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ABSTRACT

The largest commercial bank stocks, ranked by total size of the balance sheet, have significantly lower risk-adjusted returns than small- and medium-sized bank stocks, even though large banks are significantly more levered. We uncover a size factor in the component of bank returns that is orthogonal to the standard risk factors, including small-minus-big, which has the right covariance with bank returns to explain the average risk-adjusted returns. This factor measures size-dependent exposure to bank-specific tail risk. These findings are consistent with government guarantees that protect shareholders of large banks, but not small banks, in disaster states.

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Banks are different from nonfinancial 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 (2012) 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, the expected return on its stock is lower in equilibrium than that of smaller banks holding the exact same assets in their portfolio because the government absorbs some of the large bank's tail risk. We find evidence that the pricing of bank-specific tail risk in the stock market 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 nonfinancial 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 2.23% per annum. For nonfinancial 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 the largest commercial banks, measured by deciles of total book value, and a short position in the stock portfolio of the smallest banks underperforms an equally risky portfolio of all (nonbank) stocks and bonds by more than 7% per annum. The average alphas are small but 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 find evidence of such a risk factor in bank stock returns: the second principal component of the risk-adjusted returns on size-sorted portfolios of commercial banks is a size factor that has 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 highly levered size portfolio, determined by the second principal component, which goes long in small bank stocks and short in large bank stocks, loses an average of 61 cents during National Bureau of Economic Research (NBER) 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 (2012), Wachter (2013), Gourio (2008), financial disasters that disproportionately impact bank cash flows contribute an additional bank-specific risk factor. These rare events are priced into the 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 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 recovery rate for bank stockholders in the 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.

In the U.S., 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 but there were no delistings in the last decile.

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 a 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, but not large banks. Acharya and Yorulmazer (2008) point out that bailouts may be ex post efficient if a sufficiently large fraction of banks is impacted. Of course, ex ante, one could have expected that the government would wipe out shareholders of large financial institutions in the case of a bailout. Our evidence suggests that this is not what market participants expect.

Government guarantees essentially grant stockholders of large banks a menu of path-dependent put options that can only be exercised after large declines in a broad index of stocks. This essentially reduces the negative co-skewness of large bank stock returns, but not of small banks. In our sample, large bank stock returns are indeed less negatively skewed and feature less co-skewness, even though the Harvey and Siddique (2000) skewness factors constructed from nonfinancial stocks cannot fully account for the variation in average returns on size-sorted bank portfolios.

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 risk price. The implicit insurance provided against financial disaster risk lowers the expected equity return for the largest U.S. commercial banks by 1.97%, but the additional exposure to bank-specific tail risk increases the expected return on the smallest bank stocks by 2.85%, compared to a portfolio of nonbank stocks and bonds with the same standard risk characteristics. The largest banks have an average market capitalization of $140 billion in 2005 dollars. For the largest commercial banks, this amounts to an annual savings of $2.76 billion 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 to support this conclusion: 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, which have access to the discount window and benefit from deposit insurance, and government-sponsored enterprises (GSEs), which 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 banks, investment banks, and GSEs. For example, the Fannie Mae subsidy tripled to 5.93% over the period 2000 to 2005. This period also coincides with 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 (2014) for a clear description of this effect of securitization).

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 that were declared "too big to fail" by the Comptroller of the Currency in 1984, and negative wealth effects for other banks. Consistent with this result, we document large increases in the implicit financial disaster subsidy to the too-big-to-fail banks after this announcement, and six other bailout announcements prior to the recent financial crisis identified by Kho, Lee, and Stulz (2000). Furthermore, we find large increases after announcements that benefited large banks during the recent financial crisis.

The rest of this paper is organized as follows. Section I discusses the related literature. In Section II we construct portfolios of commercial U.S. bank stocks sorted by size as measured by the market capitalization and the book value. Presumably, the government cares about the size of the entire balance sheet. Section III describes the size effect in bank stock returns. Section IV establishes that there is a procyclical 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 r'egulatory environment. We use a calibrated version of the model to back out the implied differences in recovery rates in Section VI, and we use the model to explain how government puts for the largest banks may also impact the expected returns of smaller banks. Section VII concludes.

I. Related Literature

A large literature in finance considers 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 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 (2012) document that those banks that 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. 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 (2012) 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 et al. (2011a), Acharya et al. (2011b), Adrian and Brunnermeier (2010), and Huang, Zhou, and Zhou (2009) 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 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. 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 billion and \$44 billion, with a benefit of more than \$86 billion.

II. Size Effect in Bank Stock Returns

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

We collect data on equity returns from the Center for Research in Security Prices (*CRSP*). There is no unique, full-proof way of identifying all of the U.S. commercial banks in *CRSP*. Many papers in the literature identify these banks manually over short samples. This not feasible in our study. Instead, we define commercial banks as all firms with header Standard Industrial Classification (SIC) codes 60 or historical SIC code 6712. This definition ensures that bank holding companies are consistently included in our sample. Bank holding companies need to be included in this definition because the banks that belong to a holding company are not publicly traded themselves.

We use the header SIC codes (HSICCD) on December 2013 rather than the historical SIC codes (SICCD) to identify these firms in the data.[1] When we screen the *CRSP* database for SICCDs equal to 60 or 67, several of the largest U.S. banks drop out of the sample, including BB&T Corp on, Banc One Corp, Barclays, Citigroup, First Bancorp and Sterling Bancorp. All of these banks are identified by the Federal Reserve as part the largest 100 deposit-taking institutions in the U.S. These banks clearly belong in our sample. The HSICCD screen correctly identifies these commercial banks throughout the sample, because the coding conventions were changed in the late 1990s. Conversely, we define nonfinancials as all firms excluding those with two-digit HSICCDs ranging from 60 to 67. The Internet Appendix includes a detailed discussion of these choices.[2]

We exclude data for all financial firms that are inactive and we also exclude financial firms that are not incorporated in the U.S. because these financial firms are subject to regulations 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. Foreign firms are identified by share codes ending in 2 or 5.

We start by building portfolios of domestic 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.

The data start in January 1970 and end in December 2013. 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 5,300 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.

Presumably, the government cares about the entire balance sheet of banks, not just their equity. As a result, book value may be the better measure of size. We follow a similar strategy for forming portfolios of commercial bank stocks sorted by book value. We rank all bank stocks by book value as of December of each year. Book values for all bank stocks are obtained from the merged *CRSP-COMPUSTAT* database. We calculate value-weighted returns for each portfolio for each month over the next year. While our market capitalization results are based on 17,594 bank-years from 1980 to 2013, the book value results are based on only 14,403 bank-years. The reduction in the number of banks is primarily due to missing balance sheet data in the *CRSP-COMPUSTAT* merged data set.

While the *CRSP* data are available from 1926, our main sample of banks begins only in 1970, as there are not enough publicly traded commercial banks prior to 1970. In addition, data for book value of commercial banks are not available for a substantial number of banks in our portfolio in Compustat prior to 1980. Hence, our main sample for book value size-sorted portfolios begins only in 1980.

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 nonfinancial stocks and bonds. We do so by comparing the performance of the bank portfolio to the performance of a portfolio of nonbank stocks and bonds with the same exposure to normal risk factors. To do so, we use the Fama and French (1993) three-factor model. We find that small banks, measured either by market cap or book value, outperform the benchmark portfolio of bonds and stocks, while large banks underperform.

A bank manages a portfolio of bonds of varying maturities and credit risk.[3] Therefore, we also include two bond risk factors in addition to three stock risk factors

$$\boldsymbol{f}_t = \left[\begin{array}{ccccc} market & smb & hml & ltg & crd \end{array} \right], \tag{1}$$

where f_t is 5×1. The terms *market*, *smb*, and *hml* represent the returns on the three Fama-French stock factors, namely, the market, small minus big, and high minus low factors respectively. The Fama-French stock factors are constructed using the six value-weighted portfolios of all stocks on NYSE, Amex and NASDAQ (including financials) formed on size and book-to-market. We capture *market* using the value-weighted 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*. 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.[4]

A. *Risk-Adjusted Returns on Commercial Bank Stock Portfolios*

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

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

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 $\widehat{R}^i_{t+1}$.

Market Capitalization Table I provides the results of the regression specified in equation 2. The portfolios are ranked from smallest (1) to largest (10). Panel A reports the results based on sorting by market capitalization into deciles. The table reports the regression coefficients for each size-sorted portfolio, along with their statistical significance and adjusted R^2. Table I excludes the recent financial crisis.

The estimated intercepts decrease nearly monotonically with bank size from 1.94% for the first decile to -5.09% for the tenth decile. The negative alpha on the tenth decile is significantly different from zero at the 1% level. A significant share of this alpha is due to the very largest banks. We also split the highest decile in two bins, 10A and 10B. In the top half of the tenth decile (10B) the alpha is -5.60% (statistically significant at the 1% level), while it is only -3.13% in the bottom half of the tenth decile. If we split the top decile into three bins instead, the top 3.33% earns -6.78% per annum (not reported in the table, statistically significant at the 1% level). The top 3.33% accounts for more than 90% of the industry's market capitalization. Clearly, the largest U.S. commercial banks earn significantly negative risk-adjusted returns.

A long-short position that goes long 1$ in a portfolio of the largest market capitalization banks in decile 10 and short 1$ in a portfolio of the smallest market capitalization banks in decile 1 loses 7.03% over the entire sample. This return spread is statistically significant at the 5% level. The difference between 10A and 10B is 2.47% and accounts for 35% of the entire 7.03% spread between the first and last deciles. The total difference between 10B and 1 is 7.54%. When we split the top decile into three bins, the spread between the first decile and the top 3.33% in the market cap distribution is even larger: 8.72% (not reported in the table). When we exclude the largest banks, the differences in risk-adjusted returns are much smaller. The average normal risk-adjusted return on a 9-minus-2 position is -4.26% per annum, and -5.29% per annum for the 8-minus-3 portfolio.

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 0.46 for the first decile to 1.22 in the last decile. However, this effect is attenuated by the lower credit risk exposure for the larger banks.

The second row of Table I 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 beta of 1.22, as compared to a beta of 0.46 for a portfolio of the smallest banks. The largest banks were 2.65 times more exposed to market risk as compared to the smallest banks. This difference can be attributed largely 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* increases from 0.40 in the first size decile to 0.42 in the ninth decile, while in the tenth decil, the loading is -0.13. Clearly, the common variation in stock returns of banks along the size dimension is very different from that in other industries. A similar pattern holds true for the loadings on *hml*, which increase from 0.50 for the first portfolio to 0.70 for the last portfolio.

There is a clear size pattern in the loadings on the bond risk factors. The slope coefficient on the excess return on an index of 10-year bonds issued by the U.S. Treasury, *ltg*, is negative and statistically insignificant for small banks, and 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. The results for the portfolios of large bank stocks seem largely consistent with the findings of Flannery and James (1984) for a value-weighted portfolio of large bank stocks. They interpret this bond factor loading as a measure of interest rate sensitivity resulting from the maturity mismatch between assets and liabilities. Small and mid-sized banks seem to be different.

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 49 cents per dollar invested.

[Place Table I about here]

Book Value Market cap measures size, but it also measures expected returns. Firms that generate more cash flows will tend to have higher market capitalization, 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. For example, while market cap sorts are likely to be picking up liquidity effects, book sorts are not. A priori, there is no reason to expect a relation between book values and expected returns.

Panel B reports the results obtained by sorting by book value. The pattern in risk-adjusted returns is similar to that obtained when sorting by the market capitalization of banks. The risk-adjusted returns remain around 100 to 200 bps for the first six portfolios. The seventh portfolio posts average risk-adjusted returns of -140 bps. After that, the average risk-adjusted returns decline to -353 bps for portfolio 8, -521 bps for portfolio 9, and -5.70% for portfolio 10, which is significantly different from zero at the 5% level. The top 5% of banks by book value earn risk-adjusted returns that are even lower: -6.14% per annum.

A long-short position that goes long $1 in a portfolio of the largest banks in decile 10 and short $1 in a portfolio of the smallest banks in decile 1 loses 7.92% over the entire sample. This return spread is statistically significant at the 1% level. The difference between 10A and 10B is 1.55%, and accounts for 1/5 of the entire 7.92% spread between the first and last deciles. The average normal risk-adjusted return on a 9-minus-2 position is -7.14% per annum, and -5.96% per annum for the 8-minus-3 portfolio. These results 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 0.11 in the first portfolio to 0.32 in the fifth portfolio, and then declines to -0.14 in the ninth portfolio. Clearly, there is strong connection between average risk-adjusted returns on bank stocks and the actual size of these banks as measured by book value. This is not the case for nonfinancials.

This size anomaly is quite robust. However, if we exclude bank holding companies from the sample, we do not find evidence of a size anomaly for the banking sector. That is not surprising, because these firms include some of the largest U.S. commercial banks.

B. Risk-Adjusted Returns on Portfolios of Non-financial Stocks

To make the results easily comparable, we sorted all banks and nonfinancials into 10 size bins using the NYSE market capitalization decile breakpoints available from Ken French's web site. Table II reports the results, Panel A for commercial banks, Panel B for nonfinancials. By design, the banks and nonfinancials in each portfolio are roughly of the same size. The value-weighted risk-adjusted returns on banks in the last size bin are 7.35 % lower than those in the first bin. The difference between the ninth and tenth bank portfolios is 3.91%, which confirms that the very largest banks which exceed the tenth NYSE decile breakpoint earn much lower risk-adjusted returns.

For nonfinancials, there is no evidence of a size anomaly. In fact, the value-weighted risk-adjusted returns on the last portfolio are now 3.38% higher than those on the first portfolio. Finally, by comparing Panel A and Panel B, we note that the risk-adjusted returns on the largest banks are a full 9.96% per annum lower than those of nonfinancials of the same size.[5]

[Place Table II about here]

C. Characteristics Regression

The portfolio sorts reveal that the actual size of a bank measured by its book value seems to be a key determinant of bank stock returns: larger banks have lower returns. This is confirmed by running standard characteristics regressions. 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 (-2.23) and a positive coefficient for market capitalization (2.79). Thus, a 100% increase in book value above the sample average lowers annual returns by 223 bps for a typical bank, holding all variables, including market capitalization, fixed. These coefficients are significant at the 1% level. The detailed results are in the Internet Appendix.

This pooled regression explains 0.42% of the variation in annual returns. Leverage seems to have no additional explanatory power for returns. We obtain identical results when we exclude leverage from the regression. When we drop book value, the regression only accounts for 0.09% of the variation in annual returns. Hence, this size effect in bank stocks is very different from the "market capitalization" effect first documented by Banz (1981).

IV. Size Factor in Bank Stock Returns

The key to activating the collective bailout clause is common variation in bank payoffs.[6] We use principal component analysis to study the common variation. We uncover a bank-specific size factor that can help us understand and interpret these anomalies. 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 bank stocks and the size factor can explain the size pattern in average risk-adjusted returns.

A. *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 factors in equation (2). We extract the loadings for the principal components $(\boldsymbol{w}_1, \boldsymbol{w}_2)$ and report the results in Table III. This table shows the loadings for the first two principal components. Together, these two principal components explain 66% of the residual variation over the entire sample. The numbers in brackets are standard errors generated by bootstrapping 10,000 samples. The first two columns in the table show results for market capitalization sorts; the last two columns show results for book sorts. The two sets of results are similar. We therefore focus on the results obtained using the market capitalization sort, as this sort provides more observations and hence the loadings are estimated more precisely.

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.

[Place Table III 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 renormalized to $(\widehat{\boldsymbol{w}}_1, \widehat{\boldsymbol{w}}_2)$ so that they sum to one. 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 $PC_{2,t} = \widehat{\boldsymbol{w}}_2' \boldsymbol{\epsilon}_t$, where $\widehat{\boldsymbol{w}_2}$ is given by

$$\begin{bmatrix} 0.53 & 0.24 & 0.20 & 0.12 & -0.02 & -0.12 & -0.31 & -0.41 & -0.43 & -0.37 \end{bmatrix}.$$

This is a highly levered portfolio with a long position of \$53 in small banks and a short position of \$37 in large banks. The return on this portfolio investment has a monthly standard deviation of 8.25%.

The size factor 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 components. The second principal component is the only candidate factor, because the second principal component 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.

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 it by the (10×1) loading of the second principal component. We denote the results of our multiplication by $R[PC_2]_{t+1} = \widehat{\boldsymbol{w}}_2 \boldsymbol{R}_t$ which 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, renormalized 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, as well as the size factor $R[PC_2]$:

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

The tail and normal risk-adjusted returns or alphas from this regression are presented in Table IV. Panel A corresponds to the pre-crisis sample (1970 to 2005) and Panel B to the whole sample (1970 to 2013). In Panel A, we want to use an ex ante measure of the risk price that excludes the effects of the crisis; the disaster model rationalizes this approach. The risk-adjusted returns on all portfolios are smaller than 250 bps over the entire sample once we account for the size factor. Not only does the magnitude of the alphas change, but nearly all of them are statistically insignificant. In addition, there is no discernible size-related pattern in these normal risk-adjusted returns. In panel B, we show the risk-adjusted returns that obtain over the entire sample, which includes the crisis. For the very largest banks, we still see significantly negative risk-adjusted returns over the sample that includes the crisis.

[Place Table IV about here]

B. *What is the Size Factor?*

We define $PC_{2,t} = \widehat{\boldsymbol{w}}_2' \boldsymbol{\epsilon}_t$ as 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 1 plots the 12-month moving average (months $t-11$ through t) of the PC_2 series along with a plot of the index for industrial production. The units are monthly returns. Recall that this portfolio is levered almost 10-to-1. The gray-shaded regions represent NBER recessions and the light-shaded regions represent banking crises. The NBER recession dates are published by the NBER Business Cycle Dating Committee. The dates for the Mexico and Long

Term Capital Management (LTCM) crises come from Kho, Lee, and Stulz (2000) and the FDIC (for the developing 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 tend to increase before the end of the NBER recession.

There are two exceptions to this cyclical pattern. The first is the double-dip recession in the early 1980s. Small bank 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 recession in the wake of the LTCM crisis. Moreover, in 2001, the NBER chose the starting point of the recession well after the decline in industrial production started (in other recessions, the starting date coincides with the decline in industrial production.) On average, during recessions, this normal risk-adjusted return drops by an average of 3.34% per month or 40.08% per annum. During the most recent recession, which coincides with a financial crisis, the levered size factor lost more than 100% of its value after adjusting for risk exposure.

[Place Figure 1 about here]

Table V, Panel A shows the value at the trough of the NBER cycle (the end of the banking crisis) of \$100 invested at the peak of the NBER cycle (the start of the banking crisis) in the size portfolio. The third column reports the dollar value without risk adjustment. The fourth column reports the dollar value after subtracting the performance of a benchmark portfolio with the same exposure to the bond and equity factors ($\$100 + x$, the 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. On average, the unhedged size portfolio loses \$36.61 during a recession or banking crisis. The hedged strategy loses more than \$40.08 per recession. As is clear from Panel B, the largest losses are concentrated in the first twelve months of the NBER recessions. Moreover, this portfolio (both hedged and unhedged) experienced steep declines during the developing country debt and LTCM crises. Panel B in Table V 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 \$41 dollars of its value.

[Place Table V 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 more than 100 cents on the dollar (see Table V). 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 financial firms 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. We did not find a similar cyclical pattern in the second principal component of nonfinancials.

In the data, there is a strong connection between the business cycle and the incidence of banking panics. We examine U.S. banking panics starting in 1873, as well as 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 come from Gorton (1988, p. 223) and Wicker (1996, p.155). Details are provided in the Internet Appendix. This is not the case for nonfinancials. Giesecke et al. (2011) examine 150 years of U.S. corporate history and find a weak relation between the business cycle and corporate bond defaults.

C. 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 30.11% for the smallest banks to 23.86% for the largest banks as compared to 36.06% and 19.19% respectively in the full sample. Details are in Appendix A. Hence, the largest percentage point increase in volatility during recessions from 19.19% to 23.86% is noted for the largest banks. For the smallest banks, the idiosyncratic volatility decreases by 5.85%. There is no evidence to suggest that the cyclicality of the size factor is due to idiosyncratic bank 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 exposed 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. We examine bank performance during the last two recessions by studying the Quarterly Banking Reports issued by the FDIC, and find that small banks tend to outperform large banks during recessions along several dimensions: return on equity, returns on assets, loan losses, and several other measures. Appendix B contains the details. We analyze the data in the report for the first three quarters of 2001, which corresponds to the recession dates provided by NBER.

D. Size and Co-Skewness

By granting the shareholders of large bank stocks a menu of out-of-the-money put options, the government reduces the negative co-skewness of large bank stock returns. Consistent with our interpretation of the size factor, we find that large bank stock returns have significantly less co-skewness with the market than small banks. We measure co-skewness by adding the squared market return as a risk factor. Table VI reports the results. We find large and statistically significant positive differences in the loadings on the squared market return between the upper and lower deciles. Given that the largest commercial banks use more leverage, this finding is surprising, unless we consider the effect of government guarantees. Harvey and Siddique (2000) show that co-skewness is priced in stocks.[7] Finally, we also find that small bank stock returns are significantly more exposed to the Fama-French momentum factor than large bank stock returns. This is not surprising given that Harvey and Siddique (2000) relate the momentum effect to systematic skewness.

[Place Table VI about here]

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. For individual banks, we measure the effect on the cost of equity capital as the loading on this factor times this risk price. When the total effect is negative, we refer to this as a tail risk subsidy; otherwise, we refer to it as a tail risk tax. Of course, this only measures the impact on equity. Since these institutions are highly levered, the direct effect on the overall cost of capital may be small, but the indirect effect is not: since shareholders are last in line, the implied subsidy to other bank creditors is even larger.

This section examines how bank-specific tail risk is priced in the stock market, and relates it to both the regulatory regime and government announcements.

A. Size of Largest Banks

The events immediately after the collapse of Lehman in September 2008 are in line with 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 occasionally be willing to let individual institutions fail. For example, over the course of 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.[8] Moreover, even if regulators are willing to let these large banks fail, uncertainty about the resolution regime for distressed banks clearly favors the creditors and shareholders of large financial institutions.

Consistent with this view, even within 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 choose banks that are in portfolio 10 in each year of our sample and then compute the loadings on PC_2 over the subsequent five-year window. As individual banks grow larger relative to GDP over time, 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 0.032, meaning that a 100% increase in the size of market capitalization relative to GDP raises the loading by 0.032 (t-stat is 5.9) in absolute value, or equivalently, increases the tail risk subsidy by 35 bps per annum, using the pre-crisis market price of 11.14%. We find a similar relation in the ninth decile, but not in the other deciles. The PC_2 itself is computed over the full 1970 to 2013 sample.

B. Regulatory Regime

We want to relate the pricing of tail risk in the pre-crisis sample, as captured by the size factor, to the regulatory regime of different banks. Commercial banks and GSEs benefit from special provisions: deposit insurance,[9] 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 VII 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.[10] 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 1.18% and the subsidy to GSEs is 2.58%. This subsidy is computed as the loading on PC_2 times the risk price (11.14%). The loadings on PC_2 are computed over 1970-2005. The loadings on $R[PC_2]$ are negative and statistically significantly different from zero for commercial banks and GSE's at the 1% level, but the loadings on $R[PC_2]$ are much smaller (investment banks) or positive (foreign banks) and not statistically significant.

Table VII also shows the same results for some of the largest commercial banks and investment banks in the U.S. Panel A reports the results for the entire sample excluding the crisis. The tail risk subsidy is largest for the large commercial banks. For BoA (from 1973 to 2005), we estimate a tail risk subsidy of 3.51% per annum, for Wells Fargo (from 1970 to 2005) it is 3.61%, and for Citibank (from 1986 to 2005) it is 1.52%. For investment banks, the loadings on PC_2 are mostly not statistically significant, except for Lehman. In contrast, BoA, Citi, Wells Fargo, Freddie Mac, and Fannie Mae have loadings that are negative and statistically significantly different from zero at the 5% level or better.

We also report the subsidies over 1990 to 2005 in Panel B. As above, the loadings on PC_2 are computed over 1970 to 2005. The subsidies are computed as the loading on PC_2 times the pre-crisis risk price (11.14%). Over this period the subsidy to commercial banks is 1.00%, but the subsidy to GSEs is 3.33%. This number is the unweighted average of the subsidy for Fannie Mae and Freddie Mac.

As a benchmark, we also compute 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 use the HFRI fund-weighted hedge fund index. These results are not reported. Over the entire sample (1991 to 2005) the loading for hedge fund returns on $R[PC2]$ is 0.02 (t-statistic 2.31) and it is 0.05 (t-statistic 2.02) over 2000 to 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.[11]

[Place Table VII about here]

C. Elimination of Glass-Steagall Act

The Glass-Steagall Act of 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 and GSEs nearly doubled to 1.75% and 4.90%, respectively. These numbers are derived by multiplying the loadings with the same risk price (11.14%) computed over the entire sample, and hence are valid only if the risk price is constant across these subsamples. These changes are large even when taking into account the statistical uncertainty. For example, the loading for commercial banks increased by almost three standard errors from -0.09 (with a standard error of 0.03) to -0.16.

The loadings for the largest banks increased dramatically in the last decade. The largest subsidies are collected by Fannie Mae (5.93% per year), Lehman (5.09%), and Freddie Mac (3.82%), in spite of their smaller size. All of these banks 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. In addition, Fannie Mae, Lehman and Freddie Mac are themselves excluded from the sample when we compute the size factor. Exposure to the size factor seems to be a good yardstick of systemic risk exposure.

D. Announcement Effects

In September 1984, the Comptroller of the Currency announced a list of 10 banks 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. The Internet Appendix 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 VIII reports the results. We report regressions for windows of 30, 45, 60, 90, and 105 days around the announcement date. Panel A reports 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 1.33% tail risk subsidy per year. This effect gradually decreases as we increase the event window. We find slightly smaller effects for the LTCM, Brazilian, Mexican, and South Korean crises. The average effect in a 30-day window is a 33 bps per annum (0.03 times 11.14%) 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 identify announcements that increased the likelihood of a bailout for all banks, and for large banks, and, we also look at events that decreased the likelihood of a bailout. These are listed in the Internet Appendix.

[Place Table VIII about here]

Table VIII, 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 78 bps (per annum) in a 30-day window around these announcements. The other announcements have small or negative effects that are statistically insignificant.

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. 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.

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

We adopt a version of models with time-varying probabilities of financial disasters proposed by Gabaix (2012) and Wachter (2013), which are extensions of the rare event models developed by Barro (2006) and Rietz (1988). The model produces a one-to-one relation between the average risk-adjusted returns and the financial disaster recovery rates. In our model, the stochastic discount factor has two components, a standard normal component and a disaster component:

$$\begin{aligned} M_{t+1} &= M^G_{t+1} \times 1 \textit{ in states without a financial disaster} \\ M_{t+1} &= M^G_{t+1} \times M^D_{t+1} \textit{ in states with a financial disaster,} \end{aligned} \tag{4}$$

where M^G_{t+1} denotes the representative investor's intertemporal marginal rate of substitution (IMRS) in normal times, that is, in states without a disaster. We use p_t to denote the probability of a financial disaster.

In the simplest CCAPM version of his model, Gabaix (2012) defines

$$\begin{aligned} \Delta \log C_{t+1} &= g_C + \sigma\eta_{t+1} \textit{ in states without a financial disaster} \\ \Delta \log C_{t+1} &= g_C + \sigma\eta_{t+1} + \log F^c \textit{ in states with a financial disaster,} \end{aligned} \tag{5}$$

where $1 \geq F^c > 0$, and η_{t+1} is Gaussian white noise. We assume that agents have standard power utility defined over consumption with coefficient of relative risk aversion γ.

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

$$\begin{aligned}\Delta \log D^i_{t+1} &= \Delta \log D^{i,G}_{t+1} \textit{ in states without banking crisis} \\ \Delta \log D^i_{t+1} &= \Delta \log D^{i,G}_{t+1} + \log F^i_t \textit{ in states with banking crisis}\end{aligned}$$

where $\Delta \log D^{i,G}_{t+1}$ is the i.i.d. Gaussian component of dividend growth, and $1 \geq F^i > 0$ can be thought of as the recovery rate, that is, in the case a rare event is realized, a fraction F^i of the dividend gets wiped out (as in Longstaff and Piazzesi (2004) and Barro (2006)). The recovery rate varies across banks depending on size, in part because the realization of the rare event can trigger a collective bailout of larger banks, but not necessarily of smaller banks.

Following Gabaix (2012), the resilience of banks is defined as the marginal utility-weighted recovery rate in disaster states: $H^i_t = p_t E_t\left[M^D_{t+1} F^i - 1\right]$. In the CCPAM case, this would be $H^i_t = p_t E_t\left[(F^c)^{-\gamma} F^i - 1\right]$. As the economy enters into a recession, p_t increases and the resilience of large banks H^B_t increases relative to that of small banks H^S_t if $F^B > F^S$. Indeed, we assume that the recovery rate $F^n > F^{n-1}$ increases monotonically in size.

The log expected return on asset i conditional on no disaster realization after adjusting for normal risk exposure becomes $\log E_t[\widehat{R}^i_{t+1}] = (r - h^i_t)$, where r denotes the rate of return on an asset with zero resilience, $\log R_t = \log E_t[M^G_{t+1}]^{-1}$, and h^i_t denotes $\log(1 + H^i_t)$. The proof is in Appendix A. This implies that, in a sample without a disaster realization, the average normal risk-adjusted return will be given by

$$\log E[\widehat{R}^i_{t+1}] \approx (\overline{r} - \overline{h}^i), \tag{6}$$

where $\overline{h}^i = E[\log\left(1 + H^i\right)]$ denotes the average resilience and $\overline{r}$ denotes the average r. 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 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.

Quantitative Implications of CCAPM Model We set the coefficient of relative risk aversion γ to five. We consider a per annum 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 authors document a cumulative drop of 5%. 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).[12]

If the spread in recovery rates is 35 cents per dollar, then the difference in risk-adjusted returns ($\log \alpha^S - \log \alpha^B = \overline{h}^B - \overline{h}^S$=3.70%-(-2.1%)) in a sample without disasters is equal to 5.8%. When the coefficient of relative risk aversion increases to 15, the spread increases to 8.9%.

Recovery Rates in the Data There is strong empirical evidence for size-dependent variation in financial disaster recovery rates. In our sample (from 1970 to 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 alone, 18% of banks in the first decile were delisted, another 30% were delisted in 2009 and 10% were delisted in 2010. None of the commercial banks in the highest decile was delisted.

Size Factor A key prediction of this model is that the variation in the probability of a financial disaster 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 $\log(1 + H^i_t) \approx p_t E_t \left[M^D_{t+1} F^i - 1 \right]$. 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 expression $\log E_t \left[\widehat{R}^B_{t+1} \right] - \log E_t \left[\widehat{R}^S_{t+1} \right] = h^S_{t+1} - h^B_{t+1}$. 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.

B. *Mergers, Acquisitions, and Risk-Adjusted Returns*

Suppose that only the very largest banks directly benefit from government guarantees. Our model does not predict that only those banks will have lower expected risk-adjusted returns. Because of the possibility of mergers, some of the effects will contaminate the expected risk-adjusted returns on smaller bank stocks.

In our model, a 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 alphas for all banks above the threshold. In that sense, the pattern we find 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 has been a large amount of consolidation in the banking sector in the last few decades, with the share of total market capitalization accounted for by the top decile of commercial banks increasing from 50% in the 1970s to 90% in the last decade. Similarly, the share of the total balance sheet accounted for by the top decile has increased from 52% to 95%. Kane (2000) and Brewer and Jagtiani (2007) document that 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, which mitigates the effect on the average risk-adjusted returns. This can account for the decreasing pattern in the alphas that we find in the data.

VII. Conclusion

Our paper documents a size anomaly in bank stock returns that is different from the size effect that has been documented for nonfinancials. 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 depends 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 tail risk. To mitigate this distortion, the government could consider taxing size in the banking sector. Our paper is the first to develop asset price-based measures of the resulting distortion to the equity component of the balance sheet. Our findings suggest 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) argues 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 to 2007 period as an exception, which is exactly when we identify the largest distortions.

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Notes

[1]The complete panel of commercial banks that fall under our definition is available from the authors.

[2]The Internet Appendix is available in the online version of the article on the Journal of Finance website.

[3]Flannery and James (1984) were the first to demonstrate a link between interest rate changes and common stock returns of commercial banks that depends on the maturity structure of their assets and liabilities. Longstaff and Myers (2009) also show that banks can be treated as active managers of fixed income portfolios.

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

[5]When sorting the nonfinancials into standard size deciles, there is a large positive risk-adjusted return of 15% per annum on the first portfolio that is driven entirely by the non-financial firms with the smallest market capitalization. This is not surprising. 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. Illiquid stocks earn abnormal returns (see, for example Brennan and Subrahmanyam (1996)). However, when we use the NYSE breakpoints, this effect disappears completely, because the smallest nonfinancials do not significantly affect the value-weighted returns in the first portfolio. These size decile results are reported in the separate Internet Appendix.

[6]In a recent paper, Acharya and Yorulmazer (2007) and Farhi and Tirole (2012) 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 nontradeables 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.

[7] However, the Harvey and Siddique (2000) skewness factors constructed from nonfinancial as well financial stocks cannot account for the variation in risk-adjusted returns on banks.

[8]Data are from the Term Auction Facility (TAF), which 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.

[9]The FDIC Improvement Act of 1991 limits the protection of creditors, but it provides a systemic risk exception.

[10]The worldwide market-cap for just the six largest banks included in the index of foreign banks is $330.21 billion in 2010.

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

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

Appendix A. Derivation of Tail Risk Premium Expression

Consider the investor's Euler equation for asset i:

$$E_t[M_{t+1}R^i_{t+1}] = 1. \tag{A1}$$

The stand-in investor's SDF M_{t+1} is described in equation (6). This Euler equation can be decomposed as

$$(1-p_t)E_t[M^G_{t+1}R^i_{t+1}] + p_t E_t[M^G_{t+1}M^D_{t+1}R^{G,i}_{t+1}R^{D,i}] = 1. \tag{A2}$$

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

$$\left((1-p_t) + p_t E_t[M^D_{t+1}R^{D,i}]\right) E_t[M^G_{t+1}R^{G,i}_{t+1}] = 1. \tag{A3}$$

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

$$\left(1 + p_t E_t[M^D_{t+1}F^i - 1]\right) E_t[M^G_{t+1}R^i_{t+1}] = 1, \tag{A4}$$

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

$$R^{G,i}_{t+1} = \frac{(P_{t+1}/D_{t+1}) + 1}{P_t/D_t}\frac{D_{t+1}}{D_t}, \tag{A5}$$

which in the case of no disaster can be stated as $R^{G,i}_{t+1} = \frac{(P_{t+1}/D_{t+1})+1}{P_t/D_t} \exp\left(g_D + \Delta \log D^{i,G}_{t+1}\right)$. In the case of a disaster, the return is given by

$$R^i_{t+1} = R^{G,i}_{t+1}F^i_{t+1}, \tag{A6}$$

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 expression

$$\left(1 + H^i_t\right) E_t[M^G_{t+1}R^{G,i}_{t+1}] = 1. \tag{A7}$$

Decomposing this expectation into a covariance term and a cross-product yields

$$E_t[M^G_{t+1}]E_t[R^i_{t+1}] + cov_t[M^G_{t+1}, R^{G,i}_{t+1}] = \left(1 + H^i_t\right)^{-1}. \tag{A8}$$

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

$$E_t[R^{G,i}_{t+1}] = E_t[M^G_{t+1}]^{-1}\left(1 + H^i_t\right)^{-1} - \frac{cov_t[M^G_{t+1}, R^{G,i}_{t+1}]}{var_t[M^G_{t+1}]}\frac{var_t[M^G_{t+1}]}{E_t[M^G_{t+1}]}. \tag{A9}$$

We let $R_t = E_t[M^G_{t+1}]^{-1}$. Note that the variation in the price/dividend ratios induced by the variation in the case of a disaster does not co-vary with the normal risk factors –by assumption– and hence is not priced in the normal risk premium. The expected return on asset i, conditional on no disaster realization, after adjusting for Gaussian risk exposure, becomes

$$E_t[\widehat{R}^i_{t+1}] = \exp(r_t - h^i_t), \tag{A10}$$

where r_t denotes $\log R_t$ and h^i_t denotes $\log(1 + H^i_t)$.

Appendix B. Other Explanations

Business Cycle Variation in Common and Idiosyncratic Risk Factors other than financial disasters that could explain the cyclicality in the size factor. In particular, 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 BI measures the standard deviation of normal risk-adjusted returns both at the portfolio level (Panel A) and 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 separately for NBER expansions and recessions 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%. 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 from 20% to 26% is noted for the largest banks. For the smallest banks, the increase is less than 2%. There is no evidence to suggest that the cyclicality of the size factor is due to idiosyncratic bank risk.

[Place Table BI about here]

Business Cycle Variation in Cash Flows We analyze 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 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 of 2008, small banks' return on equity is 1.5 times and yield on assets is 50 bps higher than corresponding values for large banks. Further, 14.16% of the 558 small banks and 26.72% of the 114 large banks were unprofitable, and, 41.22% of small banks reported an earnings gain as compared to 24.14% of large banks.

For the full year of 2008, 28.70% of small banks and 40.35% of large banks reported losses. Small banks do have lower return on assets and return on equity for the full year, but it is not obvious if this is due to higher cash flow risk. During the second half of 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.

Table I
Risk-Adjusted Returns on Size-Sorted Portfolios of Commercial Banks.

This table presents estimates from OLS regression of monthly value-weighted excess returns on each size-sorted portfolio of domestic commercial banks on the three Fama and French (1993) stock and two bond risk factors. U.S. commercial banks are defined as all firms with HSICCD equal to 60 or historical SICCD equal to 6712. We exclude foreign banks with share codes ending in 2 or 5. *market*, *smb*, and *hml* are the three Fama-French stock factors: 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. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Alphas are annualized by multiplying by 12 and are expressed in percentages. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) with three lags. The sample is 1970 to 2013 in Panel A, 1980 to 2013 in Panel B.

	Small	2	3	4	5	6	7	8	9	Large	10A	10B	10 - 1	10A-1	10B - 1
Panel A: Market Capitalization															
α	1.94	1.12	3.28*	-0.16	1.04	-0.14	-1.49	-2.01	-3.14*	-5.09***	-3.13	-5.60***	-7.03**	-5.06*	-7.54***
$market$	0.46***	0.55***	0.50***	0.59***	0.57***	0.68***	0.78***	0.81***	0.92***	1.22***	0.98***	1.24***	0.76***	0.52***	0.78***
smb	0.40***	0.42***	0.38***	0.41***	0.39***	0.44***	0.49***	0.44***	0.42***	-0.13*	0.14**	-0.15**	-0.53***	-0.26**	-0.55***
hml	0.50***	0.48***	0.44***	0.54***	0.49***	0.59***	0.69***	0.66***	0.65***	0.70***	0.58***	0.73***	0.19*	0.08	0.22**
ltg	-0.19	-0.07	-0.05	0.09	0.15*	0.06	0.14	0.24**	0.39***	0.19*	0.24**	0.24**	0.38**	0.43**	0.43***
crd	0.36*	0.23	0.29**	0.14	0.11	0.21*	0.04	-0.06	-0.16	-0.14	-0.04	-0.19	-0.49**	-0.40*	-0.55**
R^2	25.37	43.68	43.20	49.84	51.96	59.74	60.89	62.16	66.50	68.01	62.02	65.73	27.42	14.32	27.59
Panel B: Book Value															
α	2.22	1.93	2.43	2.62	1.30	1.07	-1.40	-3.53	-5.21**	-5.70**	-4.59*	-6.14**	-7.92***	-6.81**	-8.36**
$market$	0.44***	0.46***	0.54***	0.54***	0.65***	0.79***	0.89***	0.88***	0.90***	1.07***	1.07***	0.83***	0.64***	0.64***	0.40***
smb	0.38***	0.38***	0.30***	0.38***	0.46***	0.54***	0.58***	0.60***	0.32***	0.02	0.01	0.04	-0.36***	-0.37***	-0.34***
hml	0.36***	0.39***	0.44***	0.51***	0.60***	0.75***	0.85***	0.85***	0.73***	0.68***	0.69***	0.42***	0.32**	0.33**	0.07
ltg	0.11	0.11	0.11	0.06	-0.02	0.19*	0.42***	0.45***	0.35***	0.05	0.04	0.22*	-0.06	-0.07	0.11
crd	0.11	0.15	0.15	0.21*	0.32*	0.08	-0.13	-0.22	-0.14	0.20	0.17	0.17	0.09	0.07	0.06
R^2	34.01	39.85	39.29	47.66	49.13	57.53	62.47	57.68	63.47	56.53	50.03	40.27	22.54	19.90	9.73

Table II
Risk-Adjusted Returns on Size-Sorted Portfolios using the NYSE Market Capitalization Decile Breakpoints.

Panel A (B) presents estimates from OLS regression of monthly value-weighted excess returns on each size-sorted portfolio of commercial banks (nonfinancials) on the three Fama and French (1993) stock and two bond risk factors. We use the NYSE market capitalization breakpoints available from Ken French's website. U.S. commercial banks are defined as all firms with HSICCD equal to 60 or historical SICCD equal to 6712. We exclude foreign banks with share codes ending in 2 or 5. Nonfinancials are defined as all firms excluding those with two-digit HSICCDs ranging from 60 to 67. *market*, *smb*, and *hml* are the three Fama-French stock factors: 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. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Alphas are annualized by multiplying by 12 and are expressed in percentages. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) with three lags. The sample is 1970 to 2013.

	Small	2	3	4	5	6	7	8	9	Large	10 - 1
					Panel A: Commercial Banks						
α	0.88	-0.31	-0.08	-1.95	-2.53	-4.16**	-1.28	-4.29*	-3.44*	-7.35***	-8.23***
market	0.58***	0.67***	0.73***	0.83***	0.83***	0.92***	1.00***	1.09***	1.15***	1.03***	0.45***
smb	0.43***	0.49***	0.51***	0.45***	0.38***	0.15**	0.13*	-0.08	-0.10	-0.16**	-0.58***
hml	0.54***	0.61***	0.65***	0.61***	0.65***	0.67***	0.61***	0.66***	0.60***	0.75***	0.22*
ltg	-0.05	0.20**	0.13	0.29**	0.11	0.17	0.29***	0.16	0.35***	0.09	0.14
crd	0.23*	-0.03	0.07	-0.10	0.10	0.13	-0.05	0.10	-0.15	-0.42*	-0.65***
R^2	56.39	58.48	60.50	61.85	62.36	63.17	61.36	59.55	62.07	47.29	17.83
					Panel B: Nonfinancials						
α	-0.77	-1.82*	0.76	-0.83	0.04	-0.94	1.50	1.92	1.99	2.61	3.38**
market	0.94***	1.02***	1.03***	1.03***	0.99***	1.01***	1.03***	1.08***	1.02***	0.94***	-0.01
smb	0.95***	0.94***	0.90***	0.81***	0.68***	0.50***	0.44***	0.32***	0.20***	0.11*	-0.85***
hml	0.25***	0.12**	0.00	0.08*	-0.08*	-0.12***	-0.11**	-0.24***	-0.32***	-0.32***	-0.57***
ltg	-0.28***	-0.08	0.03	0.03	0.07	0.01	0.06	0.01	-0.04	-0.15*	0.13
crd	0.17	0.04	-0.04	-0.12**	-0.05	0.01	-0.09	-0.09	-0.06	0.05	-0.12
R^2	86.07	91.08	91.74	91.18	89.24	87.18	84.49	80.66	74.13	68.64	32.12

Table III
Principal Components of Size-Sorted Commercial Bank Stock Returns.

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 (3). U.S. commercial banks are sorted into deciles by market capitalization. The last row indicates the percentage of variation explained by each principal component. Standard errors in brackets generated by bootstrapping from the data $10,000$ times. First, we bootstrapped the returns for each size-sorted portfolio and the risk factors 10,000 times. For each bootstrapped sample, we regress the returns on the standard risk factors. We then compute the first and second principal components from the residuals of this regression. This results in 10,000 samples of the first and second principal components, which we use to compute the standard errors.

	Market Cap 1970 - 2013		Book Value 1980 - 2013	
Portfolio	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$
Small	0.47	0.53	0.25	0.34
	[0.02]	[0.05]	[0.02]	[0.10]
2	0.34	0.24	0.27	0.28
	[0.02]	[0.03]	[0.02]	[0.07]
3	0.31	0.20	0.32	0.27
	[0.02]	[0.05]	[0.02]	[0.08]
4	0.32	0.12	0.31	0.19
	[0.02]	[0.02]	[0.01]	[0.06]
5	0.31	-0.02	0.39	0.16
	[0.01]	[0.04]	[0.01]	[0.05]
6	0.30	-0.12	0.39	-0.02
	[0.02]	[0.03]	[0.03]	[0.05]
7	0.31	-0.31	0.36	-0.16
	[0.01]	[0.04]	[0.01]	[0.09]
8	0.25	-0.41	0.37	-0.27
	[0.01]	[0.05]	[0.02]	[0.12]
9	0.24	-0.43	0.27	-0.27
	[0.01]	[0.04]	[0.01]	[0.11]
Large	0.24	-0.37	0.18	-0.71
	[0.01]	[0.05]	[0.02]	[0.17]
%	49.19	18.86	47.93	15.15

Table IV
Size-Factor-Adjusted Returns for Size-Sorted Portfolios of Commercial Banks.

This table presents estimates from OLS regression of monthly value-weighted excess returns on each size-sorted portfolio of U.S. commercial banks on the three Fama and French (1993) stock and two bond risk 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 renormalized so that they sum to 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. Standard errors were adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) with three lags. In panel A, the weights of the second principal component are computed over 1970 to 2005 and the sample is 1970 to 2005. The annualized price of risk is 11.14% in the sample ending in 2005. In panel B, the weights of the second principal component are computed over 1970 to 2013 and the sample is 1970 to 2013. The annualized price of risk is 9.36% in the sample ending in 2013. The last line in each panel shows the loadings on the size factor PC_2 times the risk price.

	Small	2	3	4	5	6	7	8	9	Large	10A	10B
Panel A: Pre-Crisis Sample (1970 - 2005)												
Risk-adjusted Returns	0.55	0.62	3.92^{**}	0.94	2.49	1.66	1.67	0.75	-0.02	-1.23	-0.77	-1.76
PC_2	0.15^{***}	0.07^{***}	0.07^{**}	0.05^{***}	-0.01	-0.03^{*}	-0.06^{***}	-0.09^{***}	-0.11^{***}	-0.12^{***}	-0.12^{***}	-0.12^{***}
Size	1.71	0.82	0.78	0.50	-0.07	-0.29	-0.69	-1.00	-1.20	-1.37	-1.34	-1.37
Panel B: Full Sample (1970 - 2013)												
Risk-adjusted Returns	0.06	0.26	2.56^{**}	-0.58	1.12	0.27	-0.38	-0.57	-1.62	-3.78^{**}	-1.72	-4.31^{**}
PC_2	0.30^{***}	0.14^{***}	0.12^{***}	0.07^{***}	-0.01	-0.07^{***}	-0.18^{***}	-0.24^{***}	-0.25^{***}	-0.21^{***}	-0.23^{***}	-0.21^{***}
Size	2.85	1.30	1.10	0.65	-0.12	-0.62	-1.69	-2.20	-2.32	-2.00	-2.15	-1.97

Table V
Cumulative Return On 2nd PC Portfolio in Recessions and Financial Crises.

This table shows the value of \$100 invested in a portfolio that goes long in small commercial banks and short in large commercial banks. The weights of the portfolio are given by the second principal component, renormalized so that they sum to one ($\widehat{\boldsymbol{w}}_2$). \$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) as of 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 using NBER dating conventions. The bottom panel shows the value of a \$100 investment n months into the recession.

Panel A: Portfolio Value at NBER Trough			
Start	End	Value	Hedged Value
01: 1970	11: 1970	14.00	55.14
11: 1973	03: 1975	91.14	115.07
01: 1980	11: 1982	24.18	36.75
07: 1990	03: 1991	66.13	60.85
03: 2001	11: 2001	110.29	82.67
12: 2007	06: 2009	-12.58	-1.44
Average		48.86	58.17
Panel B: Average Portfolio Value n Months after NBER Peak			
		Value	Hedged Value
Month 1		113.12	101.84
Month 2		94.42	93.31
Month 3		112.51	88.19
Month 4		98.11	84.30
Month 5		94.05	83.15
Month 6		101.77	81.45
Month 12		63.39	59.92

Table VI
Betas to Market Squared.

This table presents the estimates from an OLS regression of monthly value-weighted excess returns on each size-sorted portfolio of U.S. commercial banks on the three Fama and French (1993) stock and two bond risk factors, and $market^2$. *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. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. Standard errors were adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) with three lags. The sample is 1970 to 2013.

	Small	2	3	4	5	6	7	8	9	Large	10A	10B	10 - 1	10A - 1	10B - 1
Panel A: Market Capitalization															
market	0.44***	0.54***	0.49***	0.57***	0.56***	0.67***	0.77***	0.81***	0.92***	1.22***	0.99***	1.25***	0.78***	0.55***	0.80***
smb	0.39***	0.42***	0.37***	0.39***	0.38***	0.44***	0.48***	0.44***	0.43***	-0.12*	0.15**	-0.14*	-0.51***	-0.23**	-0.53***
hml	0.50***	0.48***	0.43***	0.53***	0.49***	0.59***	0.69***	0.66***	0.66***	0.70***	0.59***	0.73***	0.21*	0.09	0.23**
ltg	-0.18	-0.07	-0.05	0.10	0.16*	0.06	0.15	0.24**	0.39***	0.19*	0.23**	0.24**	0.37**	0.42**	0.42***
crd	0.37**	0.23	0.30**	0.15	0.13	0.21*	0.05	-0.06	-0.17	-0.14	-0.05	-0.20	-0.51**	-0.42*	-0.57***
$market^2$	-0.86*	-0.29	-0.54	-0.93**	-0.86**	-0.17	-0.53	0.11	0.44	0.36	0.61	0.38	1.22**	1.46*	1.23**
R^2	25.60	43.63	43.32	50.39	52.48	59.68	60.97	62.10	66.54	68.00	62.12	65.72	27.88	15.08	28.03
Panel B: Book Value															
market	0.41***	0.42***	0.50***	0.52***	0.64***	0.78***	0.91***	0.92***	0.92***	1.07***	1.07***	0.85***	0.67***	0.66***	0.44***
smb	0.36***	0.35***	0.26***	0.36***	0.45***	0.54***	0.59***	0.63***	0.34***	0.02	0.00	0.06	-0.34***	-0.36***	-0.30**
hml	0.34***	0.36***	0.40***	0.49***	0.59***	0.75***	0.86***	0.88***	0.74***	0.68***	0.68***	0.44***	0.34**	0.35**	0.10
ltg	0.12	0.12	0.13	0.07	-0.01	0.19*	0.42***	0.44***	0.34***	0.05	0.04	0.21*	-0.08	-0.08	0.09
crd	0.12	0.18	0.17	0.23*	0.32*	0.08	-0.13	-0.24	-0.15	0.20	0.18	0.16	0.08	0.06	0.04
$market^2$	-1.03**	-1.55***	-1.69**	-0.80*	-0.53	-0.12	0.47	1.36***	0.71	0.00	-0.32	0.74	1.03	0.71	1.77***
R^2	34.82	41.97	41.43	48.09	49.17	57.43	62.48	58.40	63.65	56.42	49.94	40.35	22.82	19.90	10.84

Table VII

Bank Tail Risk Pricing for Investment Banks, Foreign Banks, and GSEs.

This table presents the estimates from OLS regression of monthly excess returns on a value-weighted index of U.S. commercial banks, U.S. investment banks and foreign banks on the Fama-French stock factors, bond factors, and the second principal component weighted returns. The table also reports results for individual banks. U.S. commercial banks are defined as all firms with HSICCD equal to 60 or historical SICCD equal to 6712. U.S. Investment banks are those with two-digit HSICCD of 62. We exclude foreign banks with share codes ending in 2 or 5. For individual banks, the longest available sample for each bank till 2005 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 renormalized so that they sum to 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors were adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) with three lags. The implicit subsidy is the risk price (the 1970-2005 average return on PC_2 11.14%) times minus the loading on PC_2). The risk price is fixed at 11.14% in the different subsamples, but we recompute the loading on PC_2 in Panel B over shorter sub-samples. The full sample is 1970 to 2005.

	Index of Banks			Individual Banks								
	Commercial	Investment	Foreign	BoA	Citi	WFC	FNM	FRE	GS	LEH	ML	MS
Mkt Cap(Jan 05)	118.57	24.12	44.71	187.30	254.56	52.22	34.33	55.78	61.25	103.71	62.48	44.95
start				(1970)	(1986)	(1970)	(1970)	(1989)	(1999)	(1994)	(1971)	(1986)
Panel A: Pre-Crisis Sample (1970-2005)												
market	0.78***	1.53***	1.16***	0.90***	1.38***	0.65***	0.79***	0.72***	1.46***	1.36***	1.70***	1.51***
smb	0.01	0.24**	0.65***	-0.14	-0.44***	-0.46***	-0.31**	-0.15	0.00	-0.28	0.18	-0.17
hml	0.42***	0.05	0.58***	0.40**	0.15	0.30**	0.18	0.34*	-0.35*	-0.33	0.07	-0.23
ltg	-0.03	0.06	-0.18	0.03	-0.08	-0.10	1.30***	1.11**	0.85	-0.01	-0.30	-0.13
crd	0.25**	-0.21	0.36	0.35	0.32	0.35	-0.23	-0.35	-0.45	0.74	0.37	-0.25
PC_2	-0.11***	-0.04**	0.04	-0.32***	-0.14*	-0.32***	-0.16***	-0.30***	-0.18	-0.33**	-0.10	-0.13*
size	1.18	0.48	-0.42	3.51	1.52	3.61	1.78	3.37	2.03	3.63	1.06	1.50
Panel B: Pre-Crisis												
1990-2005												
PC_2	-0.09***	-0.06***	0.04	-0.26**	-0.13*	-0.35***	-0.28***	-0.32***	-0.18	-0.33**	-0.12*	-0.15**
size	1.00	0.65	-0.50	2.91	1.48	3.89	3.15	3.51	2.03	3.63	1.30	1.70
2000-2005												
PC_2	-0.16***	-0.01***	0.00	-0.35***	-0.17*	-0.34***	-0.53***	-0.35***	-0.21	-0.46**	-0.17	-0.32**
size	1.75	0.12	-0.02	3.91	1.89	3.82	5.93	3.87	2.39	5.09	1.92	3.55

Table VIII
Bailout Announcements.

This table presents the results of OLS regression $R_t^{TBTF} - R_t^f = \alpha + \beta_1 PC_2 + \beta_2 PC_2 D + \epsilon$, where $TBTF$ represents the value-weighted return of the 10 banks that were declared too-big-to-fail by the Comptroller of Currency in September of 1984, PC_2 represents the daily return of the portfolio that goes long in small U.S. commercial banks and short in large U.S. commercial banks, the weights for the portfolio are given by the second principal component and sum to one, and D represents a dummy variable that equals one after the announcement date and zero 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 is excluded from the sample while estimating coefficients. Dates for the announcements are from O'Hara and Shaw (1990) and Kho, Lee, and Stulz (2000). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors were adjusted for heteroskedasticity and autocorrelation using Newey-West (1987).

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 BI
Measuring Residual Risk Exposure.

This table presents the standard deviation of residuals from OLS regression of monthly value-weighted excess returns of each size-sorted portfolio of U.S. commercial banks on the three Fama and French (1993) stock and two bond risk factors. In panel A the row labeled "Recession" computes the (time series) standard deviation of residuals during recession months and the row labeled "Full Sample" computes the (time series) standard deviation for the 1970 to 2013 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 residuals during recession months and the row labeled "Full sample" lists the standard deviation for the full 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	19.02	15.57	11.25	14.46	13.15	12.44	15.25	15.50	15.65	18.45
Full Sample	14.64	11.68	11.36	11.34	10.73	10.72	11.70	11.37	11.21	12.70
Panel B: Individual Banks										
Recession	30.11	29.85	20.34	22.91	23.89	23.68	23.66	26.53	24.31	23.86
Full Sample	36.06	27.88	26.21	25.24	24.29	23.28	23.29	22.95	21.12	19.16

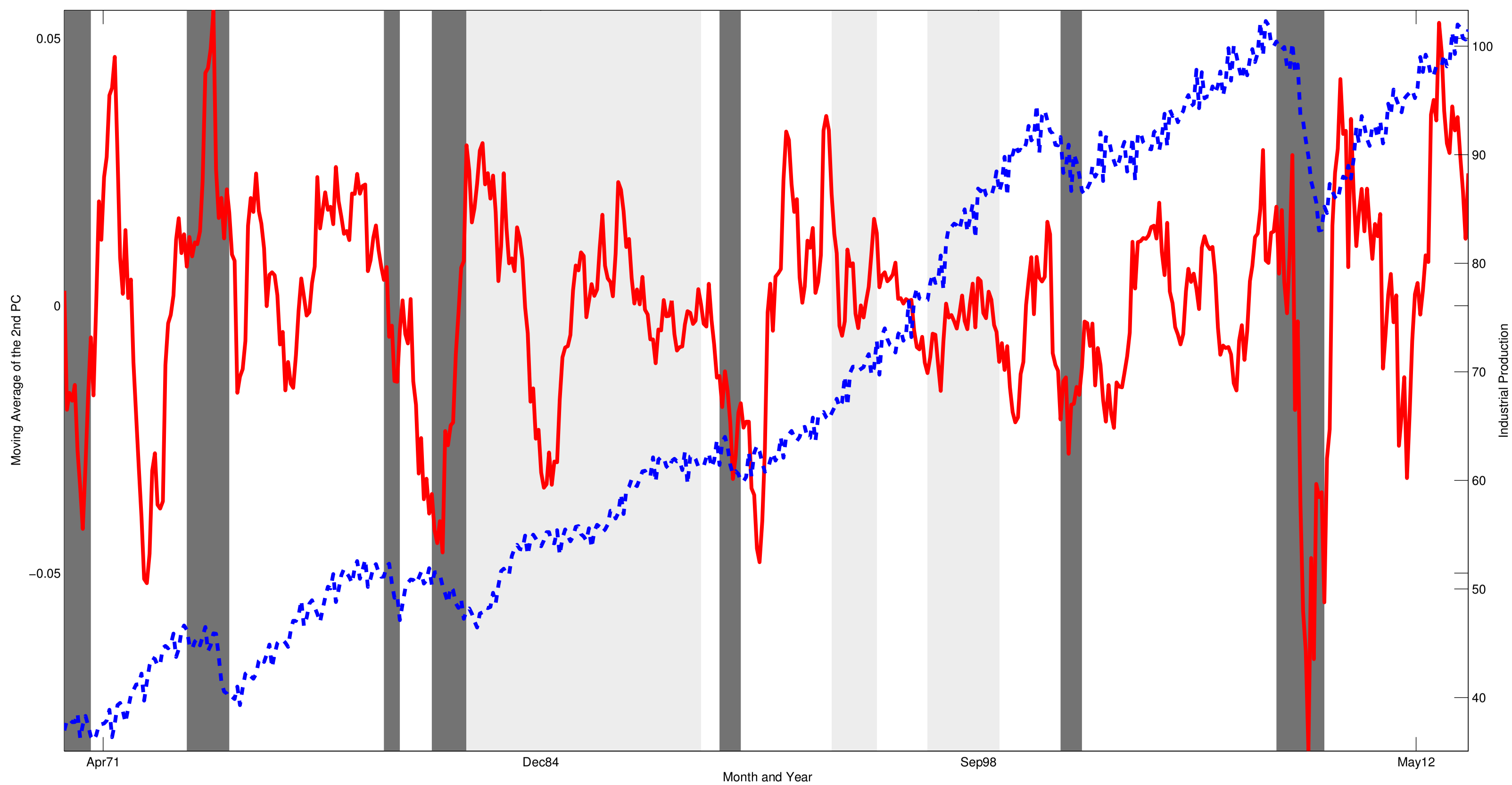

Figure 1. Size factor in normal risk-adjusted returns of commercial banks. The solid line plots the 12-month (backward-looking) moving average (months $t-11$ through t) of the time series of the weighted sum of the residuals from the OLS regression of monthly value-weighted excess stock returns for each size-sorted portfolio of U.S. commercial banks on the Fama-French and bond risk factors. The weights are given by the second principal component and sum to one. The dashed line represents the 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 are obtained from Kho, Lee, an Stulz (2000) and the FDIC (for the developing 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.

Internet Appendix to "Size Anomalies in U.S. Bank Stock Returns"*

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This appendix lists supplementary tables and figures to accompany the main text. This appendix also presents the details regarding our definition of commercial banks.

I. *Additional Tables and Figures*

Table IA.I Risk-Adjusted Returns on Size-Sorted Portfolios of Nonfinancials
Table IA.I provides results of the regression specified in equation (2) for nonfinancials sorted by market capitalization (Panel A) and book value (Panel B). The table reports regression coefficients for each size-sorted portfolio along with their statistical significance and the adjusted R^2. In Panel A, we see that nonfinancial stocks with market capitalization in the lowest decile earn much higher risk-adjusted returns. This is not surprising. 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. The average market capitalization in the second portfolio is much larger (\$65.7 million in 1980). These small cap stocks are typically highly illiquid stocks. Other than this illiquidity effect in the first decile, there is no clear pattern in risk-adjusted returns. The risk-adjusted returns on the largest nonfinancials in decile 10 are positive, but small and statistically insignificant. Interestingly, the risk-adjusted returns on the top 5% are much larger than those on the next 5% of the size distribution. 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 only marginally significant. The largest nonfinancials earn risk-adjusted returns that are positive but small and statistically insignificantly different from zero.

Table IA.I NBER reference cycle peaks and banking panics
This table presents a lists of banking panics taken from Gorton (1988, p. 223) and Wicker (1996, p. 155). In this table, "Months Before Peak" and "Months After Peak" refer to the number of months relative to the peak of the business cycle when the banking crisis occurs.

Table IA.II Characteristics Regression
This table presents the results of a pooled regression in which the dependent variable is the annual return of each bank in our sample and the independent variables are the bank's market capitalization, the book value of the bank, and leverage. All variables are measured as of time t. The table shows that a 1% increase in the log book value of the bank results in a 2.45% decline in the annual return of the bank.

Table IA.III Announcement Dates
Table IA.IV presents the dates for the pre-crises announcements 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. These dates are used in the event study analysis the results of which are in Table VIII in the main paper.

Figure IA.1 A Size Factor in Normal Risk-Adjusted Returns of All Banks
This figure presents the time series plot of the size factor in normal risk-adjusted returns of all banks. In the figure, 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 OLS regressions 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 one. The dashed line represents growth in the industrial production index. 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.

Table IA.1 Risk-Adjusted Returns on Size-Sorted Portfolios of Nonfinancials

This table presents estimates from an OLS regression of monthly value-weighted excess returns on each size-sorted portfolio of nonfinancials on the three Fama and French (1993) stock and two bond risk factors. nonfinancials are defined as all firms excluding those with two-digit HSICCDs ranging from 60 to 67. *market*, *smb*, and *hml* are the three Fama-French stock factors: 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. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Alphas are annualized by multiplying by 12 and are expressed in percentages. Standard errors were adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) with three lags. The sample is 1970 to 2013.

	1	2	3	4	5	6	7	8	9	Large	10A	10B	10 - 1	10A - 1	10B - 1
								Panel A: Market Capitalization							
α	15.51***	1.35**	-1.82	-1.79	-4.57***	-2.56*	-3.81***	-2.10*	-2.80**	2.34*	-1.47	3.20**	-13.18**	-16.98**	-12.31**
market	0.67***	0.80***	0.84***	0.91***	0.94***	0.96***	0.99***	1.01***	1.03***	0.97***	1.06***	0.95***	0.30***	0.40***	0.28***
smb	1.22***	1.13***	1.02***	1.09***	1.10***	1.05***	1.07***	0.92***	0.79***	0.21***	0.50***	0.17***	-1.00***	-0.71***	-1.05***
hml	0.17	0.25**	0.26***	0.31***	0.32***	0.22***	0.16***	0.11**	-0.04	-0.42***	-0.05	-0.46***	-0.58***	-0.22	-0.62***
ltg	-0.70***	-0.50***	-0.34***	-0.34***	-0.24***	-0.15**	-0.05	0.11*	0.07	-0.02	0.07	-0.03	0.68***	0.77***	0.67***
crd	0.70***	0.50**	0.32**	0.19	0.13	0.05	0.00	-0.15*	-0.08	0.02	-0.11	0.03	-0.68***	-0.81***	-0.67***
R^2	52.88	64.34	70.22	78.44	81.67	86.18	89.12	91.29	90.06	78.77	86.31	74.38	25.89	33.43	21.50
								Panel B: Book Value							
α	3.56**	3.17*	3.15**	3.16*	0.42	-0.65	0.56	-0.03	-0.13	-0.15	0.78	0.52	-2.78**	-3.00**	-3.03**
market	0.87***	0.96***	0.95***	0.96***	1.01***	1.04***	0.99***	1.12***	1.12***	1.13***	1.06***	0.98***	0.18***	0.12***	0.11***
smb	1.24***	1.12***	1.22***	1.09***	1.02***	0.98***	-0.14***	0.87***	0.71***	0.37***	0.13**	-0.19***	-1.11***	-1.38***	-1.43***
hml	-0.10	-0.12	-0.03	-0.14	-0.02	0.08	0.29***	0.19***	0.26***	0.31***	0.29***	0.29***	0.39***	0.39***	0.39***
ltg	-0.48***	-0.44***	-0.40***	-0.46***	-0.38***	-0.35***	-0.14***	-0.27***	-0.22***	-0.20***	-0.14*	-0.14***	0.34**	0.34**	0.34**
crd	0.44***	0.42*	0.39***	0.45***	0.32**	0.35***	0.17***	0.21**	0.18	0.18*	0.17	0.18***	-0.27**	-0.27**	-0.27**
R^2	77.65	81.71	84.97	82.32	88.67	92.49	94.22	93.27	91.78	91.08	90.60	93.29	12.95	16.57	15.63

Table IA.2 NBER reference cycle peaks and banking panics.

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 IA.3 Characteristics Regression

Pooled Regression. The dependent variable is the annual return for each individual bank in our sample. The independent variables are the bank's market capitalization, the book value, and leverage. All variables are at date t. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors were adjusted for heteroskedasticity and autocorrelation using Newey-West (1987). Annual data. The sample is 1970 to 2013.

	Regression 1	Regression 2
$constant$	5.56	-4.52
$\log Book$	-2.23***	
$\log Marketcap$	2.79***	0.82***
$Leverage$	0.00	0.02
$adj - R^2$	0.0042	0.0009

Table IA.4 Announcement Dates

Dates for the pre-crises 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		

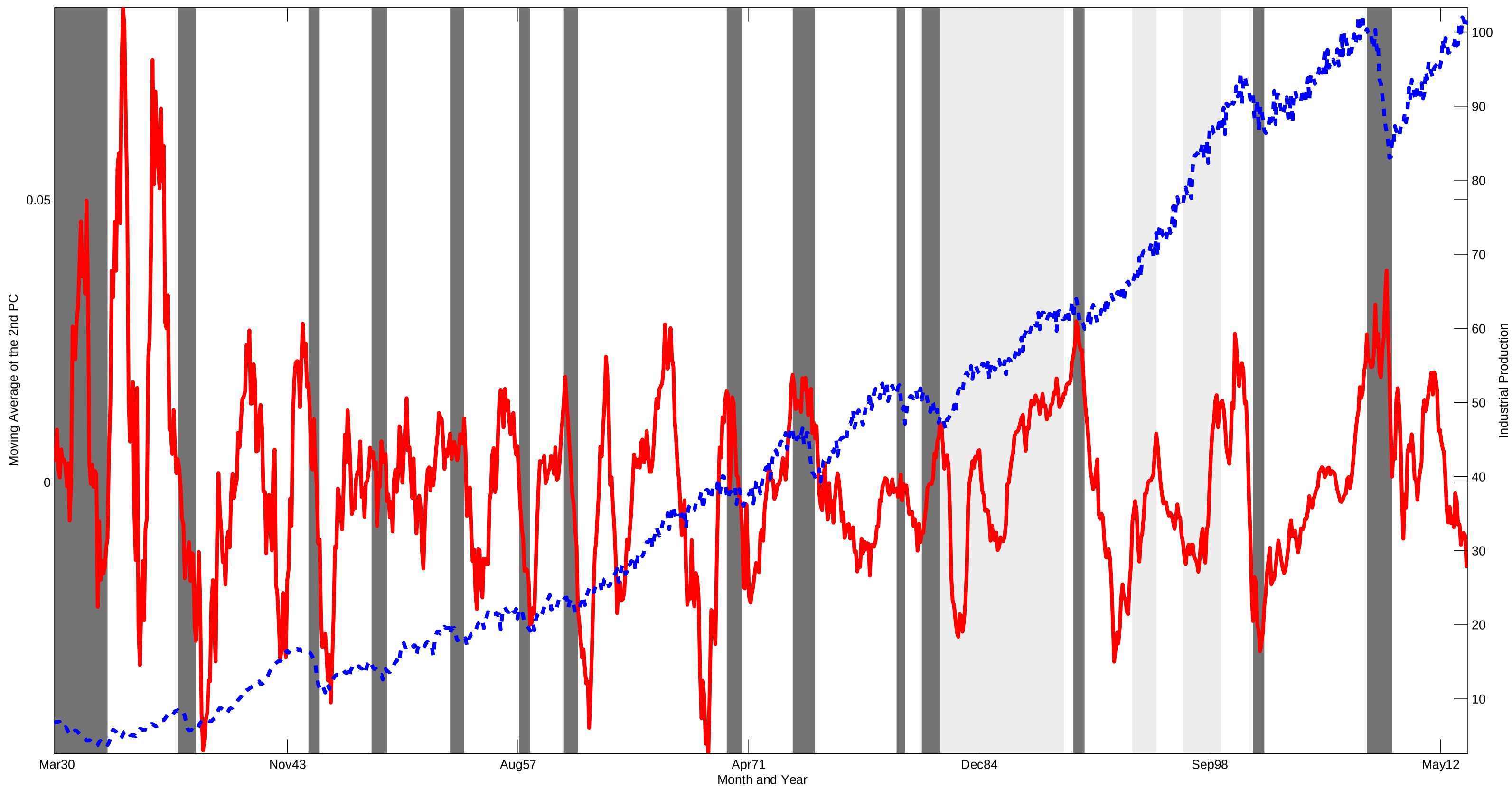

Figure IA.1. Size factor in normal risk-adjusted returns of all banks. The solid line plots the 12-month (backward-looking) moving average (months $t-11$ through t) of the time series of the weighted sum of the residuals from OLS regression of monthly excess stock returns for each size-sorted portfolio of all financial firms on the Fama-French and bond risk factors. The weights are given by the second principal component and sum to one. The dashed line represents growth in the industrial production index. 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.

II. Identifying Commercial Banks

This section presents the details regarding our definition of commercial banks. We also explore some alternative methods for identifying commercial banks in *CRSP*. In the text, U.S. commercial banks are defined as all firms with two-digit HSICCD equal to 60 or historical SICCD equal to 6712.

A review of the asset pricing literature suggests that it is more common to map firms to a particular industry using the four-digit historical SIC code (SICCD) in *CRSP*. In this section, we evaluate the challenges of this approach to identifying commercial banks. The primary reason why we cannot identify commercial banks as those firms in *CRSP* for whom the first two digits of the SICCD equals 60 alone is that such a definition excludes all commercial bank holding companies which are organized under the SICCD beginning with 67. The largest commercial banks in the United States are part of bank holding companies. Prior to 1998, almost all bank holding companies were listed under the SICCD beginning with 67, not under the SICCD beginning with 60. Commercial banks owned by bank holding companies always trade as part of the holding company and are not separately listed on the market.

Given that bank holding companies in the U.S. are often organized under a separate SIC code, it should still be possible for a researcher to define commercial banks using SICCDs from *CRSP*. For example, one could define commercial banks as firms for which the first two digits of SICCD equals 60 or 67. A careful analysis of the data reveals that there are at least two potential problems with the use of SICCDs.

First, SICCDs beginning with 67 identify not only bank holding companies but are also used to identify financial holding companies of investment banks, real estate invest trusts, oil traders, patent owners and lessors, educational trusts, religious trusts, charitable trusts, and investors not classified elsewhere in the SIC system.

Second, these SICCDs vary a lot over time. This variation does not seem to reflect changes in the main economic function of the firm. As a result, any combination of SICCDs beginning with 60 or 67 still potentially misses quite a few firms that should have been correctly identified as commercial banks. For example, BB&T Corp with SICCD = 2000, Banc One Corp with SICCD = 0, Barclays with SICCD = 6281, Citigroup with SICCD = 6153, 6211, and 6311, First Bancorp with SICCD = 0, and Sterling Bancorp with SICCD = 6144 will be filtered out using any permutation of a rule that combines SICCDs beginning with 60 or 67. All of these banks are among the 100 largest bank holding companies by the Federal Financial Institutions Examination Council in 2014. We can identify other commercial banks for which the HSICCD begins with 60 but for whom the SICCD does not begin with either 60 or 67 (or even 61 or 62).

Based on just the short list of examples cited above it appears that for commercial banks, SICCDs can begin with 0, 20, 30, 61, 62, and 63s with no apparent logic or pattern while the HSICCDs are remarkably stable and almost always equal 60. It seems improbable that BB&T, the 17^{th} largest commercial bank in the United States, for a brief period of time in its history, converted to a manufacturing firm, with an SICCD beginning with 20.

This analysis confirms that the exclusive use of SICCDs to filter commercial banks does not allow for a time-consistent definition of commercial banks that ensures actual banks are never excluded from the sample. Any filter based on SICCDs to define/identify commercial banks either implies that commercial banks randomly drop in and out of our sample or that, we manually (and randomly) add or exclude SICCDs in our definition of commercial banks over time.

Around 1999, the SEC eliminated the bank holding company option from its menu of choices for financial firms when filing their SIC codes (see `http://www.sec.gov/info/edgar/siccodes.htm`). Hence, bank holding companies were essentially forced to state that they are banks. This can easily be confirmed by tracking the SICCD for individual bank holding companies. In the late 90s and early 00s, they all switch to SICCD codes starting with 60. To sum up, our analysis reveals that a sample of commercial banks based on HSICCDs would more or less (correctly) identify all commercial banks that are in existence in 1998 including bank holding companies. This is also perhaps the reason that the Federal Reserve advocates the of 3-digit header SIC industry group codes.

As a result of the change in the coding conventions, the HSICCDs correctly capture banks in all of the instances mentioned as in all these cases banks are listed in *CRSP* with HSICCD beginning with 60. Therefore, this is the approach we adopt in our paper.

There is one potential weakness of using HSICCDs to define commercial banks. The use of HISCCDs beginning with 60 to identify/define commercial banks implies that our sample excludes all firms classified as commercial banks in 1998 that did not have an HSICCD beginning with 60 and that exited the sample before 1998-99 for reasons other than mergers and acquisitions. This is why we decide to include firms with historical SICCD equal to 6712. SIC code 6712 appears to be reserved only for bank holding companies[1].

We infer from our review of the banking literature that none of the approaches used in the literature are completely free from problems. In fact, any filter based on historical SIC codes to identify commercial bank stocks in *CRSP* is almost always augmented by a manual search to eliminate (include) irrelevant (relevant) firms in the sample. However, none of the papers that we came across analyzed commercial bank stocks from an investment perspective using more than 40 years of monthly data. A manual filter, while easy to implement for data spanning short periods of time and a selective sample of commercial banks, is not feasible given the time-period and the cross-section of the data analyzed our paper.

There is no perfect SIC-code-based algorithm for identifying commercial banks over the entire period covered by our sample. The change in the coding convention in 1999 possibly addresses all of the concerns that we highlight in this note regarding SIC codes, but this fix occurs too late for us. Even the definition advocated by regulators does not produce a satisfactory solution. The Federal Reserve Bank of New York suggests that one use the three-digit header SIC codes equal to 602 and 671 to identify commercial banks.

While HSICCD is a reasonable alternative, given the issues identified above, we do not claim that HSICCDs are the best approach to identify commercial banks. Indeed, one can do better if one manually sifts through *CRSP* data to carefully identify commercial banks to form a sample, a project that is underway (and incomplete) at the Federal Reserve Bank of New York.[2] The methodology is available at `http://www.newyorkfed.org/research/banking_research/datasets.html`. However, this project only covers bank holding companies and excludes more than 20% of the commercial banks in the United States that are not part of a bank holding company. The sample period starts in 1990 and thus potentially only covers half of the sample we analyze in our paper.

Given these limitations, the use of HSICCDs to filter commercial banks is reasonably efficient, as it enables to use the change in the coding convention to obtain better coverage of commercial banks, as can be seen from looking over our sample and comparing it to other sources. To summarize, the use of HSICCDs (a) ensures that all bank holding companies and commercial banks are included in our sample over the entire sample period, (b) does not require us to change the SIC code definition of commercial banks to ensure that the largest commercial banks are consistently included in our sample across time, (c) does not require us to manually add and remove firms from our sample

[1]See definitions for SIC codes available at `https://www.osha.gov/pls/imis/sicsearch.html?p_sic=67&p_search=`.

[2]However, the project at the Federal Reserve Bank of New York identifies bank holding companies in the United States and will not cover publicly listed banks among that are not part of the bank holding companies.

based on a manual search and to ensure that our sample is relatively complete, (d) does not expose us to sample selection concerns that go together with a manual selection procedure.

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