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ABSTRACT

The largest commercial bank stocks, measured by book value, have significantly lower risk-adjusted returns than small- and medium-sized bank stocks, even though large banks are significantly more levered. We find a size factor in the component of bank returns that is orthogonal to the standard risk factors. This size factor, which has the right covariance with bank returns to explain the average risk-adjusted returns, measures size-dependent exposure in banks to bank-specific tail risk. The variation in exposure can be attributed to differences in the financial disaster recovery rates between small and large banks. A general equilibrium model with rare bank disasters can match these alphas in a sample without disasters provided that the difference in disaster recovery rates between the largest and smallest banks is 35 cents per dollar of dividends.

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Banks are different from non-financial firms in many ways. One of the most salient distinctions is that banks are subject to bank runs during banking panics and crises, not just by depositors, but also by other creditors (see Gorton and Metrick (2009) and Duffie (2010)). Because financial crises are high marginal utility states for the average investor, the expected return on bank stocks should be especially sensitive to variation in the anticipated financial disaster recovery rates of bank shareholders related to bank size, the regulatory regime, implicit government guarantees and other characteristics. For example, if a bank is deemed too-big-to-fail, its expected return would be lower in equilibrium than that of smaller banks holding the exact same assets in their portfolio, as the government absorb some of the large bank's tail risk. We find evidence that the pricing of bank-specific tail risk held in financial markets depends on all of these bank characteristics.

To explore the asset pricing implications of financial disasters, our paper studies historical bank stock returns in the U.S. We find that there is a size effect in bank stock returns that is different from the market capitalization effects that have been documented in non-financial stock returns (see Banz (1981) and many others). All else equal, a 100% increase in a bank's book value lowers its annual return by 2.45% per annum. For non-financial stocks, there is no similar relation between book value and returns (Berk (1997)).

These return differences cannot be imputed to differences in standard risk exposure. A long position in the stock portfolio of largest commercial banks, measured by deciles of total book value, and a short position in the stock portfolio of the smallest banks under-performs an equally risky portfolio of all (non-bank) stocks and government and corporate bonds by more than 5.85% per annum. The average alphas are large and positive for commercial banks in the first five deciles and then decrease for the largest banks in the top three deciles.

Small banks differ from large banks in many ways, but these differences should not lead to differences in average risk-adjusted returns on bank portfolios unless there is bank-specific tail risk that is priced but not spanned by the traded returns on other stocks in the sample. We found evidence of such a risk factor in bank stock returns: The second principal component (p.c.) of the risk-adjusted returns on size-sorted portfolios of commercial banks is a size factor that has the exactly the right covariance with the portfolio returns to account for most of this pricing anomaly. By construction, this size factor is orthogonal to the stock and bond risk factors.

This size portfolio, determined by the second p.c., which goes long in small bank stocks and short in large bank stocks, loses an average of 61 cents during NBER (National Bureau of Economic Research) recessions per dollar invested at the start, after hedging out exposure to standard stock and bond risk. We attribute the cyclical banking size factor in the data to size-dependent differences in the perceived shareholder recovery rates on these bank portfolios during financial disasters.

In a version of the Barro (2006), Rietz (1988) and Longstaff and Piazzesi (2004) asset pricing model with a time-varying probability of rare events, developed by Gabaix (2008), Wachter (2008), and Gourio (2008), financial disasters which disproportionately impact bank cash flows contribute an additional bank-specific risk factor. These rare events are priced into expected returns on portfolios of banks, but are not fully spanned by the returns on other assets in a small sample. A general equilibrium version of our model that is calibrated to match the equity premium can match the average alphas in a sample without disasters if the financial disaster recovery rate is 35 cents higher for large banks, in line with the failure rate of banks in the lowest decile during the latest crisis.

Historically, the probability of a financial disaster increases during recessions. Because of the size-contingent nature of the the recovery rate for bank stockholders in case of a financial disaster, the variation in the probability of a financial disaster generates a common business cycle factor in the normal-risk-adjusted returns of size-sorted bank stock portfolios; the loadings of bank stock portfolio returns on this size factor are determined by the recovery rates and hence by size. Small banks have positive loadings while large banks have negative loadings. As the probability of a financial disaster increases, the expected return gap between small and large banks grows.

Shareholder recovery rates for banks depend on size. During financial disasters, large banks fare much better, even though they are more levered than their smaller counterparts. A total of 30% of publicly traded commercial banks in the first size decile were delisted in 2009 alone although there were none in the last decile. During the recent U.S. financial crisis, the size portfolio of commercial banks, hedged against exposure to commercial banks, lost 90 cents per dollar invested at the start of the crisis, while the same hedged size portfolio of all banks lost all of its value during the Great Depression.

To back out the implicit financial tail risk premium or discount charged by the shareholders of commercial banks, we multiply the loadings on the size factor by its market risk price. The implicit insurance provided against financial disaster risk lowers the expected equity return for the largest U.S. commercial banks by 3.10%, but the additional exposure to bank-specific tail risk increases the expected return on the smallest bank stocks by 3.25%, compared to a portfolio of non-bank stocks and bonds with the same standard risk characteristics. The largest banks have an average market capitalization of $152 bn in 2005 dollars.[1] For the largest commercial banks, this amounts to an annual savings of $4.71 bn per bank. The market imposes large financial tail risk 'subsidies' ('taxes') on large (small) bank stocks compared to a portfolio of stocks and bonds with the same observed risk profile. There is direct evidence from option markets: Kelly, Lustig, and Nieuwerburgh (2011) find that out-of-the-money put options on large banks were cheap during the crisis.

The pricing of financial tail risk depends not only on bank size. We relate the financial disaster premium of banks to the regulatory regime. Commercial banks, who have access to the discount window and benefit from deposit insurance, and Government-sponsored enterprises (GSE), who benefit from an explicit guarantee, are imputed a large financial tail risk subsidy while investment and foreign banks are not. On the other hand, hedge funds are imputed a financial tail risk tax, just like small banks.

After the repeal of key provisions in the Glass-Steagall Banking Act in 1999, we find large across-the-board increases in the size of the subsidy for large commercial, investment banks and GSE. For example, the Fannie Mae subsidy tripled to 6.57% in 2000-2005. This period also coincides with the dramatic growth in securitization, which allows financial institutions to benefit from the collective bailout option more aggressively by eliminating idiosyncratic risk exposure (see Brunnermeier and Sannikov (2008) for a clear description of this effect of securitization).

[1]This number only includes the market capitalization of the commercial bank, not the bank holding company.

Furthermore, we provide a direct link to bailouts; we show that the financial disaster subsidy of the largest 10 banks increases immediately after bailout announcements. O'Hara and Shaw (1990) document large positive wealth effects for shareholders of banks who were declared 'too-big-to-fail' by the Comptroller of the Currency in 1984, and negative wealth effects for those banks that were not included. Consistent with this, we document large increases in the implicit financial disaster subsidy to these too-big-to-fail banks after this announcement, and six other bailout announcements prior to the recent financial crisis that were identified by Kho, Lee, and Stulz (2000). Furthermore, we find large increases after announcements that benefited large banks during the recent financial crisis as well.

The rest of this paper is organized as follows. The first section discusses the related literature. In Section II we construct portfolios of commercial U.S. bank stocks sorted by size. Section III describes the size effect in bank stock returns. Section IV establishes that there is a pro-cyclical size factor in the normal-risk-adjusted returns of these portfolios. Section V relates the pricing of bank tail risk to government announcements and the regulatory environment. We use a calibrated version of the model to back out the implied differences in recovery rates in section VI. Section VII concludes.

I Related Literature

There is obviously a large literature on size effects in stock returns (see Banz (1981), Basu (1983), Lakonishok, Shleifer, and Vishny (1993), Fama and French (1993), Berk (1995) and others), but most of these papers actually do not include financial stocks, presumably because of their high leverage. Our paper is the first to document that the size effect in financial stocks is really about size, rather than market capitalization. We attribute the size effect to how tail risk is priced in financial stocks.

There is direct evidence from option markets that tail risk in the financial sector is priced differently. Kelly, Lustig, and Nieuwerburgh (2011) find that the out-of-the-money index put options of bank stocks were relatively cheap during the recent crisis, as a consequence of the government absorbing sector-wide tail risk. In related work on bank stock returns, Fahlenbrach, Prilmeier, and Stulz (2011) document that those banks which incurred substantial losses during previous crises were more likely to incur losses during the recent crisis. If some banks benefit from a larger perceived tail risk subsidy, they have an incentive to load up on this type of risk risk. In fact, shareholder value maximization requires that they do so, as pointed out by Panageas (2010a) who analyzes optimal risk management in the presence of guarantees. Interestingly, Fahlenbrach and Stulz (2011) find some evidence that banks whose managers' interests were more aligned with shareholders actually performed worse during the recent financial crisis.

Our work contributes to the important task of measuring systemic risk in the financial sector. Acharya, Pedersen, Philippon, and Richardson (2010), Adrian and Brunnermeier (2010) and Huang, Zhou, and Zhu (2011) develop novel methods for measuring systemic risk. Our measure of the banking tail risk premium is determined by the bank's loading on the size factor, which gauges a firm's systemic risk exposure. Firms that are deemed systemically important have large negative loadings on the size factor, because these are less likely to be allowed to fail in the event of a financial disaster, and they trade at a premium as a result. As far as we know, our paper is the first to link the subsidy that accrues to banks who are deemed systemically important with exposure to systemic risk. To the extent that these differences in bank tail risk pricing are directly attributable to government policies, they are an ex ante measure of the distortion created by the implicit guarantee extended to some U.S. financial institutions.[2]

Why study the effect of bailouts on bank equity? The anticipation of future bailouts of bondholders and other creditors always benefits shareholders (see Kareken and Wallace (1978)) ex ante. Furthermore, during the crisis, there may be massive uncertainty about the resolution regime, especially for large financial institutions. As a result, government guarantees will inevitably tend to benefit shareholders ex post as well. Clearly, the U.S. government and regulators are willing to let small banks fail, not so for large banks. Of course, ex ante, one could have expected that the

[2]Estimating the entire ex post, realized cost of the various measures implemented by the U.S. Treasury, the Federal Reserve system, the FDIC and other regulators in the face of the recent crisis is hard. Veronesi and Zingales (2010) estimate the cost to be between \$21 and \$44 billion, with a benefit of more than \$86 billion.

government would wipe out shareholders of large financial institutions in case of a bailout.[3]Our evidence suggests that this is not what market participants expected. A number of events have been important in creating and sustaining the too-big-too fail perception in the market. Among these are the Federal Deposit Insurance Corporation's intervention to prevent the failure of Continental Illinois National Bank in 1984, Federal Deposit Insurance Corporation Improvement Act of 1991, and the Federal Reserve's intervention in 1998 to save Long Term Capital Management.

Finally, our findings suggests that cost of capital distortions might have contributed to the pre-crisis growth in the size of the financial sector relative to the overall economy. Philippon (2008) has argued that much of the variation in the size of the U.S. financial sector can be imputed to standard corporate finance forces. However, he notes the 2002-2007 period as an exception, which is exactly when we measure the largest distortions.

II Size Effect in Bank Stock Returns.

This section reports the returns on size-sorted portfolios of bank stocks. We also show the results of a cross-sectional regression of returns on firm characteristics that confirms the portfolio results.

II.1 Data

We collect data on equity returns from the Center for Research in Security Prices (CRSP) for all firms with Standard Industrial Classification (SIC) codes 60, 61, and 62. The data starts in January 1970 and ends in December 2009. Firms with these SIC codes are defined as commercial banks, non-depository credit institutions, and investment banks respectively. Henceforth, we refer to commercial banks, credit institutions, and investment banks collectively as banks. We exclude data for all financial firms that are inactive and/or not incorporated in the U.S., and we also

[3]The key to activating the collective bailout clause is common variation in bank payoffs. In a recent paper, Acharya and Yorulmazer (2007) and Farhi and Tirole (2009) explore the incentives for banks in this type of environment to seek exposure to similar risk factors. The government's guarantee creates complementarities in firm payoffs. In earlier work, Schneider and Tornell (2004) explain the currency mismatch on firm balance sheets in emerging markets endogenously by means of a bailout guarantee for the non-tradeables sector. Ranciere and Tornell (2011) discuss how to design regulation in the context of government bailout guarantees. Panageas (2010b) explores the optimal taxation implications of bailouts.

exclude financial firms not incorporated in the U.S. because these financial firms will be influenced by regulations applicable both in the country of operation and the country of incorporation. Since these policies vary across countries, our focus on financial firms operating and incorporated inside the U.S. ensures that all firms in our analysis are subject to a uniform regulatory regime.

We start by focusing on portfolios of commercial bank stocks. We employ the standard portfolio formation strategy of Fama and French (1993). We rank all bank stocks by market capitalization as of January of each year. The stocks are then allocated to 10 portfolios based on their market capitalization. We calculate value-weighted returns for each portfolio for each month over the next year. At the end of this exercise, we have monthly value-weighted returns for each size-sorted portfolio of banks.

While the CRSP data are available from 1926, our main sample only begins only in 1970 for banks, as there are not enough publicly traded commercial banks prior to 1970. Only a small fraction of all banks that operate in the U.S. are publicly listed. For instance, for the years 2000 to 2008, data are available from CRSP for approximately 630 banks, as compared to more than 7000 FDIC-insured banks operating in the U.S. over the same period. However, the largest 600 banks control more than 88% of all commercial bank assets in the U.S. Most of these large banks are publicly listed. To the extent that small banks that are not publicly listed are very different from those that are, some of our results need to be qualified.

We also use book value data from the CRSP-Compustat merged data-set. While our market capitalization results are based on 15,536 bank-years, the book-value results are based on only 12,556 bank-years. The reduction in the number of banks is primarily due to missing balance sheet data in the CRSP-Compustat merged data-set.

II.2 Summary Statistics

Table I reports the total market capitalization of banks in each of 10 size-sorted portfolio as a fraction of the total market capitalization of the banking sector in January of each year. The numbers are reported in percentages. We also report the the average number of banks in the portfolio.

Panel A in Table I shows that during the 1970 - 1980 subsample the smallest banks (those in portfolio 1) on average represented just 0.36% of the total market capitalization of all commercial banks, as compared to 49.78% represented by the largest banks (those in portfolio 10). During any year between 1970 and 1980, the banks in portfolio 1 at most accounted for 0.57% of the total market capitalization of the commercial banking sector.

Table I clearly shows the increasing concentration of the U.S commercial banking sector. The top 10% of banks account for nearly 50% of the total sector market capitalization in the 70s while they account for more than 90% during the 2000-2009; nearly 84% of this accounted for by the largest 1/2 in this group. In any given year between 1970 and 1980, there are at least 9 banks per size-sorted portfolio, which increases to 62 banks for any year between 2000 and 2009.

Panel B of Table I reports the total book value of banks in each size-sorted portfolio as a fraction of the total asset value of the banking sector in January of each year. Total book value is the better measure of size. These results are very close to those obtained by sorting on market capitalization. We also report leverage. Leverage is computed as total book value divided by the book value of equity. Bank leverage clearly increases with bank size. Between 1980 and 1990, the average leverage in the first decile is 13.55, and it gradually increases to 22.37 in the last decile. We document the same pattern in subsequent decades.

[Table 1 about here.]

II.3 Returns on Commercial Bank Stock Portfolios

When we report portfolio return averages, we exclude the recent financial crisis, as we consider samples that exclude realizations of the rare events in the model. However, the results that we report are quite robust to extending the sample.

Table II provides mean returns for the size-sorted portfolios of banks over the 1970-2005 sample. In panel A, the stocks are sorted into deciles by market capitalization. The mean monthly returns for all portfolios are annualized by multiplying by 12 and are expressed in percentages. The last column reports the difference in mean annual returns between portfolio 10 and portfolio 1. Over the entire sample, a portfolio that goes long in a basket of large banks and short in a basket of small banks on average loses 4.47% per annum. The average returns on the first (last) portfolio are 17.47% (13.01%). There is a monotonic decline in average returns from the first to the last portfolio.

Market cap measures size, but it also measures expected returns. Firms which generate more cash flows will tend to have higher market cap, but firms with lower expected returns, holding cash flows constant, also have larger market capitalization. As a result, Berk (1995) argues that there should be a relation between expected returns and market capitalization. Of course, this argument does not apply to other measures of size such as book value. A priori, there is no reason to expect a relation between book values and expected returns.

In Panel B of Table II, we sort stocks into deciles by total book value. The pattern in realized returns is quite different. There is an inverted U-shaped pattern. The average returns between 1980 and 2005 increase from 16% in the first portfolio to 21.75% in the sixth portfolio, and then decline to 13.68% in the last portfolio. The difference between the sixth and the 10th portfolio is 8.07% per annum. This is remarkable because the largest commercial banks are more levered than medium-sized banks, and hence, if anything, one would expect to see the opposite pattern.

[Table 2 about here.]

II.4 Characteristics Regression

The portfolio results in table II suggest there is a negative relation between total book value and returns for commercial banks, at least for the largest banks. We investigated this relation in the 1970-2005 sample. When we run a cross-sectional regression of average annual returns on firm characteristics: the log of market capitalization, the log of book value, book-to-market, and leverage, we obtain a large and significant negative coefficient for log book value (-2.45) and a positive coefficient for market capitalization (2.76). These coefficients are significant at the 1% level. The detailed results are in the appendix in section C.

This pooled regression explains 0.38% of the variation in annual returns. Thus a 100% increase in book value above the sample average lowers annual returns by 245 bps for a typical bank, holding all variables, including market capitalization, fixed. Leverage and book-to-market ratio seem to have no additional explanatory power for returns. We obtain identical results when we exclude leverage and book-to-market ratios from the regression. When we drop book value, the regression only accounts for 0.004% of the variation in annual returns. Hence, this size effect in bank stock returns is very different from the market capitalization effect first documented by Banz (1981).

II.5 Returns on size-sorted portfolios of non-financials.

What we usually refer to as a size effect is really a market capitalization effect in most industries. Berk (1997) points out that there is only a moderate size effect in the raw returns of non-financials when size is measured by book value rather than market capitalization. The same conclusion applies when other measures of actual firm size are used, such as the number of employees (Berk (1997)). When we perform the same sorting exercise using book values for non-financials, we do not find similar patterns.

Panel A of Table III reports the average returns on portfolios of non-financial firms sorted by market capitalization. The average returns on firms in the first decile of market capitalization are high (24.51%). These small cap stocks have smaller market capitalization than the smallest banks, are highly illiquid and hence earn much higher expected returns. Between the second and the tenth portfolio, average returns gradually decline from 15.76% to 11.39%.

The book-sorting results are reported in Panel B of Table III. Between 1970 and 2005, the average returns in the first decile are 276 bps higher than the average returns in the last portfolio. The average returns on the the first portfolio are 16.05% per annum. Returns increase to 16.75% in the second portfolio and subsequently decrease to 13.29% in the last portfolio. The difference between the sixth and the tenth portfolio is only 2.10 % per annum (compared to 8.07% for non-financials).

[Table 3 about here.]

III Size Effect in Normal Risk-Adjusted Bank Stock Returns

We start by adjusting the portfolio returns for exposure to the standard risk factors that explain cross-sectional variation in average returns on other portfolios of non-financial stocks and bonds. We do so by comparing the performance of the bank portfolio to the performance of a portfolio of non-bank stocks with the same exposure to normal risk factors.

A bank manages a portfolio of bonds of varying maturities and credit risk.[4] Therefore, we also include two bond risk factors in addition to three stock risk factors. The vector of normal risk factors:

$$\boldsymbol{f}_t = \begin{bmatrix} market & smb & hml & ltg & crd \end{bmatrix}, \tag{1}$$

is 5×1. *market*, *smb*, and *hml* represent the returns on the three Fama-French stock factors: the market, small minus big, and high minus low respectively. The Fama/French factors are constructed using the 6 value-weight portfolios of all stocks on NYSE, AMEX And NASDAQ (including financials) formed on size and book-to-market. *market* is the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates). We use *ltg* to denote the excess returns on an index of 10-year bonds issued by the U.S. Treasury as our first bond risk factor. The USA 10-year Government Bond Total Return Index (*ltg*) is downloadable from Global Financial Data. In addition, active participation by banks in markets for commercial, industrial, and consumer loans exposes them to credit risk. We use *crd* to denote the excess returns on an index of investment grade corporate bonds, maintained by Dow Jones, as our second bond risk factor. To compute excess returns, we use the one-month risk-free rate.[5]

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[4]Longstaff and Myers (2009) also show that banks can be treated as active managers of fixed income portfolios.

[5]Data for the risk-free rate and the Fama-French factors was collected from Kenneth French's website. The Dow Jones Corporate Bond Return Index (*crd*) is downloadable from Global Financial Data.

III.1 Returns on Commercial Bank Stock Portfolios

We regress monthly excess returns for each size-sorted portfolio on the three Fama-French factors and two bond factors. For each portfolio i we run the following time-series regression to estimate the vector of betas $\boldsymbol{\beta}_i$:

$$R^i_{t+1} - R^f_{t+1} \quad = \quad \alpha^i + \boldsymbol{\beta}^{i,\prime} \boldsymbol{f}_{t+1} + \varepsilon^i_{t+1}, \tag{2}$$

where R^i_{t+1} is the monthly return on the i^{th} size-sorted portfolio. Since all of the risk factors in $\boldsymbol{f}_t$ are traded returns, the estimated residuals in the time series regression are estimates of the normal-risk-adjusted returns $\widehat{R}^i_{t+1}$.

Table IV provides the results of the regression specified in equation (2). Panel A reports the results based on sorting by market capitalization. The table reports the regression coefficients for each size-sorted portfolio, along with their statistical significance and the adjusted R^2. Table IV excludes the recent financial crisis. The estimated intercepts decrease nearly monotonically with bank size from 5.45% for the first portfolio to -2.53% for the tenth portfolio. The implicit risk prices for the factors $\boldsymbol{f}_t = \begin{bmatrix} market & smb & hml & ltg & crd \end{bmatrix}$ are given by:

$$\boldsymbol{\lambda}_t = \begin{bmatrix} 5.80 & 0.88 & 6.62 & 2.92 & 4.01 \end{bmatrix}.$$

A long-short position that goes long one dollar in a portfolio of the largest market capitalization banks and short one dollar in a portfolio of the smallest market capitalization banks loses 7.97% over the non-disaster sample. This return spread is statistically significant at the 1% level. The average normal-risk-adjusted return on a 9-minus-2 position is -6.62% per annum, and -3.95% per annum for the 8-minus-3 portfolio. These are statistically significant at the 1% and the 5% level respectively. The differences in risk-adjusted portfolio returns tend to be larger than the differences in raw portfolio returns, because larger banks are more levered and hence impute higher market betas to large bank stock portfolios. The market beta increases from 0.36 for the first decile to 1.07 in the last decile. However, this effect is attenuated by the lower credit risk exposure for the larger banks.

The second row of Table IV reports the coefficient on excess market return, *market*, for each size-sorted portfolio. The market beta increases monotonically with bank size. Over the entire sample, a portfolio of large banks has a market β of 1.07, as compared to a β of 0.36 for a portfolio of the smallest banks. The largest banks were 2.9 times more exposed to market risk as compared to the smallest banks. This difference can be attributed to differences in leverage.

The loadings on *smb* and *hml* also depend systematically on size. We first look at the exposure to the size factor. Contrary to what one expects to find, over the entire sample, the loading on smb_{t+1} actually increases from 0.39 for the first portfolio to 0.50 for the fifth portfolio, and then it drops to -0.03 for the tenth portfolio. Clearly, the common variation in stock returns of banks along the size dimension is very different from that in other industries. The same pattern holds true for the loadings on *hml* which increase from 0.32 for the first portfolio to 0.42 for the last portfolio.

There is a clear size pattern in the loadings on the bond risk factors as well. *ltg*, the slope coefficient on the excess return on an index of 10-year bonds issued by the U.S. Treasury, is negative and statistically insignificant for small banks and is positive and almost always statistically significant for large banks. The loadings vary monotonically in size. A $1 long position in large banks and a $1 short position in small banks results in a net exposure of 30 cents to long-term government bonds over the entire sample. On the other hand, the loadings on the credit risk factor, *crd*, are surprisingly small for large banks and positive for small banks. A long-large-banks-short-small-banks position delivers a net negative exposure to credit markets of 38 cents per dollar invested.

[Table 4 about here.]

Panel B reports the results obtained by sorting by book value. The pattern in risk-adjusted returns is different from the one obtained when sorting by the market capitalization of banks. The risk-adjusted returns remain around 400 bps for the first six portfolios. The seventh portfolio posts average risk-adjusted returns of 212 bps. After that, the the average risk-adjusted returns decline to -139 bps for portfolio 8, -317 bps for portfolio 9, and - 256 bps for portfolio 10. A long-short position that goes long one dollar in a portfolio of the largest banks and short one dollar in a portfolio of the smallest banks loses 5.85% over the non-disaster sample. This return spread is statistically significant at the 1% level. The average normal-risk-adjusted return on a 9-minus-2 position is -7.15% per annum, and -6.30% per annum for the 8-minus-3 portfolio. These are statistically significant at the 1% and 5% levels respectively.

Larger banks have higher market betas, consistent with leverage increasing in size, although the increase is smaller than the difference in leverage suggests. However, the negative effect of higher market betas on risk-adjusted returns is partly offset by a strong inverse U-shaped pattern in the credit risk loading. The loading increases from 0.06 in the first portfolio to 0.43 in the fifth portfolio, and then it declines to 0.07 in the tenth portfolio.

III.2 Returns on Portfolios of Non-financial Stocks

Table V provides the results of the regression specified in equation (2) for non-financials sorted by market capitalization (Panel A) and book value (Panel B). The table reports the regression coefficients for each size-sorted portfolio along with their statistical significance and the adjusted R^2. Table IV excludes the recent financial crisis.

In the top panel, stocks with market capitalization in the lowest decile earn much higher risk-adjusted returns. This is not surprising. These small cap stocks are typically highly illiquid stocks. It has been documented that illiquid stocks earn abnormal returns (see, e.g., Brennan and Subrahmanyam (1996)). However, these are stocks with very small market capitalization, which are much smaller than the banks in the first portfolio. In 1980, the average market capitalization of a firm in the first portfolio is only $22.8 million, compared to $75.9 million for the banks in the first portfolio in 1980. The average market capitalization in the second portfolio is much larger ($ 65.7 million in 1980). Other than this illiquidity effect in the first decile, the risk-adjusted returns are small and statistically insignificant. In Panel B, we sort by book values. While smaller firms seem to earn higher risk-adjusted returns, the effects do not exceed 300 bps, and are statistically insignificant.

[Table 5 about here.]

III.3 Robustness

These results are robust. First, we checked the robustness of our results by building three portfolios of all banks, including investment banks, sorted by market capitalization, starting in 1927. This is when the CRSP data starts. There are only a few banks in each portfolio at the start of the sample in 1927. Over the entire 1927-2009 sample, the banks in the first portfolio earned 5.48% per annum more than banks in the last portfolio after adjusting for exposure to the same five stock and bond risk factors.

Second, we also split the 1970-2005 benchmark sample to check the stability of our results. In particular, we want to make sure that our results are not driven by the banking merger and acquisition wave of the 1990's. In fact, we find that the differences in the normal-risk-adjusted returns are fairly constant throughout our 1970-2005 sample.

Third, when we extend the sample to include the recent financial crisis (1970-2009), we obtain a 778 bps spread in risk-adjusted returns on commercial bank portfolios between the first and the last market decile. This spread is statistically significant at the 1% level. Hence, our findings are quite robust.

IV Size Factor in Bank Stock Returns

The second principal component of normal-risk-adjusted returns on size-sorted portfolios of bank stocks has loadings that depend monotonically on size. The covariance between the returns on size-sorted portfolios of banks stocks and the size factor can explain the size pattern in average risk-adjusted returns. In the next section, we interpret this slope factor in normal-risk-adjusted returns as a measure of financial tail risk.

IV.1 Constructing the Size Factor

We compute the residuals from the time series regression of returns of each size-sorted portfolio on the equity and bond risk factor in 2. We extract the loadings for the principal components $(\boldsymbol{w}_1, \boldsymbol{w}_2)$ and we report the results in Table VI. This table only shows the loadings for the first two principal components. The other eight are plotted in figure 1. Together, these two principal components explain 66% of the residual variation over the entire sample.

The first two columns in the Table shows results for market capitalization sorts; the last two columns show results for book sorts. They are very similar. We focus on the results obtained using the market capitalization sort, mainly because this sort provides more observations.

The first principal component is a banking industry ('level') factor with roughly equal weights on all 10 portfolios. The second principal component is a size factor that loads positively on portfolios of small banks and negatively on portfolios of large banks. The loadings vary monotonically in size. This is a candidate risk factor because the loadings align with the average normal-risk-adjusted returns that we want to explain.

[Table 6 about here.]

Next, we take our $(T \times 10)$ matrix of estimated residuals, $\boldsymbol{\epsilon}_t$, and multiply it by the (10×10) loadings of the principal components, to construct the asset pricing factors. The weights $(\boldsymbol{w}_1, \boldsymbol{w}_2)$ are re-normalized to $(\widehat{\boldsymbol{w}}_1, \widehat{\boldsymbol{w}}_2)$ so that they sum to 1.[6] This results in a $(T \times 10)$ linear combination of the residuals. We focus on the first two principal components, denoted $PC_t^1 = \widehat{\boldsymbol{w}}_1' \boldsymbol{\epsilon}_t$ and $PC_{2,t} = \widehat{\boldsymbol{w}}_2' \boldsymbol{\epsilon}_t$.

The size factor not only has an appealing macro-economic interpretation, but it also is a natural candidate for explaining the size pattern in normal-risk-adjusted returns, because the average normal-risk-adjusted returns align with the covariance between the size factor (second principal component) and the returns on the portfolios. This is not the case for any of the other principal

[6] $\boldsymbol{w}_2$ is given by:

$$\begin{bmatrix} 2.70 & 2.24 & 1.94 & 1.68 & 1.00 & 0.00 & -1.31 & -1.65 & -2.34 & -3.26 \end{bmatrix}$$

.

components, as is clear from Figure 1. This figure plots the average normal-risk-adjusted returns (labeled x) against the covariance of that return with the n-th principal component (labeled o). The second principal component is the only candidate factor, because the second p.c. is the only one for which the covariances line up with the average excess returns, suggesting that the common variation in banks stock returns captured by the second principal component can explain the size anomaly in bank stock returns.

[Figure 1 about here.]

To check whether the size factor actually explains the average normal-risk-adjusted returns, we define a new independent variable. We take the $(T \times 10)$ matrix of returns for each of the size-sorted portfolio of banks and multiply this by the (10×1) loading of the second principal component. We re-normalize the loadings of the second principal component so that they sum to one. As above, we use $\widehat{\boldsymbol{w}}_2$ to denote the re-normalized weights. Then: $R[PC_2]_{t+1} = \widehat{\boldsymbol{w}}_2 \boldsymbol{R}_t$ denotes the results of our multiplication and is a $(T \times 1)$ vector of the returns weighted by the second principal component. Thus for each month, the returns of each of the 10 portfolios are multiplied by their corresponding weights in the second principal component and added together. This portfolio is long in small banks and short in large banks. The weights of the portfolio are given by the second principal component loadings, re-normalized to sum to one. We then run a time-series regression of the returns on the size-sorted bank portfolios on the equity and bond factors, and the size factor $R[PC_2]$:

$$R^i_{t+1} - R^f_{t+1} = \alpha^i + \boldsymbol{\beta}^{i,\prime} \boldsymbol{f}_{t+1} + \beta^i_{PC,2} R[PC_2]_{t+1} + \varepsilon^i_{t+1}. \tag{3}$$

The tail-and-normal-risk-adjusted returns or α's from this regression are presented in Panel A of Table VII. The risk-adjusted returns on all portfolios are smaller than 250 bps over the entire sample. The average risk-adjusted return on the long-short position is reduced to 20 bps. Not only does the magnitude of the alphas change, but all of them are statistically insignificant. In addition, there is no discernible size-related pattern in these normal-risk-adjusted returns.

[Table 7 about here.]

IV.2 What is the Size Factor?

PC_2 is the normal-risk-adjusted return on a portfolio that is long small banks and short large banks. The weights of the portfolio are given by the second principal component. Figure 2 plots the 12-month moving average (months $t-11$ through t) of PC_2 series along with a plot of the index for industrial production. The units are monthly returns. The gray-shaded regions represent NBER recessions and the light-shaded regions represent banking crisis. The NBER recession dates are published by the NBER Business Cycle Dating Committee. The dates for the Mexico and LTCM crisis were obtained from Kho, Lee, and Stulz (2000) and the FDIC (for the Less-Developed-Country debt crisis of 1982).

The size factor, which by construction is orthogonal to the bond and equity pricing factors, declines during recessions and financial crises. Moreover, it is very sensitive to large slowdowns in the growth rate of industrial production. We plot a backward looking 12-month moving average, which explains why the returns appear to drop a couple of months after the start of the NBER recessions. The returns also tends to increase before the end of the NBER recession.[7] On average, during recessions, this normal-risk-adjusted return drops by an average of 3.30% per month or 39.57% per annum. During the most recent recession, which coincides with financial crisis, the size factor lost 89% of its value, after adjusting for risk exposure.

[Figure 2 about here.]

We also extended our sample to the pre-war era by including all banks and sorting these by market capitalization. We used the same principal component weights on this sample; see Figure 4 in the appendix. We observe the same pattern in the size factor in risk-adjusted returns. In every

[7]There are two exceptions to this cyclical pattern. One is the double-dip recession in the early eighties. Small banks stocks were already recovering from the huge declines suffered relative to large bank stocks, and hence starting from very low valuations, when the second recession started. The second is the 2001 recessions in the wake of the Long Term Capital Management crisis. Moreover, in 2001, the NBER chose the starting point of the recessions well after the decline in industrial production started (in other recessions, the starting date coincides with the decline in industrial production.)

NBER recession that we examined, the size factor decreases substantially; the largest losses in this sample are incurred towards the end of the Great Depression.

Panel A in Table VIII shows the value at the trough of the NBER cycle (the end of the banking crisis) of a \$100 invested at the peak of the NBER cycle (the start of the banking crisis) in the slope portfolio – the weights are given by the normalized second principal component. The second column reports the dollar value after subtracting the performance of a benchmark portfolio with the same exposure to the bond and equity factors ($\$100 + x$ means the a cumulative return of $x\%$ in excess of the benchmark portfolio). This is the return on a portfolio that is hedged to have zero betas with respect to the standard risk factors. The third column reports the dollar value without risk-adjustment. On average, the unhedged size portfolio loses \$35 during a recession or banking crisis. The fourth column column reports the returns on the same investment strategy after hedging out the exposure to the standard equity and bond factors. That hedged strategy loses more than \$60 per recession. As is clear from panel B, the largest losses are concentrated in the first six months of the NBER recessions, just under \$30 in normal-risk-adjusted terms. Moreover, this portfolio (both hedged and unhedged) experienced steep declines during the Less Developed Country and the LTCM crises.

Panel B in Table VIII shows the average value of the portfolio n months into a recession. The hedged portfolio gradually drops more in value. Twelve months after the peak it has lost almost \$63 dollars of its value.

[Table 8 about here.]

The size factor appears to be a reliable measure of bank-specific tail risk. During the most recent U.S. recession, a full-fledged banking crisis, the hedged size portfolio of commercial banks lost close to 90 cents on the dollar (see Table VIII). This is not a surprise. In 2008, 18% of the commercial banks in the first market capitalization decile were delisted, followed by another 30% in 2009. We also went back to 1926 by including all banks in our sample. During the Great Depression (NBER recession dates), the hedged size portfolio of all financials was trading at -44 cents at the end of the recession per \$100 invested at the peak.

In the data, there is a strong connection between the business cycle and the incidence of banking panics. We examined the U.S. banking panics starting in 1873, as well as the NBER business cycle peaks and troughs. Except for the first banking panic, all of these occur during the contraction phase of the U.S. business cycle. The dates of the banking panics were taken from Gorton (1988, p. 223) and Wicker (1996, p. 155). The details are provided in Table XIV in the separate appendix. This is not the case for non-financials. Giesecke, Longstaff, Schaefer, and Strebulaev (2010) examine 150 years of U.S. corporate history and they find a weak relation between the business cycle and corporate bond defaults.

IV.3 Alternative Explanations

Large idiosyncratic shocks can cause bank failures. If the volatility of these shocks increases more in recessions for small banks, that could explain some of our findings. Smaller banks are much more exposed to idiosyncratic risk than large banks, but the amount of idiosyncratic risk exposure of small banks does not seem to increase very much during recessions. During NBER recessions, the standard deviation ranges from 38% for the smallest banks to 26% for the largest banks as compared to 36% and 20% respectively in the whole sample. The details are in the separate appendix (section B). Hence, the largest percentage point increase in volatility during recessions is noted for the largest banks: from 20% to 26%. For the smallest banks, the increase is less than two percentage points. There is no evidence to suggest that the cyclicality of the size factor is due to idiosyncratic banks risk. While smaller banks are more exposed to idiosyncratic risk, we do not see large increases in this type of risk during recessions.

There is no evidence that business cycle variation in cash flows can explain our findings. If anything, the evidence suggests that large financial institutions are more exposes to business cycle risk. Boyd and Gertler (1993) analyze the impact of size on the performance of banks as measured by accounting data. They show that increased competition and financial innovation have induced the largest banks to participate in riskier investments.[8] We examined bank performance during

[8]This is consistent with the findings of Gatev, Schuermann, and Strahan (2007); they document a reverse bank-run phenomenon for large deposit-taking institutions in periods of tight aggregate liquidity. In related work, Gatev

the last two recessions by studying the Quarterly Banking Reports issued by the FDIC, and we found that small banks tend to outperform large banks during recessions. Section B of the separate appendix contains the details.

V The Pricing of Bank Tail Risk and the Government

The average return of this size factor is the price of banking tail risk insurance, and it can be measured for individual banks as the loading on this factor times this risk price. When the price of tail risk measured by the size factor is negative, we will refer to this as a tail risk subsidy. If not, it is a tail risk tax. This section examines how bank-specific tail risk is priced in the stock market, and relates it to the regulatory regime and to government announcements.

V.1 Size of Largest Banks

The events immediately after the collapse of Lehman in September 2008 confirm the commonly-held view that the U.S. government and monetary authorities are reluctant to let large financial institutions fail collectively, even though they may be occasionally willing to let individual institutions fail. For example, over the course the recent financial crisis, the Federal Reserve made emergency loans totaling about $9.99 trillion to 10 of the largest U.S. financial institutions, which accounted for 83% of the emergency credit extended to all U.S. institutions.[9] Moreover, even if regulators are willing to let these large banks fail, the uncertainty about the resolution regime for distressed banks clearly favors the creditors and shareholders of large financial institutions.

Consistent with this view, even in the highest market capitalization decile of commercial banks, we find a strong negative relation between the market capitalization of individual firms relative to GDP and the loading on the size factor. We chose banks that were in portfolio 10 in each year of our sample and then computed the loadings on PC_2 over the subsequent five-year window. As

and Strahan (2006) find that large banks provide aggregate liquidity insurance to non-financial corporations.

[9]Data from the Term Auction Facility (TAF) (provided emergency loans to commercial banks), the Primary Dealer Credit Facility (PDCF)(provided emergency loans to investment banks and other broker-dealers, which typically do not have access to Fed funds) and the Term Securities Lending Facility (TSLF)(which allowed financial firms to borrow Treasury securities).

individual banks grow larger over time relative to GDP, their loadings on this size factor clearly tend to increase. The slope coefficient in the regression of PC_2 loadings on market capitalization/GDP is 0.018, meaning that a 100% increase in the size of market capitalization relative to GDP raises the loading by 0.018 in absolute value or, equivalently, it increases the tail risk subsidy by 68 bps per annum.

V.2 Regulatory Regime

We want to relate the pricing of tail risk, as captured by the size factor, to the regulatory regime of different banks. Commercial banks and GSEs benefit from special provisions: deposit insurance[10], access to the discount window at the Federal reserve and other special lending facilities in the case of commercial banks, and widely acknowledged debt guarantees in the case of GSEs. Foreign banks and investment banks do not enjoy the same level of protection.

Table IX compares the results for a value-weighted index of commercial banks, investment banks, foreign banks, and GSEs. The first row reports the value-weighted average market capitalization for each index. For foreign banks, this only includes the market capitalization of U.S. listed shares.[11] Investment and foreign banks do not benefit from the tail risk subsidy to commercial banks, but the GSEs (Fannie Mae and Freddie Mac) clearly do. Over the entire sample, the subsidy to commercial banks is 2.32% and the subsidy to GSEs is 1.95%. The loadings on $R[PC_2]$ are much smaller (investment banks) or positive (foreign banks) and not statistically significant.

Table IX shows the same results for the largest commercial, investment banks and GSEs. Panel A shows the results for the entire sample excluding the crisis. The tail risk subsidy is largest for the large commercial banks. For BoA (1973-2009), we estimate a tail risk subsidy of 3.12% per annum, for Wells Fargo (1970-2009) it is 3.27%, and for Citibank (1986-2009) it is 1.94 %. For investment banks, these effects are much smaller and not statistically significant. Lehman is the only exception.

[10]The FDIC Improvement Act of 1991 limits the protection of creditors, but it provides a systemic risk exception.
[11]The worldwide market-cap for just the 6 largest banks included in the index of foreign banks is $330.21 billion in 2010

As a benchmark, we also computed the loading on $R[PC_2]$ for an index of hedge fund returns. Hedge funds do not benefit from the umbrella extended to large banks. We used the HFRI fund-weighted hedge fund index. These results are not reported. Over the entire sample (from 1991 - 2005) the loading for hedge fund returns on $R[PC2]$ is 0.02 (t-stat 2.66) and this reduces to 0.01 (t-stat 0.91) over 2000 - 2005. Hence, as expected, hedge funds face a tail risk tax, because the loadings are positive, just like small banks.

These results lend some support to a government-based interpretation of the size factor, as commercial banks and GSEs benefit from more extensive government guarantees than other financial institutions.[12]

V.3 Elimination of Glass-Steagall

The Glass-Steagall Act (1933) effectively separated U.S. commercial banking from investment banking. The provisions of this act preventing bank holding companies from owning financial companies were repealed in 1999. Its repeal allowed large commercial banks to originate and trade collateralized debt obligations.

After 2000, the tail risk subsidy to commercial banks more than doubled to 4.76%, and the subsidy to GSEs more than tripled to 6%. These numbers were determined by multiplying the loadings with the same risk price (38.93%) computed over the entire sample. There was also a marked increase in the exposure of investment and foreign banks to the size factor.

[Table 9 about here.]

The loadings for the largest commercial banks increased dramatically in the last decade. The BoA tail risk subsidy increased from 3.17% to 4.53% in 2000-2005, while the Citi subsidy increased from 2.18% to 4.59%. This is exactly what one would have expected to see given the enormous increase in total asset size realized by these banks. Wells Fargo collected a subsidy of 6.15% in 2000-2005, compared to 4.40% in the 1990-2005 sample. The largest subsidy is collected by Fannie Mae (6.57%), in spite of its smaller size. Lehman also collect a large subsidy in this period. Both

[12]The GSEs and foreign banks were suggested to us by Martin Bodenstein.

Lehman and Fannie Mae were building up substantial exposure to the subprime mortgage market during this period. Note that there is no mechanical connection between our size factor and the subprime exposure, since we exclude the financial crisis from the sample. Exposure to the size factor seems a good yardstick of systemic risk exposure.

V.4 Announcement Effects

In September 1984, the Comptroller of the Currency announced a list of 10 banks that were deemed too big to fail. We examine the pricing of the financial tail risk embedded in the stocks of these 10 banks around this announcement date. Table X lists all the announcement dates.

Pre-crisis Announcement Dates We also look at six other announcement dates listed by Kho, Lee, and Stulz (2000). Table XI reports the results. We report regressions for windows of 30, 45, 60, 90, and 105 days around the announcement date. Panel A lists results from a pooled regression for all seven announcement dates. In the 30-day window after the Comptroller announcements, the loading increases by 0.12. This amounts to an annualized 4.56 % tail risk subsidy. This effect gradually decreases as we increase the window around the event. We find slightly smaller effects for the LTCM, Brazilian, Mexican and South-Korean crisis. The average effect is a 1.14 pps (0.03 times 38%) increase in the tail risk subsidy. This average effect is roughly constant across the windows. These effects are economically and statistically significant.

Crisis Announcement Dates In the crisis sample, we identified announcements that increased the likelihood of a bailout for all banks, for large banks and, finally, we also looked at events that decreased the likelihood of a bailout. These are listed in Panel B of Table X.

[Table 10 about here.]

[Table 11 about here.]

Panel B looks at the financial crisis announcements. Only the positive announcements for large banks have an economically and statistically significant effect on the pricing of tail risk. The tail risk subsidy for the too-big-to-fail banks increases by 2.66 pps in a 30-day window around these announcements. The other announcements have small or negative effects that are not statistically significant.

VI Recovery Rates and Equilibrium Pricing of Tail Risk in the Banking Sector

To help us interpret our empirical findings, we use a stylized dynamic asset pricing model with time-varying probability of banking panics that reproduces the size anomalies, as well as the size factor in returns. The driving force is the size variation in recovery rates.

VI.1 A Simple Model of the Size Anomaly in Bank Stock Returns

The model yields a key testable prediction: a size factor in normal-risk-adjusted returns on banking portfolios that is tied to the U.S. business cycle.

We adopt a version of the models with time-varying probabilities of financial disasters proposed by Gabaix (2008) and Wachter (2008). These are extensions of the rare event models developed by Barro (2006) and Rietz (1988). In our model, the stochastic discount factor has two components: a standard normal component and a disaster component:

$$
\begin{aligned}
M_{t+1} &= M_{t+1}^{G} \times 1 \textit{ in states without a financial disaster} \qquad (4)\\
M_{t+1} &= M_{t+1}^{G} \times M_{t+1}^{D} \textit{ in states with a financial disaster.}
\end{aligned}
$$

M_{t+1}^{G} denotes the representative investor's intertemporal marginal rate of substitution (IMRS) in normal times, i.e., in states without a disaster. In the simplest version of his model, Gabaix (2008) defines $\Delta \log C_{t+1} = g_C + \sigma\eta_{t+1}$ as the growth rate of consumption in normal times, and $\Delta \log C_{t+1} = g_C + \sigma\eta_{t+1} + \log F_t^c$ as the consumption growth rate in the financial disaster state, where $1 \geq F_t^c > 0$. η_{t+1} is Gaussian white noise. p_t denotes the probability of a financial disaster.

In the absence of a financial disaster, the IMRS is completely determined by normal risk. We assume that the normal component of the stochastic discount factor is linear in the normal risk factors:

$$M_{t+1}^{G} = \boldsymbol{b}'\boldsymbol{f}_{t+1}. \tag{5}$$

We use $\boldsymbol{\beta}_t^i$ to denote the vector of conditional normal risk factor betas for the returns on asset i, and we use $\boldsymbol{\lambda}_t$ to denote the vector of normal risk prices. We make some additional simplifying assumptions in order to characterize disaster risk premia analytically. First, we assume that the conditional distribution of the normal risk factors $\boldsymbol{f}_t$ is independent of the disaster realization. Second, we assume that p_t does not co-vary with the normal risk factors f_t. This second assumption implies that the recession risk itself is not priced, only the financial disaster risk itself is.

The dividend process of a portfolio of bank stocks of size i is given by:

$$\begin{aligned} \Delta \log D_{t+1}^{i} &= \Delta \log D_{t+1}^{i,G} \; \textit{in states without banking crisis} \\ \Delta \log D_{t+1}^{i} &= \Delta \log D_{t+1}^{i,G} + \log F_t^i \; \textit{in states with banking crisis} \end{aligned}$$

$\Delta \log D_{t+1}^{i,G}$ is the Gaussian component of dividend growth. $1 \geq F_t^i > 0$ can be thought of as the recovery rate; in case the rare event is realized, a fraction F^i of the dividend gets wiped out (See Longstaff and Piazzesi (2004) and Barro (2006)). This recovery rate will vary across banks depending on size, partly because the realization of this rare event can trigger a collective bailout of larger banks, but not necessarily of smaller banks. There is strong empirical evidence for size-dependent variation in disaster recovery rates. In our sample (1970-2009), the average delisting rate for banks in the first market capitalization decile is 1.77%, compared to 0.018% for the ninth decile and 0% for the tenth decile. During 2008, 18% of banks in the first decile were delisted, another 30% were delisted in 2009, and, finally, 10% in 2010. None of the commercial banks in the highest decile were delisted. Including acquisitions increases these numbers to 19% and 32% respectively.

The resilience of banks is defined as the marginal-utility-weighted recovery rate in disaster states (Gabaix (2008)): $H_t^i = p_t E_t\left[M_{t+1}^D F^i - 1\right]$. In the simplest CCPAM case, this would be $H_t^i = p_t E_t\left[(F_{t+1}^c)^{-\gamma} F_{t+1}^i - 1\right]$. As the economy enters into a recession, p_t increases and the resilience of large banks H_t^B increases relative to small banks H_t^S if $F_{t+1}^B > F_{t+1}^S$. In fact, we assume that the recovery rate $F_t^n > F_t^{n-1}$ increases monotonically in size.

The expected return on asset i, conditional on no disaster realization, after adjusting for normal risk exposure, becomes $E_t[\widehat{R}_{t+1}^i] = \exp(r - h_t^i)$, where $E_t[\widehat{R}_{t+1}^i] = E_t[R_{t+1}^i] - \boldsymbol{\beta_t^i \lambda_t}$, and r denotes $\log R_t = \log E_t[M_{t+1}^G]^{-1}$, and h_t^i denotes $\log(1 + H_t^i)$. The proof is in the Appendix .

To derive a simple expression for average normal-risk-adjusted returns, we abstract from variation in normal betas and risk prices. In the interest of tractability, we assume that the recovery rates F^i are constant over time, and we also assume that the size of the consumption disaster F^C is constant over time. The conditional beta $\boldsymbol{\beta}_t$ and the conditional risk prices $\boldsymbol{\lambda}_t$ are constant. In a sample without a disaster realization, the average normal-risk-adjusted return will be given by:

$$E[\widehat{R}_{t+1}^i] = E[R_{t+1}^i] - \boldsymbol{\beta^i \lambda} = exp(\overline{r} - \overline{h}^i),$$

where $\overline{h}^i = E[\log(1 + H^i)]$. The difference in alphas in a sample without a rare event realization measures the differences in average resilience between different bank stock portfolios: $\log \alpha^B - \log \alpha^S = \overline{h}^S - \overline{h}^B$. Hence, we can interpret the 6% difference between small and large bank portfolios in the normal-risk-adjusted returns as measuring differences in the resilience of these bank portfolios to banking crises.

A key prediction of this model is that this variation in the probability of a financial disaster in turn imputes common variation to the normal-risk-adjusted stock returns along the size dimension, since we assumed that the recovery rate depends on size, even in a sample without disasters. The loadings on this common factor are proportional to $F^i - 1$. To see why, note that $\log(1 + H_t^i) \approx p_t E_t\left[M_{t+1}^D F^i - 1\right]$. This is a size factor because the loadings depend on the recovery rates and hence (by assumption) on size. The conditional normal-risk-adjusted multiplicative risk premium on a long-short portfolio is given by the following expression: $\log E_t\left[\widehat{R}_{t+1}^B\right] - \log E_t\left[\widehat{R}_{t+1}^S\right] = h_{t+1}^S - h_{t+1}^B$. As p_t increases during recessions, the risk premium on this long-short portfolio becomes more negative. This variation in risk premia is the driving force. The size factor tracks the variation in p_t.

The characteristic (the size of the bank) actually determines the financial disaster risk premium, because of the collective bailout guarantee for large banks. This creates an opening for arbitrage opportunities. Let us assume that there is a single critical size threshold. In this case, the low recovery rate ($F^i = \underline{F}$) applies for all bank portfolios with size below the cutoff. Also, suppose banks do not switch between portfolios as a result of growth, mergers or acquisitions. For banks in portfolios above the cutoff, the higher recovery rate applies: $F^i = \overline{F}$. The baseline model predicts large positive, but constant, $\underline{\alpha}$'s for all the banks in size-sorted portfolios below the threshold, and much smaller, negative $\overline{\alpha}$'s for all banks above the threshold. In that sense, the pattern we found in the data is surprising. However, this stark $(\underline{\alpha}, \overline{\alpha})$ outcome can only be an equilibrium if there are prohibitively large costs associated with merging and acquiring banks.

Suppose there are no such costs. Consider two banks (A and B) just below the threshold with recovery rates $F^A = F^B = \underline{F}$. By bundling the cash flows of these two banks (A and B), the recovery rate increases to $F^{A+B} = \overline{F}$, and the value of a claim to the cash flows of A and B will exceed the sum of the value of these cash flows: $P(A) + P(B) \leq P(A+B)$. In the absence of costs, this represents an arbitrage. However, if there are positive costs C, then the value of A and B has to increase such that $P(A) + P(B) \geq P(A+B) - C[A, B]$ to eliminate the arbitrage opportunities. This increase reflects the probability that these banks end up crossing the size threshold because of growth or because of a future merger or acquisition. Hence, the α's for these banks (A and B) will decrease, as their value rises, even though they do not directly benefit from the guarantee yet. Alternatively, A and B will actually merge right away.

There was a large amount of concentration in the banking sector in the last decades. Table I reports an increase from 50% (in the 1970's) to 90 % (in the last decade) in the share of total market capitalization accounted for by the top decile. The increase in the share of total balance sheet accounted for by the top decile is from 52% to 95%. Kane (2000) and Brewer and Jagtiani (2007) document acquiring banks are willing to pay larger premiums for banks that put them over critical size thresholds, consistent with our hypothesis. By backward induction, the same argument applies to smaller banks in other portfolios. However, the costs of bundling the cash flows ($C[D, E, F, \ldots, Z]$) of many smaller banks to reach this critical threshold increase, and this mitigates the effect on the average risk-adjusted returns. This can account for the decreasing pattern in the alphas that we have found in the data.

VI.2 Calibrated GE Asset Pricing Model

Obviously, the independence of risk factors and p_t that we need to derive simple, analytical characterizations of the risk-adjusted returns is very restrictive. This section develops a general equilibrium version of this model, in which these restrictions are relaxed. We show there is a qualitatively similar relation between the average risk-adjusted returns and the financial disaster recovery rates provided that the market itself is not as exposed to financial disaster risk as banks.

We use a modified version of Gourio (2008)'s model. The stand-in agents has Epstein-Zin utility over non-durable consumption streams:

$$V_t(C^t) = \left[(1-\beta)C_t^{1-\alpha} + \beta(\mathcal{R}_t V_{t+1})^{1-\alpha}\right]^{\frac{1}{1-\alpha}}, \tag{6}$$

where $\mathcal{R}$ denotes the following operator: $\mathcal{R}_t V_{t+1} = \left(E_t V_{t+1}^{1-\theta}\right)^{1/1-\theta}$. This agent cares about the intertemporal composition of risk. α^{-1} controls the intertemporal elasticity of substitution, while θ controls risk aversion. When $\alpha = \theta$, preferences are time-separable. The equilibrium SDF is given by:

$$M_{t+1} = \beta^{\frac{1-\theta}{1-\alpha}} \left(\frac{C_{t+1}}{C_t}\right)^{-\alpha\frac{1-\theta}{1-\alpha}} R_{w,t+1}^{\frac{\alpha-\theta}{1-\alpha}}, \tag{7}$$

where R^w denotes the return on a claim to aggregate consumption.

The process for aggregate consumption growth is given by:

$$\begin{aligned}
\Delta \log C_{t+1} &= g_C + \sigma\eta_{t+1}, \textit{ in states without financial disaster} \\
\Delta \log C_{t+1} &= g_C + \sigma\eta_{t+1} + \log F^c, \textit{ in states with financial disaster.}
\end{aligned}$$

When p is i.i.d., this model can be solved analytically. We are interested in the case in which p varies over the business cycle. We solve a version of this model with two aggregate states.

We choose σ, the standard deviation of Gaussian aggregate consumption growth shocks, equal to 3%, and g_C equal to 2%. The time discount factor β is set to 0.975. Following Gourio (2008), we use a two-state discretization for the aggregate state of the economy. In the recession state, the probability of a financial disaster is high. In the expansion state, the probability of a financial disaster is low. The average length of an expansion is 44 months. The average length of a recession is 16 months. The ratio of the average length of an expansion to the average length of a recession is 2.62. We set the average probability of a banking crisis to 13%, because the U.S. spent 13% of all years since 1800 in a banking panic according to Reinhart and Rogoff (2009).[13] The aggregate state of the economy follows a 2-state Markov chain with transition probability matrix:

$$Q = \begin{bmatrix} \phi & 1-\phi \\ 1-\varphi & \varphi \end{bmatrix}$$

with stationary distribution $\{\frac{(1-\varphi)}{(1-\varphi)+(1-\phi)}, \frac{(1-\phi)}{(1-\varphi)+(1-\phi)}\}$. To match the average length of a recession (16 months), we set φ equal to 0.25. The same transition matrix Q applies in disaster and non-disaster states. To match the ratio, we choose ϕ equal to 0.71. In an expansion, the conditional probability of a banking panic $p_{ex} = 0$. In a recession, the conditional probability of a banking panic $p_{re} = 0.466$. Finally, we consider a cumulative consumption drop of 5% ($F^C = 0.95$) in the financial disaster state. This scenario matches the experience of all developed economies considered by Reinhart and Rogoff (2009) during banking crises. The market (equity) is a levered claim to aggregate consumption C^λ:

$$\begin{aligned} \Delta \log D^m_{t+1} &= \lambda^m g_C + \lambda^m \eta_{t+1}\sigma, \textit{in states without financial disaster} \\ \Delta \log D^m_{t+1} &= \lambda^m g_C + \lambda^m \eta_{t+1}\sigma + \lambda^m \log F^c, \textit{in states with financial disaster.} \end{aligned}$$

[13]This matches 13 U.S. financial crises over 210 years with an average length of 2.1 years.

Bank cash flows are also a levered claim to aggregate consumption:

$$\Delta \log D^i_{t+1} = \lambda^i g_C + \lambda^i \sigma \eta_{t+1}, \textit{ in states without financial disaster}$$
$$\Delta \log D^i_{t+1} = \lambda^i g_C + \lambda^i \sigma \eta_{t+1} + \lambda^i \log F^i, \textit{ in states with financial disaster.}$$

We assume that small and large banks have the same cash flow properties in normal times. However, small banks will have recovery rates below the $F^S < F^c$, and large banks will have recovery rates in excess of $F^L > F^c$.[14]

First, we consider the benchmark case in which the market is exposed to levered normal and disaster risk. Panel A in Table XII reports the results for different values of the recovery rates. These results were generated by generating 25,000 draws from the model. The first column reports the equity premium conditional on no disaster in the sample ($E[R^{m,e}|\textit{no disaster}]$). The second column reports the actual equity premium ($E[R^{i,e}]$). The third and fourth column report the conditional equity premium in expansions and recessions. Finally, the last two columns report the average normal-risk-adjusted returns and the market beta.

We replicate the treatment of the actual data on model-generated data. To compute the alpha, we assume that the Gaussian component of the SDF is linear in the market excess return ($M^G = a + bR^{m,e}$), and hence we project the excess returns on the bank stocks on the excess return on the market in a sample without disasters. In a sample with disasters, the alphas are very close to zero, even though the CAPM does not hold exactly (see equation 7: The log SDF depends on the (unlevered) total wealth return and consumption growth).

The left panel of Table XII considers the benchmark case of a 5% drop in aggregate consumption. The leverage of the market is 2.5. The banks have leverage of 2. With a 10% difference in the unlevered financial disaster recovery rate, the difference in the equity premium between small (7.11%) and large banks (2.29%) is 482 bps. However, most of this difference is accounted for by

[14]One might conjecture that small banks simply under-perform during recessions. Although this should not lead to differences in α, but rather differences in exposure to the standard risk factors, we want to check this, because it might be important for how cash flows are modeled. Actually, we find small bank cash flows to be less exposed to aggregate risk. The evidence is reported in section B of the appendix.

the higher beta, not by α differences.

As a result, the unlevered difference in the recovery rates needs to exceed 35% to match the spread in normal risk-adjusted returns we have observed in the data. Given that 32% of banks in the first decile were delisted in 2010 alone, that seems reasonable. When the difference in recovery rates is 35 cents, the differences in α is 551 bps. However, because the market itself is exposed to financial disaster risk, small banks have much higher loadings (2.10) on the market than large banks (0.59). This is at odds with the data.

The right panel Table XII considers the case of a 2.5% drop in aggregate consumption. In this case, a smaller differences in recovery rates of 30% is sufficient to match the difference in normal-risk-adjusted returns.

[Table 12 about here.]

The model can match the large betas of large banks and small betas of small banks, while still matching the average normal risk-adjusted-returns provided that the stock market is less exposed to financial disaster risk: The market (equity) is a levered claim to aggregate consumption C^{λ}, but the leverage only applies to the normal risk, not the disaster risk:

$$\begin{aligned}\Delta \log D^m_{t+1} &= g_C + \lambda^m \sigma \eta_{t+1}, \textit{ in states without financial disaster} \\ \Delta \log D^m_{t+1} &= g_C + \lambda^m \sigma \eta_{t+1} + \log F^c, \textit{ in states with financial disaster.}\end{aligned}$$

The dividend growth process for bank stocks is unchanged. In this calibration, we increased σ to 3.50 % and we increased θ to match the same ex-disaster equity premium of 5.80%. The results are shown in Panel II of Table XII. The top right panel considers the benchmark case of a 5% drop in aggregate consumption. The leverage of the market is 2.5, but leverage only applies to the Gaussian component. This seems reasonable. Between June 2007 and March 2009, the market lost about 50% of its value, while the financial sector lost more than 80% of its value during the same period.

The key difference is that the equity premium contains a much smaller financial disaster risk premium. As a result, a larger fraction of the difference in risk premia ends up in the alpha. Consider the case of a 5% aggregate consumption drop. When bank leverage is equal to 2, and with a 20% difference in the unlevered financial disaster recovery rate, the difference in alphas exceeds 600 bps, while the betas for the large banks are larger than the betas for small banks. In fact, when we choose large bank leverage equal to 3, and small bank leverage equal to 1, there is a 57 bps spread in the betas, and a 642 basis point spread in the alphas. The required difference in the recovery rates is 35 cents on the dollar.

Figure 3 plots the simulated returns on a small-minus-big bank portfolio (dotted line) for this calibration. A period denotes one year. The dotted line plots the stock market return. The stock market return is driven by normal risk, while the small-minus-big portfolio responds mostly to the probability of a financial disaster, which increases in recessions. The shaded areas are recession states. The small-minus-big portfolio is a recession factor, as in the data. Moreover, this portfolio has negative market beta.

[Figure 3 about here.]

Finally, if we consider a 2.5% aggregate consumption drop, and we set the leverage of small banks equal to one, we can actually match the spread in betas of more than 100 bps between portfolio 1-10 observed in the data. However, the spread in alphas is only 500 bps.

VII Conclusion

We document a size anomaly in bank stock returns that is different from the size effect that has been documented for non-financials. This size effect can be explained by the covariance with a new size factor that we extract from that component of bank stock returns that is orthogonal to standard risk factors. This size factor is a measure of bank-specific tail risk. Our evidence from bank stock returns reveals how the pricing of bank-specific tail risk in financial markets may depend on which bank is holding the risk. To the extent that these effects reflect implicit bailout guarantees in financial disasters, the government subsidizes large financial institutions to take on bank-specific tail risk.

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Table I: Market capitalization and book value for size-sorted portfolios

Notes: This table presents the total market capitalization (book value) of firms in each size-sorted portfolio as a percentage of total market capitalization (book value) for the entire banking sector. The market values (book values) are measured in January of each year. Mean represents the average value of this percentage over the years specified. N is the average number of banks in each portfolio over the same period.

	1	2	3	4	5	6	7	8	9	10
Panel A: Market Capitalization										
1970-1980										
Mean	0.36	0.92	1.50	1.95	3.50	4.67	7.61	11.51	18.21	49.78
N	8.00	9.00	9.00	9.00	9.00	8.00	9.00	9.00	9.00	9.00
1980-1990										
Mean	0.33	0.72	1.10	1.66	2.39	3.61	5.71	8.84	17.28	58.34
N	26.00	27.00	26.00	27.00	27.00	26.00	27.00	26.00	26.00	27.00
1990-2000										
Mean	0.17	0.34	0.52	0.76	1.10	1.56	2.32	3.99	8.52	80.71
N	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00
2000-2009										
Mean	0.13	0.24	0.35	0.50	0.68	0.95	1.42	2.33	4.62	88.78
N	62.00	62.00	62.00	62.00	62.00	62.00	62.00	62.00	62.00	63.00
Panel B: Book Value										
1980-1990										
Mean	0.34	1.04	1.83	2.44	3.39	4.33	6.06	9.90	18.72	51.94
N	10.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00
Leverage	13.55	15.86	16.04	16.42	16.59	17.22	17.67	17.73	18.54	22.37
1990-2000										
Mean	0.13	0.31	0.50	0.73	1.02	1.46	2.41	4.14	10.75	78.56
N	45.00	46.00	45.00	46.00	45.00	45.00	46.00	45.00	45.00	46.00
Leverage	11.42	11.16	12.17	11.82	14.03	13.56	13.73	14.40	13.83	15.86
2000-2009										
Mean	0.08	0.14	0.20	0.27	0.36	0.51	0.79	1.35	3.33	92.96
N	61.00	61.00	61.00	61.00	61.00	61.00	61.00	62.00	61.00	62.00
Leverage	8.38	10.82	5.86	14.36	11.64	11.97	12.35	12.27	10.77	14.01

Table II: Mean returns for size-sorted portfolios of commercial banks

Notes: This table presents the mean returns for each size-sorted portfolio of banks sorted by market capitalization in the top panel and by total balance sheet in the bottom panel. The first column indicates the years over which mean returns were computed. The monthly mean returns have been annualized by multiplying by 12 and are expressed in percentages.

Panel A: Market Cap										
Year	1	2	3	4	5	6	7	8	9	10
1970 – 2005	17.47	16.73	16.15	15.96	16.05	17.03	15.89	14.37	13.77	13.26
1980 – 2005	19.81	19.18	18.09	17.84	18.31	19.94	19.38	17.15	16.31	16.17
1990 – 2005	19.61	20.90	18.24	17.67	20.32	19.15	18.69	17.34	16.62	16.90
Panel B: Book Value										
Year	1	2	3	4	5	6	7	8	9	10
1980 – 2005	16.36	17.57	19.46	18.84	20.68	21.75	20.12	16.89	13.95	13.68
1990 – 2005	13.65	18.03	19.44	18.76	20.54	20.00	21.34	17.96	13.67	11.00

Table III: Mean returns for size-sorted portfolios of non-financial firms

Notes: This table presents the mean returns for each size-sorted portfolio of non-financial firms sorted by market capitalization in the top panel and by total balance sheet in the bottom panel. Non-financial firms are defined as those for which the SIC code lies outside 6000 - 6799. The first column indicates the years over which mean returns were computed. The monthly mean returns have been annualized by multiplying by 12 and are expressed in percentages. The first column indicates the years over which mean returns were computed. The monthly mean returns have been annualized by multiplying by 12 and are expressed in percentages.

Year	1	2	3	4	5	6	7	8	9	10
Panel A: Market Cap										
1970 – 2005	24.51	15.76	13.38	12.41	11.61	12.12	12.21	12.55	13.30	11.39
1980 – 2005	26.29	15.47	13.25	12.02	11.27	11.51	12.07	12.57	14.32	13.18
1990 – 2005	30.13	17.75	14.96	14.11	12.43	12.04	11.47	10.65	12.56	10.61
Panel B: Book Values										
1970 – 2005	16.05	16.75	15.90	15.15	14.90	15.39	15.63	15.26	15.02	13.29
1980 – 2005	16.08	17.14	16.59	15.65	15.19	15.81	16.52	15.92	15.94	14.74
1990 – 2005	21.06	19.68	18.32	17.62	16.28	16.43	16.24	15.80	14.75	12.56

Table IV: Mean Risk-adjusted returns in size-sorted portfolios of commercial banks

Notes: This table presents the estimates from an OLS regression of monthly excess returns on each size-sorted portfolio of banks on the Fama-French stock and bond risk factors. *market*, *smb*, and *hml* are the three Fama-French stock factors: the market, small minus big, and high minus low respectively. *ltg* is the excess return on an index of long-term government bonds and *crd* is the excess return on an index of investment-grade corporate bonds. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. The sample is 1970-2005.

	1	2	3	4	5	6	7	8	9	10	8 - 3	9 - 2	10 - 1
							Panel A: Market Cap						
α	5.45**	4.11*	3.25	2.05	1.75	2.11	0.64	-0.70	-2.51	-2.53	-3.95**	-6.62***	-7.97***
market	0.36***	0.44***	0.49***	0.55***	0.59***	0.63***	0.69***	0.71***	0.87***	1.07***	0.23***	0.43***	0.71***
smb	0.39***	0.44***	0.41***	0.47***	0.50***	0.47***	0.47***	0.44***	0.43***	-0.03	0.02	-0.01	-0.42***
hml	0.32***	0.38***	0.39***	0.50***	0.52***	0.53***	0.54***	0.55***	0.57***	0.42***	0.15**	0.19*	0.09
ltg	-0.16	-0.11	-0.05	0.10	0.15	0.12	0.07	0.12	0.26**	0.15	0.17	0.37***	0.30*
crd	0.51***	0.41***	0.35**	0.21	0.17	0.29*	0.30**	0.18	0.11	0.13	-0.17	-0.30*	-0.38*
R^2	29.12	40.47	42.80	53.16	53.56	55.36	61.49	62.99	65.09	63.62	6.21	18.83	27.91
							Panel B: Book Value						
α	3.29	3.98	4.91*	4.54**	3.80	4.53*	2.12	-1.39	-3.17	-2.56	-6.30**	-7.15***	-5.85*
market	0.49***	0.50***	0.56***	0.54***	0.69***	0.74***	0.81***	0.83***	0.85***	0.91***	0.27**	0.35***	0.41***
smb	0.50***	0.51***	0.46***	0.51***	0.60***	0.57***	0.55***	0.59***	0.32***	0.05	0.13	-0.19***	-0.45***
hml	0.44***	0.45***	0.50***	0.51***	0.65***	0.65***	0.64***	0.72***	0.57***	0.42***	0.22**	0.12	-0.02
ltg	0.17	0.19	0.09	0.14	0.00	0.03	0.21*	0.29***	0.19	0.18	0.20	-0.00	0.00
crd	0.06	0.14	0.26	0.19	0.43**	0.40***	0.31**	0.16	0.16	0.07	-0.09	0.03	0.01
R^2	38.53	44.04	46.66	52.12	53.17	60.49	63.50	54.84	62.13	46.24	8.04	15.03	14.46

Table V: Mean risk-adjusted returns in size-sorted portfolios of non-financials

Notes: This table presents the estimates from an OLS regression of monthly excess returns on each size-sorted portfolio of non-financials on the Fama-French stock and bond risk factors. *market*, *smb*, and *hml* are the three Fama-French stock factors: the market, small minus big, and high minus low respectively. *ltg* is the excess return on an index of long-term government bonds and *crd* is the excess return on an index of investment-grade corporate bonds. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. The sample is 1970-2005.

Year	1	2	3	4	5	6	7	8	9	10	8 - 3	9 - 2	10 - 1
Panel A: Market Cap													
α	11.17***	1.55	-1.22	-2.10	-3.03**	-2.36**	-2.02**	-1.06	0.20	0.61	0.16	-1.35	-10.56***
market	0.77***	0.89***	0.95***	0.99***	1.05***	1.13***	1.14***	1.12***	1.10***	0.95***	0.17***	0.21***	0.19*
smb	0.82***	0.96***	1.02***	0.97***	0.94***	0.90***	0.80***	0.67***	0.41***	-0.14***	-0.35***	-0.55***	-0.96***
hml	0.34**	0.37***	0.36***	0.29**	0.27**	0.25**	0.18	0.11	0.09	-0.10***	-0.25***	-0.29***	-0.44***
ltg	-0.47***	-0.37***	-0.36***	-0.31***	-0.24**	-0.20**	-0.18**	-0.14*	-0.07	-0.10***	0.21*	0.30***	0.37***
crd	0.36*	0.23	0.24	0.25	0.19	0.05	0.09	0.09	0.03	0.13***	-0.15	-0.20	-0.23
R^2	52.70	67.11	74.48	76.89	82.69	86.57	89.16	89.62	91.22	97.03	17.42	22.76	34.76
Panel B: Book Value													
α	3.02	2.91	2.16	1.13	0.62	1.00	0.73	0.80	0.55	-0.07	-1.36	-2.36	-3.09
market	0.99***	1.02***	1.04***	1.06***	1.09***	1.12***	1.16***	1.14***	1.14***	0.98***	0.10	0.12	-0.01
smb	0.92***	0.97***	1.00***	0.99***	0.94***	0.87***	0.80***	0.66***	0.45***	-0.05	-0.35***	-0.51***	-0.97***
hml	0.14	0.23	0.18	0.20	0.22*	0.24**	0.29***	0.31***	0.31***	0.27***	0.13	0.08	0.13
ltg	-0.42**	-0.39***	-0.30***	-0.32***	-0.29***	-0.23***	-0.16***	-0.06	-0.03	-0.07*	0.25***	0.37***	0.35**
crd	0.23	0.20	0.16	0.19	0.17	0.08	0.04	-0.11	-0.09	0.07	-0.27*	-0.29	-0.15
R^2	55.54	67.97	75.48	83.02	86.01	88.98	91.62	92.07	93.97	93.32	14.89	16.70	27.23

Table VI: Principal components of size-sorted commercial bank stock returns

Notes: This table presents the loadings for the first and second principal components ($\boldsymbol{w}_1, \boldsymbol{w}_2$) extracted from the residuals of the regression specified in equation 2. The last row indicates the % explained by each principal component.

	Market Cap 1970 - 2009		Book Value 1980 - 2009	
Portfolio	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$
1	0.31	0.42	0.21	0.34
2	0.29	0.35	0.25	0.30
3	0.28	0.31	0.31	0.26
4	0.28	0.26	0.28	0.19
5	0.33	0.16	0.38	0.20
6	0.34	0.00	0.37	-0.01
7	0.35	-0.21	0.36	-0.11
8	0.32	-0.26	0.40	-0.19
9	0.32	-0.37	0.30	-0.24
10	0.33	-0.51	0.23	-0.74
%	47.63	18.37	47.56	15.39

Table VII: Size-factor-adjusted returns for size-sorted portfolios of commercial banks

Notes: This table presents the estimates from OLS regression of monthly excess returns on each size-sorted portfolio of commercial banks on the Fama-French stock factors, bond factors, and the second principal component weighted returns. *mkt*, *smb*, and *hml* are the three Fama-French factors: the market, small minus big, and high minus low respectively. *ltg* is the excess return on an index of long-term government bonds and *crd* is the excess return on an index of investment-grade corporate bonds. R^{PC_2} is the time-series of the returns of the size-sorted portfolios weighed by the loadings of the second principal component $\widehat{\boldsymbol{w}}_2$. The weights of the second principal component have been re-normalized so that they sum to 1. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. The last two lines show the loadings on the size factor and the implicit tax (risk price times loading on PC_2). The annualized risk price is 38.93% in the sample ending in 2005.

Year	1	2	3	4	5	6	7	8	9	10
					Risk-adjusted Returns					
1970 - 2005	0.78	0.60	0.26	-0.41	0.56	2.28	1.77	0.87	0.27	1.66
					Loading on 2nd PC					
1970 - 2005	0.08***	0.06***	0.05***	0.04***	0.02**	0.00	-0.02**	-0.03***	-0.05***	-0.07***
					Size Factor Adjustment					
1970 – 2005	3.25	2.44	2.08	1.71	0.83	-0.12	-0.79	-1.10	-1.94	-2.92

Table VIII: Cumulative return on 2nd pc portfolio in recessions and financial crises

Notes: This table shows the value of a \$100 invested in a portfolio that goes long in small banks and shorts large banks. The weights of the portfolio are given by the second principal component, re-normalized so that they sum to 1 ($\widehat{\boldsymbol{w}}_2$). \$100 is invested in this portfolio at the 'Start' date and its value, given in columns 3 and 4, is measured on the 'End' date. The column labeled *Value* represents the value of \$100 invested at the peak (or start of the crisis) at the trough (or end of the crisis) on this portfolio and the column labeled *Hedged Value* represents the normal-risk-adjusted returns on this portfolio. The average is computed for all NBER recessions only using the NBER dating conventions. The bottom panel shows the value of a \$100 investment n months into the recession. The first two columns use all portfolios. The last two columns exclude the first portfolio containing the smallest banks.

Panel A: Portfolio Value at NBER Trough			
Start	End	Value	Hedged Value
NBER Recessions			
01: 1970	11: 1970	-12.23	32.74
11: 1973	03: 1975	-17.10	26.50
01: 1980	11: 1982	47.34	8.51
07: 1990	03: 1991	19.54	17.05
03: 2001	11: 2001	287.33	138.48
12: 2007	06: 2009	63.53	11.77
Average		64.73	39.17
Panel B: Average Portfolio Value n months after NBER Peak			
		Value	Hedged Value
Month 1		128.26	112.52
Month 2		88.76	86.04
Month 3		105.17	84.70
Month 4		86.36	65.93
Month 5		75.06	60.55
Month 6		99.79	65.32
Month 12		8.80	37.21

Table IX: Bank Tail Risk Pricing for investment banks, foreign banks, and GSEs.

Notes: This table presents the estimates from OLS regression of monthly excess returns on a value-weighted index of commercial banks, investment banks, and GSEs on the Fama-French stock factors, bond factors, and the second principal component weighted returns. The table also reports results for individual banks. Foreign banks were selected based on the share-code in CRSP. Investment banks are those with SIC code 62. A share-code ending in two indicates that firms were incorporated outside the US. For individual banks, the longest available sample for each bank till 2009 was selected. The starting year for each bank is mentioned in parentheses under the name of the bank. PC_2 is the time-series of the returns of the size-sorted portfolios weighed by the loadings of the second principal component $\widehat{\boldsymbol{w}}_2$. The weights of the second principal component have been re-normalized so that they sum to 1. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. The implicit subsidy is the risk price (38.93%) times (minus) loading on PC_2). The risk price is fixed in the different subsamples.

	Index of Banks				Individual Banks								
	Commercial	Investment	Foreign	GSE	BoA	Citi	GS	LEH	ML	MS	WFC	FNM	FRE
Market Cap(Jan 05)	118.57	24.12	44.71	50.61	187.30	254.56	52.22	34.33	55.78	61.25	103.71	62.48	44.95
start					(1973)	(1986)	(1999)	(1994)	(1971)	(1986)	(1970)	(1970)	(1989)
					Panel A: Full Sample								
market	0.83***	1.65***	0.97***	0.82***	1.12***	1.37***	1.50***	1.54***	1.85***	1.63***	0.82***	0.8***	0.68***
smb	0.17**	0.14	0.36	-0.01	0.08	-0.17	0.21	-0.09	0.06	-0.15	-0.12	-0.07	0.38
hml	0.41***	0.13	0.54	0.16	0.56***	0.17	-0.28	-0.10	0.20	-0.12	0.39***	0.16	0.43**
ltg	0.04	0.09	0.07	1.39***	0.08	-0.07	1.09	-0.08	-0.31	-0.16	-0.01	1.34***	1.23***
crd	0.26**	-0.25	-1.24	-0.22	0.44	0.44	-0.66	0.91	0.37	-0.20	0.44*	-0.15	-0.25
PC_2	-0.06***	-0.02	0.01	-0.05***	-0.08***	-0.05**	-0.07	-0.09*	-0.02	-0.04**	-0.08***	-0.05***	-0.10***
size	2.32	0.77	-0.38	1.95	3.12	1.94	2.57	3.43	0.70	1.47	3.27	1.83	3.94
					Panel B: Subsamples								
						1990-2005							
PC_2	-0.07***	-0.03**	-0.02	-0.09***	-0.08**	-0.06**	-0.07	-0.09*	-0.02	-0.04**	-0.11***	-0.08***	-0.11***
size	2.58	1.13	0.84	3.57	3.17	2.18	2.57	3.43	0.61	1.55	4.40	3.39	4.06
						2000-2005							
PC_2	-0.12***	-0.07***	-0.06**	-0.16***	-0.12***	-0.12***	-0.06	-0.16***	-0.04	-0.11***	-0.16***	-0.17***	-0.14***
size	4.76	2.59	2.23	6.07	4.53	4.59	2.53	6.22	1.61	4.12	6.15	6.57	5.37

Table X: Announcement Dates

Dates for the pre-crisis announcements are from O'Hara and Shaw (1990) and Kho, Lee, and Stulz (2000). Dates for the crisis announcements are from the New York Fed Timeline of the Financial Crisis.

		+ All	+ large	- large
Panel A: Pre-Crisis Bailout Announcement Dates				
9/19/1984	Comptroller of Currency		x	
9/24/1998	LTCM		x	
9/15/1998	Brazilian Crisis		x	
10/08/1998	Brazilian Crisis		x	
11/13/1998	Brazilian Crisis		x	
11/14/1997	South Korean Crisis		x	
01/25/1995	Mexico Crisis			
Panel B: Crisis Announcement Dates				
2007/08/10	The FR provides liquidity	x		
2007/12/12	Term auction facility is announced	x		
2007/12/17	First Term auction takes place	x		
2007/12/21	Term auction facility is extended	x		
2008/03/11	Term securities lending facility is extended	x		
2008/03/14	Emergency lending from the Fed to Bear Stearns	x	x	
2008/03/17	Bear Stearns is bought for $2 per share			x
2008/03/17	Primary dealer credit facility is extended **delayed by a day*	x	x	
2008/05/02	TSLF collateral eligibility is expanded	x		
2008/07/15	Paulson requests govnmt funds for Fannie Mae and Freddie Mac	x	x	
2008/07/30	84-day TAF auctions are introduced	x		
2008/09/15	Lehman files for bankruptcy			x
2008/09/29	House votes down bailout plan			x
2008/10/03	Revised plan passes House	x		
2008/10/06	TALF increased to $900 billion	x		
2008/10/14	Treasury announces $250 billion capital injection			
2008/11/7	Bush Speech			x
2008/11/13	TARP not used for buying troubled assets from banks			x
2008/11/25	Term Asset-Backed Securities Loan Facility (TALF)	x		
2009/01/16	Treasury/ Federal Reserve and the FDIC Provide Assistance to Bank of America	x	x	
2009/02/10	The FRB expands TALF to as much as $1 trillion	x		
2009/03/18	The FRB purchases up to $300 billion of longer-term Treasury securities	x		

Table XI: Bailout announcements

Notes: This table presents the results of the regression $R_t^{TBTF} - R_t^f = \alpha + \beta_1 PC_2 + \beta_2 PC_2 D + \epsilon$. $TBTF$ represents the value-weighted return of the 10 banks that were announced to be by the Comptroller of Currency in September of 1984. PC_2 represents the daily return of the portfolio that goes long in small banks and shorts large banks. The weights for the portfolio are given by the second principal component and sum to 1. D represents a dummy variable that equals 1 after the announcement date and 0 otherwise. The regression is estimated over a 30-, 60-, 90-, and a 105-day window around the announcement date. A 7-day window around the exact announcement date was excluded from the sample while estimating coefficients. Dates for the announcements are from O'Hara and Shaw (1990) and Kho, Lee, and Stulz (2000) .

Coeff	30D	45D	60D	90D	105D
			Panel A: Pre-crisis Announcements		
			9/19/1984; Comptroller of Currency		
PC_2	-0.19***	-0.19***	-0.20***	-0.21***	-0.20***
PC_2D	-0.12*	-0.05	-0.03	-0.02	0.00
			9/24/1998; LTCM		
PC_2	-0.22***	-0.23***	-0.24***	-0.23***	-0.24***
PC_2D	-0.05	-0.05	-0.05	-0.05	-0.05*
			9/15/1998; Brazilian Crisis		
PC_2	-0.24***	-0.25***	-0.25***	-0.26***	-0.26***
PC_2D	-0.03	-0.03	-0.03	-0.02	-0.03
			10/08/1998; Brazilian Crisis		
PC_2	-0.24***	-0.24***	-0.25***	-0.25***	-0.25***
PC_2D	-0.08*	-0.09**	-0.09***	-0.08***	-0.06**
			11/13/1998; Brazilian Crisis		
PC_2	-0.27***	-0.26***	-0.27***	-0.25***	-0.25***
PC_2D	-0.06	-0.05	-0.03	-0.05	-0.03
			11/14/1997; South Korean Crisis		
PC_2	-0.27***	-0.27***	-0.27***	-0.26***	-0.26***
PC_2D	-0.01	0.00	0.00	0.00	0.00
			01/25/1995; Mexico Crisis		
PC_2	-0.17*	-0.11*	-0.12***	-0.15***	-0.14***
PC_2D	-0.06	-0.12*	-0.08	-0.05	-0.05
			Pooled Regression		
PC_2	-0.24***	-0.24***	-0.24***	-0.24***	-0.24***
PC_2D	-0.03**	-0.04***	-0.04***	-0.04***	-0.04***
			Panel B: Crisis Announcements		
			Positive Announcements: All Banks		
PC_2	-0.17***	-0.17***	-0.17***	-0.16***	-0.16***
PC_2D	0.00	-0.00	-0.01	-0.01	-0.01
			Positive Announcements: Large Banks		
PC_2	-0.11***	-0.15***	-0.16***	-0.15***	-0.14***
PC_2D	-0.07***	-0.04**	-0.02	-0.02	-0.03*
			Negative Announcements		
PC_2	-0.15***	-0.15***	-0.16***	-0.16***	-0.16***
PC_2D	-0.01	-0.01	0.00	-0.01	-0.01

Table XII: Baseline model with levered normal and financial disaster risk in the market

Calibrated version of model with Gaussian aggregate consumption growth shocks and two aggregate states. In Panel A, θ is 13.25 and α is 0.75. σ is 3% and μ is 2%. In Panel B, θ is 15 and α is 0.75. σ is 3.5% and μ is 2%. Results shown for 25,000 random draws.

λ^i	F^i	$E[R^{i,e}\|nd]$	$E[R^{i,e}]$	$E[R^{i,e}\|exp]$	$E[R^{i,e}\|rec]$	$\alpha^i\|no\ dis.$	$\beta^i\|no\ dis$	$E[R^{i,e}\|nd]$	$E[R^{i,e}]$	$E[R^{i,e}\|exp]$	$E[R^{i,e}\|rec]$	$\alpha^i\|no\ dis.$	$\beta^i\|no\ dis$
Panel A: Baseline Model with Levered Normal and Financial Disaster risk in the Market													
		5% aggregate consumption drop						2.5% aggregate consumption drop					
		Market						Market					
2.5	0.95	5.80	4.09	3.49	5.64			4.21	3.33	3.19	3.71		
		Large Banks						Large Banks					
2	1.00	2.29	2.29	2.30	2.26	−0.63	0.59	2.44	2.44	2.45	2.43	−0.40	0.74
		Small Banks						Small Banks					
2	0.90	7.11	4.18	3.18	6.78	0.71	0.98	6.19	3.28	2.79	4.59	1.30	0.93
2	0.80	12.54	6.16	3.98	11.87	2.22	1.41	10.23	4.16	3.09	6.95	3.21	1.12
2	0.75	15.49	7.19	4.35	14.64	3.07	1.63	12.53	4.60	3.23	8.20	4.25	1.23
2	0.70	18.61	8.25	4.69	17.56	3.96	1.86	14.81	5.05	3.36	9.49	5.31	1.33
2	0.65	21.88	9.33	5.01	20.63	4.88	2.10	17.17	5.51	3.48	10.81	6.44	1.43
2	0.60	27.63	10.43	5.31	23.84	5.92	2.36	19.59	5.96	3.60	12.17	7.56	1.53
Panel B: Baseline Model with Levered Normal and Unlevered Financial Disaster risk in the Market													
		5% aggregate consumption drop						2.5% aggregate consumption drop					
		Market						Market					
2.5	0.95	5.83	5.12	4.87	5.75			5.23	4.88	4.83	5.03		
		Large Banks						Large Banks					
2	1.00	3.59	3.59	3.61	3.53	−0.59	0.76	3.78	3.78	3.79	3.75	−0.20	0.78
3	1.00	5.54	5.54	5.58	5.45	−0.85	1.17	5.75	5.75	5.76	5.76	−0.36	1.20
4								5.54	5.54	5.58	5.45	−0.56	1.56
		Small Banks						Small Banks					
2	0.90	10.5	5.80	4.68	8.74	2.32	0.89	7.69	4.76	4.19	6.24	2.05	0.84
2	0.80	14.63	8.13	5.63	14.64	5.48	1.03	12.02	5.77	4.55	8.96	4.56	0.89
2	0.75	17.84	9.35	6.09	17.87	7.23	1.11	14.33	6.28	4.71	10.40	5.86	0.93
2	0.70	21.24	10.62	6.51	21.31	9.03	1.19	16.73	6.81	4.87	11.90	7.21	0.97
1	0.70	10.32	5.27	3.34	10.34	4.50	0.56	8.33	3.43	2.47	5.94	3.71	0.46
1	0.65	12.13	5.98	3.62	12.17	5.57	0.60	9.66	3.74	2.58	6.77	4.50	0.47

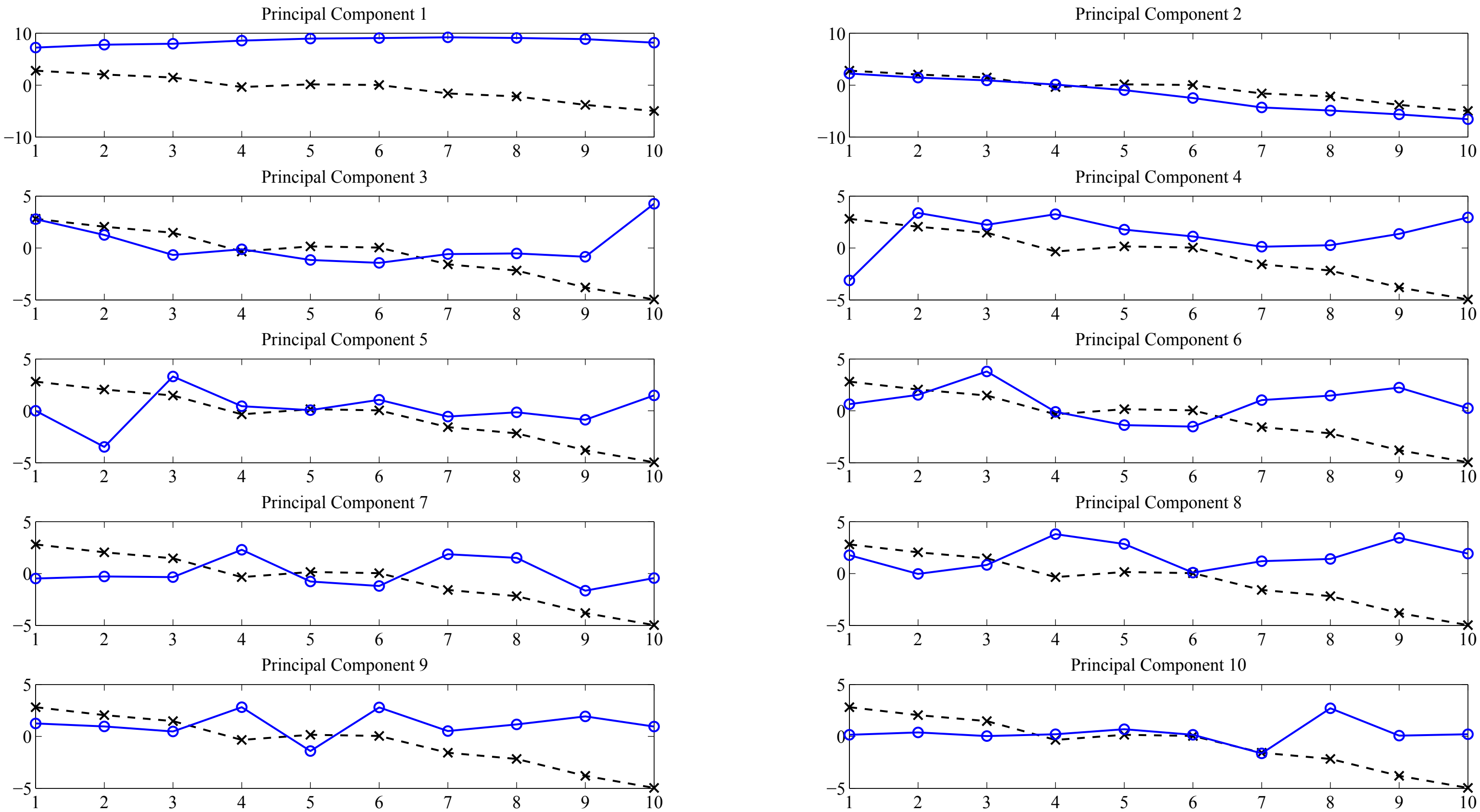

Figure 1: Covariances between risk adjusted returns and principal components

Each panel corresponds to a principal component. The upper left panel uses the first principal component. The black 'X' represent the average risk adjusted returns for the 10 size-sorted portfolios of banks. Each blue circle represents a covariance between a given principal component and a given bank portfolio. The covariances are re-scaled. The normal-risk-adjusted returns are annualized (multiplied by 12) and reported in percentage points.

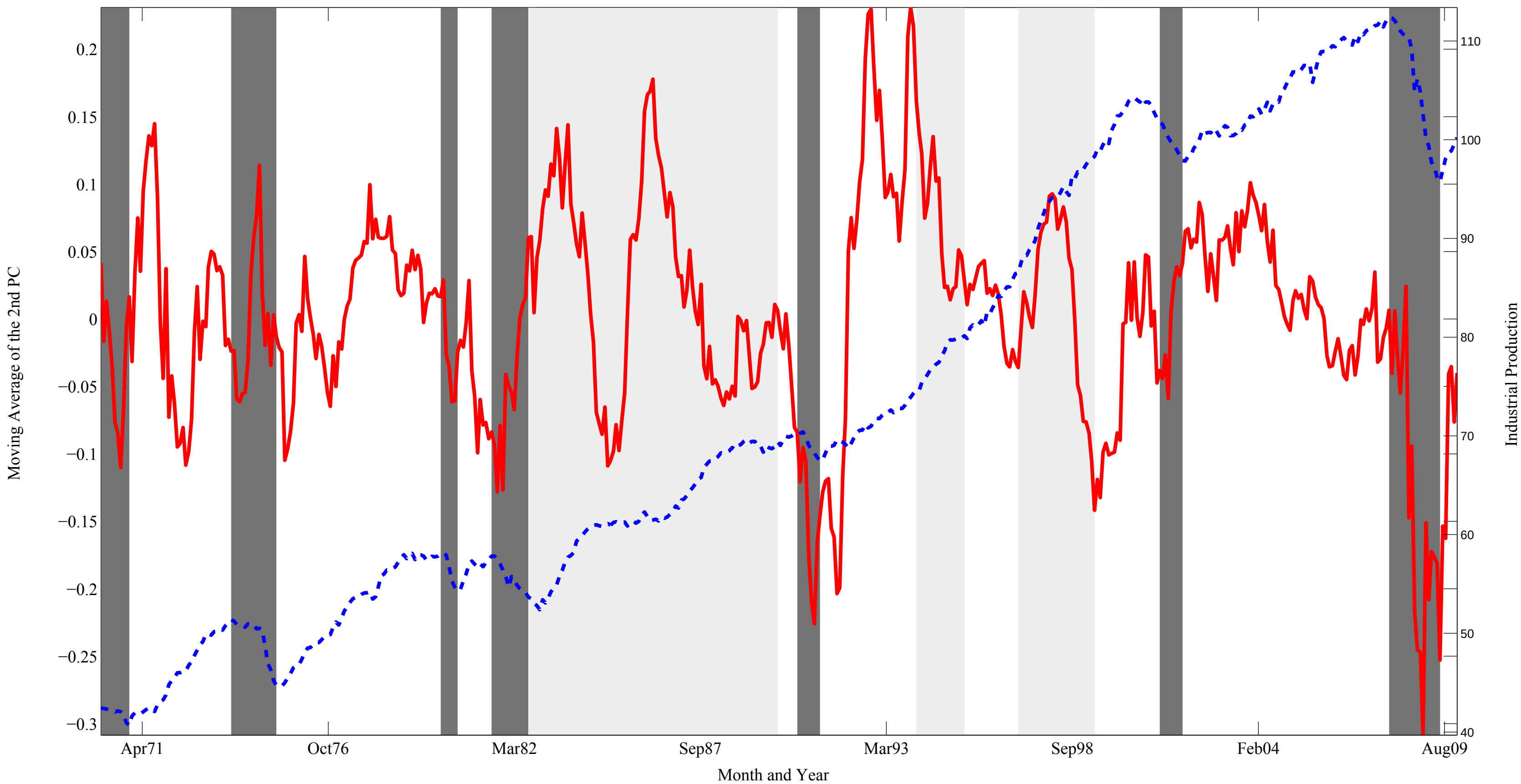

Figure 2: Size factor in normal risk-adjusted returns of commercial banks

The solid line plots the 12-month (backward looking) moving average (months $t-11$ through t) of the time-series of the weighted sum of the residuals from the OLS regression of monthly excess stock returns for each size-sorted portfolio of commercial banks on the Fama-French and bond risk factors. The weights are given by the second principal component and sum to 1. The dashed line represents the growth of index of industrial production. The gray-shaded regions represent NBER recessions and the light-shaded regions represent banking crisis. The NBER recession dates are published by the NBER Business Cycle Dating Committee. The dates for the Mexico and LTCM crisis were obtained from Kho, Lee, and Stulz (2000) and the FDIC (for the Less-Developed-Country debt crisis of 1982). The left-axis references the moving average of the residuals and the right-axis references the index of industrial production.

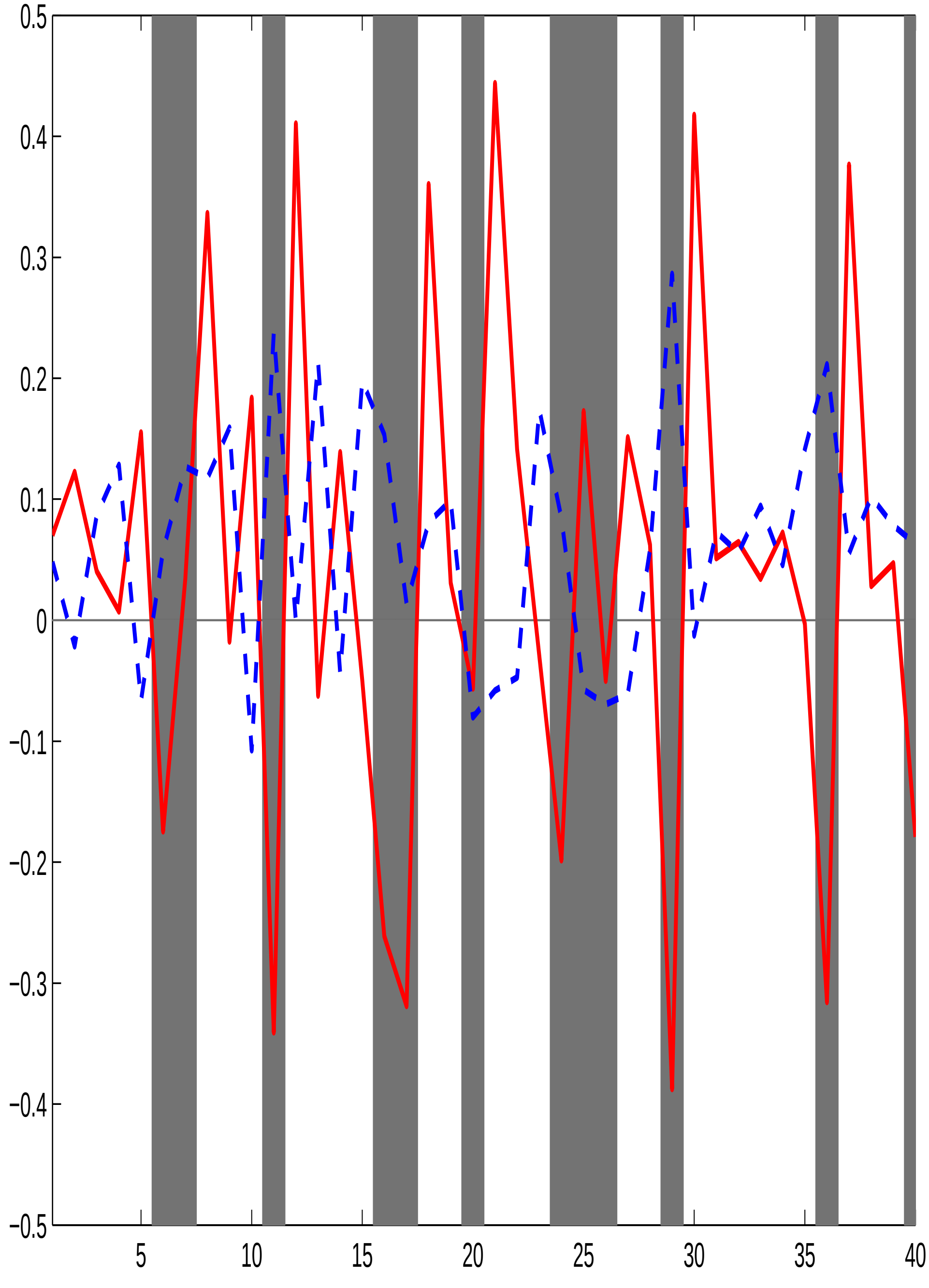

Figure 3: Size factor in bank stocks and recessions

Notes: Simulation of 40 years. The full line is Return on *smb*; the dotted line is Return on market. θ is 15 and α is 0.75. σ is 3.5% and μ is 2%. Small bank leverage is 1 and $F^S = 0.65$. Large bank leverage is 3 and $F^B = 1$. The shaded areas are recessions.

Separate Appendix

A Derivation of Tail Risk Premium Expression

We use F to denote F^C. Consider the investor's Euler equation for asset i: $E_t[M_{t+1}R^i_{t+1}] = 1$. The stand-in investor's SDF M_{t+1} is described in equation (5). This Euler equation can be decomposed as follows:

$$(1-p_t)E_t[M^G_{t+1}R^i_{t+1}] + p_t E_t[M^G_{t+1}M^D_{t+1}R^{G,i}_{t+1}R^{D,i}] = 1.$$

We assume that the distribution of the Gaussian factors is (conditionally) independent of the realization of the disaster:

$$\left((1-p_t) + p_t E_t[M^D_{t+1}R^{D,i}]\right) E_t[M^G_{t+1}R^{G,i}_{t+1}] = 1.$$

Given these assumptions, this expression can be further simplified to yield:

$$\left(1 + p_t E_t[M^D_{t+1}F^i - 1]\right) E_t[M^G_{t+1}R^i_{t+1}] = 1,$$

where we have substituted the recovery rate F^i for $R^{D,i}$. To see why, note that the Gaussian return on stock i can be stated as:

$$R^{G,i}_{t+1} = \frac{(P_{t+1}/D_{t+1}) + 1}{P_t/D_t}\frac{D_{t+1}}{D_t}$$

which can be stated as follows, in the case of no disaster: $R^{G,i}_{t+1} = \frac{(P_{t+1}/D_{t+1})+1}{P_t/D_t} \exp\left(g_D + \Delta \log D^{i,G}_{t+1}\right)$. In case of a disaster, the return is given by: $R^i_{t+1} = R^{G,i}_{t+1}F^i_{t+1}$, which only reflects the effect of the recovery rate on the dividend growth realization. Using the definition of resilience $p_t E_t[M^D_{t+1}F^i - 1]$, this yields the following expression:

$$\left(1 + H^i_t\right) E_t[M^G_{t+1}R^{G,i}_{t+1}] = 1.$$

Decomposing this expectation into a covariance term and a cross-product produces:

$$E_t[M^G_{t+1}]E_t[R^i_{t+1}] + cov_t[M^G_{t+1}, R^{G,i}_{t+1}] = \left(1 + H^i_t\right)^{-1}.$$

Given the linear specification of the stochastic discount factor, this equation can in turn be written in the conditional beta representation:

$$E_t[R^{G,i}_{t+1}] = E_t[M^G_{t+1}]^{-1}\left(1 + H^i_t\right)^{-1} - \frac{cov_t[M^G_{t+1}, R^{G,i}_{t+1}]}{var_t[M^G_{t+1}]}\frac{var_t[M^G_{t+1}]}{E_t[M^G_{t+1}]},$$

or equivalently: $E_t[R^i_{t+1}] - \boldsymbol{\beta^i_t \lambda_t} = R_t\left(1 + H^i_t\right)^{-1}$, where β^i_t is the vector of multiple regression coefficients in regression of returns on the factors and λ_t is the vector of risk prices, and $R_t = E_t[M^G_{t+1}]^{-1}$. Note that the variation in the p/d ratios induced by the variation in the probability of a disaster does not co-vary with the normal risk factors–by assumption– and hence is not priced in the normal risk premium. In addition, we assume that the market price of Gaussian risk is constant $\boldsymbol{\lambda}$ and that the Gaussian factor betas $\boldsymbol{\beta^i_t}$ are constant. In that case, the expected return on asset i, conditional on no disaster realization, after adjusting for Gaussian risk exposure, becomes: $E_t[\widehat{R}^i_{t+1}] = exp(r_t - h^i_t)$, where $E_t[\widehat{R}^i_{t+1}] = E_t[R^{G,i}_{t+1}] - \boldsymbol{\beta^i \lambda}$, and r_t denotes $\log R_t$, and h^i_t denotes $\log(1 + H^i_t)$.

B Other Explanations

Business Cycle Variation in Common and Idiosyncratic Risk Finally, there are factors other than financial disasters that could explain the cyclicality in the size factor. Large idiosyncratic shocks can cause bank failures. If the volatility of these shocks increases more in recessions for small banks, that could explain some of our findings. Table XIII measures the standard deviation of normal-risk-adjusted returns at the portfolio level (Panel A) and at the bank level (Panel B). The first one measures the quantity of residual common risk. The second one measures the quantity of residual idiosyncratic risk. The portfolio-level measure in Panel A is the time series standard deviation of normal risk-adjusted returns, reported for NBER expansions and recessions separately. The bank-level measure in panel B is the average over time of the cross-sectional standard deviation within each portfolio of normal-risk-adjusted returns.

During recessions, the exposure of the largest banks to residual common risk increases from 14.2 to 21.6%. For the smallest banks, the increase is only 3 percentage points. As expected, smaller banks are much more exposed to idiosyncratic risk than large banks, but the amount of idiosyncratic risk exposure of small banks does not seem to increase very much during recessions. The standard deviation ranges from 38% for the smallest banks to 26% for the largest banks during recessions, and from 36% to 20% in the whole sample. However, the largest percentage point increase in volatility during recessions is noted for the largest banks: from 20% to 26%. For the smallest banks, the increase is less than two percentage points. There is no evidence to suggest that the cyclicality of the size factor is due to idiosyncratic banks risk.

[Table 13 about here.]

Business Cycle Variation in Cash Flows We analyzed the data in the report for the first three quarters of 2001 which corresponds to the recession dates provided by NBER. During this period, small banks outperform large banks on almost all 13 performance parameters measured. Small banks had a higher return-on-equity (14.00% versus 13.80%), a higher return-on-assets (1.15 times that of large banks), a lower loan-loss-charge, a higher net-interest-margin (4.34% versus 3.62%), and comparable cost-of-funds (approximately 3.75% for both). During this recession, 70% of small banks and 60% of large banks reported earnings gains.

In 2008, large banks are again unable to match the performance of small banks on most measures. For the first-half 2008, small banks' ROE is 1.5 times and yield-on-assets is 50 basis-point higher than corresponding values for large banks. 14.16% of the 558 small banks and 26.72% of the 114 large banks were unprofitable. Finally, 41.22% of small banks reported an earnings gain as compared to 24.14% of large banks.

For the full-year 2008, 28.70% of small banks and 40.35% of large banks reported losses. Small banks do have lower return-on-assets and ROE for the full year, but it is not obvious if this is due to a higher cash flow risk. During second-half 2008, small banks not only earned a higher yield on assets and a higher net interest margin, but also provisioned more conservatively for losses. The ratio of loan-loss provisions to assets increases to 1.93% for small banks by 4Q 2008 from 0.76% during 1Q 2008 but this ratio hardly changes for the largest banks.

C Additional Tables

[Table 14 about here.]

[Table 15 about here.]

[Figure 4 about here.]

Table XIII: Measuring residual risk exposure

Notes: This table presents the standard deviation of the residuals from the OLS regression of monthly excess returns of each size-sorted portfolio of commercial banks on Fama-French factors and bond factors. In panel A the row labeled Recession computes the (time series) standard deviation of the residuals during recession months and the row labeled Entire Sample computes the (time series) standard deviation for the entire sample. In Panel B we examine the cross-sectional standard deviation of the residuals of banks in each bin for each period t. Panel B reports the time-series average of the cross-sectional standard deviation for each bin. The row labeled Recession lists the standard deviation of the residuals during recession months and the row labeled Entire sample lists the standard deviation for the entire sample. The standard deviations have been annualized by multiplying by $\sqrt{12}$ and are expressed in percentages.

Panel A: Portfolios										
Period	1	2	3	4	5	6	7	8	9	10
Recession	15.77	14.39	12.80	12.43	13.76	13.46	15.77	14.79	18.11	21.13
Entire Sample	13.18	11.92	11.43	10.54	10.93	11.17	11.38	10.96	11.95	14.26
Panel B: Individual Banks										
Recession	38.40	30.94	32.45	28.86	30.33	27.61	27.48	28.05	26.01	25.54
Entire Sample	36.36	30.05	28.79	27.45	25.88	25.13	24.68	24.03	22.43	20.83

Table XIV: NBER reference cycle peaks and banking panics

Notes: The dates of the banking panics were taken from Gorton (1988, p. 223) and Wicker (1996, p.155). Months before peak and Months after peak indicate the number of months relative to the peak when the banking crisis occurs.

Peak	Trough	Panic	Months before peak	Months after peak
October 1873	March 1879	September 1873	1	
March 1882	May 1885	May 1884		17
July 1890	May 1891	November 1890		4
January 1893	June 1894	February 1893		1
December 1895	June 1897	October 1896		10
May 1907	June 1908	October 1907		5
January 1913	December 1914	August 1914		20
August 1929	March 1933	October-November 1930		19
		September-October 1931		
		February-March 1933		
July 1981	November 1982	February-July 1982		8
December 2007		September-December 2008		9

Table XV: Coefficients for the cross-sectional regression of annual returns on size as measured by market capitalization

Notes: Pooled regression. The dependent variable is the annual return for each individual bank in our sample. The independent variables are the market capitalization of the bank, the book to market value for the bank, the book value of the bank, and the leverage of the bank. All variables are at date t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. Annual data. The sample is 1970-2005.

$constant$	9.85 **	-0.14
$\log Book$	-2.45***	0.00
$\log Marketcap$	2.76***	0.54**
$\frac{Book}{Marketcap}$	0.00	
$Leverage$	0.00	-0.01
$adj - R^2$	0.0038	0.0004

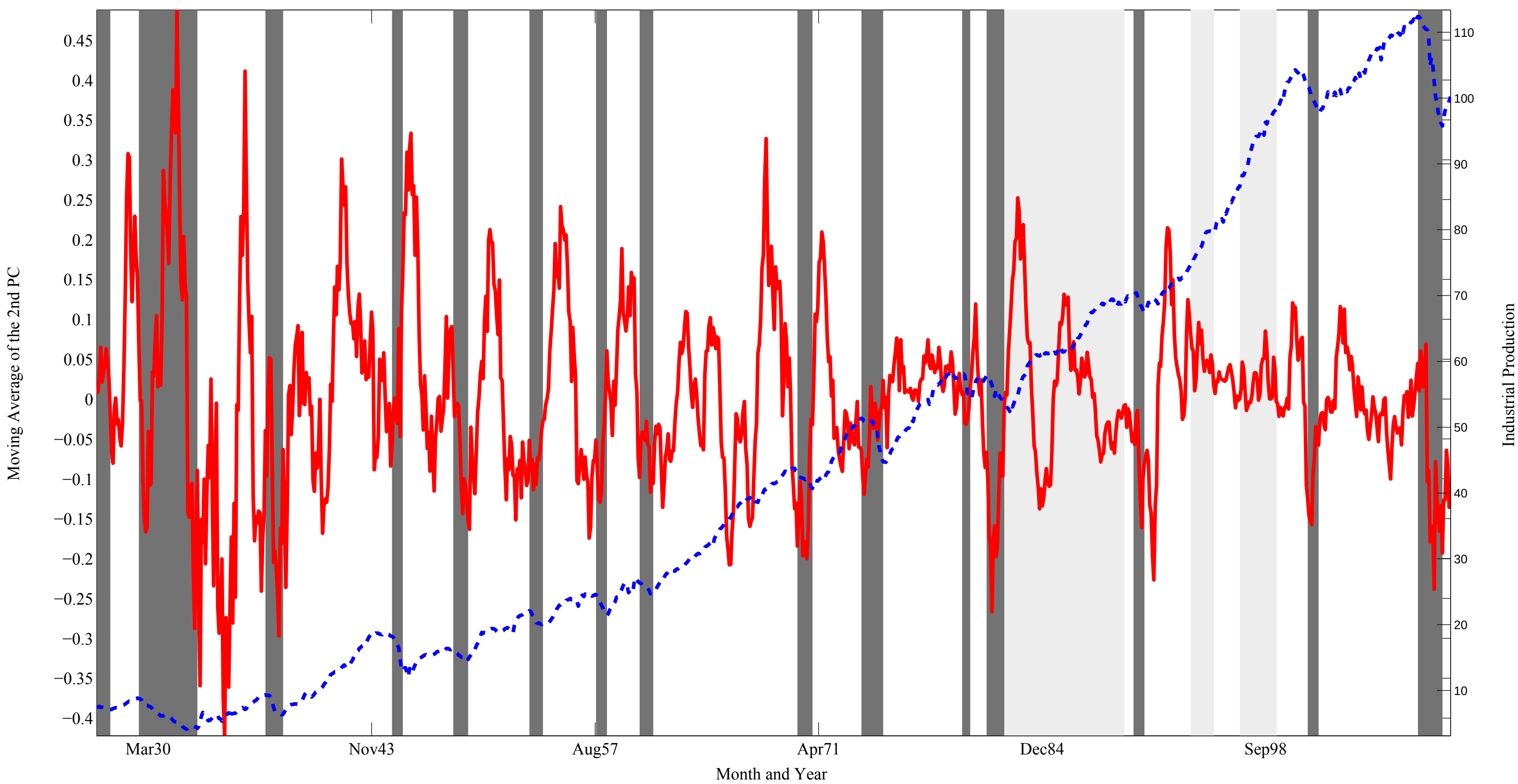

Figure 4: Size factor in normal risk-adjusted returns of all banks

The solid line plots the 12-month (backward looking) moving average (months $t-11$ through t) of the time-series of the weighted sum of the residuals from the OLS regression of monthly excess stock returns for each size-sorted portfolio of all financial firms on the Fama-French and bond risk factors. The weights are given by the second principal component and sum to 1. The dashed line represents the growth of index of industrial production. The dates are indicated on the x-axis. The left-axis references the moving average of the residuals and the right-axis references the index of industrial production.