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What Can Volatility Smiles Tell Us About the Too Big to Fail Problem?

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Abstract

We exploit the information content of option prices to construct a novel measure of bank tail risk. We document a persistent increase in tail risk for the U.S. banking industry following the global financial crisis, *except* for banks designated as systemically important by the Dodd–Frank Act. We show that this post-crisis difference in tail risk for large and small banks is consistent with the too-big-to-fail (TBTF) status of large banks being reinforced by the Dodd–Frank designation: Naming the banks whose failure could threaten the financial stability of the U.S. gave investors a list of banks the government deemed as TBTF.

I. Introduction

The Global Financial Crisis (GFC) of 2008–2009 brought the question of whether some financial institutions are too-big-to-fail (TBTF) to the forefront of the academic and policy debate. The billions of taxpayer dollars spent on bank bailouts during the GFC exacerbated the perception of a TBTF problem in the U.S. banking industry (e.g., Hett and Schmidt (2017)), leading to calls from different sectors of society to make banks accountable for their risk-taking behavior.[1] The U.S. 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 fulfill 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

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

U.S. economy and established a more stringent set of regulatory requirements for those banks above the $50 billion in assets threshold (above 50B banks).

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 in the post-crisis period, yet a definitive answer remains elusive (see Bongini, Nieri, and Pelagatti (2015), Moenninghoff, Ongena, and Wieandt (2015), Schäfer, Schnabel, and Weder di Mauro (2015), Acharya, Anginer, and Warburton (2016), and Sarin and Summers (2016)). Our article adds to this literature by exploiting the information content of option prices to offer a fresh insight into whether the TBTF problem for U.S. banks has declined in the post-crisis period. To do so, we use option prices to construct a forward-looking measure of bank tail risk and explore the evolution of tail risk for large banks identified as systemically important (i.e., above 50B banks) and smaller banks around the GFC.

For a given bank, we estimate this tail-risk measure using bank options with varying strike prices and their corresponding implied volatilities. Unlike in the idealized 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" of a given asset. 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) puts. 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, Kapadia, and Madan (2003)). Thus, steeper volatility smiles reflect a higher (investor-perceived) exposure to downside risk for the underlying stock. We 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]

This options-based measure of tail risk behaves in a predictable way following market crashes: It displays a sharp and persistent rise, a phenomenon Rubinstein (1994) dubbed "crash-o-phobia." That is, investor's update their expectations of future crash-like events upward following a market crash.

Similarly, we document a persistent increase in the average tail risk of the U.S. banking industry following the GFC, *except* for banks designated systemically important by Dodd–Frank. Specifically, we report a 64.4% increase in the average tail risk 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.

We 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.

[2]See Collin-Dufresne, Goldstein, and Martin (2001), Tang and Yan (2010), Yan (2011), and Hett and Schmidt (2017) for previous literature using similar slope measures to estimate perceived exposure to sudden drops in value. We discuss the advantages of this measure over other tail-risk measures such as Value-at-Risk (VaR), expected shortfall (ES), and Moody's KMV model in Section III.

A key empirical challenge to identifying the effects of implicit guarantees on bank tail risk is that the post-crisis period was characterized not only by raised investor expectations of future bailouts for above 50B banks but also tougher regulation for these larger institutions, both of which can result in relatively low tail risk for larger banks. To identify the effects of implicit guarantees on bank tail risk, we perform short-window tests around a salient event that altered the value of the implicit guarantee for large banks but did not change the regulatory treatment of large and small banks: the U.S. government credit rating downgrade. The idea here is that the value of implicit government guarantees depends on the government's financial circumstances (see Mäkinen, Sarno, and Zinna (2020)), thus a credit rating downgrade can influence investor perceptions regarding the government's cost of borrowing and capacity to provide assistance to large banks in distress.[3]

Therefore, we examine the tail risk of above and below 50B banks in the month before and after the U.S. downgrade and show that a deterioration in the U.S. government's creditworthiness leads to a three-fold increase in the average tail risk of above 50B banks, whereas below 50B banks show no significant change. These results thus provide the first evidence differences in the tail risk of large and small banks in the post-crisis period are driven by investor beliefs about the TBTF status of banks designated as systemically important under Dodd–Frank.

Dodd–Frank also defined other regulatory size thresholds around which regulatory demands differ substantially. Thus if the sized-based regulatory framework explains the lower tail risk for above 50B banks, then we should also observe significant shifts in tail risk around all regulatory thresholds. We examine whether tail risk varies significantly around the other salient regulatory size thresholds and find no evidence of significant shifts in tail risk. For example, we 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 the \$10B threshold – so much so that Bouwman, Hu, and Johnson (2018) document significant changes in bank operations around the threshold to avoid crossing over. These results are therefore inconsistent with the idea the tail-risk differences between above and below 50B banks are driven by differences in regulatory stringency: Tail risk drops significantly only at the \$50B threshold when banks are designated systemically important by the government.

Next, we 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 and regulation making large banks safer. 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. That is, consistent with Moenninghoff et al. (2015), the systemically important designation perversely reinforced the TBTF status for the above 50B group by reducing the ambiguity over which banks were deemed TBTF by the government.

Finally, we examine the actual post-crisis risk-taking behavior of below and above 50B banks and show that above 50B banks have become relatively riskier,

[3]In Section V.B, we discuss in detail the characteristics of this event which makes it a good candidate for identifying the effects of implicit guarantees on bank tail risk.

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.

Putting it all together, the evidence suggests that differential regulatory treatment of large versus small banks is not driving the difference in tail risk for these two groups of banks in the post-crisis period. Rather, the difference is due to the designation of above 50B banks as systemically important, which led investors to revise their expectations of bailout probabilities for designated banks. Therefore, we provide evidence that the size-based regulatory framework introduced by Dodd–Frank was unsuccessful in ending the TBTF problem. Revealing the identities of systemically important banks reinforced the presence of government guarantees for these banks, and stifled the attempt to eliminate the TBTF problem as was intended by Dodd–Frank.

Our article contributes to the recent debate examining the efficacy of new regulatory measures introduced in the aftermath of the GFC in ending (or reducing) the TBTF problem. That is, does the TBTF problem still exist in the post-crisis period?[4] This literature has produced decidedly mixed results and so the answer to this question depends on the particular study. For example, Moenninghoff et al. (2015), Acharya et al. (2016), and Sarin and Summers (2016) find evidence that TBTF remains a problem whereas studies like Bongini et al. (2015) and Schäfer et al. (2015) conclude the opposite.

Our article provides new insights to this debate by employing an options-based forward-looking measure of bank tail risk. Kelly et al. (2016) also use options markets to document the existence of government guarantees. Specifically, they document that OTM put options for the financial sector stock *index* were extraordinarily cheap relative to OTM put options on the individual banks that comprise the index *during* the 2007–2009 financial crisis. They argue that this divergence is due to the bailout guarantee that the entire banking sector received during the crisis. Our article differs in a few important ways. First, Kelly et al. (2016) do not examine the time series of the volatility smile per se which is the focus of our article. Second, the focus of our article is to compare tail risk for above and below 50B banks before and after the crisis, whereas their focus is to compare the cost of insurance for the entire banking sector versus the cost of insuring the individual banks that make up the index, during the crisis. Finally, the main take-away in their article is that investors priced in the likelihood of a government bailout for the entire financial system whereas our article shows that investors priced in the likelihood of future bailouts for above large banks designated as systemically important by Dodd–Frank.

Using options data to study bank tail risk has important advantages over much of the existing literature. For example, studies relying on the sensitivity of bond prices to bank risk (or lack thereof) to detect the existence of TBTF subsidies (e.g., Acharya et al. (2016)) face the problem that bond prices are informationally insensitive unless the underlying entity is close to failure. That is, because of the

[4]The TBTF problem has been widely studied, some papers addressing the TBTF problem more generally include O'Hara and Shaw (1990), Volz and Wedow (2011), Demirgüç-Kunt and Huizinga (2013), Ueda and Di Mauro (2013), and Kelly, Lustig, and Van Nieuwerburgh (2016).

"hockey-stick" payoff functional form for debt, it does not pay for debt holders to worry when debt is deep in the money (Dang, Gorton, and Holmström (2012), (2013)). This problem can be circumvented by looking at credit default swap (CDS) markets (e.g., Schäfer et al. (2015)). However, CDS contracts are usually only available to the largest institutions. Therefore many of the conclusions are based on how CDS spreads vary overtime for large banks. However, without a comparison group, strong conclusions are difficult to draw. A key innovation in our article is to investigate structural differences in tail risk around regulator-defined size bins, something that cannot be done using information from CDS markets.[5] Compared to credit markets (i.e., bond and credit default swap (CDS) markets), option markets are standardized and therefore much more transparent and liquid. Further, since options are exchange-traded they trade at lower transaction costs and do not face problems associated with counter-party risk.[6]

Similarly, studies exploiting the information content in equity prices (e.g., Bongini et al. (2015), Moenninghoff et al. (2015)) using *only* an event study methodology around certain key dates where legislative changes took place find it difficult to draw strong conclusions for two reasons. First, the results hinge crucially on the dates chosen for the analysis, but ex ante it is difficult to know which of the multiple dates in the process of legislative action (e.g., introduction, amendments, signing into law) is the appropriate date to use. Second, and more important, examining equity returns is problematic as variation in returns can come from either changes in cash flow expectations or discount rate expectations, which confounds the interpretation. For example, Bongini et al. (2015) report negative abnormal returns upon the publication of the first list of systemically important financial institutions (SIFIs) by the Financial Stability Board (FSB). While this result may be driven by banks becoming riskier (because of the removal of the safety net) it may well also be the result of higher expected compliance costs. The latter tells us little about the existence of the TBTF problem. Our approach allows us to estimate investor perceptions of the TBTF problem directly.

II. Background and Argument

The financial crisis of 2007–2009 revealed two important facts: It exposed fundamental weaknesses of the U.S. banking industry, and it affirmed the U.S. government's commitment to rescue large financial institutions in distress. For instance, of the $439 billion disbursed under the Troubled Asset Relief Program (TARP), $204.9 billion was committed to direct capital injections between Oct. 2008 and Dec. 2009.[7] Of this, 81.9% ($167.9 billion) was invested in the group of banks with assets exceeding $50 billion banks – those that will later be designated as

[5]Only 17 of the 85 banks in our sample had CDS contracts available in 2010.

[6]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)).

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

systemically important – and only 4.8% ($9.9 billion) in banks with assets less than $50 billion banks.[8] The government's commitment to rescue large banks went beyond the TARP funding. Of the 20 listed banks allowed to fail since the crisis, 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))

The regulatory response to the financial crisis lead to the introduction of the Dodd–Frank Act in the U.S. House of Representatives in Dec. 2009 which was subsequently enacted into law in July 2010. At its core, Dodd–Frank was designed to end the TBTF problem, and to protect taxpayers by eliminating bailouts. To achieve this, Dodd–Frank 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.[9]

In addition, 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.[10] Banks with more than $50 billion in assets were thus subjected to enhanced supervisory standards such as stringent liquidity requirements, periodic resolution plans, and concentration limits. Table 1 presents a summary of the different size-based regulatory requirements for U.S. banks under Dodd–Frank.[11]

Our 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 above 50B financial institutions. Since bailout expectations are reflected in asset prices (see Gandhi and Lustig (2015), Kelly et al. (2016) we argue that, though well-intentioned, the designation of certain institutions as systemically important effectively gave investors a list of banks the government deemed TBTF. This raised

[8]See the U.S. Department of The Treasury website (https://home.treasury.gov/) for the full list.

[9]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).

[10]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 …"

[11]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.

TABLE 1
Size-Based Regulation

Table 1 presents size-based regulatory requirements for U.S. banks originated with the Dodd–Frank Act of 2010. [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.

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

investor expectations of future bailouts for above 50B banks and, in turn, lowered expectations of large stock price declines (i.e., downside tail risk) relative to smaller banks, in the post-crisis period. Thus, we predict a significant decrease in the tail risk for banks around the 50B designation threshold in the post-crisis period. We refer to this as the “designation and implicit guarantee” hypothesis.

That said, it is evident from Table 1 that Dodd–Frank established a direct relationship between bank size and regulation stringency. After all, the main objective of Dodd–Frank was to address the deficiencies in financial stability of large banks and put an end to the TBTF problem. Therefore, it is possible that the relatively lower tail-risk levels for above 50B banks in the post-crisis period we predict is a reflection of the more stringent regulatory requirements imposed on larger banks. We refer to this alternative explanation as the “effective regulation” hypothesis.

In the remainder of this article, we conduct a series of tests to differentiate between these two competing hypotheses. Overall, we show that the evidence favors the designation and implicit guarantee hypothesis.

III. Data and Measurement

In this section, we discuss our data sources and the construction of our main variables of interest. We argue that the designation of above 50B banks as being systemically important reinforced investors’ expectations of the TBTF status for this group and therefore lowered investors’ expectations of large price declines or downside tail risk.

We propose using information from the options market to construct a forward-looking measure of tail risk. For put options, implied volatilities from the BSM model are typically high for OTM options and low for ITM options, a phenomenon known as the "volatility smile." Bakshi et al. (2003) show that the more negatively skewed the risk-neutral-density (RND) of a given equity asset, the steeper 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 exposure to downside risk for the underlying asset, as perceived by investors. We exploit this fact to 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).[12]

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 by actively trading on those expectations in the options markets. Thus, this tail-risk measure not only reflects actual risk exposures, but it also incorporates any other factor, such as implicit government guarantees, that may alter investors' beliefs about a stock's exposure to downside risk.

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.

To construct this tail-risk measure, we collect daily implied volatility data from OptionMetrics for all U.S. bank holding companies for which an active options market exists as of Sept. 2009.[13] Precisely, a bank is included in our sample if for each trading day there is at least one OTM put option contract traded. This results in a sample of 85 banks, of which 62 correspond to banks with assets less than $50 billion (below 50B) and 23 to banks with assets equal to or greater than $50 billion (above 50B). On any given trading day, the mean (median) number of OTM contracts traded for below- and above-50B banks are 3 (2) and 16 (6), respectively. Table 2 shows the full list of banks included.

As most traded options are American style, we rely on OptionMetrics' computation of implied volatilities which is based on the Cox, Ross, and Rubinstein (1979) algorithm. OptionMetrics then estimates an implied "volatility surface" by employing a kernel smoothing technique.[14] This "volatility surface" comprises of fitted implied volatilities on a grid of option deltas (and maturities) which we then

[12]Refer to Appendix A of the Supplementary Material for technical details on the relationship between volatility smiles and tail risk.

[13]We chose this date because it represents the quarter before the Dodd–Frank bill was introduced in the U.S. House of Representatives in Dec. 2009.

[14]Details on this estimation process are provided by OptionMetrics in their data manual.

TABLE 2

List of Bank Holding Companies

Table 2 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 to 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		

use to compute the volatility smile of each bank stock in our sample as well as our measure for bank tail risk.[15]

For each trading day, we measure the steepness of each bank's implied volatility curve as the sum of differences between the implied volatility of OTM puts with varying deltas and the implied volatility of an at-the-money (ATM) put option.[16] The relevant OTM put option deltas range from −0.45 to −0.20 and we employ 1-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.

$$\text{TAIL\_RISK}_{i,t} = \sum_{\delta \in \Delta} (\sigma_{i,\delta,t} - \sigma_{i,-0.5,t}), \tag{1}$$

where $\sigma_{\delta,i,t}$ represents the implied volatility for bank i, for a put option with delta δ, on trading day t, and $\Delta := \{-0.45, -0.40, \ldots, -0.20\}$ 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.[17]

We construct a series of bank characteristics using quarterly accounting data from the Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) filed with the Federal Reserve. We construct three measures of bank profitability namely, i) RETURN_ON_ASSETS, defined as the ratio of net income to total assets; ii) RETURN_ON_EQUITY, defined as the ratio of net income to total equity capital; and iii) NET_INTEREST_MARGIN, defined as the ratio of net interest margin to total assets.

Next, we construct proxies for the business risk of banks, including i) LOAN_TO_DEPOSITS ratio, defined as the ratio of total loans to total deposits; ii) EXPOSURE_TO_FINANCIAL_INSTITUTIONS, defined as the dollar value of funds lent to other depository institutions scaled by total assets; iii) SHORT_TERM_WHOLESALE_FUNDING, measured as the total amount of wholesale funding scaled by total liabilities; iv) NON_PERFORMING_LOANS, calculated as the dollar value of 90 days past due loans over total loans; v) NET_CHARGE_OFFS, defined as the value of net charge-offs to total assets; vi) Z_SCORE, an

[15] A similar methodology is used by Yan (2011).

[16] 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 normalizes the implied volatilities across strike prices and expirations (Derman and Miller (2016)).

[17] In the literature, the "slope" of the volatility smile is measured by taking the implied volatility of an OTM put option and subtracting the implied volatility of an ATM one. Our measure follows the same approach save that, in addition, we add the differences between the implied volatility of *all* OTM put options and the corresponding implied volatility of the ATM put. We do this to account for differences in convexity across smiles. Thus, the traditional slope measure is a special case of our measure. In cases when there is only a single OTM option contract traded then our measure is synonymous with the traditional slope measure.

estimate of bank insolvency risk, which we calculate following Lepetit and Strobel (2013); and vii) BANK_SIZE, measured as the natural logarithm of total assets.

We construct four alternative measures to capture capital adequacy, namely i) LEVERAGE_RATIO, defined as the ratio of tier 1 capital to total assets; ii) RISK_WEIGHTED_ASSETS scaled by total assets; iii) TIER_1_RATIO, defined as the ratio of Tier 1 capital to risk-weighted assets; and iv) CAPITAL_ADEQUACY_RATIO, defined as the ratio of total capital to risk-weighted assets.

Finally, we estimate four measures of market risk: i) TOTAL_RETURN_VOLATILITY which is the return volatility calculated over the observed quarter using daily data; ii) BETA (i.e., quantity of market risk), is calculated each quarter by fitting a linear regression model of daily bank returns on market portfolio returns[18]; iii) SYSTEMATIC_RISK; and iv) UNSYSTEMATIC_RISK. These are obtained by decomposing total return variance into systematic variance and unsystematic variance. Systematic risk (systematic variance) is then defined as $\beta\sigma_{\text{market}}$ ($\beta^2\sigma^2_{\text{market}}$), where β represents bank return sensitivity to changes in the market portfolio returns, and σ_{market} the market return volatility.

Table 3 shows summary statistics for these bank and market characteristics for a sample of 85 bank holding companies (23 above 50B banks and 62 below 50B banks) observed quarterly over the period of Jan. 2001 to Dec. 2017, presented separately for above and below 50B banks.

Average bank tail risk is positive, with a mean (median) of 0.158 (0.125) for large banks and 0.298 (0.229) for small banks, implying a downward-sloping volatility smile. Tail risk is highly volatile with a standard deviation of 0.142 for large banks and 0.298 for small banks.

The mean large (small) bank has assets totaling \$459.1 billion (\$15.2 billion) with a considerably large standard deviation of \$646.6 billion (\$18.9 billion), indicating significant heterogeneity across bank size. The average large bank obtains roughly 28% of its funding from short-term wholesale markets, compared to 20% for small banks. Large banks are slightly less profitable recording a return on assets of 2.4% compared to 2.6% for small banks. Finally, large banks have a capital adequacy ratio (Total Capital/RWA) of 14.1% compared to 16.5% for small banks.

IV. What Do Volatility Smiles Measure?

A. Bailouts and Bailout Expectations

Recent literature has shown that bank bailouts raised expectations of future bailouts during the financial crisis (e.g., Hett and Schmidt (2017)). To bolster the case for inferring bailout expectations from options prices, we explore the behavior of the tail-risk measure described in Section III around one of the largest bailouts in U.S. history – the rescue of American International Group (AIG).[19]

[18]Daily bank return data for the construction of these risk estimates are from the Center for Research in Security Prices (CRSP). Daily market returns are obtained from Keneth R. French's which comprise a portfolio of all NYSE, AMEX, and NASDAQ firms. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

[19]On Sept. 16, 2008, the Fed rescued AIG with a \$85 billion 2-year emergency loan. In exchange, the U.S. government effectively got a 79.9% equity stake in the company (Karnitschnig, Solomon, Pleven,

TABLE 3

Summary Statistics

Table 3 reports summary statistics for selected bank and market characteristics. The sample corresponds to an unbalanced panel of 85 bank holding companies observed quarterly over the period of Jan. 2001 to Dec. 2017.

	No. of Obs.	Average	Std. Dev.	Min	Median	Max
			ABOVE_50B			
TAIL_RISK	1,356	0.158	0.142	−1.487	0.125	1.299
RETURN_VOLATILITY	1,356	0.021	0.035	0.005	0.015	1.105
BETA	1,356	1.289	0.609	0.248	1.197	12.452
SYSTEMATIC_RISK	1,356	0.014	0.014	0.002	0.010	0.102
UNSYSTEMATIC_RISK	1,356	0.015	0.032	0.004	0.011	1.100
LOAN_TO_DEPOSITS	1,356	0.905	0.363	0.064	0.926	2.774
EXPOSURE_TO_ FINANCIAL_INSTITUTIONS	1,356	0.048	0.086	0.000	0.007	0.428
SHORT_TERM_ WHOLESALE_FUNDING	1,356	0.280	0.181	0.039	0.221	0.903
NON_PERFORMING_LOANS	1,356	0.019	0.017	0.000	0.014	0.080
NET_CHARGE_OFFS	1,356	0.023	0.031	−0.006	0.011	0.278
Z_SCORE	1,356	23.841	7.381	5.708	24.111	43.025
LEVERAGE_RATIO	1,356	0.085	0.019	0.040	0.084	0.179
TIER_1_RATIO	1,356	0.111	0.026	0.066	0.111	0.205
CAPITAL_ADEQUACY_RATIO	1,356	0.141	0.022	0.101	0.140	0.230
RISK_WEIGHTED_ASSETS	1,356	0.759	0.176	0.262	0.798	1.223
RETURN_ON_ASSETS	1,356	0.024	0.026	−0.236	0.023	0.149
RETURN_ON_EQUITY	1,356	0.241	0.256	−2.298	0.220	1.138
NET_INTEREST_MARGIN	1,356	0.076	0.049	−0.003	0.068	0.301
OPTIONS_VOLUME	1,356	12.227	32.925	0.002	1.528	469.805
OPTIONS_BID_ASK_SPREAD	1,356	0.382	0.327	0.018	0.258	2.236
TOTAL_ASSETS (millions)	1,356	459,135	646,602	23,487	150,599.453	2,609,785
BANK_SIZE	1,356	12.224	1.229	10.064	11.922	14.775
			BELOW_50B			
TAIL_RISK	2,817	0.298	0.298	−2.011	0.229	2.578
RETURN_VOLATILITY	2,785	0.025	0.064	0.005	0.016	2.075
BETA	2,785	1.297	0.901	−31.343	1.240	10.930
SYSTEMATIC_RISK	2,785	0.013	0.013	−0.256	0.010	0.083
UNSYSTEMATIC_RISK	2,785	0.019	0.063	0.005	0.012	2.074
LOAN_TO_DEPOSITS	2,817	0.896	0.263	0.121	0.905	3.737
EXPOSURE_TO_ FINANCIAL_INSTITUTIONS	2,817	0.009	0.031	0.000	0.000	0.454
SHORT_TERM_ WHOLESALE_FUNDING	2,817	0.196	0.128	0.000	0.170	0.919
NON_PERFORMING_LOANS	2,817	0.019	0.025	0.000	0.010	0.203
NET_CHARGE_OFFS	2,817	0.017	0.033	−0.008	0.006	0.358
Z_SCORE	2,817	26.405	12.799	1.040	27.387	86.660
LEVERAGE_RATIO	2,781	0.109	0.072	0.044	0.096	0.763
TIER_1_RATIO	2,781	0.149	0.099	0.067	0.128	1.078
CAPITAL_ADEQUACY_RATIO	2,781	0.165	0.096	0.086	0.144	1.079
RISK_WEIGHTED_ASSETS	2,781	0.717	0.122	0.263	0.730	1.235
RETURN_ON_ASSETS	2,817	0.026	0.058	−0.686	0.021	0.771
RETURN_ON_EQUITY	2,817	0.175	0.528	−13.199	0.185	2.474
NET_INTEREST_MARGIN	2,817	0.088	0.047	0.000	0.083	0.345
OPTIONS_VOLUME	2,817	0.085	0.298	0.000	0.006	5.918
OPTIONS_BID_ASK_SPREAD	2,817	1.278	1.347	−0.705	0.650	10.000
TOTAL_ASSETS (millions)	2,817	15,189.	18,920	1,499	9,896	248,320
BANK_SIZE	2,817	9.284	0.769	7.313	9.200	12.422

To examine the effect of the bailout on AIG's perceived exposure to downside risk, we estimate 5-day tail-risk averages around the time of the rescue plan. For comparison purposes, we also estimate tail-risk averages for two qualitatively similar insurance companies, namely MetLife and Prudential Financial.[20]

and Hilsenrath (2008)). The total aid package to AIG was $184.6 billion, which meant a 92% equity stake for the U.S. government (Scism (2014)).

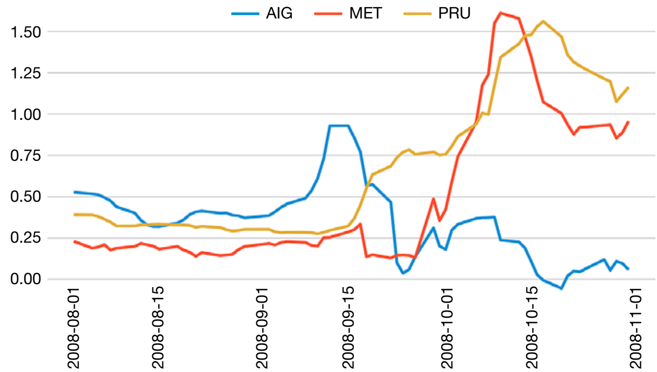
[20]All these firms had total assets exceeding $400 billion as of 2007:Q4.

FIGURE 1

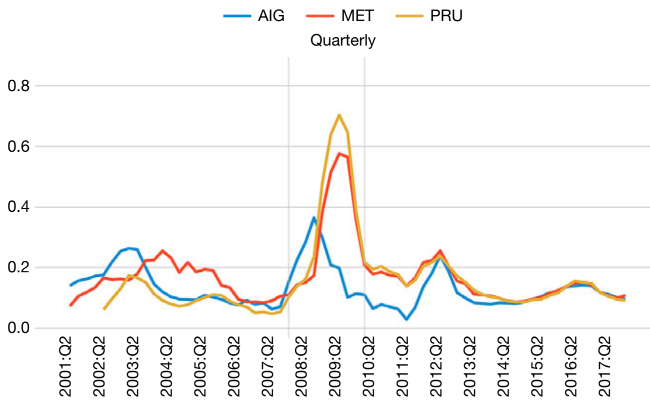
Tail Risk for Insurance Firms

Figure 1 shows tail-risk averages for the insurance firms AIG, MetLife, and Prudential Financial. Graph A shows 5-day tail-risk averages between July and Nov. 2008: around the time of the U.S. bailout of AIG. Graph B shows quarterly averages between 2001 and 2017.

Graph A. 5-Day Tail Risk



Graph B. Extended Quarterly Tail Risk



Graph A of Figure 1 shows 5-day averages for the tail risk of these firms between Aug. and Nov. 2008. For AIG, its average tail risk experienced a sharp decline (93%) in the month immediately after its bailout on Sept. 16. For the other 2 insurers, however, tail risk surges by 262% (MetLife) and 378% (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.[21] We argue that the 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 behavior of AIG. In Graph B, we extend the time horizon and show that, following a sharp rise during the crisis, the tail risk for MetLife and Prudential Financial remained persistently higher than

[21]AIG net loss for 2008 was $99.3 billion.

that of AIG in the post-crisis period until these 2 institutions were themselves designated as systemically important by the Financial Stability Oversight Council (FSOC).[22]

B. Tail Risk Around Crises and Case of Systemically Important Banks

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. 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 Appendix B of the Supplementary Material, we 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 (for both nonfinancial firms as well as the banking industry as a whole). Thus, investors consistently adjust their expectations of future crash events upward following crises.

However, Table B1 in the Supplementary Material also shows that 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 at least $50 billion in assets).

Although the 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. For above 50B banks, designated as systemically important, tail risk peaks during the crisis and then reverts (almost exactly) back to pre-crisis levels in the post-crisis period. In the remainder of this article, we show that this pattern is consistent with the "designation and implicit guarantee" hypothesis.

V. Empirical Strategy and Results

A. Baseline Results

We start by validating the stylized facts presented in Section IV in a difference-in-differences (DiD) regression framework that also accounts for other covariates likely correlated with bank tail risk. Our DiD design is aimed at identifying the effect of being designated as systemically important (above $50B in assets) relative to a control group of smaller banks (below $50B in assets). Though $50B is an arbitrary number there may be a concern that Congress chose the $50B threshold based on its expectations about future tail risk for banks above $50B in assets. We argue that this is unlikely given the lengthy deliberations in Congress over what constituted systemically important as well as the numerous amendments made to the bill in response to the heavy lobbying by the banks (Wilmarth (2012)). Even after the enactment of Dodd–Frank, the debate in Congress continued as to whether the $50B threshold was "correct" (Labonte and Perkins (2017)).[23]

[22]Graph B of Figure 1 plots quarterly tail-risk averages.

[23]We discuss additional threats to identification in Section V.F.3.

Specifically, we employ a DiD model of the form:

$$\text{(2)}\qquad \begin{aligned} \text{TAIL\_RISK}_{i,t} = {} & \alpha_1 \text{POST\_CRISIS}_t + \alpha_2 \text{ABOVE\_50B}_i \\ & + \alpha_3 \text{POST\_CRISIS}_t \times \text{ABOVE\_50B}_i \\ & + \sum_{k=1}^{n} \beta_k X_{i,k,t} + T_t + \varepsilon_{i,t}, \end{aligned}$$

where $\text{TAIL\_RISK}_{i,t}$ is the average tail risk of bank i for period t. POST_CRISIS_t is a dummy variable which takes the value of 1 for the post-crisis period 2010–2017 (after the introduction of the Dodd–Frank bill in the U.S Congress), and 0 otherwise. Similarly, ABOVE_50B_i is a dummy variable which takes 1 for banks with assets equal to or greater than $50 billion as of 2009Q3, and 0 otherwise.

The explanatory variable of interest in equation (2) is the interaction term $\text{POST\_CRISIS}_t \times \text{ABOVE\_50B}_i$. The coefficient on α_3 corresponds to the average post-crisis change 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 $X_{i,k,t}$. Pena, Rubio, and Serna (1999) study the determinants of the volatility smile and conclude that transaction costs (proxied by the options market bid–ask spread) as well as aggregate factors such as uncertainty associated with the market and relative market momentum (3-month market index average relative to the current index level) are a key determinant of the smile. We therefore control for OPTIONS_BID_ASK_SPREAD as well as OPTIONS_VOLUME to account for transactions costs (available from OptionMetrics). To control for *all* aggregate factors that are correlated with the smile, our specification also includes time (i.e., year-quarter) fixed effects. Additionally, we also control for a host of bank characteristics possibly correlated with tail risk.[24] Standard errors are clustered at the bank level to allow for error correlation within each bank.

Table 4 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.[25] 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 5 times larger in the post-crisis period compared to pre-crisis.

These findings corroborate the stylized facts documented in Section IV. In the post-crisis period, markets perceive above 50B banks as significantly less

[24]Specifically, at the bank level, we control for TIER_1_RATIO; RISK_WEIGHTED_ASSETS; RETURN_ON_EQUITY; LOAN_TO_DEPOSITS; EXPOSURE_TO_FINANCIAL_INSTITUTIONS; SHORT_TERM_WHOLESALE_FUNDING; NON_PERFORMING_LOANS; BANK_SIZE; Z_SCORE; SYSTEMATIC_RISK; UNSYSTEMATIC_RISK. The construction of these variables is discussed in Section III.

[25]POST_CRISIS dummy coefficients are omitted due to the use of time-fixed effects.

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TABLE 4

Baseline Model

Table 4 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 of 2010 to 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 the tail-risk measure. An unbalanced panel of 85 banks observed quarterly over the period of 2001 to 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. Robust *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	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)
TIER_1_RATIO		−0.211***	−0.223***	−0.231***
		(−3.437)	(−3.646)	(−3.541)
RISK_WEIGHTED_ASSETS		−0.000	−0.001	−0.004
		(−0.006)	(−0.019)	(−0.063)
RETURN_ON_EQUITY		0.019*	0.019*	0.019*
		(1.712)	(1.863)	(1.874)
LOAN_TO_DEPOSITS		0.016	0.017	0.017
		(0.923)	(0.764)	(0.726)
EXPOSURE_TO_FINANCIAL_INSTITUTIONS		0.168	0.182	0.189
		(1.476)	(1.466)	(1.508)
SHORT_TERM_WHOLESALE_FUNDING		−0.069	−0.069	−0.073
		(−1.171)	(−1.123)	(−1.167)
NON_PERFORMING_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)
BANK_SIZE		−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)
No. of obs.	4,173	4,105	4,105	4,105
Time-fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.168	0.184	0.184	0.184

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 a proportion of total assets, are associated with lower tail-risk exposures (i.e., lower exposure to significant price drops). Specifically, a 1-standard-deviation increase in a bank's leverage ratio is associated with a 6% reduction (relative to the mean) in tail risk.

B. Identification Using the U.S. Government Credit Rating Downgrade

We have presented evidence that in the post-crisis period the tail risk of above 50B banks is significantly lower than that of smaller banks. Our interpretation is that this difference is driven by the designation of above 50B banks as systemically important. However, as discussed in Section II, this pattern may also be attributed to the sized-based regulatory framework introduced under the Dodd–Frank Act. To identify the "designation and implicit guarantee" hypothesis from the alternative "effective regulation" hypothesis this section performs short-window tests around a salient event that altered the value of the implicit guarantee for large banks but did not change the regulatory treatment of large and small banks: the U.S. government 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 (Makinen et al. (2020)). Hence, changes to the government's creditworthiness and fiscal position can also affect the extent to which systemically important banks are perceived as more or less exposed to tail risk.

Accordingly, we exploit S&P's decision to downgrade the U.S. government's long-term debt (from AAA to AA+) on Aug. 5, 2011, as a shock to the government's creditworthiness. This unprecedented and unexpected change caused stocks in the U.S. and global markets to tumble, recording the largest declines in the 3 years since the collapse of Lehman Brothers in 2008.[26]

We examine the effect of this downgrade on the tail risk of systemically important (above 50B) and smaller banks (below 50B). Under the designation and 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 fulfill 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 have little effect on tail risk.

We employ equation (1) to construct daily tail-risk estimates for both systemically important and nonsystemically important banks over the period of July and Aug. 2011. That is, approximately 1 month before and after the U.S. credit-rating downgrade.

Figure 2 plots 5-day moving averages for the tail risk of systemically important banks and nonsystemically important banks around the date of the downgrade. This figure shows that the average tail risk of systemically important banks experiences a threefold increase following the downgrade, relative to the average tail risk in the previous month.[27] On the contrary, the average tail risk of nonsystemically important banks remains relatively constant between July and Aug. 2011.

These findings are consistent with the designation and implicit guarantee hypothesis. A deterioration in the U.S. government's creditworthiness leads to a

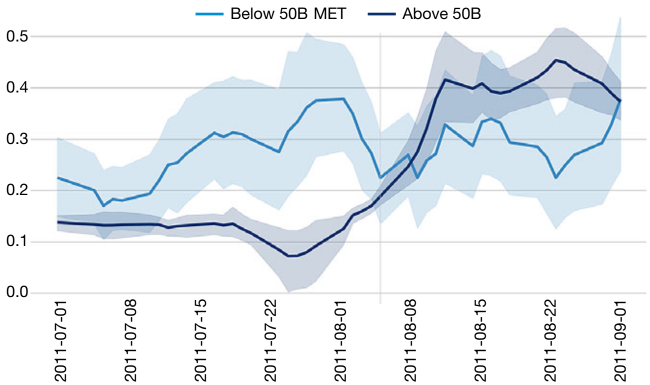
[26]Ngo and Stanfield (2022) note that the downgrade was justified over concerns around the fiscal position of the U.S. and its political posture on increasing the debt ceiling and provide a detailed account of the surprising elements associated with the downgrade event.

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

FIGURE 2

Tail Risk Around the U.S. Credit-Rating Downgrade

Figure 2 shows 5-day moving averages for the tail risk of systemically important banks (ABOVE_50B) and nonsystemically important banks (BELOW_50B) before and after S&P downgraded the credit rating of the U.S. government on Aug. 5, 2011.



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 not designated as systematically important, and therefore not subject to implicit guarantees, the downgrade does not affect the probability investors assign to future price drops.

It is possible that the above differential behavior around the downgrade is influenced by differences in the holdings of U.S. debt between systemically and nonsystemically 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, we estimate relative changes in tail risk around the credit-rating downgrade in a regression setting where we control for each bank's U.S. debt securities holdings.

Specifically, we use the specification model in equation (2) restricted to the sample period of July to Aug. 2011 and with the variable POST_CRISIS_t replaced by POST_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 is the 5-day moving average of each bank's daily tail risk, and we add the variable US_TREASURY_HOLDINGS as an additional control. For each bank, this covariate measures the proportion of U.S. Treasury securities held in relation to total assets.[28] The specification also includes 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.

[28]Bank characteristics are estimated using the Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) filed with the Federal Reserve as of 2011Q.

TABLE 5

U.S. Credit-Rating Downgrade

Table 5 presents coefficient estimates for the specification model in equation (2) restricted to the sample period of July to Aug. 2011 and with the variable POST_CRISIS replaced by POST_DOWNGRADE. The latter corresponds to a dummy variable which takes 1 for the period after the U.S. credit rating was downgraded on Aug. 5, 2011, and 0 otherwise. The dependent variable corresponds to a 5-day moving average of each bank's daily tail risk. Above 50B is a dummy variable which takes 1 for banks with assets equal to or greater than $50 billion as of 2009Q3, and 0 otherwise. Column 2 includes the variable US_TREASURY_HOLDINGS as a control, which measures the proportion of U.S. Treasury securities held in relation to total assets. In addition, column 3 controls for all other bank and market characteristics in column 4 in Table 4. Regressions include time-fixed effects and standard errors are clustered at the bank level. Robust *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: TAIL_RISK		
	1	2	3
ABOVE_50B	−0.152***	−0.150***	−0.064
	(−3.759)	(−3.712)	(−0.762)
ABOVE_50B × POST_DOWNGRADE	0.240***	0.239***	0.237***
	(4.666)	(4.721)	(4.678)
US_TREASURY_HOLDINGS		−1.394	−2.460*
		(−1.099)	(−1.958)
US_TREASURY_HOLDINGS × POST_DOWNGRADE		0.377	0.343
		(0.249)	(0.226)
No. of obs.	3,193	3,193	3,193
Controls	No	No	Yes
Quarter-fixed effects	Yes	Yes	Yes
Adj. R^2	0.0387	0.0421	0.123

Table 5 presents coefficient 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 are 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 important banks after the U.S. downgrade. In an additional specification (not reported), we add a triple interaction term between the variables LOW_US_TREASURY_HOLDINGS, ABOVE_50B, and POST_DOWNGRADE, where LOW_US_TREASURY_HOLDINGS takes one for banks which, before the downgrade, had below median holdings of U.S. debt. The purpose of this test was to rule out the possibility of moral suasion, that is, the possibility that large banks with low U.S. debt holdings were being influenced to increase their U.S. debt holdings after the downgrade, and that this explained the increase in bank tail risk (Ongena, Popov, and Van Horen (2019)). The coefficient on this triple-interaction term is not statistically different from zero.

In summary, we show the tail risk of TBTF banks rises sharply in response to a downgrade in the governments' credit rating. Whereas for smaller banks, the impact of the U.S. downgrade is negligible. Since there was no regulatory change that impacted large and small banks differently during this 2 month window, these findings provide evidence in support of the designation and implicit guarantee hypothesis as the main driver of the cross-sectional differences in tail risk between above and below 50B banks observed in the post-crisis period. The remainder of our article provides additional corroborating evidence to reinforce this interpretation.

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C. Other Salient Regulatory Thresholds

The post-crisis regulatory framework in the U.S. contains a series of bank-size thresholds with increasing regulatory stringency as banks move 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 1 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.

We exploit the monotonic relationship between bank size and regulatory stringency to show that the lower tail risk for above 50B banks in the post-crisis period is inconsistent with the effective regulation hypothesis. If lower tail risk for above 50B banks is driven by tighter regulatory standards, then one should also observe lower tail risk for i) banks between $10B and $50B (Group 2) relative to banks below $10B (Group 1); ii) banks between $50B and $250B (Group 3) relative to banks between $10B and $50B (Group 2); and iii) banks above $250B (Group 4) relative to banks between $50B and $250B (Group 3). Indeed, Bouwman et al. (2018) show that the additional regulatory burden imposed on larger banks is enough to alter the behavior of banks near the salient regulatory thresholds.

To test this, we classify banks into one of the four size-based regulatory groups and then, using the DiD model outlined in equation (2), we explore tail-risk differences between adjacent regulatory groups (two at a time). If stricter regulation does in fact reduce bank tail risk, we 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 is inconsistent with the idea that a stricter regulatory regime for larger banks is what explains the post-crisis tail-risk differences between above and below 50B banks documented above.

In contrast, the designation and implicit guarantee hypothesis predicts that only as banks cross over the 50B threshold, and are explicitly designated by Dodd–Frank as institutions whose failure could threaten the financial stability of the U.S. economy, will there be a significant drop in tail risk. That is, when we compare the tail risk of Group 3 with Group 2. In contrast, comparing Group 2 with Group 1 should not produce significant differences in tail risk because neither group of banks are deemed systemically important. Further, 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.

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TABLE 6

Other Salient Regulatory Thresholds

Table 6 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 of 2010 to 2017, and 0 otherwise. Column 1 shows estimates where the two regulatory groups analyzed 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 the series of control variables in tab2_baseline column 4, as well as year-quarter fixed effects. Standard errors are clustered at the bank level. Robust *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	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)
No. of obs.	2,749	1,954	1,356	1,356
Controls	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.132	0.274	0.701	0.700

Table 6 shows the results of 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 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. We 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, 3, and 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, we observe no differences in tail risk around these other size thresholds.

Thus, we only observe a sharp decline in tail risk at one point: when banks cross over the $50B threshold and are designated as systemically important. The results are therefore inconsistent with the effective regulation hypothesis. Rather, the findings in Table 6 are compatible with the designation and implicit guarantees explanation for the lower tail risk of above 50B banks in the post-crisis period. We 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.

D. Wealth Effects

To further understand the source of the tail-risk differences between small and large banks in the post-crisis period, we analyze the stock market reaction to the announcement of changes in bank regulation related to the passage of the Dodd–Frank Act. 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. Further, the removal of the government's safety net can also lead to negative returns. 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 SIFIs by the FSB. They attribute this wealth effect to the heavier regulatory burden expected on low-capitalized SIFIs.

On the other hand, the implicit designation and guarantee hypothesis argues that the official designation of above 50B banks as systemically important reinforces the TBTF problem for this group of banks and so predicts positive wealth effects for shareholders. Consistent with this argument, 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 TBTF 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 (designation and implicit guarantee hypothesis). That is, despite a larger regulatory burden, evidence of positive wealth effects accruing to the shareholders of large banks can be interpreted as evidence in favor of the designation and implicit guarantee hypothesis.

We analyze 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:

- Dec. 2, 2009: Dodd–Frank is introduced in the U.S. House of Representatives (House) as bill H.R. 4173.
- Dec. 11, 2009: The Dodd–Frank bill is passed by the House.
- Apr. 15, 2010: Dodd–Frank is introduced in the U.S. Senate (Senate) as bill S.3217.
- May 20, 2010: Dodd–Frank is passed by the Senate.
- June 30, 2010: The House agreed to conference report on Dodd–Frank.
- July 15, 2010: The Senate closed debate and agreed to conference report.
- July 21, 2010: Dodd–Frank is signed into law by the U.S. President.

Following Bouwman et al. (2018), for each date, we employ a 2-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):

$$R_{i,t} = a_i + b_i R_{M,t} + e_{i,t}, \quad (3)$$

where $R_{i,t}$ is the observed return for bank i on day t, and $R_{M,t}$ is the return on the market portfolio.[29] For a given bank, daily abnormal returns (AR) are then calculated as:

$$\text{AR}_{i,t} = R_{i,t} - \widehat{a}_i - \widehat{b}_i R_{M,t} \quad (4)$$

with $\widehat{a}_i$ and $\widehat{b}_i$ 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, we employ the test statistic proposed by Kolari and Pynnonen (2010) in all of our tests.[30]

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.

TABLE 7

Wealth Effects

Table 7 reports average cumulative abnormal returns (CAR) for a series of salient events related to the passage of the Dodd–Frank Act. 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 to or greater than \$50 billion as of 2009Q3. For each date, a 2-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 Pynnonen (2010), which accounts for cross-sectional correlation and event-induced variance inflation. Robust *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Event	Date	BELOW_50B	ABOVE_50B
INTRODUCED_IN_THE_HOUSE	2009-12-02	−0.002 (−0.47)	−0.016 (−0.91)
PASSED_BY_THE_HOUSE	2009-12-11	−0.012 (−0.73)	−0.014 (−0.89)
INTRODUCED_IN_THE_SENATE	2010-04-15	0.013 (0.81)	−0.010 (−0.64)
PASSED_BY_THE_SENATE	2010-05-20	0.016 (1.31)	0.052** (2.06)
HOUSE_AGREED_TO_CONFERENCE_REPORT	2010-06-30	0.014 (1.10)	0.014* (1.66)
SENATE_AGREED_TO_CONFERENCE_REPORT	2010-07-15	−0.026** (−2.33)	−0.019 (−1.05)
SIGNED_INTO_LAW	2010-07-21	−0.035 (−1.46)	−0.020 (−0.54)

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

[30]Refer to Appendix C of the Supplementary Material for more details regarding the test. This test statistic is an adjusted version of the test statistic originally proposed by Boehmer, Masumeci, and Poulsen (1991).

Senate passed the Dodd–Frank bill. We 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. As such, for above 50B banks, markets seem to interpret the development of 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.

In contrast, we 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 is likely the product of the higher regulatory costs imposed on some of these nonsystematically-important banks following the passage of Dodd–Frank (i.e., above 10B but below 50B banks).

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.

Finally, 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), we run a cross-sectional regression of banks' CARs on an indicator for above 50B banks and a series of bank controls (as of 2009:Q4) that might explain the differential market responses for small and large banks. Table 8 presents the results from this exercise. Column 1 presents the univariate regression whereas column 2 adds 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. The point estimate from column 2 suggests that above 50B banks experienced a 3.2% abnormal increase in returns around this date.

Moreover, we find that larger CARs on this date are also associated with higher exposure to other financial institutions (i.e., interconnectedness) and higher systematic 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.

E. Risk-Taking Differences

In this section, we analyze the actual risk-taking behavior of large and small banks in the post-crisis period. The two alternative explanations make differing predictions regarding banks risk-taking. The implicit guarantee hypothesis predicts

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TABLE 8

Cross-Sectional Wealth Effects

Table 8 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 to 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 2009:Q4. All regressions include robust standard errors. Robust *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: CAR	
	1	2
ABOVE_50B	0.035***	0.032***
	(5.630)	(3.880)
TIER_1_RATIO		0.013
		(0.894)
RISK_WEIGHTED_ASSETS		−0.026
		(−0.814)
RETURN_ON_EQUITY		0.001
		(0.161)
LOAN_TO_DEPOSITS		0.012
		(0.803)
EXPOSURE_TO_FINANCIAL_INSTITUTIONS		0.076*
		(1.685)
SHORT_TERM_WHOLESALE_FUNDING		−0.038*
		(−1.700)
NON_PERFORMING_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)
No. of obs.	82	82
Adj. R^2	0.321	0.316

that, due to moral hazard generated by government guarantees (see Kane (2009), Duchin and Sosyura (2014), and Kaufman (2014)), 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 reduce banks' risk-taking, which in turn is reflected in lower tail risk.

Here, we 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 measures, we employ consolidated financial statements filed with the Federal Reserve and historical stock performance data from CRSP. Next, we compare 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 9 reports the results for these tests. Columns 1 and 3 show above 50B *minus* below 50B differences in means for the pre- and post-crisis periods, respectively. Column 5 reports difference-in-differences estimates obtained by subtracting the mean differences in column 3 from column 1.

1. Market Risk

In regard to market risk, we use four measures: TOTAL_RETURN_VOLATILITY, BETA (i.e., quantity of market risk), SYSTEMATIC_RISK

TABLE 9

Risk-Taking Differences

Table 9 shows estimates for a series of difference-between-means tests contrasting banks with less than $50 billion in total assets as of 2009Q3 (BELOW_50B) and banks with assets equal or greater than $50 billion as of 2009Q3 (ABOVE_50B) across various dimensions of bank risk. Reported *p*-values show the probability of observing a greater absolute value (2-tailed) of the test statistic under the null hypothesis of equal means. Pre-crisis corresponds to the time period of 2001 to 2007 and post-crisis to the period of 2010 to 2017. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Pre-Crisis		Post-Crisis			
	ABOVE_50B–BELOW_50B	*p*-Value	ABOVE_50B–BELOW_50B	*p*-Value	Diff-in-Diff	*p*-Value
	1	2	3	4	5	6
Panel A. Market Risk						
TOTAL_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
Panel B. Business Risk						
EXPOSURE_TO_FINANCIAL_INSTITUTIONS	0.011	0.007***	0.051	0.000***	0.041	0.000***
SHORT_TERM_WHOLESALE_FUNDING	0.030	0.001***	0.102	0.000***	0.072	0.000***
NON_PERFORMING_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***
Panel C. Capital Adequacy						
LEVERAGE_RATIO	−0.041	0.000***	−0.016	0.000***	0.025	0.000***
TIER_1_RATIO	−0.075	0.000***	−0.020	0.000***	0.055	0.000***
CAPITAL_ADEQUACY_RATIO	−0.059	0.000***	−0.008	0.000***	0.051	0.000***
RISK_WEIGHTED_ASSETS	0.104	0.000***	0.002	0.719	−0.101	0.000***

(i.e., $\beta\sigma_{\text{market}}$), and UNSYSTEMATIC_RISK (i.e., total return volatility less systematic risk). One can see that the difference-in-differences estimates on total, systematic, and unsystematic risk, in Panel A of Table 9, are all insignificant. Interestingly, the tests do reveal that the Beta coefficient with respect to the market is significantly larger for above 50B banks post-crisis, suggesting that large banks' exposure to market risk has increased relative to smaller banks.

2. Business Risk

Similarly, we 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_FINANCIAL_INSTITUTIONS (interconnectedness). Panel B of Table 9 shows that, across three of these 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 (*z*-score) difference between these bank groups is also significant. The average insolvency risk for above 50B banks goes from

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being 10.3% *lower* pre-crisis (relative to below 50B banks) to 20.4% higher after the GFC.[31]

Finally, above 50B banks' exposure to other financial institutions (relative to below 50B banks) surges more than 4 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, Gounopoulos, Kizys, and Koutelidakis (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 (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 – also shown in 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. Thus, in spite of the fact that their actual risk exposure increased relative to banks of smaller size, the expectation of future bailouts resulted in relatively lower tail risk for above 50B banks.

3. Capital Adequacy

But did enhanced capital regulation for larger banks achieve its intended goal of increasing the capital ratios for large banks by more than that of smaller banks? To answer this question, we examine the evolution of four regulatory ratios using the same approach as above. Panel C of Table 9 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.

Moreover, it should be noted that most of the reduction in the gap between the average capital ratios of these bank groups happens during the crisis, as depicted in Figure 3. 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.[32]

Overall, we show here that, although regulatory ratios for systemically important institutions improved considerably relative to smaller banks, their risk-taking appears to have increased in the post-crisis period. This finding is consistent with

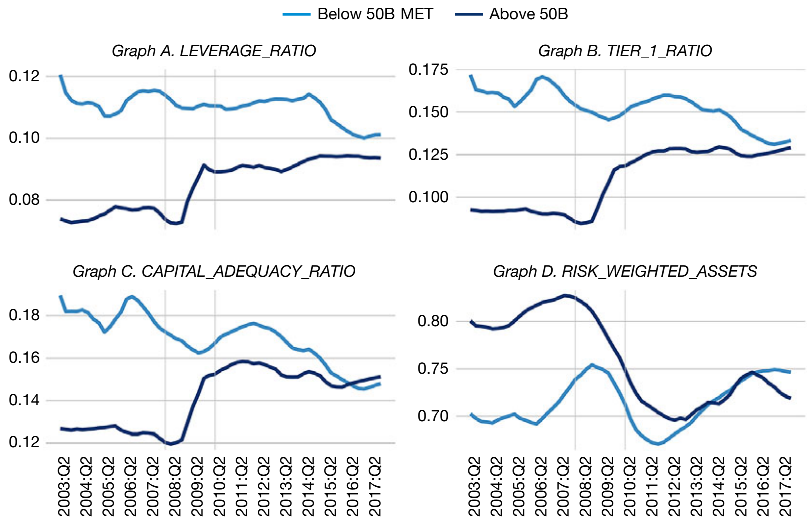
[31]By construction, the z-score is inversely related to a bank's probability of insolvency, and thus larger values reflect a lower probability of insolvency. The estimated z-score maps into an upper bound of the probability of insolvency by the inequality $\Pr(\text{roa} \leq -\text{car}) \leq z\text{-score}^{-2}$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

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

FIGURE 3

Capital Adequacy Measures

Figure 3 shows quarterly measures of capital adequacy for banks with assets less than $50 billion (BELOW_50B), and banks with assets equal to or greater than $50 billion (ABOVE_50B).



Duchin and Sosyura (2014) who show that, despite an improvement in capitalization 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 our claim that the size-based difference in tail risk observed post-crisis is driven mainly by a reinforcement of the TBTF status for banks above the $50B threshold.

F. Robustness

1. Alternative Tail-Risk Measures

In order to provide a robustness result for our measure of tail risk, we use two alternative methods: i) the Bakshi et al. (2003) slope measure as estimated using equation (30) in their article; and ii) the Collin-Dufresne et al. (2001) measure of jump risk (see page 2183 in their article). We estimate our main model using these alternative measures and present the findings in columns 1 and 2 in Table 10, respectively. The results show that our main finding is robust to using these alternative measures of tail risk.

2. Alternative Interpretations

The slope of the implied volatility curve can be mapped to features of the risk-neutral distribution and therefore they reflect both physical tail risk and risk premia. Our interpretation relies on the fact that differences in the tail risk for large and small banks is not due to differences in risk premia demanded by investors for these two groups of banks. We consider this alternative explanation by looking at

TABLE 10

Robustness

Table 10 presents coefficient estimates for a series of robustness tests for the specification model in equation (2). ABOVE_50B is a dummy variable which takes 1 for banks with assets equal to or greater than $50 billion as of 2009Q3, and 0 otherwise. POST_CRISIS takes 1 for the period of 2010 to 2017, and 0 otherwise. In column 1, the dependent variable is Bakshi et al. (2003) slope measure as estimated using equation (30) in their article (multiplied by minus one). In column 2, the dependent variable is Collin-Dufresne et al. (2001) measure of jump risk (see page 2183 in their article). In columns 3–8, the dependent variable is the tail-risk measure defined in equation (1). Columns 3 and 4 include bank-level controls for institutional ownership and illiquidity, respectively. In column 5, the tail-risk measure is estimated using longer-dated options (6-month). In columns 6 and 7, the Post-Crisis dummy variable is redefined to take 1 for the period after 2008:Q4, and after 2010:Q4, respectively. Finally, column 8 excludes results for banks within $10 billion of the $50 billion SIFI threshold. All regressions include controls for all other bank and market characteristics in column 4 in Table 4, 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. Robust *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: TAIL_RISK							
	Bakshi et al. (2003) Slope	Collin-Dufresne et al. (2001)	Inst. Ownr	Illiquidity	Longer Maturity Options	Post-Crisis (>2008: Q4)	Post-Crisis (>2010: Q4)	Excluding Within 10B Banks
	1	2	3	4	5	6	7	8
ABOVE_50B	−0.130	−0.021**	0.002	0.005	0.045**	−0.005	0.005	−0.006
	(−1.434)	(−2.412)	(−0.043)	(−0.140)	(−2.09)	(−0.124)	(−0.130)	(−0.156)
ABOVE_50B × POST_CRISIS	−0.529***	−0.041***	−0.179***	−0.180***	−0.117***	−0.142***	−0.205***	−0.182***
	(−7.297)	(−5.284)	(−6.812)	(−6.512)	(−6.104)	(−4.701)	(−7.790)	(−6.548)
INSTITUTIONAL_ OWNERSHIP			0.001*	0.001*	0	0.001*	0.001*	0.001*
		(−1.879)	(−1.674)	(−0.827)	(−1.675)	(−1.666)	(−1.841)	
STOCK_ILLIQUIDITY				−0.140*	−0.007	−0.184**	−0.130*	−0.129*
				(−1.934)	(−0.096)	(−2.238)	(−1.848)	(−1.725)
Constant	1.540***	0.137***	0.272**	0.317**	−0.099	0.305**	0.323**	0.272*
	−4.62	−4.103	−2.147	−2.348	(−1.037)	−2.286	−2.4	−1.882
No. of obs.	3,932	3,932	3,855	3,645	2,876	3,645	3,645	3,406
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.337	0.346	0.204	0.201	0.276	0.191	0.208	0.196

the presence of institutional ownership in small versus large banks. Since the institutional-retail investor mix is a likely first-order determinant of the risk aversion of the marginal investor, differences in the proportion of institutional ownership in the two groups of banks may indicate that differences in risk premia may be an important source of heterogeneity explaining the observed pattern in tail risk. However, using Thomson Reuters 13f data, we find that institutional ownership in big versus small banks is very similar during our sample period: institutional ownership in above 50B banks is 69% compared to 64% for below 50B banks. Thus, it is unlikely that differences in investors risk aversion are a primary driver of our result. Furthermore, when we include institutional ownership as an additional control variable in our regressions, our main finding remains unchanged (see column 3 in Table 10). The evidence, therefore, suggests that differences in investor risk aversion for small versus large banks are trivial in explaining our main finding.

Next, because hedging options is more difficult if the underlying stock is not liquid–which may cause options prices to deviate from those predicted by the Black and Scholes's model used to compute the implied volatility – another concern is that differences in the stock liquidity between small and large banks (more precisely, differences in the change in liquidity in the post-crisis period) may explain our results. To address this concern, we calculate the Amihud measure of stock illiquidity and include it as an additional control. The result in column 4 in Table 10 shows that our main finding is robust to controlling for stock liquidity.

Finally, Pena et al. (1999) note that time to expiration is also an important determinant of the smile. To ensure that our result is not an artifact of our choice to use short-maturity options contracts, we perform a robustness test using 6-month maturity options to reestimate our main regression and find very similar results (column 5 in Table 10).

3. Threats to Identification

The identifying assumption with our DiD estimation is that the pre-event (i.e., pre-crisis) trends in tail risk for large and small banks are similar. To ensure that our results are not due to a violation of the common pre-trends assumption, we first plot in Figure D1 in the Supplementary Material the time series evolution of our tail-risk measure for the 2 sets of banks over the sample period.[33] We can see that in the period immediately before the crisis (2005:Q4 to 2007Q2) there is no discernible difference between the trajectories of tail risk for the two groups of banks: the tail risk for both large and small banks was trending downward and are almost parallel; and if anything the tail risk for large banks is trending down slightly faster which biases against our documented effect.

In our second test, we vary the exact date for the "Post-Crisis" dummy. We use two alternative definitions post-crisis: i) after 2008:Q4; and ii) after 2010:Q4. We reestimate our main regression using these alternative definitions and present the results in columns 6 and 7 in Table 10. We can see that our main result is not sensitive to these alternatives, implying that any difference in pre-crisis trends is unlikely to explain our results.

The second threat to identification is that there is a possibility that selection drives our results: that banks manipulate their size to stay under the \$50B threshold (or perhaps just tip over the threshold). To address this concern, we show that our main result is robust to the exclusion of banks that are close (e.g., within \$10B) to the \$50B threshold (see column 8 in Table 10). In unreported tests, we also find that our results are robust to excluding banks within \$5B of the threshold; and also robust to excluding banks within \$20B of the threshold.

VI. Conclusion

We employ option prices to construct a forward-looking measure of bank exposure to significant price drops (i.e., tail risk) and explore differences between large banks identified as systemically important and smaller banks, around the GFC. We document a persistent increase in the average tail risk of the U.S. banking industry as a whole following the GFC, except for banks above the \$50B size threshold deemed systemically important. We 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 by their subsequent designation as systemically important by the Dodd–Frank Act. This, in turn, raised investor

[33]Because tail risk is highly volatile, we plot the eight-quarter moving average to better visualize the trends.

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, we show these findings are inconsistent with the alternative explanation that these tail-risk differences are due to the stricter regulatory regime large banks face in the post-crisis period. In particular, we show that a deterioration in the U.S. governments' creditworthiness leads to a sharp tail-risk increase only for systemically important banks. Further, we find no significant changes in tail risk around other salient regulatory size thresholds, even though regulatory stringency varies substantially around these thresholds. We also document positive wealth effects 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. Overall, the evidence documented in this article is aligned with the existence of implicit government guarantees as the main cause of the aforementioned differences in tail risk between banks above and below the $50B mark.

Our findings offer new insights regarding 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 and may have run counter to the regulators' determination to eliminate the TBTF problem as was intended by the Dodd–Frank Act.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000157.

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