What can volatility smiles tell us about the Too Big to Fail problem?

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November 4, 2019

Abstract

This paper exploits the information content of option markets to offer insight into the too-Big-to-Fail (TBTF) problem for banks. Using option prices, I construct a forward-looking measure of bank exposure to significant price drops (i.e. tail-risk) and use this to examine cross-sectional differences between large banks (with at least $50B in assets) and smaller banks. I document a permanent increase in the average tail-risk of the U.S. banking industry following the Global Financial Crisis, except for banks above the $50B size threshold (systemically important financial institutions (SIFIs)). I provide evidence that the post-crisis difference in tail-risk for banks above and below the $50B threshold owes to the TBTF status of SIFIs that was reinforced by the Dodd-Frank Act.

Keywords: too-big-to-fail, volatility smile, implicit guarantees, bank regulation.

JEL classifications: G01, G20, G21, G28

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1 Introduction

The Too Big To Fail (TBTF) problem has attracted increasing attention from academics and policy makers, especially after the 2008 Global Financial Crisis (GFC). Under the TBTF premise, bank size constitutes a crucial feature determining the extent to which certain financial institutions benefit from implicit (or explicit) government guarantees. In particular, the larger the financial institution the higher its probability of receiving government support in the face of potential failure.

In the aftermath of the GFC, the billions of dollars spent on bank bailouts exacerbated the public perception of the TBTF problem with calls from different sectors of society to make banks accountable for their risk-taking behaviour.[1] In the U.S., the government responded by enacting the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank). At its core, this piece of legislation was designed to end the TBTF problem and to protect taxpayers by ending bailouts. To fulfil these goals, Dodd-Frank explicitly defined $50 billion as the size threshold above which a bank is deemed a large and interconnected financial institution whose failure could threaten the financial stability of the U.S. economy, and established a more stringent set of regulatory requirements for those banks above the $50 billion mark (above 50B banks).

Accordingly, several recent papers have attempted to determine whether the multiple changes to bank regulation since the GFC have resulted in a decline in the TBTF problem. The results have been decidedly mixed. For example, using different approaches, Schäfer et al. (2015) and Bongini et al. (2015) present evidence consistent with a decline in the bailout expectations of large financial institutions upon the announcement of major regulatory reforms, whereas Moenninghoff et al. (2015) concludes the opposite. Moreover, using various market measures of bank risk, Sarin and Summers (2016) show that risk for large banks has actually increased after the crisis. This paper adds to this literature by exploiting the information content of option markets to offer a fresh insight into whether

[1] Under the Troubled Assets Relief Program (TARP), $204.9 billion were committed to direct capital injections in banks between October and December 2009.

the TBTF problem for U.S. banks has declined or not in the post-crisis period. To do so, I use option prices to construct a forward-looking measure of bank tail-risk and explore cross-sectional differences between large banks identified as systemically important (i.e. above 50B banks) and smaller banks.

For a given bank, I define tail-risk as the perceived exposure of the bank's stock to a significant drop in price, and estimate it using bank options with varying strike prices and their corresponding implied volatilities. Unlike in the idealised world of the Black-Scholes-Merton (BSM) model, in practice, implied volatilities vary with strike prices in a phenomenon known as the implied "volatility smile". For stock options, volatility smiles are typically downward sloping with higher implied volatilities for out-of-the-money (OTM) puts relative to in-the-money (ITM) ones. This downward sloping shape has been shown to correspond to negative skewness in the risk-neutral density (RND) of the underlying stock (see Corrado and Su (1996), Dennis and Mayhew (2002), and Bakshi et al. (2003)). Thus, steeper volatility smiles reflect a higher (perceived) exposure to downside risk for the underlying stock. I exploit this fact and use the slope of the implied volatility smile for OTM put options as a forward-looking measure of a stock's perceived exposure to significant drops in value (i.e. tail-risk).[2]

A key characteristic of this tail-risk measure is that, unlike other methods such as Value-at-Risk (VaR), expected shortfall (ES), and Moody's KMV model, it does not rely on past information nor does it assume any particular form for the underlying stock price distribution. On the contrary, this measure exploits higher moments in the risk-neutral distribution of stock prices which investors construct by forming expectations about the future prospects of each bank stock and actively trading on those expectations in the options markets. In this sense, this tail-risk measure does not only reflect actual risk exposures, but it also incorporates any other factors, such as implicit government guarantees, that may alter investors' beliefs about a stock exposure to downside risk.

Using this options-based measure, I document a permanent increase in the average

[2]Previous literature using similar slope measures to estimate perceived exposure to sudden drops include: Collin-Dufresne et al. (2001), Tang and Yan (2010), and Yan (2011), Hett and Schmidt (2017).

tail-risk of the U.S. banking industry following the GFC, *except* for systemically important banks. Specifically, I report a 64.4% increase in the average tail-risk (i.e. slope of the smile) for banks with less than $50 billion in assets (below 50B banks) between the pre-crisis (2001-2007) and post-crisis (2010-2017) periods. In contrast, there is virtually no difference in tail-risk for above 50B banks between the pre and post-crisis periods.

This surge in tail-risk after the GFC is consistent with what Rubinstein (1994) dubbed "crash-o-phobia". That is, an increase in investor's expectations of future crash-like events following a market crash. For above 50B banks, however, post-crisis average tail-risk reverts back to pre-crisis levels after a short-lived spike in the most critical months of the crisis. I argue that the stark post-crisis difference in tail-risk for banks above and below the 50B threshold is consistent with the notion that the TBTF status of above 50B banks was reinforced by the series of bailouts targeted at them during the crisis and their subsequent designation as systemically important by the Dodd-Frank Act. This in turn raised investors expectations of future bailouts for above 50B banks and reduced their perceived exposure to downside risk as captured by the tail-risk measure.

In a series of tests, I consider and rule out, the alternative explanation that the post-crisis difference in tail-risk for banks above and below the 50B threshold is due to the stricter supervisory standards and regulatory requirements applied to above 50B banks under the Dodd-Frank Act.[3]

First, I find no other differences in tail-risk across other salient regulatory size thresholds, even when regulatory demands differ substantially around these thresholds. For example, I find no tail-risk differences for banks with assets between $10 and $50 billion, and banks with less than $10 billion, even though the regulatory burden increases substantially at $10B threshold – so much so that Bouwman et al. (2018) document significant changes in bank operations around the threshold to avoid crossing over. Tail-risk drops significantly only at the 50B threshold when banks are designated systemically important by the government.

[3]In 2018, this threshold was raised to $250 billion by the Economic Growth, Regulatory Relief, and Consumer Protection Act.

Next, I report evidence of positive wealth effects only for above 50B banks around the time Dodd-Frank was passed by the U.S. Congress. These abnormal returns are incompatible with markets reacting to the expected higher costs of regulatory compliance. Instead, positive wealth effects imply that despite the larger regulatory costs imposed on large banks, there is a net-gain from being designated systemically important. The systemically important designation perversely reinforced the TBTF status for the above 50B group of banks by reducing the ambiguity over which banks were deemed TBTF by the government (see Moenninghoff et al. (2015)).

Finally, I examine the actual post-crisis risk-taking behavior of below and above 50B banks and show that above 50B have become relatively riskier even though their regulatory ratios have improved significantly more than small banks. These findings are similar to Duchin and Sosyura (2014) and are consistent with government guarantees inducing moral hazard.

The contribution of this paper is to provide a different insight into the study of implicit government guarantees – and its related TBTF problem – by employing an options-based forward-looking measure of bank tail-risk. In particular, this measure captures the perceived exposure to significant price drops of individual bank stocks. Using options data to study bank tail-risk has important advantages. Compared to other market-based measures like CDS spreads, option markets are much more transparent, liquid, and trade at lower transaction costs, especially in recent years.[4] In addition, this approach permits to account for the potential benefits of implicit guarantee guarantees accruing to equity holders, even when these guarantees may primarily benefit debt holders.

This paper also provides indirect evidence of whether the size-based regulatory framework triggered by Dodd-Frank was successful in ending the TBTF problem. Apparently, it did not. Revealing the identities of systemically important banks reinforced the presence of government guarantees for these banks, and stifled the attempt to eliminate the TBTF

[4]CDS markets around the world have experienced a continuous decline after the GFC. Notional amounts outstanding have gone from roughly $61.2 trillion at the end of 2007 to less than $10 trillion in 2017 (Aldasoro and Ehlers, 2018) .

problem as was intended by Dodd-Frank.

The rest of this paper is organised as follows. Section 2 provides a brief recount of the existing literature on the TBTF problem. In Section 3, I discuss the key aspects of the methodology for estimation of bank tail-risk. I then examine how tail-risk has tended to vary around past crises before documenting the different tail-risk behaviour of above 50B and below 50B banks in the most recent GFC. Section 4 elaborates on the possible explanations for the tail-risk differences reported in Section 3. In Section 5, I report my results. Section 6 concludes.

2 Related Literature

The TBTF problem in the banking sector has been widely studied. Several papers have aimed to measure the extent to which large banks benefit from implicit government guarantees. For instance, O'hara and Shaw (1990) employ an event study methodology to investigate bank equity changes following the announcement by the Comptroller of the Currency that some banks were TBTF. They report positive wealth effects accruing to those banks identified as TBTF. Using a different approach, Ueda and Di Mauro (2013) measure the extent of the government subsidy by contrasting banks' individual credit ratings against their so-called support ratings, which account for the likelihood of receiving external support – either from a parent company or the government - in the event of a crisis. Using a worldwide sample of banks, they report a significant government subsidy for systemically important banks, amplified right after the GFC.

Financial derivatives have also contributed to advance our understating of the TBTF problem in the financial sector. Völz and Wedow (2011) present evidence consistent with TBTF by examining the relationship between credit default swap (CDS) spreads and bank size. They find that an increase in bank size by one percentage point reduces CDS spreads by approximately two basis points (see also Demirgüç-Kunt and Huizinga (2013)). Similarly, Kelly et al. (2016) examine price differences between OTM put options on a basket of individual banks, and OTM puts on the financial sector index during the GFC. They document this basket-index difference increases four-fold during the crisis and attribute this behaviour to a financial sector-wide bailout guarantee.[5] In particular, they show larger banks benefit more from the sector-wide guarantee.

More recently, research has focused on examining the effectiveness of the measures designed to address the TBTF problem in the aftermath of the GFC. For example, Schäfer et al. (2015) analyse changes to banks' CDS spreads following the introduction of regulatory reforms in the U.S. and Europe. For the U.S., they report an increase in CDS spreads around the time Dodd-Frank was conceived and enacted into law, especially for those banks deemed systemically important. They interpret this as evidence that Dodd-Frank succeeded in reducing bailout expectations relative to the period immediately after the bailouts took place. Similarly, Bongini et al. (2015) use an event study methodology to investigate potential wealth effects upon the publication of the first list of systemically important financial institutions (SIFIs) by the Financial Stability Board (FSB). Banks in this list were identified as institutions whose failure would cause a significant disruption to the financial system, and hence tougher regulatory requirements were designed for them.[6] They report a negative wealth effect for SIFI banks following the list disclosure. This effect, they argue, reflects the additional regulatory burden expected for those banks. In contrast, Moenninghoff et al. (2015) find that the official designation of certain banks as SIFIs produced positive wealth effects. They suggest that revealing the identities of the systemically important banks eliminates ambiguity about the presence of government guarantees, thus reinforcing the TBTF problem. In addition, Sarin and Summers (2016) use various market measures of risk to study whether the stricter post-crisis regulatory regime has seen a decline in large banks' risk exposures. They conclude that the observed changes in bank risk are inconsistent with the view that large banks are safer post-crisis than they were before and caution against complacency.

[5]They estimate the average subsidy to equity holders to be $282 billion during the sample period.

[6]The first list was issued by the FSB on November 4, 2011.

3 Measuring bank tail-risk

The Black-Scholes-Merton (BSM) model for valuing options has a crucial free parameter, the future return volatility of the underlying asset. One cannot observe future return volatilities, but for any given option, one can use the BSM model to estimate the return volatility that yields the observed option price. This is referred to as the option's *implied volatility* and can be interpreted as the market's expectation on the future return volatility of the underlying asset. If the BSM model described option prices accurately, the implied volatilities of all options written on a particular stock – and of equal time to expiration – should be the same, irrespective of their strike price. Hence, plotting the implied volatility of different options as a function of their strike price should produce a flat line. In reality, implied volatilities vary with strike prices, a phenomenon known as the "volatility smile".[7]

For put options, implied volatilities are typically high for out-of-the-money (OTM) options and low for in-the-money (ITM) options.[8] This skewed shape has been partly attributed to empirical violations of the lognormal assumption for the distribution of stock prices embedded in the BSM model (see Derman and Miller (2016)). In practice, this assumption understates the actual probability of extreme downward moves.[9] In this regard, the risk-neutral density (RND) of stock prices has been shown to be more negatively skewed than the lognormal density assumed in the BSM model (see Birru and Figlewski (2012) and Dennis and Mayhew (2002)).[10] As an example, Figure 1 presents the risk-neutral density – extracted from option prices – of Sterling Bancorp Chase in December 2014, along

[7]Other common names for this phenomenon include volatility smirk and volatility skew.

[8]When used for hedging purposes, OTM puts serve as "catastrophe insurance". They cut off the tail of the stock return distribution at the expense of slightly reducing the mean of the overall distribution (Cochrane, 2009).

[9]Specifically, the BSM model assumes that stock log prices follow a constant volatility diffusion process where, over any finite time interval, log prices are normally distributed. In reality, stock return volatility is stochastic and correlated with price. This produces asymmetric and fat-tailed stock return distributions relative to a normal distribution (Corrado and Su, 1996).

[10]The risk-neutral density contains investors' beliefs about the true distribution of stock returns coupled with their own risk preferences (Figlewski, 2018).

with a lognormal density with the same mean and variance.[11] The visible left-skewness of this risk-neutral density makes the probability of a two standard deviations price drop almost 3 times what a lognormal density implies. A left-skewed RND suggests that investors perceive significant price drops as more likely compared to a lognormal distribution. Because of this, they are willing to pay higher prices for deep OTM put options which in turn results in a downward sloping volatility smile.

Indeed, Bakshi et al. (2003) show that the more negatively skewed the RND of a given equity asset, the stepper its volatility smile (see also Corrado and Su (1996)). Moreover, they show that negatively skewed risk-neutral distributions are a consequence of risk aversion and fat-tailed physical distributions. Thus, a steeper volatility smile constructed using OTM puts can be associated with higher (perceived) exposure to downside risk for the underlying asset. I exploit this fact and define the slope of the implied volatility smile for OTM put options as a forward-looking measure of a stock's perceived exposure to significant drops in value (i.e. *tail-risk*).

To construct this tail-risk measure, I collect daily implied volatility data from OptionMetrics for a sample of 85 U.S. bank holding companies (bank) for which an active options market exists as of September 2009.[12] Of these, 62 correspond to banks with assets less than \$50 billion in assets (below 50B) and 23 to banks with assets equal or greater than \$50 billion (above 50B). Table 1 shows the full list of banks included.

For each trading day, I measure the steepness of each bank's implied volatility curve as the sum of absolute differences between the implied volatility of at-the-money (ATM) put options (i.e. delta equal to -0.50) and the implied volatility of OTM puts with varying deltas.[13] The relevant OTM put option deltas range from -0.45, to -0.20 and I employ

[11] See Birru and Figlewski (2012) for a detailed procedure for constructing risk-neutral densities from option prices.

[12] The next section clarifies the use of this particular time to limit the sample. Access to financial statement data is another requirement for a bank to be included in the sample.

[13] By convention, implied volatility curves are created as functions of option deltas. In the BSM model, delta measures the instantaneous change in the option's value to changes in the underlying asset price. The delta for at-the-money put options is approximately -0.5. Creating implied volatility curves as functions of option deltas normalises the implied volatilities across strike prices and expirations (Derman and Miller, 2016).

one-month to expiration puts. When graphed as a function of delta, volatility smiles are steeper at longer expirations (Derman and Miller, 2016). Hence, using short maturities in the construction of this market-based measure generates a lower bound for bank tail-risk. Equation 1 presents the formula for the construction of bank tail-risk.

$$Tail\text{-}Risk_{i,t} = \sum_{\delta \in \Delta} |\sigma_{i,\delta,t} - \sigma_{i,\text{-}0.5,t}| \tag{1}$$

where $\sigma_{\delta,i,t}$ represents the implied volatility for bank i, for a put option with delta δ, on trading day t, and $\Delta := \{-0.45, -0.40, ..., -0.20\}$ is the set of available OTM put deltas. This market-based measure aims to capture each bank's perceived exposure to significant price drops. Higher bank tail-risk values denote higher weights assigned to the probability of downturn events.

Several papers have used similar slope measures to estimate perceived exposure to significant drops in market value. For instance, Collin-Dufresne et al. (2001) use changes in the slope of the volatility smile of options on S&P 500 futures to measure perceived changes in the probability of negative market jumps. Similarly, Tang and Yan (2010) measure jump risk using the slope of the volatility curve for S&P 500 index options. More recently, Yan (2011) demonstrates that the smile slope is proportional to average stock jump size. Furthermore, he provides empirical evidence of a strong relationship between smile slopes and future jump size. Likewise, in the banking literature Hett and Schmidt (2017) use smile slopes as indicators of implied default risk for individual banks.[14]

3.1 Tail-risk around crises

Following the 1987 market crash, Rubinstein (1994) documented a structural change in the shape of the implied volatility curve of S&P 500 index options: the curve went from being relatively flat in the pre-crash period to significantly downward sloping post-crash.

[14] In a related approach, Knaup and Wagner (2012) consider changes in OTM put option prices as reflecting changes in the perceived likelihood and severity of market crashes. They then define bank tail-risk as banks' price sensitivity to changes in far OTM puts on the market.

Rubinstein (1994) suggested "crash-o-phobia", that is, an increase in investors' expectations of future crash-like events, as an important reason for the appearance of the so-called volatility smile.

In this section, I show that the steepening of the implied volatility curve was not peculiar to the 1987 crash but also occurred following the dot-com crash of 2000 and the more recent GFC of 2008. Thus, it appears that investors' consistently adjust expectations of future crash like events upward following crises.

Dot-com crash

After a long speculative period known as the dot-com bubble, the market for technology firms crashed in March 2000 and did not recover until late 2002.[15] Given its economic significance, I employ this market crash to explore how it affected the technology industry's perceived exposure to downside risk (i.e. tail-risk).

To do this, I use a sample of 165 technology firms listed on NASDAQ for which an active options market was available between 1996 and 2005. The options data required for estimating tail-risk is from OptionMetrics. I define the pre-crash, crash, and post-crash periods as the time periods 1996-1999, 2000-2002, and 2003-2005, respectively. Using the options-based approach described in Section 3 to measure tail-risk, I calculate that tail-risk for this group of firms spiked during the dot-com bubble and remained at higher levels compared to the pre-crash period. Specifically, Panel C in Table 2 shows technology firms experienced a 101.8% increase in average tail-risk between the pre and post-crash periods. This substantial tail-risk surge represents a *structural* change in the shape of the implied volatility curve for these firms.

The Global Financial Crisis

The more recent crisis in 2008-2009 presents another opportunity to study the dynamics of tail-risk around crisis. Since the GFC centred on the banking sector, I examine

[15] By October 2002, the NASDAQ Composite Index had fallen by 78% from its peak in March 2000.

non-financial firms and banks separately, using data for 619 non-financial firms and 85 U.S. bank holding companies with active options markets between 2001 and 2017.

Using the same options-based approach as above and defining the pre-crisis, crisis and post-crisis periods as 2001-2007, 2008-2009, and 2010-2017, respectively, I calculate that after increasing by 28.3% between the pre-crisis and crisis periods, tail-risk for non-financial firms subsides but remains 12.6% above pre-crisis levels (see Panel B of Table 2). A similar but much more pronounced effect is observed for the U.S. banking industry as a whole: tail risk increases by 74.5% between the pre-crisis and crisis periods, and although falling slightly, remains 69.9% higher compared to the pre-crisis period (see Panel A of Table 2). Thus, consistent with Rubinstein (1994) and what happened following the dot-com crash, there is a permanent increase in tail-risk after the GFC for banks as well as non-financial firms.

Systemically important banks

The evidence above shows that investors consistently update future expectations of crash like events following major market downturns leading to starkly high tail-risk estimates post-crisis. However, this empirical regularity is absent for a subset of firms following the GFC: banks designated as systemically important by the Dodd-Frank Act of 2010 (i.e. banks with assets greater than $50 billion)

Figure 2 shows the distribution of quarterly tail-risk for all U.S. banks, and below and above 50B banks, for the pre-crisis, crisis, and post-crisis time periods. As mentioned above, consistent with the idea that the GFC raised investors expectations for future bank failures, tail-risk for the U.S banking industry as a whole rises by 69.9% between the post and pre-crisis periods. This rise is driven entirely by changes in below 50B banks tail-risk which surges by 64.4% post-crisis. However, for above 50B banks, after peaking during the crisis, tail-risk reverted (almost exactly) back to pre-crisis levels.

Large vs. small firms

A natural question is whether these differential changes in tail-risk according to bank size are an artifact of options markets. For instance, one could argue large firms have option markets that are inherently more liquid and subject to lower transaction costs, and that these market characteristics produce relative flatter smiles (i.e. lower tail-risk) especially during distress states. If this were the case, we would expect to observe different tail-risk averages for firms of varying sizes following a major market downturn, not just for banks. I investigate and rule out this possibility by studying the tail risk dynamics for (1) non-financial firms of varying size around the GFC; and (2) technology stocks of varying size around the dot-com crash.

I examine the tail-risk for non-financial firms around the GFC first. Non-financials are classified into two groups, small and large, based on their total assets as of 2009Q3.[16] The large group corresponds to firms in the top size quartile and the small group consists of all other non-financials.[17] Firm size (i.e. total assets) is obtained from Compustat.

Table 2 presents average tail-risk changes for the pre and post-crisis period for small and large firms separately. Panel A shows the numbers for banks and Panel B presents the numbers for non-financials. Unlike banks, post-crisis tail-risk increases for both small and large firms by 13.6% and 6.6%, respectively. These changes are significantly lower compared to the 64.4% surge observed for below 50B banks – which is to be expected given the nature of the crisis. This table also confirms that the tail-risk for above 50B banks did not change post-crisis (in fact, it is marginally lower, though the change is insignificant). The observed increase in in tail-risk for non-financials can also be attributed to a surge in investors' expectations of future crash-like events caused by the GFC, and its spillover effects onto other industries. These findings, however, are qualitatively different from the size tail-risk differences reported for banks.

[16]For comparability with the sample of banks, the non-financial firms sample includes non-financials with assets between \$2 and \$2,252 billion as of 2009Q3. This is the same size range observed for the sample of banks.

[17]This is consistent with the size distribution observed for banks where the above 50B group corresponds to the top size quartile.

Next I examine the tail-risk behaviour for large and small technology firms around the dot-com crash. I define firms with total assets in the top quartile as of 2000Q1 as large, and all other firms as small. Panel C of Table 2 presents changes in tail risk for large and small technology firms. Unlike banks, both size groups depict a substantial increase in tail risk post-crisis, 132.6% and 45.5% for small and large firms, respectively.

These tests show that the difference between above and below 50B banks is not simply an artifact of options markets favouring larger firms. The key argument I make in this paper is that this difference between above and below 50B banks is driven by investor expectations over future bailout probabilities for large versus small banks. That is, the series of bailout programs targeted at systemically important banks during the crisis reinforced investors expectations of future bailouts for large banks and so, despite the crisis, expectations that large systemically important banks will fail in the future did not adjust upward as they did for small banks and for non-financial firms. In the next section, I develop this argument further and also consider an alternative interpretation for the observed difference between large and small banks.

4 Potential explanations

4.1 Implicit Guarantees

My central claim is that the series of bailouts targeted at large banks during the financial crisis, and the subsequent designation of above 50B banks as systemically important by the Dodd-Frank Act, reinforced the TBTF status of large financial institutions. This raised expectations of future bailouts for large banks and led market participants lower expectations of large price declines in the post-crisis period, resulting in a flatter post-crisis smile for above 50B banks (i.e. lower tail-risk) relative to small banks. For small banks below the 50B systemically important threshold, the crisis raised investors' concerns about the possibility of future failures – as shown in Table 2 – steepening the left-tail segment of the smile for this group. I refer to this as the *implicit guarantee* hypothesis.[18]

The GFC revealed two important facts: it exposed fundamental weaknesses of the U.S. banking industry and it affirmed the U.S. government commitment to rescue large financial institutions in distress. For instance, of the $439 billion dollars disbursed under the Troubled Asset Relief Program (TARP), $204.9 billion was committed to direct capital injections between October 2008 and December 2009.[19] Of this, 81.9% ($167.9 billion) was invested in the sample of above 50B banks and only 4.8% ($ 9.9 billion) in below 50B banks.[20] Prior research shows that these large scale bailouts are reflected in asset prices. For example, Kelly et al. (2016) examine the difference in costs between a basket of OTM put options for individual banks and OTM puts on the financial sector index. They document this basket-index difference increases four-fold during the GFC and attribute this behaviour to a financial sector-wide bailout guarantee.

The government commitment to rescue large banks went beyond the TARP funding. Of the 20 listed banks allowed to fail since the GFC, none were above the 50B threshold. In the midst of the crisis, the then Chairman of the Federal Deposit Insurance Corporation (FDIC) Sheila Bair commented:

"'Too big to fail' has become worse ... It's become explicit when it was implicit before. It creates competitive disparities between large and small institutions, because everybody knows small institutions can fail. So it's more expensive for them to raise capital and secure funding (Wiseman and Gogoi, 2009)."

Consistent with this, Gandhi and Lustig (2015) show that the largest bank stocks have significantly lower risk-adjusted returns than smaller banks' stocks, even though large banks are significantly more levered. They interpret this evidence as consistent with the

[18]Note that this explanation does not require large banks to be inherently less risky. Provided that investors perceive large banks to be more likely to receive government assistance in future distress states, it follows that they will perceive large banks to be less exposed to downside risk, which will be reflected in lower tail-risk levels relative to small banks.

[19]Originally, the U.S. Congress approved $700 billion to be disbursed under TARP. The authorised amount was subsequently reduced to $475 billion by the Dodd-Frank Act, and as of March 2018 only $439 billion had been disbursed (Lerner, 2018).

[20]See the U.S. Department of The Treasury website for the full list.

existence of implicit government guarantees that protect shareholders of large U.S. banks in disaster states.

In addition, as a direct response to the crisis the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) made explicit which banks were deemed by the government as systemically important. Specifically, the Act designated $50 billion as the size threshold above which a bank holding company is deemed a large, interconnected financial institution whose failure could threaten the financial stability of the United States.[21] Investors were thus effectively given a list of banks the government deemed too-big-to-fail. In this regard, Moenninghoff et al. (2015) argue that revealing the identities of systemically important banks eliminates the ambiguity about the presence of government guarantees.

The AIG bailout

To bolster the case for inferring bailout expectations from options prices, I explore firm tail-risk variation around one of the largest bailouts in U.S. history. If implicit government guarantees reduce firm tail-risk, then the actual realisation of such guarantee in the form of a bailout should have a similar effect, especially in times when the uncertainty around the government commitment is high. This was exactly the case for the American International Group (AIG) during the GFC. The insurer was effectively nationalised by the U.S. government in September 2008, the same month Lehman Brothers was allowed to fail.[22]

To examine the effect of the bailout on AIG's perceived exposure to downside risk, I

[21]Section 165 of the Dodd-Frank Act states: "In order to prevent or mitigate risks to the financial stability of the United States that could arise from the material financial distress or failure, or ongoing activities, of large, interconnected financial institutions, the Board of Governors shall … establish prudential standards for nonbank financial companies supervised by the Board of Governors and bank holding companies with total consolidated assets equal to or greater than $50,000,000,000 that … are more stringent than the standards and requirements applicable to nonbank financial companies and bank holding companies that do not present similar risks to the financial stability of the United States … "

[22]On September 16, 2008 the Fed rescued AIG with a $85 billion two-year emergency loan. In exchange, the U.S. government effectively got a 79.9% equity stake in the company (Karnitschnig et al., 2008). The total aid package to AIG was $184.6 billion which meant a 92% equity stake for the U.S. government (Scism, 2014).

follow Section 3 and estimate monthly tail-risk averages around the time of the rescue plan. For comparison purposes, I also estimate tail-risk averages for two qualitatively similar insurance companies, namely MetLife and Prudential Financial.[23]

The top panel of Figure 3 shows monthly tail-risk averages for these firms between July and November 2008. For AIG, its average tail-risk experienced a sharp decline (72.5%) in the month immediately after its bailout. For the other two insurers, however, tail-risk surges by 385.1% (MetLife) and 128.3% (Prudential Financial) and remained high for most of the crisis period. Despite being on the brink of bankruptcy, once the U.S. government became a significant shareholder in AIG its perceived exposure to downside risk fell drastically and remained low for the entire crisis period.[24] I argue that majority ownership of AIG by the U.S. Treasury increased investors expectations of future bailouts to keep AIG afloat which was in turn reflected in the tail-risk behaviour of AIG. The bottom panel of Figure 3 expands the window before and after the AIG bailout and presents quarterly tail-risk averages. We can see that before the crisis, the variation in tail-risk for these three firms was similar and only changed after AIG's bailout. Moreover, average tail-risk converges for the three insurers in the post-crisis period. As with banks, this only occurs after the Financial Stability Oversight Council (FSOC) designated these three institutions as systemically important, that is, firms whose failure could pose a threat to the U.S. financial stability.[25] I argue that these designations contributed to increase investors' expectations of future bailouts and thus, reduce these firms' exposure to tail-type events.

4.2 An Alternative Explanation: Effective Regulation

A tighter regulatory regime for large banks is another salient characteristic of the post-crisis U.S. banking industry. This, I hypothesise, could also explain the size-based tail-risk differences documented in Figure 2.

[23] All these firms had total assets exceeding \$400 billion as of 2007Q4.
[24] AIG net loss for 2008 was \$99.3 billion.
[25] All these designations where subsequently rescinded between 2017 and 2018.

The Dodd-Frank Act was first introduced in the U.S. House of Representatives in December 2009 and subsequently enacted into law in July 2010. It was a direct response to the multiple regulatory concerns around financial stability raised by the GFC. At its core, Dodd-Frank was specifically designed to end the TBTF problem, and to protect taxpayers by eliminating bailouts. To achieve this, Dodd-Frank effectively established – and/or empowered banking regulators to establish – size-based regulatory requirements. For instance, banks with more than $10 billion in assets were required to establish a risk committee and conduct stress tests to assess their financial resilience to adverse conditions.[26] In addition, banks with more than $50 billion in assets were designated as systemically important and subjected to enhanced supervisory standards such as stringent liquidity requirements, periodic resolution plans, and concentration limits. Table 3 presents a summary of the different size-based regulatory requirements for U.S. banks originated with Dodd-Frank.[27]

It is evident from Table 3 that Dodd-Frank established a direct relationship between bank size and regulation stringency. In this sense, the relatively lower tail-risk levels of above 50B banks documented in Figure 2 may simply reflect the more stringent regulatory requirements imposed on them relative to smaller banks. After all, the main of objective of Dodd-Frank was to address the financial stability deficiencies unveiled by the GFC and put an end to the TBTF problem. I refer to this alternative explanation as the *effective regulation* hypothesis. There is some recent evidence consistent with this explanation including Balasubramnian and Cyree (2014) who show Dodd-Frank has been effective in reducing the TBTF discounts on yield spreads in the market for subordinated debt.

In the remainder of the paper, I conduct a series of test to help differentiate between these two competing hypotheses and show that the evidence favours the implicit guarantees hypothesis.

[26] U.S. banking regulators include the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve Board (Fed), and the Office of the Comptroller of the Currency (OCC).

[27] Dodd-Frank does not include a $250 billion threshold. However, this was adopted by the U.S. under the Basel III international agreement for financial regulation. Also, these size-based thresholds were modified in May 2018 under the Economic Growth, Regulatory Relief, and Consumer Protection Act.

5 Empirical Findings

I have demonstrated that the tail-risk differences of small and large banks is starkly different in the post-crisis period: the average tail-risk of smaller banks is considerably higher than that of large banks. In this section, I first show that this result is robust to controlling for bank and option market characteristics. I then conduct a series of tests to show that this difference in tail-risk between large and small banks after the GFC is consistent with an increase in bailout expectations for large banks vis-a-vis small banks (i.e. implicit guarantee hypothesis).

5.1 Baseline results

I start by validating the stylised facts presented Section 3 in a regression framework that also accounts for other covariates likely correlated with bank tail-risk. Specifically, I employ a difference-in-differences (DiD) model of the form:

$$\begin{aligned} Tail\text{-}Risk_{i,t} = {} & \alpha_1 Post\text{-}Crisis_t + \alpha_2 Above\text{-}50B_i \\ & + \alpha_3 Post\text{-}Crisis_t \times Above\text{-}50B_i \\ & + \sum_{k=1}^{n} \beta_k X_{i,k,t} + T_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $Tail\text{-}Risk_{i,t}$ is the average tail-risk of bank i for period t. $Post\text{-}Crisis_t$ is a dummy variable which takes 1 for the period 2010-2017, that is, after the GFC and following the introduction of the Dodd-Frank bill in the U.S Congress, and 0 otherwise. Similarly, $Above\text{-}50B$ is a dummy variable which takes 1 for banks with assets equal or greater than \$50 billion as of 2009Q3, and 0 otherwise.

The explanatory variable of interest in this specification model is the interaction term

$Post\text{-}Crisis_t \times Above\text{-}50B$. The coefficient on α_3 corresponds to the average post-crisis increase/decrease in tail-risk for above 50B banks relative to the tail-risk change of banks in the below 50B group. Control variables are represented by $X_{i,k,t}$. These correspond to bank and market characteristics possibly correlated with tail-risk. The specification also includes time (i.e. year-quarter) fixed effects to control for aggregate time trends that are common to all banks in the sample, and standard errors are clustered at the bank level to allow for error correlation within each bank.

At the bank level, I control for *leverage ratio*, defined as the ratio between tier 1 capital and total assets; *risk-weighted assets* scaled by total assets; *return on equity*; *loan-to-deposits* ratio; *exposure to financial institutions*, defined as the dollar value of funds lent to other depository institutions scaled by total assets; reliance on *short-term wholesale funding*, measured as the total amount of wholesale funding scaled by total liabilities; *non-performing loans*, calculated as the dollar value of 90 days past due loans over assets; *bank size*, measured as the natural logarithm of total assets; and *z-score*, an estimate of bank insolvency risk, which I calculate following Lepetit and Strobel (2013). The quarterly accounting data for the construction of these financial ratios is obtained from the Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) filed with the Federal Reserve.

In addition, I control for quarterly estimates of bank *systematic* and *unsystematic* risk. These are obtained by decomposing total return variance into systematic variance and unsystematic variance. Systematic risk (systematic variance) is then defined as $\beta\sigma_{market}$ ($\beta^2\sigma^2_{market}$), where β represents bank return sensitivity to changes in the market portfolio returns, and σ_{market} the market return volatility.[28] Whereas, unsystematic risk is defined as the square root of the difference between total return variance and systematic variance. Daily bank return data for the construction of these risk estimates is from the Center for Research in Security Prices (CRSP).[29]

I also control for specific market characteristics of the OTM put options used in the

[28]Individual bank betas are calculated each quarter by fitting a linear regression model of daily bank returns on market portfolio returns.

[29]Daily market returns are obtained from Keneth R. French's website. These market returns comprise a portfolio of all NYSE, AMEX, and NASDAQ firms.

construction of tail-risk. These include bid-ask spreads and volume estimates also obtained from OptionMetrics.[30] Table 4 shows summary statistics for selected bank characteristics observed quarterly for a sample of 85 bank holding companies (see Table 1) over the period January 2001 - December 2017. Average bank tail-risk is positive over the sample period, denoting the downward sloping smile characteristic of equity assets. Also, bank total assets range between $1.5 and $2,609.8 billions.

Table 5 presents coefficients estimates for the DiD model shown in Equation 2. Column (1) presents the simple baseline regression with no control variables. In Column (2), quarterly financial ratios from banks' consolidated statements are added as controls. In addition, Column (3) includes market-based measures of systematic and unsystematic risk, and Column (4) includes measures of liquidity and transaction costs for the options markets used in the construction of tail-risk. In all these specifications, the coefficient on the interaction term between the above 50B indicator and the post-crisis dummy is negative and significant.[31] Relative to banks with less than $50 billion in assets, the average tail-risk of larger banks is significantly lower post-crisis. In particular, the average tail-risk difference between below and above 50B banks is more than five times larger in the post-crisis period compared to pre-crisis.

These findings corroborate the stylised facts documented in Section 3. In the post-crisis period, markets perceive above 50B banks as significantly less exposed to downside risk. Another important insight from this test is the relevance the leverage ratio has in reducing tail-risk. On average, banks with higher levels of Tier 1 capital as proportion of total assets are associated with lower tail-risk exposures (i.e. lower exposure to significant price drops). Specifically, a one standard deviation increase in a bank's leverage ratio is associated with a 6% reduction (relative to the mean) in tail-risk.

[30] These controls are included to account for liquidity and transaction costs in option markets. These are also considered possible determinants of volatility smiles (see Pena et al. (1999)).

[31] Post-crisis dummy coefficients are omitted due to the use of time fixed effects.

5.2 Other salient regulatory thresholds

The post-crisis regulatory framework in the U.S. contained a series of bank size thresholds with increasing regulatory stringency as banks moved into larger thresholds. Specifically, these groups are:

- **Group 1:** banks with less than \$10 billion in assets
- **Group 2:** banks with assets of \$10 billion or greater but less than \$50 billion.
- **Group 3:** banks with assets of \$50 billion or greater but less than \$250 billion.
- **Group 4:** banks with \$250 billion in assets or more.

Table 3 outlines the different regulatory standards faced by banks in these various regulatory size buckets. Other than the \$50 billion threshold for enhanced standards, these regulatory groups are defined using two additional regulatory thresholds conceived after the GFC. These include the \$10 billion regulatory threshold for stress tests – also established in the Dodd-Frank Act – and the \$250 billion threshold at which banks become subjected to Basel III additional regulatory requirements for advanced approaches banks.

I exploit the monotonic relationship between bank size and regulatory stringency to examine whether the lower tail-risk for above 50B banks in the post-crisis period is consistent with the effective regulation hypothesis. Namely, if lower tail-risk for above 50B banks is driven by tighter regulatory standards, then one should also observe lower tail-risk for (1) banks between 10B and 50B (Group 2) relative to banks below 10B (Group 1); (2) banks between 50B and 250B (Group 3) relative to banks between 10B and 50B (Group 2); and (3) bank above 250B (Group 4) relative to banks between 50B and 250B (Group 3).

To test this, I classify banks into one of the four size-based regulatory groups and then, using the DiD model outlined in Equation 2, I explore tail-risk differences between adjacent regulatory groups (two at a time). If stricter regulation does in fact reduce bank tail-risk, I expect greater regulatory stringency to be associated with lower tail-risk. Hence, the effective regulation hypothesis predicts α_3 in Equation 2 to be negative for all cases in which the reference regulatory group corresponds to banks of smaller size relative to the larger treatment group. Any departure from this would be inconsistent with the idea that a stricter regulatory regime for larger banks is what explains the post-crisis tail-risk differences depicted in Figure 2.

Table 6 shows results for these between-group tests. Column (1) presents point estimates for a sample comprising banks in Group 1 and Group 2. Similarly, in Column (2) the sample is restricted to banks in Group 2 and Group 3, and in Column (3) to banks in Group 3 and Group 4. In all cases, the smaller regulatory group – of the two being compared – is used as the reference group. In addition, Column (4) shows estimates for the same model in Column (3) but with the post-crisis dummy redefined to equal 1 for the period after 2013Q3 and 0 otherwise. I do this to account for the actual time the U.S. adopted Basel III advanced approaches for banks with at least $250 billion in assets (i.e. July 2013). All specifications include year-quarter fixed effects to account for aggregate time trends, and standard errors are clustered at the bank level.

Only in Column (2) is the coefficient on the interaction term negative and statistically significant, suggesting a post-crisis decline in the tail-risk for above 50B banks relative to banks between 10B and 50B. On the contrary, results for the other two comparisons (i.e. Columns (1) and (3)/(4)), are insignificant: the post-crisis tail-risk of below 10B and banks between 10B and 50B are similar; likewise, 50B to 250B banks and above 250B banks have similar tail-risk. Thus, despite significant differences in the stringency of regulatory standards, I observe no differences in tail-risk between these groups.

Interestingly, I only observe a sharp decline in tail-risk at one point: when banks crossover the 50B threshold and are designated systemically important. Overall, these tests are inconsistent with the effective regulation hypothesis. On the other hand, the findings in Table 6 are compatible with implicit guarantees as the explanation for the lower tail-risk of above 50B banks following the GFC. These banks are those that have been explicitly designated by Dodd-Frank as institutions whose failure could threaten the financial stability of the U.S. economy, and are the same banks which benefited the most from government assistance during the GFC. Since the systemically important status applied equally to all banks with more than \$50 billion in assets (i.e. banks in Group 3 and Group 4), the implicit guarantee hypothesis predicts no extra tail-risk reduction for banks above the \$250 billion mark. Consistent with this, I show in Table 3, Columns (3) and (4), that the tail-risk of Group 3 and Group 4 are not statistically different in the post-crisis period. I argue that the designation of banks above 50B as systemically important reduced the ambiguity for investors about which banks are considered TBTF by the government, leading to higher bailout expectations for this group. Similar findings have been documented by Moenninghoff et al. (2015) who show positive wealth effects upon the designation of certain large banks as globally systemically important (GSIBs).

5.3 Wealth effects

To further understand the source of the tail-risk differences between small and large banks, I analyse the stock market reaction to the announcement of potential changes in bank regulation after the GFC related to the passage of the Dodd-Frank Act. As elaborated in Section 4, the two competing hypotheses have starkly different implications for the impact of Dodd-Frank on shareholder welfare. Dodd-Frank introduced a stricter set of regulatory requirements for above 50B banks, but at the same time explicitly designated them as systemically important.

On the one hand, stricter regulation and higher compliance costs imply negative welfare effects for shareholders. For example, Bongini et al. (2015) report evidence of a negative wealth effect to the announcement of tighter regulatory requirements for certain banks designated as systemically important financial institutions (SIFIs) by the Financial Stability Board (FSB). They attribute this wealth effect to the heavier regulatory burden expected on low capitalised SIFIs.

On the other hand, the implicit guarantee hypothesis argues that the official designation of above 50B banks as systemically important reinforced the TBTF problem for this group of banks and so predicts positive wealth effects for shareholders. Consistent with this, recent work by Moenninghoff et al. (2015) documents positive wealth effects for shareholders upon the announcement of large banks as globally systemically important (GSIBs). Further evidence of positive market reactions to the designation of banks as too-big-to-fail in the U.S has been documented by O'hara and Shaw (1990).

Thus, equity markets' reaction can provide indirect evidence of whether, with the passage of Dodd-Frank, large banks were viewed by investors as highly regulated low-risk financial institutions (effective regulation hypothesis) or systemically important firms more likely to receive government support in the future (implicit guarantee hypothesis). Accordingly, any evidence of positive wealth effects around the passage of Dodd-Frank for above 50B banks would be consistent with the implicit guarantee hypothesis. That is, despite a larger regulatory burden, a net benefit to the shareholders of large banks could be interpreted as a reinforcement of the TBTF status of these institutions.

I analyse seven salient dates related to the passage of Dodd-Frank, from its introduction as a bill in the U.S Congress to its enactment. These are:

– 02/12/2009 - Dodd-Frank is introduced in the U.S. House of Representatives (House) as bill H.R. 4173.

– 11/12/2009 - The Dodd-Frank bill is passed by the House.

– 15/04/2010 - Dodd-Frank is introduced in the U.S. Senate (Senate) as bill S.3217.

– 20/05/2010 - Dodd-Frank is passed by the Senate.

– 30/06/2010 - The House agreed to conference report on Dodd-Frank.

– 15/07/2010 - The Senate closed debate and agreed to conference report.

– 21/07/2010 - Dodd-Frank is signed into law by the U.S. president.

Following Bouwman et al. (2018), for each date I employ a two-day event window $[-1, 0]$ with $t = 0$ as the date of interest. The estimation window corresponds to the 200 trading days spanning the time period $[-211, -11)$. The estimation also includes a 10 day trading gap between the estimation and event windows. A market model is used to calculate daily expected returns following Equation 3.

$$R_{i,t} = a_i + b_i R_{M,t} + e_{i,t} \tag{3}$$

where $R_{i,t}$ is the observed return for bank i on day t, and $R_{M,t}$ the return on the market portfolio.[32] For a given bank, daily abnormal returns (AR) are then calculated as:

$$AR_{i,t} = R_{i,t} - \hat{a}_i - \hat{b}_i R_{M,t} \tag{4}$$

with $\hat{a}_i$ and $\hat{b}_i$ corresponding to OLS estimates of Equation 3 over the estimation period.

Because the events of interest are the same for all banks, abnormal returns are prone to cross-sectional correlation and event-induced variance inflation. Both, have been shown to lead to over-rejections of the null hypothesis of zero abnormal returns. To account for these effects, I employ the test statistic proposed by Kolari and Pynnönen (2010) in all of my tests.[33]

Table 7 reports cumulative abnormal returns (CARs) and corresponding test statistics, for below 50B and above 50B banks. This table presents evidence of positive abnormal returns (5.2%) for above 50B banks around the date the U.S. Senate passed the Dodd-Frank bill. I also find a significantly positive reaction (1.4%) for above 50B banks on the date the House agreed to the final version of the Dodd-Frank bill negotiated between the two chambers via conference committee. There are no significant market reactions on other dates for above 50B banks. For these banks, markets seem to interpret the development of

[32]Daily market returns are obtained from Keneth R. French's website. $R_{M,t}$ includes all NYSE, AMEX, and NASDAQ firms.

[33]Refer to Appendix A for more details regarding the test. This test statistic is an adjusted version of the test statistic originally proposed by Boehmer et al. (1991).

Dodd-Frank as net-positive news: despite the additional regulatory burden Dodd-Frank imposed on above 50B banks, the designation of these banks as systemically important brought with it the perceived benefit of future government support in distress states.

On the contrary, I find that abnormal returns for below 50B banks on these salient dates are insignificant, except for one date: when the Senate agreed to the final version of the Dodd-Frank bill negotiated between the two chambers via conference committee. On this date, below 50B banks experienced a negative market reaction of -2.6% which can be interpreted as the markets expectation of higher regulatory costs for some these banks following the passage of Dodd-Frank.

Thus, absent an official designation as being systemically important Dodd-Frank leads to negative shareholder wealth effects which is consistent with the higher regulatory burden demanded by the new legislation. However, for systemically important banks above the 50B threshold, Dodd-Frank resulted in net-positive shareholder wealth effects which is consistent with the view that the systemically important designation led investors to perversely view these banks as more likely to receive bailouts in future distress states.

Focusing on the date we see the largest *difference* in the magnitude of the market reactions for above and below 50B banks (i.e. when the U.S. Senate passed the Dodd-Frank bill), I run a cross-sectional regression of banks' CARs on an indicator for above 50B banks and a series of bank characteristics as of 2009Q4. Table 8 shows coefficients estimates for this specification. Column (1) presents the univariate regression whereas Column (2) adds the bank level controls into the regression. The coefficient estimate on the above 50B bank indicator is positive and significant implying that the CAR difference between above and below 50B banks is positive and significant around the passage of Dodd-Frank by the U.S. Senate. Moreover, larger CARs on this date are associated with higher exposure to other financial institutions (i.e. interconnectedness) and higher systemic risk. Both of these factors are key characteristics of systemically important institutions. These results add weight to the notion that an increase in bailout expectations for above 50B banks post-crisis is the ultimate source of their lower-tail risk.

5.4 U.S. credit-rating downgrade

The extent to which any guarantee can be considered ex-ante credible is conditional on the guarantor's creditworthiness. For large banks, the existence of an implicit government guarantee is predicated on the government's capacity to provide assistance to systemically important banks in distress states. Hence, changes to the government's creditworthiness can also affect the extent to which systemically important banks are perceived as more or less exposed to tail-risk.

In this section, I exploit Standard & Poor's (S&P) decision to downgrade the U.S. credit rating on August 5, 2011 as a shock to the government's creditworthiness.[34] I then examine the effect of this change on the tail-risk of both, systemically important (Above 50B) and smaller banks (Below 50B).

Under the implicit guarantee hypothesis, systemically important banks are perceived as less prone to significant price drops (i.e. tail-risk) because markets expect them to receive government assistance in future distress states. Hence, a reduction in the government's ability to fulfil its implicit commitment and provide assistance should also reduce the expectation of future bailouts (i.e. increase tail-risk). For banks not covered by the guarantee, however, this change in the government's creditworthiness should not have a significant effect on tail-risk.

To test this, I employ Equation 1 to construct daily tail-risk estimates for both, systemically important and non-systemically important banks over the entire months of July and August 2011. That is, approximately one month before and after the U.S. credit-rating downgrade.

Figure 4 shows five-day moving averages for the tail-risk of systemically important banks and non-systemically important banks before and after the downgrade. This figure

[34] S&P downgraded U.S. long-term debt from AAA to AA+. This unprecedented change was justified on concerns around the fiscal position of the U.S. and its political posture on increasing the debt ceiling. (Paletta and Phillips, 2011).

presents a marked change in the average tail-risk of large banks around the U.S. credit-rating downgrade. In particular, the average tail-risk of systemically important banks experiences a three-fold increase following the downgrade, relative to the average tail-risk in the previous month.[35] On the contrary, the average tail-risk of non-systemically important banks remains relatively constant between July and August 2011.

These findings are consistent with the implicit guarantee hypothesis. A deterioration in the U.S. government's creditworthiness leads to a reduction in its (expected) ability to provide assistance to large banks, which causes investors to reduce their expectations of future bailouts. This update in investors' expectations is then reflected in a higher exposure to significant price drops (i.e. tail-risk). For banks which do not benefit from implicit guarantees, the downgrade does not affect the probability investors assign to future price drops.

It is possible the above differential behaviour around the downgrade is influenced by differences in the holdings of U.S. debt between systemically and non-systemically important banks. If large banks invest, on average, more heavily in U.S. Treasury securities then the observed tail-risk change around the credit-rating downgrade may simply reflect the deterioration of that portion of their balance sheets. To exclude this possibility, I estimate relative changes in tail-risk around the credit-rating downgrade in a regression setting where I control for each bank's U.S. debt securities holdings.

Specifically, I use the specification model in Equation 2 restricted to the sample period July-August 2011 and with the variable $Post\text{-}Crisis_t$ replaced by $Post\text{-}Downgrade_t$. The latter corresponds to a dummy variable which takes 1 for the period after the credit-rating downgrade, and 0 otherwise. Moreover, the dependent variable corresponds to a five-day moving average of each bank's daily tail-risk. Also, this specification includes the variable *U.S. Treasury Holdings* as a control. For each bank, this covariate measures the proportion of U.S. Treasury securities held in relation to total assets.[36] The specification also includes

[35] After this increase in early August 2011, the average tail-risk of systemically important banks subsided back to pre-downgrade levels by December 2011.

[36] This and other bank characteristics are estimated using the Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) filed with the Federal Reserve as of 2011Q3 (see Section 5.1).

time fixed effects to control for aggregate time trends that are common to all banks, and standard errors are clustered at the bank level to allow for error correlation within each bank.

Table 9 presents coefficients estimates for this model. Column (1) shows the regression with no control variables. In Column (2), each bank's holdings of U.S. Treasury securities is added as a control, and Column (3) controls for other bank and market characteristics possibly correlated with tail-risk. Across all specifications, the coefficient on the interaction term is positive and statistically significant reflecting the relative increase in the average tail-risk of systemically after the U.S. downgrade. This even after accounting for each bank's exposure to U.S. debt securities.

Overall, these findings provide further evidence in support of the implicit guarantee hypothesis as the main cause of the cross-sectional differences in tail-risk observed in the post-crisis period. The tail-risk of banks that benefit from government guarantees (i.e. TBTF banks) is largely affected by a deterioration of the governments' creditworthiness. For smaller banks, the impact of the U.S. downgrade is negligible. In addition, no regulatory change of interest occurred during this time that can explain the differential tail-risk behaviour documented in this section.

5.5 Risk-taking differences

In this section I analyse the actual risk-taking behaviour of large and small banks in the post-crisis period. The two alternative explanations make differing predictions regarding bank risk-taking. The implicit guarantee hypothesis predicts that due to moral hazard generated by government guarantees (see e.g. Duchin and Sosyura (2014), Kaufman (2014), and Kane (2009)) the risk taking of above 50B banks is likely higher than that of smaller banks. In contrast, the effective regulation hypothesis predicts that tighter regulatory standards reduces bank risk-taking which in turn is reflected in tail-risk.

For this, I define three categories of risk measures: business or operational risk, market-based measures of risk, and regulatory (capital adequacy) measures of risk. To construct these, I employ bank consolidated financial statements filed with the Federal Reserve and historical stock performance data from CRSP. Next, I contrast above and below 50B banks across these various dimensions of risk and test for differences in their average risk-taking, before and after the crisis. Table 10 reports results for these tests. Columns (1) and (3) show above 50B-*minus*-below 50B mean differences for the pre and post-crisis periods, respectively.[37] In addition, Column (5) reports difference-in-differences estimates obtained by subtracting the mean differences in Column (3) from Column (1).

I use four measures of market risk: total return volatility, Beta (i.e. quantity of market risk), systematic risk (i.e., $\beta\sigma_{market}$) and unsystematic risk (i.e., total return volatility less systematic risk).[38] One can see that that the difference-in-differences estimates on total, systematic and unsystematic risk in Panel A are all insignificant. Interestingly, the tests do reveal that the Beta coefficient with respect to the market is significantly larger for above 50B banks relative to smaller banks, post-crisis, suggesting that large banks' exposure to market risk has increased relative to smaller banks.

Similarly, I use the following variables to capture business risk: reliance on short-term wholesale funding (liquidity risk), non-performing loans (credit risk), z-score (insolvency risk), and exposure to other financial institutions (interconnectedness).[39] Panel B shows that, across three of the four measures, large banks (relative to small banks) become increasingly risky in the post-crisis period.

Specifically, relative to smaller banks, above 50B banks' reliance on short-term wholesale funding increases by over 300% post-crisis. Since short-term wholesale funding is less stable compared to others sources of funding such as long-term debt and deposits, this change can be interpreted as a relative increase in liquidity risk.

Next, the insolvency risk (measured by z-score) difference between these bank groups is also significant. The average insolvency risk for above 50B banks goes from being 10.3%

[37]Pre-crisis comprises the time period 2001-2007, whereas post-crisis the period 2010-2017.
[38]See Section 5.1 for a detailed description of these variables.
[39]See Section 5.1 for a detailed description of these variables.

lower pre-crisis (relative to below 50B banks) to 20.4% higher after the GFC.[40]

Finally, above 50B banks' exposure to other financial institutions (relative to below 50B banks) surges more than four times in the post-crisis period. That is, above 50B banks become much more interconnected, which is consistent with their "systemically important" status. It is worth noting that a higher degree of interconnectedness can exacerbate investors' perception that large banks are more likely to receive government protection. Highly interconnected financial institutions are said to accelerate the transmission of financial shocks and to increase systemic risk (see Bluhm and Krahnen (2014), Paltalidis et al. (2015)). Hence, analogous to the TBTF problem, if large banks are considered "too-interconnected" markets may increase their expectations of future bailouts for the entire group – a feature known as the "too-many-to-fail" problem (e.g. see Acharya and Yorulmazer (2007), Brown and Dinç (2011)).

The findings from the above analysis show that above 50B banks are more risky compared to below 50B banks in the post-crisis period – a reality that has also been exposed by Sarin and Summers (2016) – which is consistent with the implicit guarantee hypothesis: the series of bank bailouts targeted at large institutions, and the designation of banks above the 50B threshold as systemically important, reinforced the TBTF status for this group resulting in relatively lower tail-risk post-crisis. This, in spite of fact that their actual risk-exposure increased relative to banks of smaller size.

But did enhanced capital regulation for larger banks achieve its intended goals of increasing capital ratios for large banks by more than that of smaller banks? I examine the evolution of four regulatory ratios around the crisis using the same approach as above. Panel C of Table 10 shows that the new post-crisis regulatory environment led to an increase in regulatory capital and a reduction in risk-weighted assets for above 50B banks relative to smaller banks. Nonetheless, these capital adequacy ratios remain, on average, below those of small banks.

[40]By construction, the z-score is inversely related to a bank's probability of insolvency, and thus larger values reflect a lower probability of insolvency. The estimated z-score maps into an upper bound of the probability of insolvency by the inequality $\Pr(roa \leq -car) \leq \textit{z-score}^{-2}$ (see Lepetit and Strobel (2013)).

Moreover, it should be noted that most of the reduction in the gap between the average ratios for these bank groups happens during the crisis (see Figure 5). This can be partly explained by the capital injections the U.S. government made in large financial institutions under the Capital Purchase Program (CPP) component of TARP. Of the $205 billion CPP package allocated to enhance the capital ratios of financial institutions, $168 billion (82%) was directed to banks above the 50B threshold.[41]

Overall, I show here that although regulatory ratios for systemically important institutions improve considerably relative to smaller banks, their risk-taking appears to have increased in the post-crisis period. This finding is consistent with Duchin and Sosyura (2014) who show that despite an improvement in capitalisation ratios, CPP participant banks increased systematic risk and probability of distress. They interpret these findings as consistent with the notion that government protections lead to an increase in risk-taking incentives. Hence, these results are inconsistent with the effective regulation hypothesis and adds weight to my claim that the size-based difference in tail-risk observed post-crisis are driven mainly by a reinforcement of the TBTF status for banks above the 50B threshold.

5.6 Market discipline

In this final section, I test for pre and post-crisis differences in the tail-risk sensitivity to changes in bank risk. An increase in bailout expectations due to size differences reduces market discipline (see Völz and Wedow (2011), and Acharya et al. (2016)). This means that in the presence of government guarantees, banks' perceived risk exposure becomes less sensitive to their actual risk-taking. Hence, evidence of a decline in tail-risk sensitivity to changes in above 50B banks' risk-taking in the post-crisis period is consistent with the implicit guarantee hypothesis. I do not expect to see a similar reduction in the tail-risk sensitivity to bank risk for the below 50B group of banks.

[41]See the U.S. Department of The Treasury website for the full list.

For both below and above 50B banks, I regress bank tail-risk on each bank risk measure used in the above analysis along with the risk measure interacted with a time dummy which identifies the post-crisis period. The variables of interest are these interaction terms which describe how the sensitivity of tail-risk to bank risk changes in the post-crisis period. Table 11 presents results for this test. Columns (1) and (2) show coefficient estimates for below and above 50B banks, respectively.

Two results are worth discussing. For above 50 banks, tail-risk sensitivity to changes in credit risk (non-performing loans) drops almost 100% post-crisis. Similarly, the interaction between z-score and the crisis indicator is positive and significant which implies a significant weakening of the tail-risk sensitivity to insolvency risk. Both of these findings are consistent with the implicit guarantee hypothesis. Due to heightened bailout expectations, markets perceive large banks to be less exposed to tail events. This in turn leads to a deterioration of market discipline, weakening the link between large banks tail-risk and their actual risk-taking behaviour.[42]

6 Conclusion

I employ option prices to construct a forward-looking measure of bank exposure to significant price drops (i.e. tail risk) and explore cross-sectional differences between large banks with at least \$50B in assets identified as systemically important and smaller banks. I document a permanent increase in the average tail-risk of the U.S. banking industry as a whole following GFC, except for banks above the \$50B size threshold. I argue that the stark post-crisis difference in tail-risk for banks above and below the \$50B threshold is consistent with the notion that the TBTF status of above 50B banks was reinforced by the

[42]Survivorship bias may also impact the tail-risk averages of below and above 50B banks differently. If bank failures are observed in the below 50B group only – as it was mostly the case - then the post-crisis average tail-risk for this group would reflect the perceived exposure to downside risk of those banks which survived. However, this survivorship bias effect acts against the results documented in this paper. By construction, the average tail-risk of those banks that survived was lower than those which failed. Once the failed banks drop out of the sample, average tail-risk would tend to decrease and dampen the size-based tail-risk differences reported here.

series of bailouts targeted at them during the crisis and their subsequent designation as systemically important by the Dodd-Frank Act. This in turn raised investor expectations of future bailouts for above 50B banks and reduced their perceived exposure to downside risk as captured by the tail-risk measure.

I do not find any evidence supporting the possibility that the post-crisis tail-risk differences between small and large banks is due to the stricter regulatory regime large banks face under Dodd-Frank. For example, I show no significant changes in tail-risk around other salient regulatory size thresholds even though regulatory stringency varies substantially around these thresholds. I also document positive wealth accruing only to above 50B banks around the passage of Dodd-Frank. Finally, *actual* risk taking for above 50B banks increases relative to smaller banks in the post-crisis period.

These findings offer insights about the unintended consequences of government interventions and the explicit singling out of firms whose failure could threaten financial stability. That is, revealing the identities of systemically important banks reinforced the presence of government guarantees for these banks, and may have run counter to the regulators' intent to eliminate the effects of TBTF as was intended by Dodd-Frank.

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Figure 1

This figure presents the Risk-Neutral-Density (RND) for Sterling Bancorp in December 2014 (in blue), along with a lognormal density with the same mean and variance (in red). This RND is constructed using the procedure proposed by Birru and Figlewski (2012).

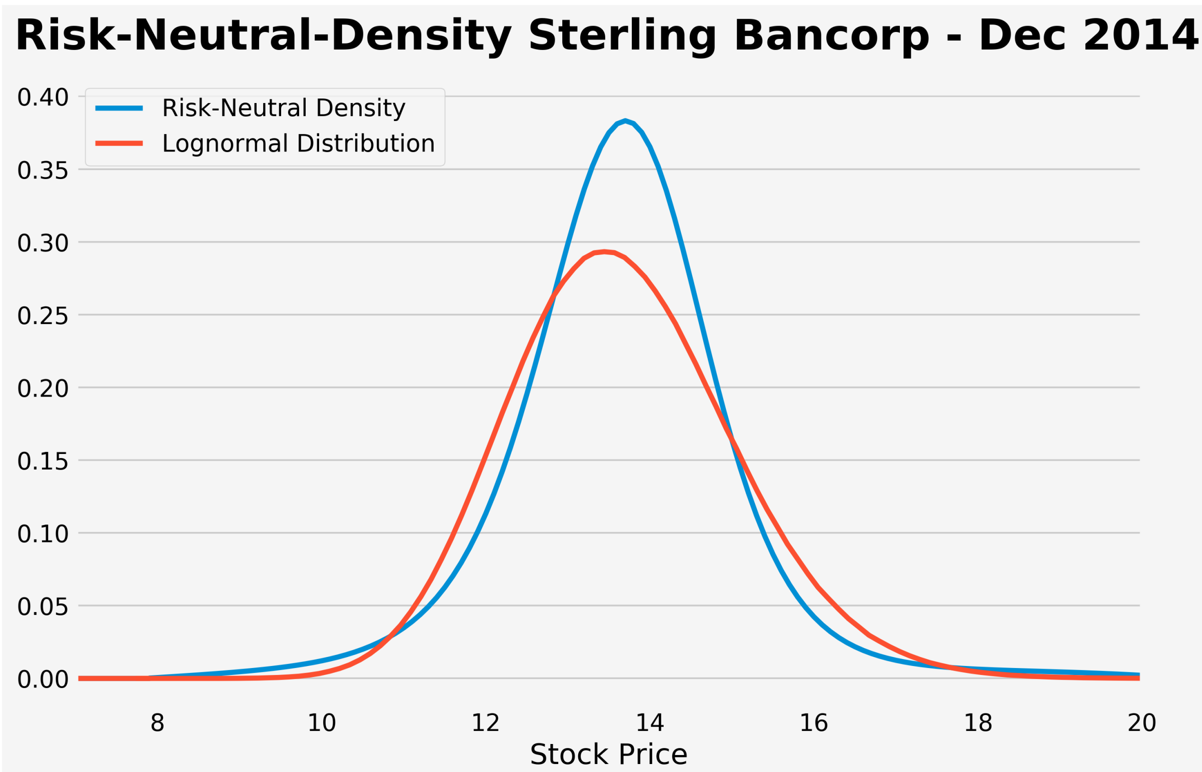

Figure 2

This figure shows the distribution of quarterly tail-risk for all U.S. banks, banks with less than $50 billion in assets (Below 50B), and banks with assets equal or greater than $50 billion (Above 50B), for the pre-crisis, crisis, and post-crisis time periods. Pre-crisis corresponds to the time period 2001-2007, crisis to the period 2008-2009, and post-crisis to 2010-2017.

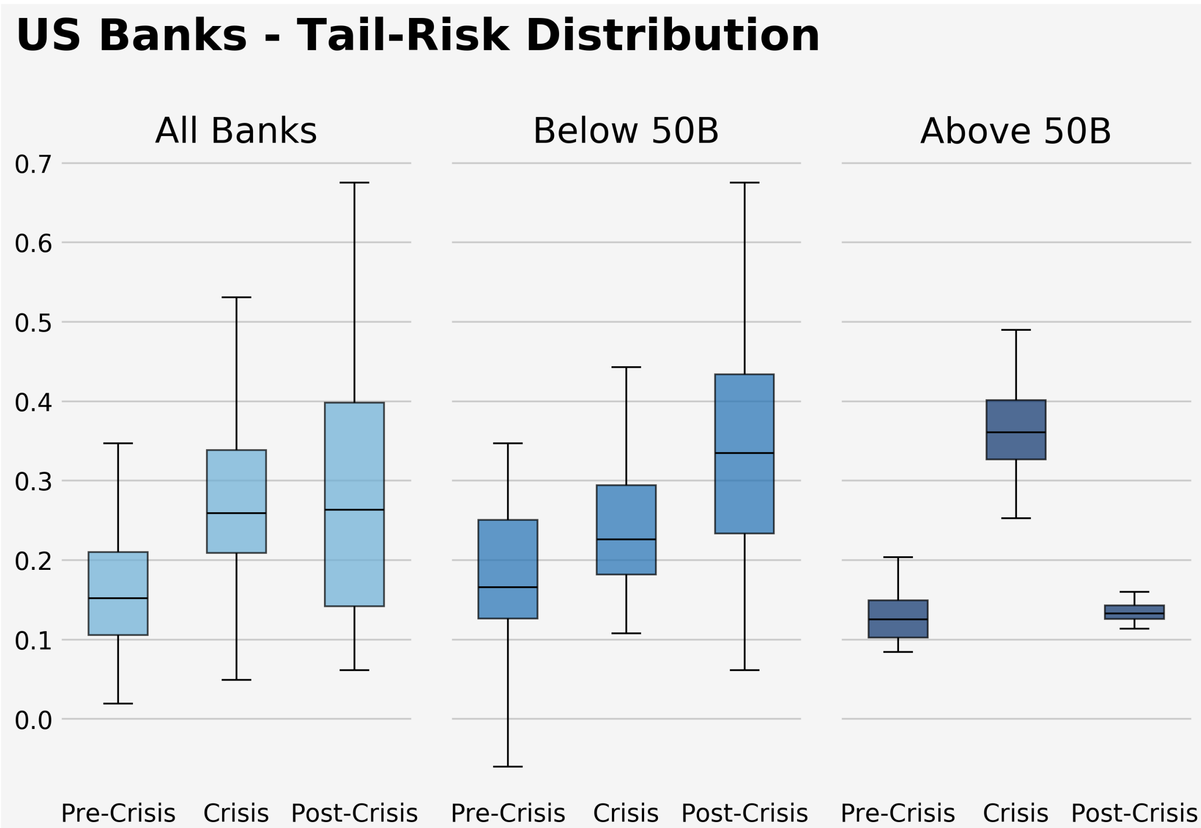

Figure 3

This figure shows tail-risk averages for the insurance firms AIG, MetLife and Prudential Financial. The top panel shows monthly tail-risk averages between July and November 2008. The bottom panel depicts quarterly averages between 2001 and 2017.

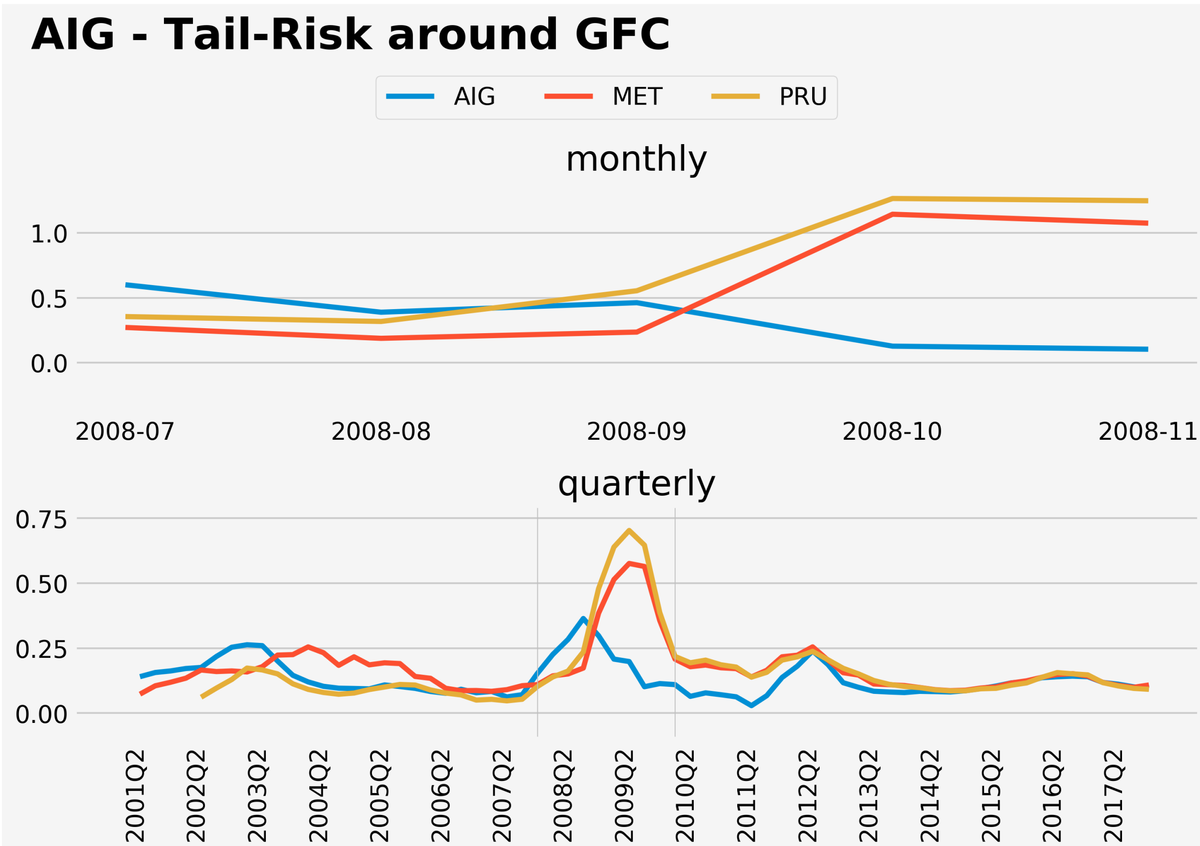

Figure 4

This figure shows five-day moving averages for the tail-risk of systemically important banks (Above 50B) and non-systemically important banks (Below 50B) before and after Standard & Poor's (S&P) downgraded the credit rating of the U.S. government on August 5, 2011.

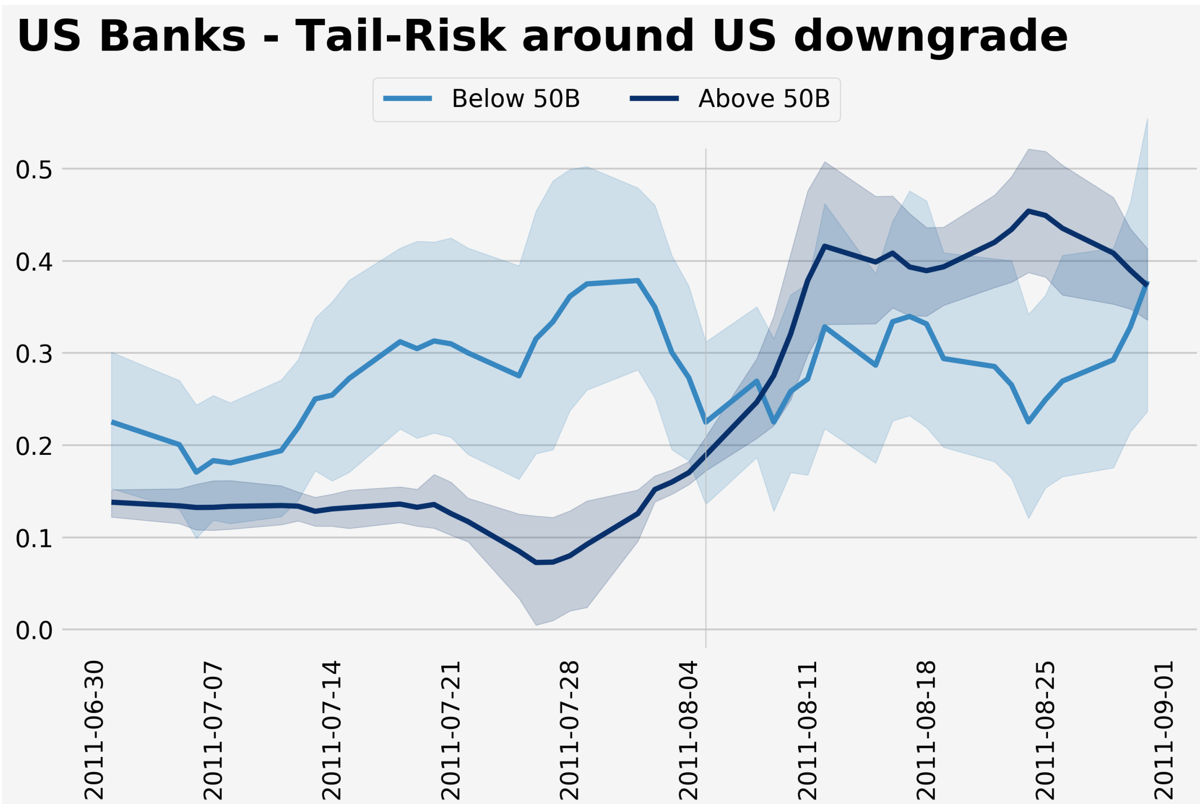

Figure 5

This figure shows quarterly measures of capital adequacy for banks with assets less than $50 billion (Below 50B), and banks with assets equal or greater than $50 billion (Above 50B).

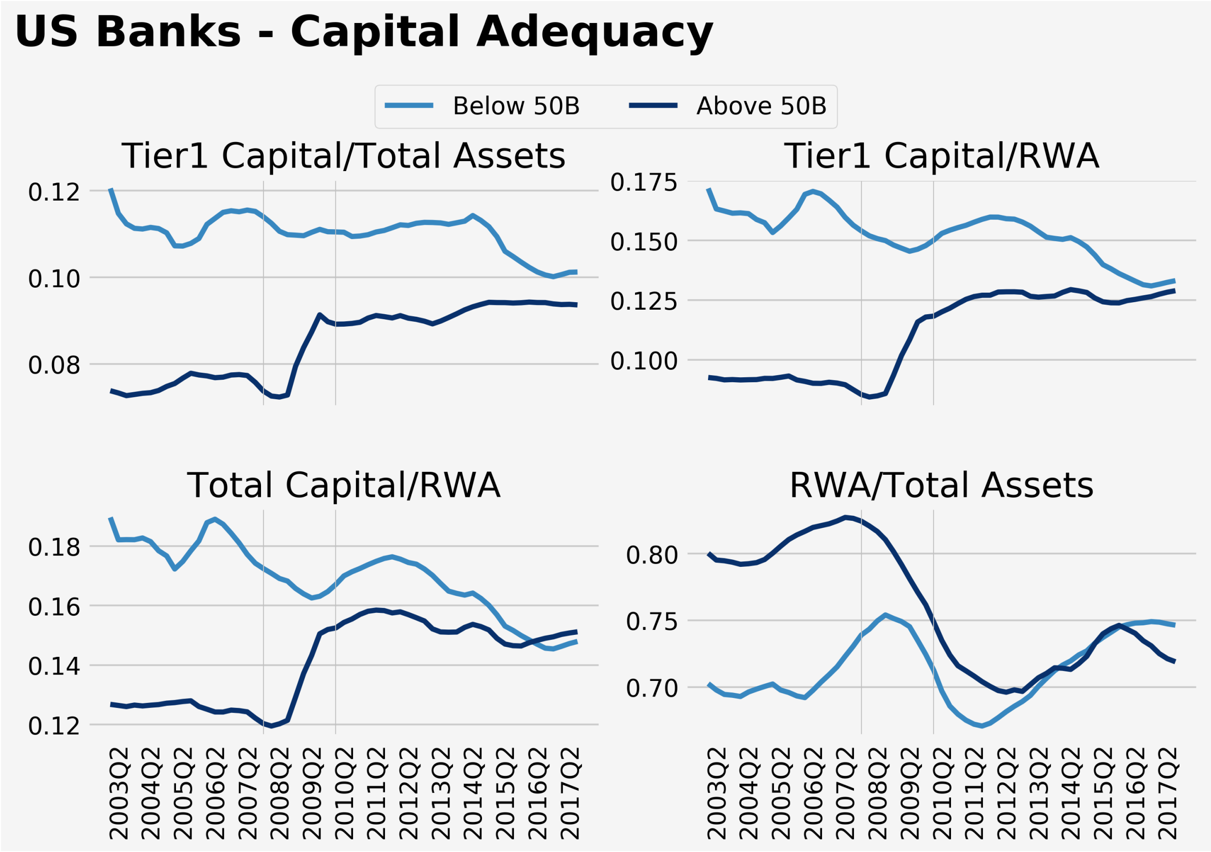

Table 1
This table presents the complete sample of bank holding companies used in this study, along with their total assets as of 2009Q3. Below 50B corresponds to a sample of banks with assets lower than $50 billion, whereas Above 50B is the group of banks with assets equal or greater than $50 billion.

Below 50B		Above 50B	
Bank Name	Total Assets (millions)	Bank Name	Total Assets (millions)
Discover Financial Services	43,815	Bank Of America Corporation	2,252,814
Popular, Inc.	35,638	Jpmorgan Chase & Co.	2,041,009
Synovus Financial Corp.	34,610	Citigroup Inc.	1,893,370
First Horizon National Corporation	26,467	Wells Fargo & Company	1,228,625
Bok Financial Corporation	23,919	Goldman Sachs Group, Inc., The	882,423
First Bancorp	20,081	Morgan Stanley	769,503
Commerce Bancshares, Inc.	17,965	Pnc Financial Services Group, Inc., The	271,450
Webster Financial Corporation	17,855	U.S. Bancorp	265,058
Fulton Financial Corporation	16,527	Bank Of New York Mellon Corporation, The	212,470
Cullen/Frost Bankers, Inc.	16,234	Suntrust Banks, Inc.	172,814
Valley National Bancorp	14,232	Capital One Financial Corporation	168,504
Mb Financial, Inc	14,135	Bb&T Corporation	165,329
Bancorpsouth, Inc.	13,281	State Street Corporation	162,730
Svb Financial Group	12,557	Regions Financial Corporation	140,169
East West Bancorp, Inc.	12,486	American Express Company	120,433
Bank Of Hawaii Corporation	12,208	Fifth Third Bancorp	110,740
Wintrust Financial Corporation	12,136	Keycorp	96,985
Cathay General Bancorp	11,750	Northern Trust Corporation	77,927
International Bancshares Corporation	11,686	M&T Bank Corporation	68,997
Wilmington Trust Corporation	11,168	Comerica Incorporated	59,753
Umb Financial Corporation	10,235	Marshall & Ilsley Corporation	58,664
Franklin Resources, Inc.	9,432	Zions Bancorporation	53,320
Trustmark Corporation	9,368	Huntington Bancshares Incorporated	52,511
Umpqua Holdings Corporation	9,210		
F.N.B. Corporation	8,596		
Newalliance Bancshares, Inc.	8,542		
United Community Banks, Inc.	8,444		
Investors Bancorp, Mhc	8,202		
United Bankshares, Inc.	8,083		
Old National Bancorp	7,974		
First Midwest Bancorp, Inc.	7,679		
First Financial Bancorp	7,260		
Hancock Holding Company	6,825		
Provident Financial Services, Inc.	6,816		
Cvb Financial Corp.	6,547		
First Commonwealth Financial Corporation	6,512		
Iberiabank Corporation	6,467		
Oriental Financial Group Inc.	6,381		
Boston Private Financial Holdings, Inc.	5,889		
Western Alliance Bancorporation	5,831		
Glacier Bancorp, Inc.	5,708		
Wesbanco, Inc.	5,566		
Nbt Bancorp Inc.	5,484		
Pacwest Bancorp	5,481		
Community Bank System, Inc.	5,378		
Texas Capital Bancshares, Inc.	5,321		
Central Pacific Financial Corp.	5,172		
Pinnacle Financial Partners, Inc.	5,098		
Westamerica Bancorporation	4,970		
Banner Corporation	4,788		
Independent Bank Corp.	4,434		
Chemical Financial Corporation	4,268		
S & T Bancorp, Inc.	4,208		
First Busey Corporation	3,974		
Columbia Banking System, Inc.	3,167		
Republic Bancorp, Inc.	3,037		
Stifel Financial Corp.	2,891		
Bank Of The Ozarks Inc	2,890		
City Holding Company	2,605		
First Community Bancshares, Inc.	2,298		
Seacoast Banking Corporation Of Florida	2,140		
Sterling Bancorp	2,136		

Table 2
This table shows estimates of average quarterly tail-risk for banks (panel A), non-financials (panel B), and technology firms (panel C). For banks and non-financials, the sample consists of 85 and 619 firms, respectively, for which active options markets exist between the period 2001-2017. Pre-Crisis refers to the period 2001-2007, Crisis to the period 2008-2009, and Post-Crisis to the period 2010-2017. For technology firms, the sample consists of 165 companies listed on NASDAQ and with active option markets in the period 1996-2005. For these firms Pre-Crisis, Crisis, and Post-Crisis represent the time periods 1996-1999, 2000-2002, and 2003-2005, respectively. For banks, Below 50B corresponds to firms with assets lower than $50 billion as of 2009Q3, and Above 50B is the group of firms with assets equal or greater than $50 billion. Non-financials with total assets in the top quartile as of 2009Q3 are classified as Large and all others as Small. Similarly, technology firms are classified as Large (top quartile) and Small based on their total assets as of 2000Q1.

(A) Banks					
	Pre-Crisis	Crisis	Post-Crisis	Post-Pre	% Change
All Banks	0.165	0.288	0.281	0.116***	69.9
Below 50B	0.203	0.255	0.333	0.131***	64.4
Above 50B	0.134	0.368	0.131	-0.003	-2.3
(B) Non-Financials					
	Pre-Crisis	Crisis	Post-Crisis	Post-Pre	% Change
All Non-Financials	0.138	0.177	0.155	0.017***	12.6
Small	0.145	0.181	0.164	0.020***	13.6
Large	0.121	0.166	0.129	0.008***	6.6
(C) Technology Firms					
	Pre-Crisis	Crisis	Post-Crisis	Post-Pre	% Change
All Tech Firms	0.072	0.142	0.145	0.073***	101.8
Small	0.066	0.133	0.152	0.087***	132.6
Large	0.085	0.166	0.124	0.039***	45.5

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3
This table presents size-based regulatory requirements for U.S. banks originated with the Dodd-Frank Act of 2010.

Size-Based Regulatory Requirements [a]		
$\$10B \leq Assets < \$50B$	$\$50B \leq Assets < \$250B$	$Assets \geq \$250B$[b]
Risk committee Firm-run stress tests	Risk committee Fed-run stress tests Periodic resolution plans Enhanced capital standards Stringent liquidity requirements Counterparty exposure limits **Special Provisions** Certifed reports to the FSOC Leverage ratio 15-to-1 limit Limitations on M&A Early remediation requirements	Risk committee Fed-run stress tests Periodic resolution plans Enhanced capital standards Stringent liquidity requirements Counterparty exposure limits **Special Provisions** Certifed reports to the FSOC Leverage ratio 15-to-1 limit Limitations on M&A Early remediation requirements **Advanced approach** Supplementary leverage ratios Capital surcharge Countercyclical capital buffer Total loss-absorbing capacity

[a] These size-based thresholds were modified in May 2018 under the Economic Growth, Regulatory Relief, and Consumer Protection Act.
[b] Dodd-Frank does not include a $250 billion threshold. This was adopted by the U.S. under the Basel III international agreement for financial regulation in July 2013.

Table 4
This table reports summary statistics for selected bank characteristics. The sample corresponds to an unbalanced panel of 85 bank holding companies observed quarterly over the period January 2001 - December 2017.

	Obs.	Average	Standard Deviation	Min	Median	Max
Tail-Risk	4173	0.253	0.266	-2.011	0.179	2.578
Return Volatility	4141	0.024	0.056	0.005	0.016	2.075
Beta	4055	1.298	0.821	-31.343	1.229	12.452
Systematic Risk	4055	0.014	0.013	-0.256	0.010	0.102
Unsystematic Risk	4055	0.018	0.055	0.004	0.012	2.074
Total Loans/Total Deposits	4173	0.899	0.299	0.064	0.911	3.737
Exposure to FIs	4173	0.021	0.058	0.000	0.001	0.454
Short-Term Wholesale/Total Liabilities	4173	0.224	0.152	0.000	0.187	0.919
Non-Performing-Loans/Total Loans	4173	0.019	0.023	0.000	0.011	0.203
Net Charge-Offs/Total Loans	4173	0.019	0.032	-0.008	0.007	0.358
Z-Score	4173	25.572	11.389	1.040	26.155	86.660
Tier1 Capital/Total Assets	4137	0.101	0.061	0.040	0.093	0.763
Tier1 Capital/RWA	4137	0.137	0.085	0.066	0.122	1.078
Total Capital/RWA	4137	0.157	0.081	0.086	0.142	1.079
RWA/Total Assets	4137	0.731	0.144	0.262	0.744	1.235
ROA	4173	0.025	0.050	-0.686	0.022	0.771
ROE	4173	0.196	0.458	-13.199	0.195	2.474
Net Interest Margin/Earning Assets	4173	0.084	0.048	-0.003	0.077	0.345
Options Volume	4173	4.030	19.608	0.000	0.027	469.805
Options Bid-Ask Spread	4173	0.987	1.198	-0.705	0.493	10.000
Total Assets (billions)	4173	159.448	423.409	1.499	17.546	2,609.785

Table 5
This table presents coefficient estimates for the specification model in Equation 2. Above 50B is a dummy variable which takes 1 for banks with assets equal or greater than \$50 billion as of 2009Q3, and 0 otherwise. Post-Crisis takes 1 for the period 2010-2017, and 0 otherwise. Column (2) includes a series of financial ratios as controls, Column (3) accounts for market estimates of systematic and unsystematic risk, and Column (4) controls for market characteristics of the put options used in the construction of tail-risk. An unbalanced panel of 85 banks observed quarterly over the period 2001-2017 is used. Regressions include year-quarter fixed effects to control for aggregate time trends that are common to all banks in the sample. Standard errors are clustered at the bank level to allow for error correlation within each panel.

DEPENDENT VARIABLE: Tail-Risk	(1)	(2)	(3)	(4)
Above 50B	-0.009	0.026	0.025	0.026
	(-0.565)	(0.909)	(0.834)	(0.842)
Above 50B × Post-Crisis	-0.192***	-0.185***	-0.183***	-0.189***
	(-8.633)	(-7.855)	(-7.477)	(-7.488)
Tier1 Capital/Total Assets		-0.211***	-0.223***	-0.231***
		(-3.437)	(-3.646)	(-3.541)
RWA/Total Assets		-0.000	-0.001	-0.004
		(-0.006)	(-0.019)	(-0.063)
ROE		0.019*	0.019*	0.019*
		(1.712)	(1.863)	(1.874)
Total Loans/Total Deposits		0.016	0.017	0.017
		(0.923)	(0.764)	(0.726)
Exposure to FIs		0.168	0.182	0.189
		(1.476)	(1.466)	(1.508)
Short-Term Wholesale/Total Liabilities		-0.069	-0.069	-0.073
		(-1.171)	(-1.123)	(-1.167)
Non-Performing Loans/Total Loans		-0.373	-0.263	-0.291
		(-0.793)	(-0.628)	(-0.684)
Z-Score		0.001	0.001	0.001
		(1.028)	(0.928)	(0.985)
Log(Assets)		-0.015*	-0.016*	-0.018*
		(-1.700)	(-1.854)	(-1.734)
Systematic Risk			1.699	1.671
			(1.440)	(1.370)
Unsystematic Risk			-0.359	-0.361
			(-1.352)	(-1.350)
Options Volume				0.000
				(0.112)
Options Bid-Ask Spread				-0.007
				(-0.734)
Constant	0.288***	0.421***	0.421***	0.447***
	(26.627)	(4.275)	(4.147)	(3.855)
Observations	4,173	4,105	4,105	4,105
Time fixed effects	Yes	Yes	Yes	Yes
Adj R-squared	0.168	0.184	0.184	0.184

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6

This table presents coefficient estimates for the specification model in Equation 2 with observations restricted to adjacent regulatory groups. Treatment group is a dummy which takes 1 for banks in the stricter regulatory group (larger banks) and 0 otherwise. Post-Crisis takes 1 for the period 2010-2017, and 0 otherwise. Column (1) shows estimates where the two regulatory groups analysed are "less than $10B" (the reference group) and "between $10B and $50B". Column (2) presents coefficients for regulatory groups "between $10B and $50B" (the reference group) and "between $50B and $250B", and Column (3) for groups "between $50B and $250B" (the reference group) and "more than $250B". Column (4) shows estimates for the same model in Column (3) but with the Post-Crisis dummy redefined to 1 for the period after 2013Q3 and 0 otherwise. All regressions include year-quarter fixed effects. Standard errors are clustered at the bank level.

DEPENDENT VARIABLE: Tail-Risk	(1)	(2)	(3)	(4)
Treatment Group	0.017	-0.043	-0.025	-0.012
	(0.432)	(-1.061)	(-1.399)	(-0.947)
Treatment Group × Post-Crisis	-0.049	-0.102***	0.025	-0.013
	(-1.078)	(-2.945)	(1.047)	(-0.948)
Tier1 Capital/Total Assets	-0.179***	-0.289	-0.215	-0.120
	(-2.656)	(-0.432)	(-0.704)	(-0.470)
RWA/Total Assets	0.017	0.083	0.018	0.028
	(0.185)	(1.022)	(0.607)	(0.832)
ROE	0.019	-0.035	0.015	0.010
	(1.613)	(-0.977)	(0.290)	(0.189)
Total Loans/Total Deposits	0.009	0.017	0.006	-0.001
	(0.231)	(0.389)	(0.588)	(-0.064)
Exposure to FIs	-0.184	0.368	0.068	0.072
	(-0.235)	(0.877)	(1.510)	(1.364)
Short-Term Wholesale/Total Liabilities	-0.110	-0.021	-0.028	-0.002
	(-1.378)	(-0.231)	(-1.237)	(-0.068)
Non-Performing Loans/Total Loans	-0.278	-0.726	0.341	0.522
	(-0.638)	(-1.294)	(0.965)	(1.421)
Z-Score	0.001	0.002	-0.000	-0.000
	(0.602)	(1.317)	(-0.927)	(-0.771)
Log(Assets)	-0.022	-0.004	0.016**	0.016**
	(-1.041)	(-0.209)	(2.422)	(2.374)
Systematic Risk	-0.783	2.673**	5.472***	5.343***
	(-0.796)	(2.115)	(4.560)	(4.520)
Unsystematic Risk	-0.476*	0.173	-0.440***	-0.426***
	(-1.896)	(1.451)	(-5.723)	(-5.340)
Options Volume	-0.049	0.013***	-0.001**	-0.001*
	(-1.495)	(3.937)	(-1.992)	(-1.932)
Options Bid-Ask Spread	-0.012	0.044***	-0.017	-0.017
	(-1.151)	(2.774)	(-1.593)	(-1.557)
Constant	0.553***	0.141	-0.086	-0.099
	(2.647)	(0.689)	(-1.032)	(-1.095)
Observations	2,749	1,954	1,356	1,356
Time fixed effects	Yes	Yes	Yes	Yes
Adj R-squared	0.132	0.274	0.701	0.700

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7
This table reports average cumulative abnormal returns (CAR) for a series of salient events related to the passage of Dodd-Frank. Below 50B corresponds to a sample of banks with assets lower than \$50 billion as of 2009Q3, whereas Above 50B is the group of banks with assets equal or greater than \$50 billion as of 2009Q3. For each date, a two-day event window $[-1, 0]$ is used with $t = 0$ as the date of interest. The estimation window corresponds to the 200 trading days spanning the time period $[-211, 11)$. The estimation also includes a 10 day trading gap between the estimation and event windows. For each bank, a market model is used to calculate daily expected returns. The reported test statistic corresponds to the one proposed by Kolari and Pynnönen (2010) which accounts for cross-sectional correlation and event-induced variance inflation.

Event	Date	Below 50B	Above 50B
Introduced in the House	2009-12-02	-0.002	-0.016
		(-0.47)	(-0.91)
Passed by the House	2009-12-11	-0.012	-0.014
		(-0.73)	(-0.89)
Introduced in the Senate	2010-04-15	0.013	-0.010
		(0.81)	(-0.64)
Passed by the Senate	2010-05-20	0.016	0.052**
		(1.31)	(2.06)
House agreed to conference report	2010-06-30	0.014	0.014*
		(1.10)	(1.66)
Senate aggreed to conference report	2010-07-15	-0.026**	-0.019
		(-2.33)	(-1.05)
Signed into law	2010-07-21	-0.035	-0.020
		(-1.46)	(-0.54)

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8
This table presents coefficient estimates for a cross-sectional regression in which the dependent variable is banks' cumulative abnormal returns (CAR) around the time the U.S. Senate passed the Dodd-Frank bill. Above 50B is a dummy variable which takes 1 for banks with assets equal or greater than $50 billion as of 2009Q3, and 0 otherwise. In Column (2), the explanatory variables correspond to bank characteristics observed over the quarter 2009Q4. All regressions include robust standard errors.

DEPENDENT VARIABLE: CAR	(1)	(2)
Above 50B	0.035***	0.032***
	(5.630)	(3.880)
Tier1 Capital/Total Assets		0.013
		(0.894)
RWA/Total Assets		-0.026
		(-0.814)
ROE		0.001
		(0.161)
Total Loans/Total Deposits		0.012
		(0.803)
Exposure to FIs		0.076*
		(1.685)
Short-Term Wholesale/Total Liabilities		-0.038*
		(-1.700)
Non-Performing Loans/Total Loans		-0.085
		(-0.805)
Z-Score		-0.000
		(-1.160)
Systematic Risk		1.141**
		(2.235)
Unsystematic Risk		-0.017
		(-0.050)
Constant	0.016***	0.027
	(6.002)	(1.329)
Observations	82	82
Adj R-squared	0.321	0.316

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9
This table presents coefficient estimates for the specification model in Equation 2 restricted to the sample period July-August 2011 and with the variable $Post\text{-}Crisis_t$ replaced by $Post\text{-}Downgrade_t$. The latter corresponds to a dummy variable which takes 1 for the period after the U.S. credit-rating was downgraded on August 5 2011, and 0 otherwise. The dependent variable corresponds to a five-day moving average of each bank's daily tail-risk. Above 50B is a dummy variable which takes 1 for banks with assets equal or greater than $50 billion as of 2009Q3, and 0 otherwise. Column (2) includes the variable *U.S. Treasury holdings* as a control which measures the proportion of U.S. Treasury securities held in relation to total assets. Column (3) accounts for other bank and market characteristics possibly correlated with tail-risk. Regressions include time fixed effects and standard errors are clustered at the bank level.

DEPENDENT VARIABLE: Tail-Risk	(1)	(2)	(3)
Above 50B	-0.152***	-0.150***	-0.064
	(-3.759)	(-3.711)	(-0.764)
Above 50B × Post-Downgrade	0.240***	0.240***	0.238***
	(4.666)	(4.667)	(4.623)
U.S Treasury Holdings		-1.227	-2.309**
		(-1.392)	(-2.213)
Tier1 Capital/Total Assets			0.087
			(0.240)
RWA/Total Assets			-0.265
			(-0.840)
ROE			0.075
			(1.074)
Total Loans/Total Deposits			-0.032
			(-0.223)
Exposure to FIs			-0.313
			(-0.874)
Short-Term Wholesale/Total Liabilities			0.107
			(0.378)
Non-Performing Loans/Total Loans			-0.124
			(-0.113)
Z-Score			0.007**
			(2.547)
Log(Assets)			-0.044
			(-1.335)
Systematic Risk			3.817
			(0.958)
Unsystematic Risk			-4.193**
			(-2.014)
Options Volume			0.001***
			(2.808)
Options Bid-Ask Spread			-0.025
			(-1.108)
Constant	0.282***	0.292***	0.692*
	(8.564)	(8.397)	(1.824)
Observations	3,193	3,193	3,193
Quarter fixed effects	Yes	Yes	Yes
Adj R-squared	0.0387	0.0423	0.123

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10

This table shows estimates for a series of difference-between-means tests contrasting below and above 50B banks across various dimensions of bank risk. Reported p-values show the probability of observing a greater absolute value (two-tailed) of the test statistic under the null hypothesis of equal means. Pre-crisis corresponds to the time period 2001-2007 and post-crisis to the period 2010-2017.

	Pre-Crisis		Post-Crisis			
	(1)	(2)	(3)	(4)	(5)	(6)
	Above 50B - Below 50B	p-value	Above 50B - Below 50B	p-value	Diff-in-Diff	p-value
(A) Market Risk						
Return Volatility	-0.001	0.014	-0.004	0.083	-0.003	0.566
Beta	-0.087	0.000	0.041	0.188	0.128	0.045
Systematic Risk	0.000	0.344	0.001	0.034	0.000	0.529
Unsystematic Risk	-0.002	0.000	-0.005	0.039	-0.003	0.536
(B) Business Risk						
Exposure to FIs	0.011	0.007	0.051	0.000	0.041	0.000
Short-Term Wholesale/Total Liabilities	0.030	0.001	0.102	0.000	0.072	0.000
Non-Performing Loans/Total Loans	0.002	0.000	0.002	0.018	-0.000	0.994
Z-Score	1.147	0.070	-2.484	0.000	-3.631	0.000
(C) Capital Adequacy						
Tier1 Capital/Total Assets	-0.041	0.000	-0.016	0.000	0.025	0.000
Tier1 Capital/RWA	-0.075	0.000	-0.020	0.000	0.055	0.000
Total Capital/RWA	-0.059	0.000	-0.008	0.000	0.051	0.000
RWA/Total Assets	0.104	0.000	0.002	0.719	-0.101	0.000

Table 11
This table shows coefficient estimates from regressing tail-risk on a series of market and business risk measures interacted with a post-crisis dummy, which takes 1 for observations in the time period 2010-2017, and 0 for the period 2001-2007. Columns (1) and (2) show estimates for below and above 50B banks, respectively. All specifications include bank fixed effects to account for unobserved time-invariant bank characteristics, and year-quarter fixed effects to control for aggregate time trends that are common to all banks in the sample. Standard errors are clustered at the bank level to allow for error correlation within each panel.

DEPENDENT VARIABLE: Tail-Risk	Below 50B	Above 50B
Systematic Risk	-2.705	4.829***
	(-0.799)	(2.900)
Post-Crisis × Systematic Risk	1.172	0.008
	(0.371)	(0.002)
Unsystematic Risk	-0.803	-0.841**
	(-0.658)	(-2.308)
Post-Crisis × Unsystematic Risk	0.762	0.465
	(0.612)	(0.983)
Exposure to FIs	0.588	-0.117
	(1.134)	(-0.954)
Post-Crisis × Exposure to FIs	2.306	-0.193
	(1.559)	(-0.756)
Short-Term Wholesale	-0.004	0.080
	(-0.025)	(1.601)
Post-Crisis × Short-Term Wholesale	-0.106	0.052
	(-0.366)	(0.642)
Non-Performing Loans	2.271	3.403**
	(0.774)	(2.268)
Post-Crisis × Non-Performing Loans	-2.842	-3.410**
	(-1.078)	(-2.121)
Z-Score	0.002	-0.002
	(0.453)	(-1.237)
Post-Crisis × Z-Score	0.004	0.005***
	(0.846)	(2.750)
Tier1 Capital/Total Assets	-0.789	0.175
	(-1.360)	(0.410)
ROE	0.082*	-0.055
	(1.936)	(-1.611)
Options Volume	-0.021	-0.000
	(-1.258)	(-0.857)
Options Bid-Ask Spread	-0.010	0.004
	(-0.318)	(0.571)
Constant	0.248***	0.030
	(3.099)	(0.899)
Observations	891	1050
Bank fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adj R-squared	0.0452	0.1584

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

A Appendix

The test statistic proposed by Kolari and Pynnönen (2010) has the following form:

$$t_{AR_g} = \frac{\overline{SAR}_g \sqrt{N_g}}{SD_g \sqrt{1 + (N_g - 1)\bar{\rho}_g}} \tag{5}$$

$\overline{SAR}_g$ is the average scaled abnormal return (SAR) for banks in group g on the event day. For each bank, scaled abnormal returns are calculated as $SAR_{i,t} = \frac{AR_{i,t}}{SD_i}$ where SD_i is bank's i sample standard deviation of abnormal returns over the estimation window. N_g corresponds to the number of banks in group g, and $\bar{\rho}_g$ is the average of the sample cross-correlations of scaled abnormal returns for banks in group g over the estimation window. That is:[43]

$$\bar{\rho}_g = \frac{1}{N_g(N_g - 1)/2} \sum_{i=2}^{N} \sum_{j=1}^{i-1} \mathbb{1}_{\{i:i \in g\}} \mathbb{1}_{\{j:j \in g\}} \frac{1}{T_1 - T_0} \sum_{t \in [T_0, T_1]} SAR_{i,t} SAR_{j,t} \tag{6}$$

Finally, SD_g corresponds to the adjusted cross-sectional sample standard deviation of scaled abnormal returns for banks in group g:

$$SD_g^2 = \frac{\frac{1}{N_g - 1} \sum_{i=1}^{N} \mathbb{1}_{\{i:i \in g\}} \left(SAR_i - \overline{SAR}_g\right)^2}{1 - \bar{\rho}_g} \tag{7}$$

For testing CARs, a robust test statistic is obtained by replacing the mean scaled abnormal return $\overline{SAR}_g$ with the mean scaled cumulative abnormal return ($SCAR$), and the standard deviation SD_g with the cross-sectional standard deviation of $SCAR$. Kolari and Pynnönen (2010) show their proposed test statistic outperforms other popular (parametric and non-parametric) tests, especially for longer CAR windows. For large estimation windows, this test statistic is approximately standard normal under the assumption of serially-independent jointly-normal abnormal returns, and an average (residual) cross-correlation $\bar{\rho}$ that goes to zero as the number of firms increases.

[43] $\mathbb{1}_{\{i:i \in g\}}$ is an the indicator function taking 1 for observations that are part of group g and zero otherwise.