	42.97	5	3.70	49.39	8	2.71	25.40
ING GROEP NV	4	3.55	29.75	6	3.63	46.03	6	3.19	26.37
HSBC HLDGS PLC	13	4.09	16.19	7	4.95	25.22	12	4.74	15.85
MITSUBISHI UFJ FINANCIAL GRP	16	3.48	16.45	8	3.82	29.92	3	4.73	23.40
MIZUHO FINANCIAL GROUP INC	10	2.80	22.29	9	3.02	36.48	5	3.75	24.28
SOCIETE GENERALE GROUP	7	2.77	28.62	10	3.08	27.64	9	2.90	22.21
SUMITOMO MITSUI FINANCIAL GR	22	1.88	18.92	11	2.36	25.94	11	3.21	19.32
CREDIT SUISSE GROUP	12	2.26	21.32	12	2.15	24.78	13	2.13	23.99
LLOYDS BANKING GROUP PLC	14	1.48	29.86	13	1.25	44.96	10	2.94	21.14
DANSKE BANK AS	23	1.07	28.78	14	1.30	36.07	15	1.10	30.68
MERRILL LYNCH & CO INC	17	1.85	21.55	15	1.31	33.37	32	1.20	12.40
BANCO SANTANDER SA	21	2.42	17.71	16	2.86	17.49	14	3.12	15.05
BBVA	27	1.19	18.46	17	1.48	20.32	20	1.41	14.75
CITIGROUP INC	15	4.14	15.73	18	3.80	13.69	19	3.69	11.54
SANTANDER UK PLC	24	0.83	61.55	19	0.66	48.17	16	0.90	24.67
JPMORGAN CHASE & CO	32	2.97	11.67	20	4.26	13.03	18	4.09	12.02
Column Average	13.85	2.83	25.90	10.5	3.40	33.49	11.25	3.23	21.35

Note: The size is defined by percentage share (%) of a bank's assets in total assets of each year sample. In Panels A and B, the ranks are based on the size and asset-weighted VaR parameter, respectively, in each year.

Table A2: Summary Estimates of Distribution

	Mean	S.D.	Min	Max	Quartiles 25%	50%	75%
Full Period: 1993 − 2018							
ϕ_{pt}: power	67.231	7.556	57.168	80.062	59.624	66.322	73.057
ϕ_{st}: scale	0.951	0.006	0.941	0.960	0.942	0.953	0.956
ϕ_{ct}: class	0.964	0.008	0.942	0.978	0.960	0.964	0.970
ϕ_{Lt}: left-tail shape	0.410	0.019	0.364	0.434	0.395	0.417	0.424
ϕ_{Rt}: right-tail shape	5.276	1.001	3.515	6.742	4.318	5.307	6.094
Period I: 1993 − 2000							
ϕ_{pt}: power	75.786	3.103	72.499	80.062	72.969	75.428	78.466
ϕ_{st}: scale	0.957	0.002	0.953	0.960	0.956	0.956	0.958
ϕ_{ct}: class	0.965	0.003	0.962	0.970	0.962	0.964	0.968
ϕ_{Lt}: left-tail shape	0.386	0.012	0.364	0.406	0.383	0.384	0.392
ϕ_{Rt}: right-tail shape	5.892	0.641	5.159	6.742	5.236	5.960	6.421
Period II: 2001 − 2008							
ϕ_{pt}: power	68.007	5.047	59.603	73.363	64.039	69.386	72.120
ϕ_{st}: scale	0.954	0.001	0.952	0.956	0.953	0.954	0.955
ϕ_{ct}: class	0.958	0.008	0.942	0.968	0.955	0.959	0.964
ϕ_{Lt}: left-tail shape	0.415	0.010	0.402	0.431	0.407	0.414	0.422
ϕ_{Rt}: right-tail shape	4.472	0.653	3.515	5.400	4.052	4.435	4.945
Period III: 2009 − 2018							
ϕ_{pt}: power	59.765	1.938	57.168	63.380	58.160	59.393	60.621
ϕ_{st}: scale	0.943	0.003	0.941	0.951	0.941	0.942	0.944
ϕ_{ct}: class	0.969	0.008	0.951	0.978	0.966	0.970	0.975
ϕ_{Lt}: left-tail shape	0.425	0.006	0.415	0.434	0.420	0.425	0.430
ϕ_{Rt}: right-tail shape	5.427	1.093	3.895	6.546	4.027	5.937	6.327

Table A3: Risk-Taking Behavior and Stock Returns: Bull vs Bear Markets

	One Year Ahead Excess Stock Returns: $r_{i,t+1}^{\text{stock}} = r_{i,t+1}^{\text{stock}} - \bar{r}_{t+1}^{\text{stock}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	$\bar{r}_{t+1}^{\text{stock}} > 0$	$\bar{r}_{t+1}^{\text{stock}} \leq 0$	$\bar{r}_{t+1}^{\text{stock}} > 0$	$\bar{r}_{t+1}^{\text{stock}} \leq 0$	$\bar{r}_{t+1}^{\text{stock}} > 0$	$\bar{r}_{t+1}^{\text{stock}} \leq 0$
VaR parameter (log)	1.00***	0.00	1.97***	0.36*	1.69***	0.25***
	(0.30)	(0.10)	(0.32)	(0.20)	(0.03)	(0.02)
Other Controls	No	No	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	No
Year-Bank Type FE	No	No	No	No	Yes	Yes
Year-Country FE	No	No	No	No	Yes	Yes
Observations	5616	2461	4755	2074	4583	1998
R-squared	0.28	0.36	0.39	0.44	0.49	0.52

Note: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors (in parentheses) are clustered at the country-bank type level. Singleton observations are dropped in all regressions. The estimation is based on equation (7). The dependent variable is the excess stock return. Other controls are dividend yield, a book to market ratio, and asset size in logs.