Tail Risk and Size Anomaly in Bank Stock Returns

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ABSTRACT

We reexamine the size anomaly in U.S. bank stock returns and suggest a new size factor capturing the size-dependent return difference. Primarily, Gandhi and Lustig (2015) construct a size factor in the component of size-sorted bank stock portfolio returns, but this size factor has limited economic meanings. We compute size factor using Kelly and Jiang (2014)'s tail risk measure. Tail risk is easily estimable from the cross-section of stock returns and measures time-varying extreme event risk. We show that tail risk captures size-related exposures to bank stock returns. We further analyze the characteristics of the tail risk and its relation with bank stock returns. These findings support that investors actually perceive the too-big-to-fail hypothesis in the bank stock markets.

Keywords: bank stock returns, too-big-to-fail, tail risk, financial disaster

JEL classification: G01, G12, G20, G28

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1. Introduction

Because banks accept deposit and make loans, it largely influences the real economy. Bankruptcy of large banks causes economic disasters.[1] Therefore, especially in the periods of financial crisis, governments are reluctant to let financial firms fail. Governments provide implicit guarantees to financial institutions.[2] According to Gandhi and Lustig (2015), because large banks are deemed to promise more credible insurance by governments than small banks (too-big-to-fail), risk-adjusted returns on large bank stocks are lower than small banks in U.S.[3] They call it as a size anomaly in U.S. bank stock returns. They also construct a size factor which captures bank-specific tail risk, however it is hard to interpret economic meanings of their size factor. They just set size factor applying PCA, econometric methodology. In this paper, we propose our new size factor which measures time-varying extreme event risk. By applying Kelly and Jiang (2014)'s tail risk measure, we make a size factor of bank stock returns and analyze how tail risk relates to bank-specific tail risk. We show that tail risk absorbs size-related exposures to bank stock returns

Kelly and Jiang (2014)'s tail risk has some advantages applying for our analysis. While many of other tail risk measures are estimable having accumulative years of tail observations, our tail risk measure is easy to compute by capturing common variation in the tail risks of individual firms over time. Because it is able to construct monthly tail risk estimate using cross-sectional returns, we can easily make time-varying size factor using tail risk measure. Furthermore, Kelly and Jiang (2014) show that economic activity is related to tail risk shocks. We can consider high tail risk periods as more likely to occur extreme negative event or financial disaster time. Our size factor made by tail risk has economic meanings not just an econometric measure.

We compute the tail exponent estimate, *TAIL*, for each month by pooling daily returns of all CRSP stocks. Tail risk measure is constructed by extreme negative stock returns in each month, and therefore it reflects the time-varying economic disasters.[4] Then we make our size factor, *TFAC*, which is monthly CRSP stock return differences between the high and low tail risk sensitive portfolios. Because *TFAC* has high correlation with *TAIL*, correlation coefficient is 0.46, it also represents the financial disasters in stock markets. In addition, because the

[1] According to World development indicators, the U.S. banks provide domestic credit for 232% of the 2012 U.S. GDP.

[2] Schich and Lindh (2012) argue that government's implicit guarantees significantly benefit funding cost of banks.

[3] There is also direct evidence from option markets to support this argument. Kelly, Lustig, and Nieuwerburgh (2011) show that out-of-the-money put options on large banks were cheaper than small banks during the crisis.

[4] Kelly and Jiang (2014) argue that tail exponent estimate has an ability of explaining time-varying extreme event risk in stock market.

largest correlation coefficient between our size factor and six risk factors (*MKTRF*, *SMB*, *HML*, *UMD*, *TERM*, and *DEF*) is 0.38, the multicollinearity would not be occurred.[5] We show that average risk-adjusted return differences between large and small bank stocks is not significantly different from zero when *TFAC* is added into risk factors.

We further analyze the characteristics of *TAIL* in order to understand how it explains bank-specific tail risk. Gabaix (2012) Wachter (2013), and Gourio (2008) analyze that financial disasters differently affect bank cash flows and contribute an additional bank-specific risk factor.[6] They argue that expected returns on bank stocks are priced by sensitivity to these rare events. *TAIL* is considered as a proxy for financial disasters. We examine the time-series variation of *TAIL* to verify how it reflects financial disasters. *TAIL* also tends to be high in NBER recessions.

According to the asset pricing model with a time-varying rare events, disaster recovery rate affects expected bank stock returns.[7] We also show that bank stock portfolios with low predictive loadings on tail risk have high cross-sectional expected returns. Investors perceive that low tail risk loading bank stocks are served as effective hedges, and therefore this banks have contemporaneously higher price and lower expected returns. Thus, tail risk loading is related to disaster recovery rate of bank stocks and captures size anomaly in bank stock returns. On the one hand, previous literatures related to bank stock returns support our results. Fahlenbrach, Prilmeier and Stulz (2012) argue that the banks with substantial losses during previous crises tend to incur losses during the recent crisis. Thus, banks have different sensitivities of financial crisis risk. Therefore, if some banks are promised tail risk subsidy, they steadily have an incentive to load up on this type of risk.

We examine how government's implicit guarantee affects the relation between tail risk loadings and size of banks. During financial crisis, U.S. government usually spent the most of emergency credit to rescue large financial institutions.[8] Thus, investors perceive that large banks are unlikely to fail. We find a negative relation between size of bank relative to GDP and the loading on the tail risk for the largest two size-sorted deciles, but other deciles have positive relation. Because government's implicit guarantee only influences for the few large

[5] The correlation coefficient between *MKTRF* and *TFAC* is 0.38.

[6] They developed an asset pricing model which is constructed Barro (2006), Rietz (1988), and Longstaff and Piazzesi (2004) with a time-varying probability of rare events in financial markets.

[7] Gandhi and Lustig (2015) prove that recovery rate is altered with size banks, so expected returns gap between small and large banks is due to sensitivity of financial disaster, recovery rate.

[8] Data are from the Term Auction Facility (TAF) and Gandhi and Lustig (2015), in the recent financial crisis, the Federal Reserve made 83% of emergency loans to 10 of the largest U.S. financial institutions.

banks, larger banks are less sensitive to tail risk only for the large bank portfolios. Then, we analyze whether the loadings on tail risk for bank stock returns actually proxy for the investors' perception of government guarantee. We find that return spreads between large and small bank portfolios are only significant for the low tail beta portfolios. Because government rescues small number of large banks, investors perceive that only low tail beta banks have an opportunity to take aids by government. Therefore, high tail beta banks have no possibility of rescue by government and there is no significant return spread between large and small bank portfolios for large tail risk sensitivity portfolios.

We additionally analyze whether other risk factors could capture the size anomaly in bank stock returns. We insert two risk factors into our six risk factors: two risk factors are liquidity factor of Pastor and Stambaugh (2003) and skewness factor of Harvey and Siddique (2000). Because small banks which have high bank-specific tail risk might be more sensitive to liquidity factor, we presume *LIQ* has ability to capture the size anomaly in bank stock returns. We clearly find that *LIQ* reduces risk-adjusted return difference between large and small bank stock portfolios, but significance level is still significant using *LIQ* and six risk factors. Following Gandhi and Lustig (2015), we also verify skewness factor cannot capture the return difference between large and small bank stock portfolios, not reported. It is possible that there are other risk factors can proxy for the bank-specific tail risk. Our main purpose of this paper is that tail risk is one of the possible measure of explaining the size anomaly in bank stock returns.

Our work contributes to develop new measure of capturing systemic risk in the financial industry. Gandhi and Lustig (2015), Adrian and Brunnermeier (2016), and Huang, Zhou and Zhu (2009) propose methods for computing systemic risk. Our tail risk measure which is absorbing the return differences of size-sorted bank stock portfolios has advantages to calculate and interpret its economic meanings easily. The size factor developed by Gandhi and Lustig (2015) has similar econometric component with our tail risk factor, but their measure is only computed by statistical method, PCA. Because government is unwilling to let large banks fail and investors recognize it, banks with less sensitive to the tail risk are trade at a premium price as a result. To our knowledge, our paper is first to proxy the tail risk measure as bank-specific tail risk. Tail risk measure also captures the implicit insurance provided by government, and therefore can explain the size anomaly in bank stock returns.

The rest of the paper is organized as follows. In section 2, we describe the methodology to construct size sorted U.S. commercial bank stock portfolios and to measure tail risk and firm-characteristic variables. In

Section 3, we reexamine the size anomaly in bank stock returns and analyze the return differences among tail beta-sorted portfolios. In section 4, we present the tail risk-adjusted returns on size-sorted portfolios. Tail risk factor captures the size anomaly in bank stock returns. In section 5, we show time-varying characteristics of tail risk and its relation with size-sorted bank stock returns. We conclude in section 6.

2. Data and Methodology

In this section we describe the methodology to classify the U.S. commercial bank stocks and decile size-sorted portfolios. We also explain calculating the tail risk measure.

2.1. Classifying Commercial Bank Stocks and Size-Sorted Portfolios

We use all common stocks with CRSP share code 10 or 11. This criterion excludes foreign firms which are not incorporated in the U.S. classification of commercial banks based on CRSP SIC codes. There is no unique, well-identified way to classify the U.S. commercial banks in CRSP. Following Gandhi and Lustig (2015), we define commercial banks which have header SIC code 60 or historical SIC code 6712. This definition ensures that bank holding companies are included in our sample. Bank holding companies need to be included in our sample because some banks which belong to a holding company are not publicly traded. And this also excludes investment banks which are not guaranteed by governments as much as commercial banks. Finally, we exclude the bank stocks with prices below $5 at the portfolio formation date.

We build decile portfolios of all commercial bank stocks by ranking market capitalization on each end of month. Gandhi and Lustig (2015) document that the book value of the bank stocks is the better measure of size.[9] They also show the market capitalization is good measure of size to appear size anomaly in bank stock returns. We adapt market capitalization as a proxy for size to minimize data reduction. Because less than 100 banks are publicly listed in the United States before 1970, our bank stocks data start in January 1970 end in December 2015. The average number of banks which are possibly traded in our sample is 462 each year.[10] We calculate value-weighted returns for each decile portfolio for each subsequent month.

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9 They say size anomaly in bank stocks caused by government guarantees. Because government more cares about the information of balance sheet of banks, book value is good proxy for size anomaly in bank stock returns.

10 Computing tail risk beta requires at least 36 months, we calculate this number from January 1973 to December 2015.

We calculate risk-adjusted portfolio returns by using well-known six risk factors. We use three Fama and French (1993) factors for stocks, which is *MKTRF*, *SMB*, and *HML*, and two Fama and French (1993) factors for bonds, which is *TERM* and *DEF*. We additionally use Carhart (1997) momentum factor, *UMD*. *MKTRF*, *SMB*, *HML*, and *UMD* are obtained from Ken French's website and *TERM* and *DEF* are taken from Goyal's website.[11] We use bond risk factors because Flannery and James (1984) show that commercial bank stock returns are related to interest rate change. Banks can be treated managers of fixed income portfolios and expose to maturities and credit risk of bonds. *TERM* is difference between returns on long-term government bonds and the risk-free rate and *DEF* is the difference between returns on corporate bonds and the risk-free rate. In the further session, we use a liquidity factor of Pastor and Stambaugh (2003), *LIQ*, which is obtained from WRDS. Finally, the risk-free rate is the one-month Treasury bill rate which is uploaded on WRDS.

2.2. Computing Tail Risk Measure

We construct tail risk measure following the approach of Kelly and Jiang (2014) and use daily CRSP data from January 1970 to December 2010 for NYSE/AMEX/NASDAQ stocks with share code 10 and 11. Tail risk measure is computed month-by-month not need for accumulated years of sample periods. It relies on commonality in the tail risks of daily individual stock returns each month. We calculate monthly tail risk measures, λ_t or *TAIL*, to apply the pooled cross-sectional daily stock returns.

$$\lambda_t = \frac{1}{K_t}\sum_{k=1}^{K_t} ln\frac{R_{k,t}}{u_t} \tag{1}$$

Where $R_{k,t}$ is the kth daily stock return that falls below an extreme value, tail threshold, u_t during month t. K_t is the total number of such exceeding returns within month t. We define threshold parameter u_t as the fifth percentile of the cross-sectional daily returns of each month. u_t is defined where the center of the return distribution ends and the tail begins.

We also compute tail risk sensitivities of bank stocks return. Kelly and Jiang (2014) show that stocks with high predictive loadings on tail risk have higher expected returns because investors are averse to tail risk. But they do not show whether expected returns on the financial firms also influenced by tail risk loading. We have to

[11] On http://www.hec.unil.ch/agoyal/, Goyal provides long-term government and corporate bond returns. He obtained long-term government and corporate bond returns from Ibbotson.

check the relation between tail beta and expected returns in commercial bank stocks. Tail beta or tail risk sensitivity, β_i, is estimated by following regression equation.

$$E_t[r_{i,t+1}] = \mu_i + \beta_i \lambda_t \tag{2}$$

We calculate the monthly tail beta for each bank stock in above regressions that use the most recent 120 months of data.[12]

3. Size and Tail Beta-Sorted Bank Stock Returns

In this section, similar with Gandhi and Lustig (2015)'s findings, we show that the size anomaly in our sample of bank stocks. Then we also examine the expected return differences among the tail beta-sorted bank stock portfolios. Then we find whether tail risk factor captures the returns difference between large and small bank stocks.

We report the monthly returns on value-weighted size and tail beta sorted decile portfolios of bank stocks. We also regress excess returns on the three Fama and French (1993) stock factors, two bond factors, and Carhart (1997) momentum factor to calculate risk-adjusted returns. For each portfolio *i*, we run the following time-series regression.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i' \boldsymbol{f}_t + \varepsilon_{i,t} \tag{3}$$

where $R_{i,t}$ is the monthly return on the i^{th} size-sorted portfolio. β_i is the (6×1) vector of risk factor loadings and f_t is the risk factors which is $[MKT\ SMB\ HML\ UMD\ \ TERM\ DEF]$.

3.1. Returns on Size and Tail Beta-Sorted Bank Stock Portfolios

In Table 1, we present monthly value-weighted returns of bank stock portfolios which are sorted by market capitalization and tail beta. Because we need at least 36 months of stock returns to compute tail beta, the results for the tail beta-sorted portfolios are presented for the sample period January 1973 to December 2015.

In Panel A, the difference between large-cap (decile 10) and small-cap (decile 1) portfolio return is −0.44% and the six-factor alpha is −0.74%, with t-statistics of −1.85 and −3.21, respectively, using Newey and West

[12] Tail beta is only obtained when the bank stock returns with at least 36 months out of 120 months.

(1987) standard errors with three lags. Even though size factor (*SMB*) is included, the six-factor alpha difference between decile 10 and 1 is even higher than return difference and significantly different from zero. That is, size anomaly in bank stock returns is cannot explained by Fama and French (1993) size factor (*SMB*). Portfolio returns monotonically increase through decile 1 to 8 but steeply decrease in decile 9 and 10. This pattern agrees with the explanation of Gandhi and Lustig (2015) that is the government mostly guarantees for large commercial banks. We also construct size-sorted portfolios rebalanced annually. Following Gandhi and Lustig (2015) and Goyal (2014), we annually sort portfolio by end of December and June market capitalization, NYSE size break point, and also sort portfolios by book value. In unreported results, we find six-factor alpha difference between decile 10 and 1 is negative and statistically significant in all of above four cases. For increasing the available number of bank data, we only report monthly rebalanced market capitalization-sorted portfolios.

In Panel B, banks in the highest tail beta decile earn 0.78% monthly returns and 0.54% monthly six-factor alpha higher than banks in the lowest decile, with a t-statistics of 3.22 and 2.03, respectively. In unreported results, there is no clear pattern of average market capitalizations among tail beta-sorted portfolios. In other words, the highest or the lowest tail beta portfolio does not mean it contains most of the largest or smallest banks. The tail risk can influence the expected returns on bank stocks but is not perfectly correlated with market capitalization of banks.

3.2. Risk-Adjusted Returns on Size and Tail Beta-Sorted Bank Stock Portfolios

In Table 2 Panel A and Panel B, we provide the results of OLS regression for size and tail beta-sorted deciles specified in Equation (3). We show the coefficients of the regression and *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The first row in each panel is the risk-adjusted returns that is already shown in the Table 1.

In Table 2 Panel A, we find the statistically significant negative alpha difference between decile 10 and 1. The factor loadings on *MKTRF* increase monotonically from 0.407 in decile 1 to 0.953 in decile 9 and steeply increase for 1.263 in decile 10. The pattern of the factor loadings on *MKTRF* is same with the results of Gandhi and Lustig (2015). Larger bank stocks are more levered, so beta of *MKTRF* in decile 10 is the highest among deciles.

We report the coefficients on *SMB*, *HML*, and *UMD* in the second, third, and fourth row. The loadings on *SMB* slightly increase from 0.285 in decile 1 to 0.505 in decile 8, but sharply decrease to 0.359 in decile 9 and

−0.133 in decile 10. When examining the financial firm excluded stocks sample, larger market capitalization portfolios have higher factor loadings on *SMB*.[13] In our results, pattern of the coefficients on *SMB* is contrary to what one expects and the loadings on *SMB* cannot capture the size anomaly in bank stock returns. That is, the return variation of commercial banks along the size-sorted portfolio is very different from the excluding financial firm stocks. The loadings on *HML* is similar with the pattern of *SMB*. They increase from 0.361 in decile 1 to 0.712 in decile 8 and decrease to 0.681 in decile 9 and 0.554 in decile 10. The coefficients on *UMD* is almost zero from decile 1 to decile 9, but −0.217 in decile 10.

The loadings on *TERM* and *DEF* exhibit similar patterns with the results of Gandhi and Lustig (2015). The coefficients on *TERM* increase from −0.029 in decile 1 to 0.342 in decile 9 and slightly decrease to 0.089 in decile 10. The factor loadings on *DEF* decrease from 0.19 in decile 1 to −0.186 in decile 9 and slightly increase to 0.002 in decile 10. The coefficients on two bond factors loadings can be interpreted by the explanations of Flannery and James (1984). They say loading on these two bond factors is a measure of interest rate sensitivity resulting from the maturity mismatch between assets and liabilities. Finally, we find that the adjusted R^2 monotonically increase from 0.372 in decile 1 to 0.743 in decile 10.

In Table 2 Panel B, we report the risk factor loadings on the tail beta-sorted portfolios. There are no striking patterns of the loadings on six risk factors. That is, six risk factors cannot capture the return difference among the tail beta-sorted portfolios. The adjusted R^2 also exhibits no special pattern. From above results, we only interpret the table that the bank stock expected returns are related to tail risk exposure. Tail risk beta has the important impact on the subsequent month of bank stock returns, but six risk factors cannot capture the return difference between high and low tail beta portfolios. In other words, tail risk has another implication on bank stock expected returns which is not covered by six risk factors.

4. Tail Risk and Size Anomaly in Bank Stock Returns

We create tail risk factor and show whether the size anomaly in bank stock returns is still valid when tail risk factor is added to risk factors. While tail risk factor has a similar role with a size factor of Gandhi and Lustig (2015), tail risk factor is created by having theoretical background and economical meaningful. The size factor of Gandhi and Lustig (2015) is only econometrically created measure that is second principal component

[13] See Fama and French (1993) Table 5, 6, and 7a.

of the returns on size-sorted portfolios. Our tail risk measure is computed by the tail distribution of the cross-sectional stock returns. In this section, we first explain the methodology to create tail risk factor, and we show this factor captures the size anomaly in bank stock returns.

4.1. Tail Risk-Adjusted Returns on Size-Sorted Portfolios.

We compute tail risk factor, *TFAC*, using NYSE/AMEX/NASDAQ listed common stocks from CRSP.[14] First, we compute monthly tail beta, β_i^{all}, for each common stock following regression Equation (2) using the most recent 120 months of data. We then rank the 121st month of stocks based on the levels of β_i^{all} and form two value-weighted portfolios: 30 percent with the most highest β_i^{all}, which we call P1; and 30 percent with the most lowest β_i^{all}, which we call P2. The 121st month return differences between P1 and P2 are then proxy for tail factor, *TFAC*. This methodology is similar with constructing the risk factor of *SMB* or *HML* in the Fama-French model.

The correlation coefficient between *TFAC* and tail risk is high, 0.46, so the return spread between P1 and P2, *TFAC*, is widened when the tail risk is high. *TFAC* is proper measure to represent tail risk. Thus, *TFAC* can capture the tail risk premium of the returns on bank stock portfolios. Because the government guarantees for the commercial banks with respect to their size, the tail risk sensitivities of size-sorted bank stock portfolios are different. We expect that the tail risk beta of the small size portfolio (decile 1) is higher than large size portfolio (decile 10).

In Table 3, we present the results of the regression for decile size-sorted portfolios specified in Equation (3). The different thing is that we insert *TFAC* into risk factors. In Panel A, β_i is the (7×1) vector of risk factor loadings and f_t is the risk factors which is $[MKT\ SMB\ HML\ UMD\ \ TERM\ DEF\ \ TFAC]$. In Panel B, β_i is the (1×1) vector of risk factor loadings and f_t is the risk factors which is $[TFAC]$. Each panel, we show the regression coefficients of the regression and denote *, **, *** as statistical significance at the 10%, 5%, and 1% levels, respectively.

In Panel A, while the alpha difference between decile 10 and 1 is negative, it is statistically insignificant. We can interpret that the tail risk factor has explaining power of size anomaly in bank stock returns. The factor

[14] The investors easily recognize that the changes of tail risk for all stock returns rather than just bank stock returns. That's why we construct *TFAC* using all stock returns.

loadings on *TFAC* are decrease monotonically from 0.179 in decile 1 to −0.018 in decile 10. It is interesting that the coefficients are significantly different from zero in decile 1 to 5, but they lose significance level in decile 6 to 10. Event thought the coefficients are negative in decile 7 to 10.[15] Because government mostly guarantee the large bank stocks, investors notify that the small bank is more risky and more sensitive to the market tail risk. Therefore, the absolute value of coefficients on tail factor is large for small banks and small for large banks. While the risk-adjusted monthly return on decile 1 is still positive, 0.002, and decile 10 is negative, −0.001, *TFAC* proportionally captures the returns difference between large and small banks.

In Panel B, excluding six risk factors, the tail risk factor reduces the risk-adjusted return difference between decile 1 and 10. The risk-adjusted returns are almost flat and the alpha difference between decile 10 and 1 is only 0.001 and it is statistically insignificant. The regression coefficients are decrease monotonically from 0.212 in decile 1 to 0.005 in decile 10 and they lose their significance level in decile 9 and 10. The returns on decile 9 and 10 is not influenced by tail risk factor. We denote that tail risk factor can replace the size factor which is proposed by Gandhi and Lustig (2015). Our tail risk factor is intuitive measure because it theoretically represents the market tail risk.

4.2. **Liquidity-Adjusted Returns on Size-Sorted Portfolios**

In this section, we show the risk-adjusted returns using Pastor and Stambaugh (2003) liquidity factor, LIQ. Rösch and Kaserer (2014) find that market liquidity is impaired when stock markets decline. Because the liquidity factor can capture the time-series variation of the stock market tail risk, we check the impact of liquidity factor to size-sorted bank stock returns. We expect that small bank portfolio is more influenced by liquidity factor than large bank portfolio.

In Table 4, we present the results of the regression for decile size-sorted portfolios specified in Equation (3). The different thing is that we insert liquidity factor into risk factors. In Panel A, β_i is the (7×1) vector of risk factor loadings and f_t is the risk factors which is $[MKT\ SMB\ HML\ UMD\ \ TERM\ DEF\ \ LIQ]$. In Panel B, β_i is the (1×1) vector of risk factor loadings and f_t is the risk factors which is $[LIQ]$. Each panel, we show the

[15] This result is similar with Gandhi and Lustig (2015)'s finding that they use the size factor instead of the tail risk factor in the regression.

regression coefficients of the regression and *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In Table 4 Panel A, the monthly risk-adjusted returns are decrease from 0.005 in decile 1 to −0.001 in decile 10 and their difference is still significantly negative, −0.007. The factor loadings on LIQ are decrease from 0.024 in decile 1 to −0.126 in decile 10 and its difference is −0.150 which is smaller than difference of coefficients on *TFAC*, −0.197. In Panel B, we find liquidity factor is proportionately capture the return difference among size-sorted bank stock portfolios. The risk-adjusted return difference between decile 10 and 1 is still negative, −0.004, but it is not significantly different from zero. Because the factor loadings on LIQ is decrease from 0.006 in decile 1 to −0.188 in decile 10, it can absorb the size anomaly in bank stock returns. While the risk-adjusted returns in Panel A still statistically insignificant, it is not sufficient evidence that LIQ is proxy for the size factor.

In Table 5, we present the monthly raw returns and five kinds of risk-adjusted returns of size-sorted bank stock portfolios. The risk factor, f_t, is denoted in the first row of the table. The first and second column present the monthly raw returns and six factor risk-adjusted returns of the size-sorted bank stock portfolios which are already shown in Table 1 Panel A. The third and fourth column show the risk-adjusted returns that each f_t includes $[MKT\ SMB\ HML\ UMD\ \ TERM\ DEF\ \ TFAC]$ and $[TFAC]$, respectively. Comparing the third column with the second, return spreads between decile 10 and 1 are both diminished and they lose their statistical significance level and there is same pattern between the fourth column and first column. *TFAC* has an important role of explaining size anomaly in bank stock returns. The fifth and sixth column present the risk-adjusted returns that the each column adopt the f_t as $[MKT\ SMB\ HML\ UMD\ \ TERM\ DEF\ \ LIQ]$ and $[LIQ]$, respectively. Comparing the fifth and sixth column with the second and first column, respectively, return spreads between decile 10 and 1 also decrease. While alpha difference between decile 10 and 1 in the sixth column is statistically insignificant, the return difference between decile 10 and 1 in the fifth column is still statistically significant. It means that LIQ cannot capture the returns difference between decile 10 and 1 when the six risk factor is inserted together. The size anomaly in bank stock returns is partially explained by LIQ and more powerfully explained by *TFAC*.

Following the result of Gandhi and Lustig (2015), the difference of the tail risk beta is main driving force of the size anomaly in bank stock returns. While they just find the size factor from the PCA, we suggest the *TFAC* which is theoretically and intuitively created by tail risk able to proxy for the size factor of the bank stock returns.

5. What is the Tail Risk?

In the last section, we empirically find that the tail risk factor reduces return spread between large and small bank stock portfolios. To support our findings, we examine the characteristics of the tail risk measure, *TAIL*, and how it influences the size-sorted bank stock portfolio returns. We show the time-series variations of the tail risk and the return differences among tail beta-sorted portfolios. Then we exhibit the interesting relations between the market capitalization of banks and tail beta sensitivities.

5.1. Time-Varying Tail Risk

We define tail risk, *TAIL*, as pooling all daily returns that fall below extreme value threshold within each month and we specify the tail risk factor, *TFAC*, as the return difference between the high and low tail beta-sorted portfolios of the bank stocks. In Figure 1, we plot the 3-month moving average of *TFAC* along with a plot of the monthly *TAIL*. Figure 1 begins end of 1975. Because the correlation coefficient between *TAIL* and *TFAC* is 0.46, they appear to be similar time-series moving. Consistent with the results of Kelly and Jiang (2014), *TAIL* and *TFAC* exhibit countercyclical.[16]

We especially look at the trend of *TAIL* and *TFAC* during economic recession periods. The gray shaded regions represent NBER recessions. *TAIL* and *TFAC* tend to rise before the end of the NBER recessions. *TAIL* and *TFAC* are above their mean because the time periods in figure start just after the first oil crisis. Then *TAIL* and *TFAC* rise quickly in the early 1980s, the double-dip recession. They fluctuate above their mean for several years. *TAIL* and *TFAC* decline in the bull market years leading to 1987, but rising sharply in the months following Black Monday. In the 1990s, during IT bubble periods, *TAIL* and *TFAC* retreat critically, however rise until the early 2003. The abnormally large collapse of *TFAC* in the 1999 is caused by the failure of LTCM. *TFAC* is the long-short return of the bank, and the returns of high tail sensitive banks fall dramatically in that periods. Then *TAIL* and *TFAC* hover around their mean, and are roughly flat until 2007-2009, latest financial crisis.

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[16] Detailed explanation of time-series movement of *TAIL* is described in Kelly and Jiang (2014). *TAIL* recedes in the bull market years and rises in the months following the market crash.

One weak point of proxy for bank-specific tail risk as *TAIL* or *TFAC* is that they cannot capture the recent financial crisis. *TAIL* and *TFAC* just fluctuate after 2009 until 2015. The reason is described in Kelly and Jiang (2014), because of high tail threshold, u_t, in this periods.[17] Although *TAIL* and *TFAC* appear not able to capture the recent financial crisis, our results suggest that, in the whole periods of our sample, effect of *TAIL* and *TFAC* is significantly explain the size anomaly in bank stock returns. The impact of *TAIL* and *TFAC* on size anomaly in bank stock returns is also available when we exclude latest financial crisis sample.

On the one hand, historically there is a strong correlation between the business cycle and the incidence of banking crisis. Following Gandhi and Lustig (2015), most of NBER business cycle peaks and troughs coincide with U.S. banking panics. Since *TAIL* and *TFAC* exhibit increasing patterns in the most of NBER recessions, they are possibly related to banking crisis periods so they appear to be a reliable measure of bank-specific tail risk. On the one hand, as already analyzed by Giesecke et al. (2011), there is weak relation between the business cycle and all U.S. corporate bond defaults for 150 years. The size anomaly which is only linked to tail risk for the case of bank stocks.

5.2. The Size-Varying Tail Risk Sensitivities

Historically, (큰 금융회사 망하면 안되는 이유랑 참고문헌 쓸까) the government and monetary authorities are reluctant to let large financial firms fail collectively As mentioned in Gandhi and Lustig (2015), during the recent financial crisis, the Federal Reserve spent 83% of the emergency loans to 10 of the largest U.S. financial institutions which amounts $9.99 trillion. Investors anticipate that the government preferentially rescue large financial firms when financial crisis is expected to occur. So, even though regulators are willing to let large banks fail, most of the investors regard the large financial firms as stable and are not much influenced by financial crisis.

To confirm the above view, we examine the relation between the market capitalization and tail risk sensitivity of the banks. Within each decile of the size-sorted bank stock portfolios, we estimate a following regression,

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[17] During the crisis period, the threshold rises drastically and persistently along with market volatility. Therefore, TAIL remains calm in the crisis periods because tail threshold becomes denominator to calculate tail risk.

$$\beta_{TAIL,i,t} = a_1 + b_1 \frac{SIZE_{i,t}}{GDP_t} + \varepsilon_t \tag{4}$$

where $\beta_{TAIL,i,t}$ is the monthly tail beta which is obtained from the result of the regression, $E_t[r_{i,t+1}] = \mu_i + \beta_{TAIL,i,t}\lambda_t$, that uses the most recent 120 months of data. $SIZE_{i,t}$ is the market capitalization of individual banks and GDP_t is U.S. domestic GDP which is quarterly announced. We divide the $SIZE_{i,t}$ by GDP_t in order to adjust for the time-series growth of the market capitalization.

In Table 6, we present the slope coefficients in the regression of tail beta loadings on market capitalization divided by GDP, b_1, and its t-statistics value for each decile of the size-sorted bank stock portfolios. We find statistically significant negative value of b_1 in decile 9 and 10, and positive value in the other deciles. The negative value of b_1 means that if market capitalization relative to GDP of each bank increases, tail beta of bank would decrease. Thus, in decile 9 and 10, larger banks have smaller tail risk. In decile 1 to 8, however, we find positive and statistically significant b_1 which means larger banks seem to be larger tail risk. Because leverage of the banks tends to increase as size of the banks increasing, it is natural that larger banks have higher tail risk. But the interesting point is that only large size deciles of the bank stocks portfolio have negative coefficients. So in decile 9 and 10, the negative value of b_1 is largely affected by investors' expectations that the government preferentially guarantees for the large financial firms. The top two deciles of the size-sorted bank stock portfolios are more benefited from the government than other deciles.

5.3. Size Anomaly in Tail Beta-Sorted Portfolio Returns

In the previous sections, we show that the tail risk can represent the bank-specific tail risk. In this section, we examine whether size anomaly in bank stock returns is valid in each tail beta-sorted portfolio. Because the government guarantees for only small portion of commercial banks, we expect that there are rare banks in high tail beta portfolios which are protected by government. Therefore, if investors actually perceive tail beta as a measure of implicit government guarantee, significance level of return difference between large and small banks is possibly varied with high and low tail beta portfolios.

In Table 7, we present monthly value-weighted returns and risk-adjusted returns for two-way sorted portfolios. Each month we first independently divide bank stocks into quantile tail beta-sorted portfolios, and then sort quantile portfolios based on market capitalization. In Panel A, monthly return differences between large-cap and small-cap portfolios are −0.53% and −0.52% for quantile 1 (low tail beta) and quantile 2 of tail beta-sorted portfolios with t-statistics of −2.06 and −1.90, respectively. In quantile 5 (high tail beta) and quantile 4, however, return differences are statistically insignificant. Monthly return difference between large-cap and small-cap portfolio for these tail beta portfolios are only −0.111% and −0.004%, respectively.

The risk-adjusted return differences of large and small size portfolios for each tail beta-sorted portfolios have similar pattern with raw return differences. We calculate the risk-adjusted returns estimating the OLS regression of Equation (3). In Panel B, monthly alpha differences between large-cap and small-cap portfolios are −0.897% and −1.114% for quantile 1 (low tail beta) and quantile 2 of tail beta-sorted portfolios with t-statistics of −3.99 and −4.73, respectively. While in quantile 5 (high tail beta) and quantile 4, risk-adjusted return differences of large and small size portfolio are −0.150% and −0.377%, respectively, with statistically insignificant t-statistics.

The banks with more sensitive to the tail risk are gathered in the portfolios of the high tail beta. In other words, investors perceive high tail beta banks as risky banks because they seem not protected by the government. Because the government only guarantees for a small number of banks, most of banks in the high tail beta portfolios might be not guaranteed by the government. As a results, there is no size anomaly in the high tail beta portfolios.

On the other hand, low tail beta portfolios meet different situation. Some banks implicitly protected by government are included in these portfolios, so the size anomaly in bank stock returns appear in these portfolios. Thus, the low tail beta portfolios actually contain the banks which are largely protected by the government. We conclude that the tail beta is suitable measure as a proxy for the implicit government guarantee and tail risk measure can capture the bank tail-specific risk.

6. Conclusion

We reexamine the size anomaly in bank stock returns and find a new size factor which can absorb this size effect. Following Gandhi and Lustig (2015), we define U.S. commercial banks using SIC code and compute monthly tail risk measure which is described in Kelly and Jiang (2014). We first suggest the size factor, *TFAC*, which is made by applying the tail risk measure not just computed from principal component analysis. Our tail risk measure and tail risk factor have economical meaning of capturing bank-specific tail risk. We further analyze the characteristics of the tail risk measure and its relation with bank stock returns.

We find a negative (positive) relation between size (tail beta) of the bank and its subsequent month of stock returns. When we form decile portfolios based on size (tail beta) of the bank stocks, the subsequent month of the return and alpha spreads between the large and small (high and low) deciles are −0.441% and −0.737% (0.777% and 0.539%) and both are statistically significant. Identical with nonfinancial firms, our analysis confirms that bank stock returns are also influenced by their market capitalization and loadings on tail risk.

We additionally examine the size-sorted bank stock portfolio returns adjusting for two types of risk factors, *TFAC* and *LIQ*. Inserting *TFAC* with the six risk factors, *MKTRF*, *SMB*, *HML*, *UMD*, *TERM*, and *DEF*, subsequent month of the risk-adjusted return difference between large and small bank stock decreases to −0.3% and loses significance level. When we adopt risk factor as a *TFAC* only, the monthly return difference also loses their significance level. While, the liquidity factor, *LIQ*, has partial influential power of capturing the bank-specific tail risk. The risk-adjusted returns lose their significance level when using LIQ as a risk factor alone, however, the risk-adjusted returns still have its significance level when applying risk factors as both of *LIQ* and six risk factors. We conclude that the tail risk factor has powerful ability to explain the size anomaly in bank stock returns and it can substitute for size factor described in Gandhi and Lustig (2015).

We additionally analyze the characteristics of tail risk measure to know how to absorb the size anomaly in bank stock returns. First, the time-series variation of the tail risk is enough to capture the most of the financial disaster periods. We also find that the relation between the market capitalization and tail beta of the bank stocks are different from which size-sorted deciles they belong to. Only decile 9 and 10 exhibit negative relation that means the government only guarantees for large banks. We also find that the size anomaly in bank stock returns is only valid in the low tail beta-sorted portfolios. Thus, investors recognize that the low tail beta banks are possibly subsidized by government.

Our size factor in bank stock returns has more advantages than another size factor which is proposed by Gandhi and Lustig (2015). Because our measure is computed by the individual whole stock’s extreme negative returns of certain month, it is intuitive to interpret. From our analysis, we conclude that investors recognize the too-big-to-fail hypothesis in the stock market, and the tail risk measure explains the returns difference between large and small bank stock portfolios. Our paper has the meaning of developing an economic intuitive measure of capturing the bank-specific tail risk.

Figure 1

Tail risk measure and tail risk factor

The solid line plots the tail risk, λ_t and the dashed line plots the 3-month moving average of the tail risk factor, TFAC. Tail risk estimates are calculated each month by pooling all daily returns that fall below extreme value threshold with each month, and the tail risk factor is the return difference between high high and low tail beta portfolios of the bank stocks. To emphasize comparison, both series are standardized to have mean zero and variance one. The gray shaded regions present NBER recessions.

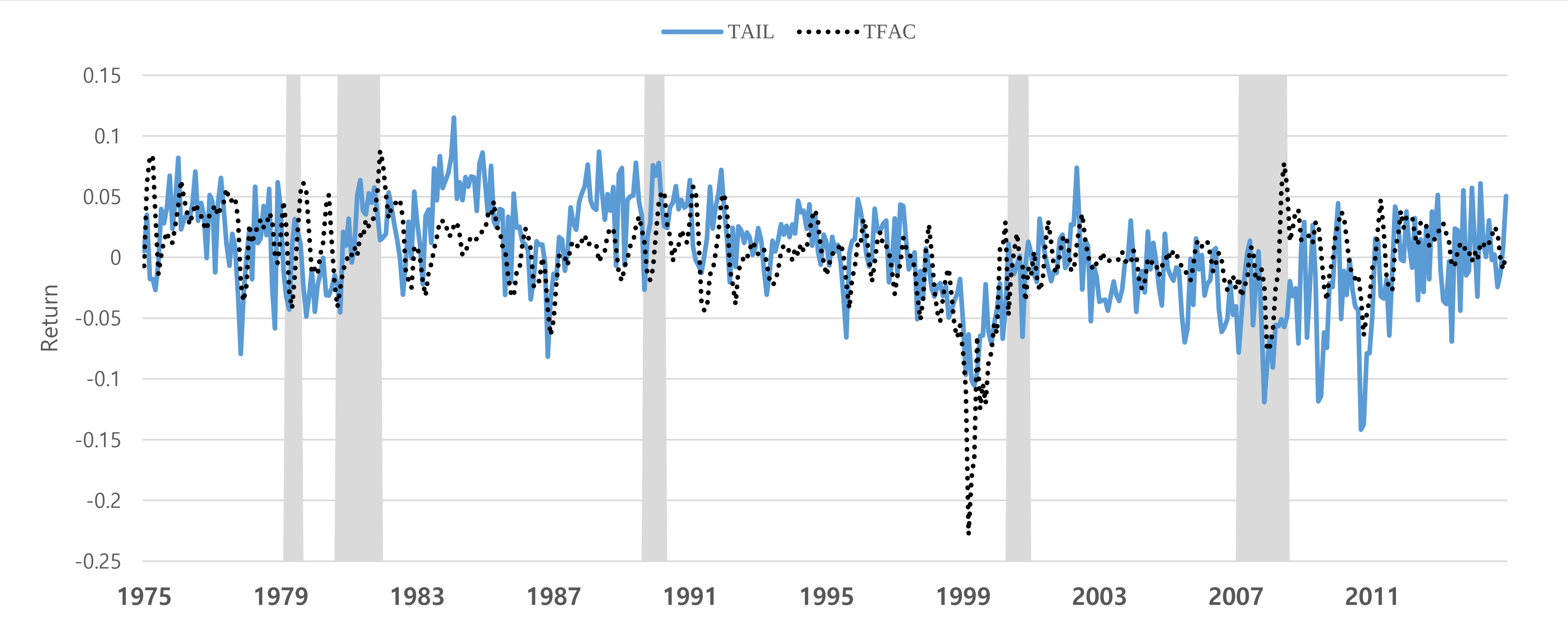

Table 1

Returns and Alphas on Bank Stock Portfolios Sorted by Size and Tail Beta

The table reports monthly value-weighted returns and risk-adjusted returns for the size and tail beta sorted bank stock portfolios. Each month bank stocks are sorted into decile portfolios based on the market capitalization and predictive tail loadings. The market capitalization is measured on end of each month and tail beta is estimated from the monthly data over the previous ten years. Portfolios are based on U.S. commercial banks which are defined as all stocks with CRSP share code 10 and 11 with HSICCD equal to 60 or historical SICCD equal to 6712. Six factor alphas are estimated from OLS regressions of excess returns on each portfolio on the six risk factors which are *MKTRF*, *SMB*, *HML*, *UMD*, *TERM*, and *DEF*. *MKTRF*, *SMB*, and *HML* are the three Fama and French (1993) stock factors, *TERM* and *DEF* are the two bond factors, and *UMD* is Carhart (1997) momentum factor. The last two rows present the differences in monthly returns and alphas between decile 10 and 1 and corresponding t-statistics. T-statistics use Newey and West (1987) standard errors based on three lags. The sample period is from January 1970 to December 2015. Stocks with prices below $5 at the portfolio formation date are excluded.

Panel A : Size-Sorted Portfolios			Panel B : Tail Beta-Sorted Portfolios		
Decile	Average Return	Six Factor Alpha	Decile	Average Return	Six Factor Alpha
1 (Small)	1.342%	0.532%	1 (Low)	0.811%	−0.362%
2	1.307%	0.476%	2	1.026%	−0.168%
3	1.229%	0.338%	3	1.158%	0.083%
4	1.159%	0.201%	4	0.836%	−0.338%
5	1.247%	0.188%	5	1.116%	−0.086%
6	1.114%	−0.020%	6	1.128%	−0.053%
7	1.126%	−0.069%	7	1.291%	0.226%
8	1.127%	−0.111%	8	1.039%	−0.289%
9	0.949%	−0.297%	9	1.276%	−0.032%
10 (Large)	0.902%	−0.205%	10 (High)	1.588%	0.177%
10−1	−0.441%	−0.737%	10−1	0.777%	0.539%
t-stat	−1.85	−3.21	t-stat	3.22	2.03

Table 2
Risk-Adjusted Returns on Size-Sorted Portfolios

The table presents the results from OLS regression of monthly value-weighted excess returns on each portfolio of bank stocks on the six risk factors which are *MKTRF*, *SMB*, *HML*, *UMD*, *TERM*, and *DEF*. We define the U.S. commercial banks as all stocks with CRSP share code 10 and 11 with HSICCD equal to 60 or historical SICCD equal to 6712. *MKTRF*, *SMB*, and *HML* are the three Fama and French (1993) stock factors, *TERM* and *DEF* are the two bond factors, and *UMD* is Carhart (1997) momentum factor. The first row shows the risk-adjusted returns and the second row to seventh row present the factor loadings on each risk factors. The last row indicates the adjusted R^2. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are adjusted for autocorrelation using Newey and West (1987) with three lags. The sample period is from January 1970 to December 2015. Stocks with prices below $5 at the portfolio formation date are excluded.

Panel A : Risk-Adjusted Returns and Factor Loadings of Size-Sorted Portfolios

	1 (Small)	2	3	4	5	6	7	8	9	10 (Large)	10−1
α	0.005***	0.005***	0.003**	0.002	0.002	0	−0.001	−0.001	−0.003*	−0.002	−0.007***
MKTRF	0.407***	0.453***	0.487***	0.577***	0.614***	0.703***	0.795***	0.825***	0.953***	1.263***	0.857***
SMB	0.285***	0.303***	0.323***	0.397***	0.464***	0.523***	0.501***	0.505***	0.359***	−0.133**	−0.418***
HML	0.361***	0.341***	0.424***	0.487***	0.549***	0.679***	0.689***	0.712***	0.681***	0.554***	0.194*
UMD	−0.029	−0.015	−0.022	−0.052	0	−0.012	−0.019	0.002	−0.024	−0.217***	−0.187***
TERM	−0.088	−0.012	0.076	0.106	−0.009	0.082	0.209	0.164	0.342	0.089	0.178
DEF	0.19	0.083	0.033	0.018	0.166	0.008	−0.065	−0.003	−0.186	0.002	−0.188
Adjusted R^2	0.372	0.431	0.483	0.534	0.574	0.63	0.642	0.648	0.653	0.743	0.448

Panel B : Risk-Adjusted Returns and Factor Loadings of Tail Beta-Sorted Portfolios

	1 (Small)	2	3	4	5	6	7	8	9	10 (Large)	10−1
α	−0.004*	−0.002	0	−0.003*	−0.001	−0.001	0.002	−0.003	0	0.002	0.005**
MKTRF	0.996***	1.092***	1.089***	1.131***	1.082***	1.150***	1.092***	1.089***	1.244***	1.185***	0.189**
SMB	0.145	0.017	−0.067	−0.075	0.068	−0.018	0.012	−0.013	0.222**	0.108	−0.037
HML	0.682***	0.629***	0.407***	0.617***	0.697***	0.688***	0.511***	0.697***	0.807***	0.836***	0.154
UMD	−0.103*	−0.06	−0.137*	−0.180***	−0.139*	−0.192***	−0.248***	−0.056	−0.260***	−0.079	0.023
TERM	−0.087	0.416	0.116	0.237*	0.490**	0.198	0.001	−0.222	−0.026	−0.251	−0.165
DEF	0.07	−0.502*	−0.135	−0.135	−0.472*	−0.184	0.027	0.487	0.105	0.429	0.36
Adjusted R^2	0.553	0.552	0.565	0.614	0.586	0.6	0.593	0.483	0.588	0.542	0.028

Table 3

Tail Risk-Adjusted Returns on Size-Sorted Portfolios

The table presents the results from OLS regression of monthly value-weighted excess returns on each portfolio of bank stocks on the seven risk factors, which are *MKTRF*, *SMB*, *HML*, *UMD*, *TERM*, *DEF*, and *TFAC* in Panel A, and one risk factor, which is *TFAC* in Panel B. *TFAC* is the return difference between P1 and P2: P1 is the value-weighted portfolio returns with 30 percent of the highest tail beta and P2 is the value-weighted portfolio returns with 30 percent of the lowest tail beta each month. *MKTRF*, *SMB*, and *HML* are the three Fama and French (1993) stock factors, *TERM* and *DEF* are the two bond factors, and *UMD* is Carhart (1997) momentum factor. In Panel A, the first row shows the risk-adjusted returns and the second row to eighth row present the factor loadings on each risk factors. In Panel B, first row shows the risk-adjusted returns, the second row presents the factor loadings on *TFAC*. The last row indicates the adjusted R^2. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are adjusted for autocorrelation using Newey and West (1987) with three lags. The sample period is from January 1970 to December 2015. Stocks with prices below $5 at the portfolio formation date are excluded.

Panel A : Tail Risk Factor With Six Risk Factors Adjusted Returns

	1 (Small)	2	3	4	5	6	7	8	9	10 (Large)	10−1
α	0.002	0.002	0.001	0.001	0.001	0	0.001	0	−0.001	−0.001	−0.003
MKTRF	0.379***	0.445***	0.472***	0.555***	0.610***	0.689***	0.789***	0.813***	0.916***	1.247***	0.868***
SMB	0.188***	0.257***	0.290***	0.336***	0.439***	0.521***	0.525***	0.534***	0.375***	−0.123**	−0.311***
HML	0.299***	0.323***	0.413***	0.449***	0.544***	0.690***	0.704***	0.731***	0.703***	0.572***	0.272***
UMD	−0.027	−0.02	−0.035	−0.052	−0.005	−0.018	−0.033	−0.006	−0.019	−0.216***	−0.189***
TERM	−0.098	0.021	0.106	0.166	−0.003	0.112	0.246	0.251	0.410**	0.156	0.254
DEF	0.222	0.065	0.008	−0.046	0.166	−0.03	−0.128	−0.137	−0.298	−0.097	−0.319
TFAC	0.179***	0.139***	0.144***	0.117***	0.085*	0.052	−0.003	−0.005	−0.036	−0.018	−0.197***
Adjusted R^2	0.369	0.424	0.485	0.514	0.551	0.606	0.625	0.622	0.624	0.725	0.463

Panel B : Tail Risk Factor Adjusted Returns

	1 (Small)	2	3	4	5	6	7	8	9	10 (Large)	10−1
α	0.005**	0.005**	0.005**	0.005*	0.006**	0.005*	0.007***	0.006**	0.006**	0.006	0.001
TFAC	0.212***	0.183***	0.191***	0.170***	0.157***	0.141***	0.085*	0.088*	0.037	0.005	−0.207***
Adjusted R^2	0.068	0.049	0.052	0.034	0.023	0.016	0.004	0.004	−0.001	−0.002	0.025

Table 4

Liquidity Risk-Adjusted Returns on Size-Sorted Portfolios

The table presents the results from OLS regression of monthly value-weighted excess returns on each portfolio of bank stocks on the seven risk factors, which are *MKTRF*, *SMB*, *HML*, *UMD*, *TERM*, *DEF*, and *LIQ* in Panel A, and one risk factor, which is *LIQ* in Panel B. *MKTRF*, *SMB*, and *HML* are the three Fama and French (1993) stock factors, *TERM* and *DEF* are the two bond factors, *UMD* is Carhart (1997) momentum factor, and *LIQ* is Pastor and Stambaugh (2003) liquidity factor. In Panel A, the first row shows the risk-adjusted returns and the second row to eighth row present the factor loadings on each risk factors. In Panel B, first row shows the risk-adjusted returns, the second row presents the factor loadings on *TFAC*. The last row indicates the adjusted R^2. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are adjusted for autocorrelation using Newey and West (1987) with three lags. The sample period is from January 1970 to December 2015. Stocks with prices below $5 at the portfolio formation date are excluded.

Panel A : Liquidity Risk Factor With Six Risk Factors Adjusted Returns

	1 (Small)	2	3	4	5	6	7	8	9	10 (Large)	10−1
α	0.005***	0.005***	0.004**	0.002	0.002	0	0	−0.001	−0.002	−0.001	−0.007***
MKTRF	0.408***	0.452***	0.486***	0.577***	0.610***	0.699***	0.790***	0.820***	0.948***	1.258***	0.850***
SMB	0.285***	0.303***	0.323***	0.397***	0.463***	0.522***	0.500***	0.504***	0.358***	−0.134**	−0.419***
HML	0.360***	0.341***	0.424***	0.487***	0.551***	0.681***	0.692***	0.714***	0.683***	0.557***	0.197**
UMD	−0.029	−0.015	−0.022	−0.052	0	−0.012	−0.019	0.001	−0.024	−0.217***	−0.188***
TERM	−0.082	−0.014	0.07	0.11	−0.029	0.056	0.179	0.137	0.313	0.056	0.138
DEF	0.186	0.084	0.037	0.015	0.179	0.026	−0.045	0.015	−0.167	0.025	−0.161
LIQ	0.024	−0.008	−0.024	0.016	−0.075*	−0.099**	−0.113**	−0.100*	−0.107*	−0.126**	−0.150**
Adjusted R^2	0.371	0.43	0.482	0.533	0.577	0.635	0.647	0.652	0.657	0.747	0.465

Panel B : Liquidity Risk Factor Adjusted Returns

	1 (Small)	2	3	4	5	6	7	8	9	10 (Large)	10−1
A	0.009***	0.009***	0.008***	0.008***	0.009***	0.008***	0.008***	0.008***	0.006**	0.006*	−0.004
TAIL	0.006	−0.031	−0.052	−0.017	−0.107	−0.131	−0.158	−0.147	−0.167	−0.188	−0.194
Adjusted R^2	−0.002	−0.001	0.001	−0.002	0.005	0.008	0.01	0.008	0.01	0.008	0.013

Table 5

Various Factor Adjusted Returns on Size-Sorted Portfolios

The table reports monthly value-weighted returns and various factor adjusted returns for the size sorted bank stock portfolios. Each month bank stocks are sorted into decile portfolios based on the market capitalization which is measured on end of each month. Portfolios are based on U.S. commercial banks which are defined as all stocks with CRSP share code 10 and 11 with HSICCD equal to 60 or historical SICCD equal to 6712. Column 1 presents the time-series average of the deciles. Column 2 to 6 report the alphas that is estimated from OLS regressions of excess returns on each portfolio on the various risk factors. Column 2 uses the six risk factors, column 3 uses six risk factors and *TFAC*, column 4 uses only *TFAC*, column 5 uses the six risk factors and *LIQ*, and column 6 uses only *LIQ*. The six risk factors are *MKTRF*, *SMB*, *HML*, *UMD*, *TERM*, and *DEF*. *MKTRF*, *SMB*, and *HML* are the three Fama and French (1993) stock factors, *TERM* and *DEF* are the two bond factors, *UMD* is Carhart (1997) momentum factor, and *LIQ* is Pastor and Stambaugh (2003) liquidity factor. *TFAC* is the return difference between P1 and P2: P1 is the value-weighted portfolio returns with 30 percent of the highest tail beta and P2 is the value-weighted portfolio returns with 30 percent of the lowest tail beta each month. The last two rows present the differences in monthly returns and alphas between decile 10 and 1 and corresponding t-statistics. T-statistics use Newey and West (1987) standard errors based on three lags. The sample period is from January 1970 to December 2015. Stocks with prices below $5 at the portfolio formation date are excluded.

Decile	(1) Average return	(2) Six Factor Alpha	(3) Tail and Six Factor Alpha	(4) Tail Factor Alpha	(5) Liquidity and Six Factor Alpha	(6) Liquidity Factor Alpha
1 (Small)	1.342%	0.532%	0.230%	0.543%	0.520%	0.937%
2	1.307%	0.476%	0.201%	0.542%	0.480%	0.918%
3	1.229%	0.338%	0.131%	0.517%	0.350%	0.849%
4	1.159%	0.201%	0.060%	0.495%	0.192%	0.763%
5	1.247%	0.188%	0.076%	0.600%	0.226%	0.892%
6	1.114%	−0.020%	−0.033%	0.522%	0.029%	0.770%
7	1.126%	−0.069%	0.114%	0.742%	−0.012%	0.794%
8	1.127%	−0.111%	−0.040%	0.620%	−0.061%	0.790%
9	0.949%	−0.297%	−0.084%	0.632%	−0.244%	0.621%
10 (Large)	0.902%	−0.205%	−0.113%	0.617%	−0.142%	0.583%
10−1	−0.441%	−0.737%	−0.343%	0.075%	−0.662%	−0.354%
t-stat	−1.85	−3.21	−1.42	0.27	−2.94	−1.47

Table 6

Regressions of Tail Beta on Size

The table reports the estimates of the regression of tail beta on market capitalization relative to GDP. The model is:

$$\beta_{TAIL,i,t} = a_1 + b_1 \frac{SIZE_{i,t}}{GDP_t} + \varepsilon_t$$

where $\beta_{TAIL,i,t}$ is the monthly tail beta which is obtained from the result of the regression, $E_t[r_{i,t+1}] = \mu_i + \beta_i \lambda_t$ that use the most recent 120 months of data. $SIZE_{i,t}$ is the monthly market capitalization of individual bank and GDP_t is U.S. quarterly GDP obtained from FRED. We divide the $SIZE_{i,t}$ by GDP_t in order to adjust for the time-series growth of the market capitalization. The first column shows the slope coefficients in the regression of tail beta on market capitalization relative to GDP and the second column shows its t-statistics. Standard errors are adjusted for autocorrelation using Newey and West (1987) with three lags.

Decile	$\boldsymbol{b_1}$	**t-stat**
1 (Small)	39.213	12.06
2	21.433	10.70
3	8.391	6.65
4	8.344	8.98
5	6.827	12.05
6	5.623	15.12
7	3.866	14.83
8	0.960	6.83
9	−0.200	−3.70
10 (Large)	−0.003	−5.00

Table 7

Size Anomaly in Tail Beta-Sorted Portfolio Returns

The table reports monthly value-weighted returns and risk-adjusted returns for double-sorted portfolios that are formed on the basis of size and tail beta. Each month bank stocks are independently sorted into quantile portfolios based on tail beta, and quantile portfolios based on market capitalization of banks. The market capitalization is measure on end of each month and tail beta is estimated from the monthly data over the previous ten years. Portfolios are based on U.S. commercial banks which are defined as all stocks with CRSP share code 10 and 11 with HSICCD equal to 60 or historical SICCD equal to 6712. Six factor alphas are estimated from OLS regressions of excess returns on each portfolio on the six risk factors which are *MKTRF*, *SMB*, *HML*, *UMD*, *TERM*, and *DEF*. *MKTRF*, *SMB*, and *HML* are the three Fama and French (1993) stock factors, *TERM* and *DEF* are the two bond factors, and *UMD* is Carhart (1997) momentum factor. The last two rows present the differences in monthly returns and alphas between decile 10 and 1 and corresponding t-statistics. T-statistics use Newey and West (1987) standard errors based on three lags. The sample period is from January 1970 to December 2015. Stocks with prices below $5 at the portfolio formation date are excluded.

Panel A : Average Return

	1 (Small)	2	3	4	5 (Large)	5−1	t-stat
Low	1.057%	1.165%	1.271%	1.040%	0.524%	−0.533%	−2.06
2	1.615%	1.253%	1.323%	1.188%	1.094%	−0.521%	−1.90
3	1.542%	1.513%	1.533%	1.332%	1.067%	−0.475%	−1.65
4	1.276%	1.424%	1.332%	1.268%	1.273%	−0.004%	−0.01
High	1.030%	1.113%	1.177%	0.980%	0.919%	−0.111%	−0.51

Panel B : Six Factor Alpha

	1 (Small)	2	3	4	5 (Large)	5−1	t-stat
Low	0.195%	0.202%	0.096%	−0.214%	−0.702%	−0.897%	−3.99
2	0.796%	0.335%	0.174%	−0.098%	−0.318%	−1.114%	−4.73
3	0.737%	0.500%	0.314%	0.035%	−0.335%	−1.072%	−3.81
4	0.273%	0.339%	0.027%	−0.091%	−0.104%	−0.377%	−1.23
High	−0.275%	−0.203%	−0.080%	−0.329%	−0.425%	−0.150%	−0.78

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