Implicit and Explicit Government Guarantees and Their Impact on Bank Risk

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Declaration

I declare that, except where indicated otherwise, this thesis comprises only my original work towards the PhD, and that due acknowledgement has been made in the text to all other material used. This thesis does not contain any material that has been submitted, previously, in whole or in part, for the award of other academic degree or diploma.

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Abstract

This thesis investigates the impact of implicit and explicit government guarantees on perceived and actual bank risk. It is comprised of three chapters. The first chapter, *"What Can Volatility Smiles Tell Us About the Too Big to Fail Problem?"*, exploits the information content of option prices to offer insight into the Too Big to Fail (TBTF) problem for banks. Using option prices, I construct a forward-looking measure of bank exposure to significant price drops (i.e. tail risk) and use this to examine cross-sectional differences between large and small banks. I document a permanent increase in the average tail risk of the U.S. banking industry following the Global Financial Crisis (GFC), except for banks that were explicitly designated as systemically important. That is, banks with more than $50B in assets.

I argue that this post-crisis difference in tail risk, between banks above and below the $50B threshold, is consistent with the notion that the TBTF status of banks *above* this asset threshold 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 of 2010. This in turn raised investors' expectations of future bank bailouts for this group and reduced their perceived exposure to downside risk, as captured by the tail-risk measure. In a series of tests, I then provide evidence consistent with this explanation by exploiting key events and regulatory changes that took place in the post-crisis period.

Overall, this chapter offers new insights into the existence of implicit government guarantees in the banking industry, and the unintended consequences of singling out banks whose failure could threaten the financial stability of a country. The findings in this chapter suggest that revealing the identities of systemically important banks reinforced the presence of government guarantees extended to them, and may have run counter to the regulators' determination to eliminate the TBTF problem, as was intended by the Dodd-Frank Act.

The second chapter, *"The Two Sides of Deposit Insurance: Evidence from the 2005 FDI Reform Act"*, examines the trade-off between moral hazard and stability induced by an explicit government guarantee for banks: deposit insurance. I use the Federal Deposit

Insurance (FDI) Reform Act of 2005 as an exogenous shock to the existing insurance scheme in the U.S. and study its impact on bank risk and financial stability. Under this Act, the insurance coverage limit for individual retirement accounts (IRAs) more than doubled from $100K to $250K. I argue that this effectively caused a new set of bank liabilities – those exceeding, or expected to exceed the previous coverage limit – to become insured by the government. Therefore, I use this reform to analyse the ex-post risk-taking behaviour of banks that benefited more from extending the government guarantee, that is, banks with higher ex-ante IRA balances.

Using this approach, I report evidence of an increase in bank risk-taking, in the form of higher leverage and lower liquidity ratios, following this reform. These results are consistent with the theoretical channels through which deposit insurance is said to increase bank risk, namely a *leverage effect* and an *asset substitution effect*. In addition, I show that banks more impacted by the 2005 reform were significantly less prone to fail during the GFC. Overall, the findings in this chapter suggest that deposit insurance does indeed generate a moral hazard problem, but it also shows that this moral hazard effect is somewhat counterbalanced by the stabilising attributes of deposit insurance during times of high economic uncertainty.

The third and final chapter, co-authored with Phong Ngo, is titled *"De Facto Bank Bailouts"*. Here, we show that the likelihood a defaulting sovereign is granted a loan from the International Monetary Fund (IMF) is increasing in the level of exposure U.S. banks have to that country in default.

The dominant status the U.S. government has over the IMF's governance structure places it in a position to direct IMF loans to developing countries for reasons other than the actual economic needs of the recipient nation. Therefore we argue that, given the high political and fiscal costs of using taxpayer funds to support local banks in distress, U.S. politicians have great incentive to exert their unique influence in the IMF to direct IMF funds to countries where U.S. banks stand to lose the most from sovereign defaults: a *de facto bailout*.

Consistent with this, we show that: (1) de facto bailouts are more likely in federal election years and in years when the government's fiscal position is weak, that is, when the costs of direct bailouts are the greatest; (2) U.S. Congressional voting on IMF funding increases is consistent with special interests from the banking sector; and (3) U.S. banks exposed to a defaulting sovereign experience positive wealth effects around the time an IMF loan is granted. Given these results, in this chapter we identify an alternative mechanism through which the U.S. government can backstop the losses of large banks while, at the same time, reducing the high political and economic costs associated with direct bank bailouts.

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Chapter 1

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

1.1 Introduction

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

In the aftermath of the GFC, the billions of taxpayer dollars spent on bank bailouts exacerbated the public perception of a TBTF problem in the U.S. banking industry, with calls from different sectors of society to make banks accountable for their risk-taking behaviour.[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

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

fulfil these goals, Dodd-Frank explicitly defined \$50 billion as the size threshold above which a bank is deemed a large and interconnected financial institution whose failure could threaten the financial stability of the U.S. economy, and established a more stringent set of regulatory requirements for those banks above the \$50 billion mark (above 50B banks).

Accordingly, several recent papers have attempted to determine whether the multiple changes to bank regulation since the GFC have resulted in a decline in the TBTF problem. The results have been decidedly mixed. For example, Schäfer et al. (2015) and Bongini et al. (2015) present evidence consistent with a decline in the bailout expectations of large financial institutions upon the announcement of major regulatory reforms. On the contrary, also relying on regulatory announcements and designation events, Moenninghoff et al. (2015) conclude the opposite. Moreover, using various market measures of bank risk, Sarin and Summers (2016) show that risk for large banks has actually increased after the crisis. This chapter 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, I use option prices to construct a forward-looking measure of bank tail risk and explore cross-sectional differences between large banks identified as systemically important (i.e. above 50B banks) and smaller banks.

For a given bank, I define tail risk as the perceived exposure of the bank's stock to a significant drop in price. I estimate this tail-risk measure using bank options with varying strike prices and their corresponding implied volatilities. Unlike in the idealised world of the Black-Scholes-Merton (BSM) model, in practice, implied volatilities vary with strike prices in a phenomenon known as the implied *volatility smile* 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) ones. This downward sloping shape has been shown to correspond to negative skewness in the risk-neutral density (RND) of the underlying stock (see Bakshi et al., 2003;

Corrado and Su, 1996; Dennis and Mayhew, 2002). Thus, steeper volatility smiles reflect a higher (perceived) exposure to downside risk for the underlying stock. I exploit this fact and use the slope of the implied volatility smile for OTM put options as a forward-looking measure of a stock's perceived exposure to significant drops in value (i.e. tail risk).[2]

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

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

This surge in tail risk after the GFC is consistent with what Rubinstein (1994) dubbed "crash-o-phobia". That is, an increase in investor's expectations of future crash-like events following a market crash. For above 50B banks, however, post-crisis average tail risk reverts back to pre-crisis levels after a short-lived spike in the most critical months of the crisis. I argue that the stark post-crisis difference in tail risk for banks

[2]See Collin-Dufresne et al. (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.

above and below the $50B threshold is consistent with the notion that the TBTF status of above 50B banks was reinforced by the series of bailouts targeted at them during the crisis and their subsequent designation as *systemically important* by the Dodd-Frank Act. This in turn raised investors expectations of future bailouts for above 50B banks and reduced their perceived exposure to downside risk as captured by the tail-risk measure.

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

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

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

Moreover, I show that a deterioration in the U.S. government's creditworthiness

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

(post-crisis) leads to a three-fold increase in the average tail risk of above 50B banks, whereas below 50B banks show not significant change. For large banks, any TBTF gains are predicated on the government's capacity to provide assistance in distress states, hence this increase in tail risk for the above 50B group is consistent with the existence of cross-sectional differences in the extent to which above and below 50B banks benefit from government guarantees.

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

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

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

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

The rest of this chapter is organised as follows. Section 1.2 provides a brief recount of the existing literature on the TBTF problem. In Section 1.3, I discuss the key aspects of the methodology for estimating bank tail risk. I then examine how tail risk has tended to vary around past crises before documenting the different tail-risk behaviour of above 50B and below 50B banks in the most recent GFC. Section 1.4 elaborates on the possible explanations for the tail-risk differences reported in Section 1.3. In Section 1.5, I report my results. Section 1.6 concludes.

1.2 Related Literature

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

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

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

[5]They estimate the average subsidy to equity holders to be $282 billion during the sample period.
[6]The first list was issued by the FSB on November 4, 2011.

1.3 Measuring Bank Tail Risk

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

For put options, implied volatilities are typically high for out-of-the-money (OTM) options and low for in-the-money (ITM) options.[8] This skewed shape has been partly attributed to empirical violations of the lognormal assumption for the distribution of stock prices embedded in the BSM model (see Derman and Miller, 2016). In practice, this assumption understates the actual probability of extreme downward moves.[9] In this regard, the risk-neutral density (RND) of stock prices has been shown to be more negatively skewed than the lognormal density assumed in the BSM model (see Birru and Figlewski, 2012; Dennis and Mayhew, 2002).[10] As an example, Figure 1.1 presents the risk-neutral density – extracted from option prices – for Sterling Bancorp Chase in

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

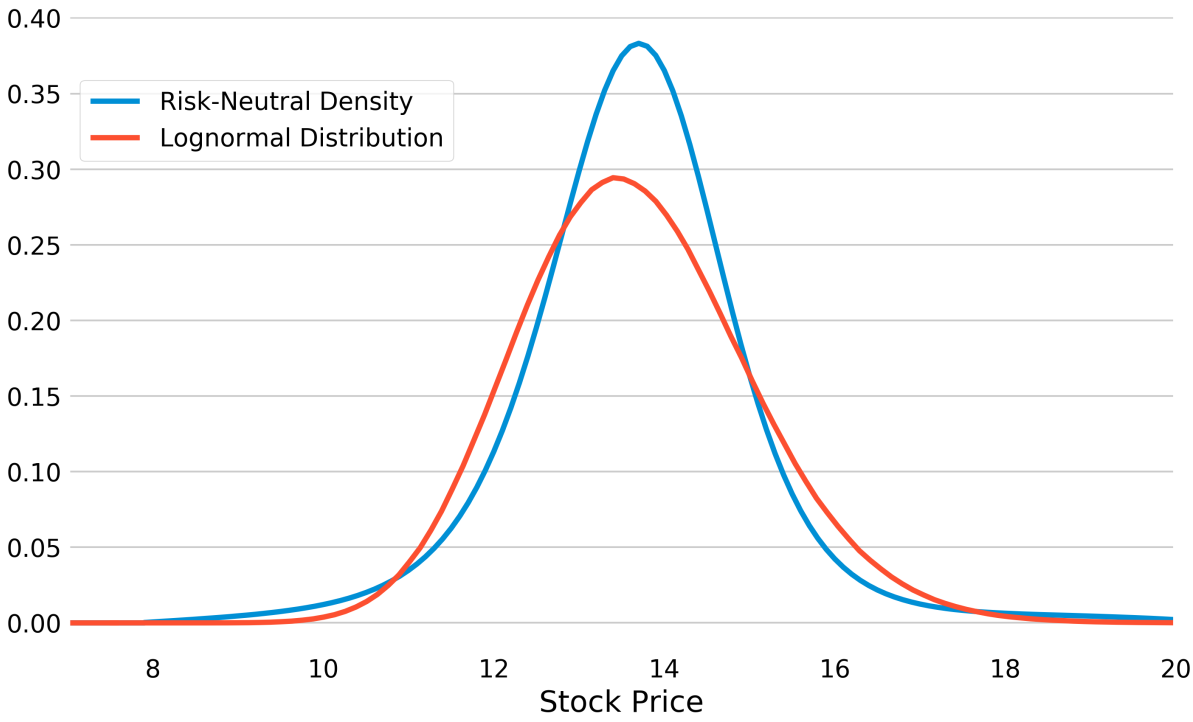
[8]When used for hedging purposes, OTM puts serve as "catastrophe insurance". They cut off the tail of the stock return distribution at the expense of slightly reducing the mean of the overall distribution (Cochrane, 2009, p. 315).

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

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

Figure 1.1: Risk-neutral density

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



December 2014, along with a lognormal density with the same mean and variance.[11] The visible left-skewness of this risk-neutral density makes the probability of a two standard deviations price drop almost three times what a lognormal density implies. A left-skewed RND suggests that investors perceive significant price drops as more likely compared to a lognormal distribution. Because of this, they are willing to pay higher prices for deep OTM put options, which in turn results in a downward sloping volatility smile.

Indeed, Bakshi et al. (2003) show that the more negatively skewed the RND of a given equity asset, the stepper its volatility smile (see also Corrado and Su, 1996). Moreover, they show that negatively skewed risk-neutral distributions are a consequence of risk aversion and fat-tailed physical distributions. Thus, a steeper volatility smile

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

constructed using OTM puts can be associated with higher (perceived) exposure to downside risk for the underlying asset. I exploit this fact and define the slope of the implied volatility smile for OTM put options as a forward-looking measure of a stock's perceived exposure to significant drops in value (i.e. *tail risk*).

To construct this tail-risk measure, I collect daily implied volatility data from OptionMetrics for a sample of 85 U.S. bank holding companies (bank) for which an active options market exists as of September 2009.[12] Of these, 62 correspond to banks with assets less than $50 billion in assets (below 50B) and 23 to banks with assets equal or greater than $50 billion (above 50B). Table 1.1 shows the full list of banks included.

For each trading day, I measure the steepness of each bank's implied volatility curve as the sum of differences between the implied volatility of OTM puts with varying deltas and the implied volatility of an at-the-money (ATM) put option.[13] The relevant OTM put option deltas range from -0.45 to -0.20 and I employ one-month to expiration puts. When graphed as a function of delta, volatility smiles are steeper at longer expirations (Derman and Miller, 2016). Hence, using short maturities in the construction of this market-based measure generates a lower bound for bank tail risk. Equation 1.1 presents the formula for the construction of bank tail risk.

$$Tail\text{-}Risk_{i,t} = \sum_{\delta \in \Delta} (\sigma_{i,\delta,t} - \sigma_{i,\text{-}0.5,t}) \tag{1.1}$$

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

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

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

Table 1.1: List of bank holding companies

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

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

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

In regard to other measures of tail-risk such as Value-at-Risk (VaR), expected shortfall (ES), and Moody's KMV model, these are either backward-looking (i.e. rely on historical information) and/or assume returns follow a normal distribution – two important limitations.

On the one hand, tail-risk measures that rely on historical (backward-looking) information are not relevant for the research question at hand. This chapter aims to assess whether, either new targeted regulations or the designation of certain banks as systemically important, changed investors' beliefs about banks' exposure to downside risk. Therefore, the tail-risk measure needs to take into account investors' expectations about the future prospects of each bank stock – not their historical performance.

On the other hand, the existing literature shows stock returns are not normally distributed. Under the assumption of normality, for instance, a tail event such as the market crash of October 1987 (analysed in this chapter) has a probability of less than one in 10^{50}. According to Mandelbrot and Hudson (2006):

> [these are] odds so small they have no meaning. It is a number outside the

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

scale of nature. You could span the powers of ten from the smallest subatomic particle to the breadth of the measurable universe—and still never meet such a number. (p. 4)

Hence, the tail-risk measure proposed in this chapter overcomes those two limitations by exploiting the information content of option markets to capture investors' expectations about the future prospects of individual bank stocks and their propensity to experience significant price drops.

1.3.1 Tail Risk Around Crises

Following the 1987 market crash, Rubinstein (1994) documented a structural change in the shape of the implied volatility curve of S&P 500 index options: the curve went from being relatively flat in the pre-crash period to significantly downward sloping post-crash. Rubinstein (1994) suggested "crash-o-phobia", that is, an increase in investors' expectations of future crash-like events, as an important reason for the appearance of the so-called volatility smile.

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

Dot-Com Crash

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

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

To do this, I use a sample of 165 technology firms listed on NASDAQ and with an active options market between 1996 and 2005. The options data required for estimating tail risk is from OptionMetrics. I define the pre-crash, crash, and post-crash periods as the time periods 1996-1999, 2000-2002, and 2003-2005, respectively. Using the options-based approach described in Section 1.3 to measure tail risk, I calculate that tail risk for this group of firms spiked during the dot-com bubble and remained at higher levels compared to the pre-crash period. Specifically, Panel C in Table 1.2 shows technology firms experienced a 101.8% increase in average tail risk between the pre and post-crash periods. This substantial tail-risk surge represents a *structural* change in the shape of the implied volatility curve for these firms.

The Global Financial Crisis

The more recent crisis in 2008-2009 presents another opportunity to study the dynamics of tail risk around crises. Since the GFC centred on the banking sector, I examine non-financial firms and banks separately, using data for 619 non-financial firms and 85 U.S. bank holding companies with active options markets between 2001 and 2017.

Using the same options-based approach as above and defining the pre-crisis, crisis and post-crisis periods as 2001-2007, 2008-2009, and 2010-2017, respectively, I calculate that, after increasing by 28.3% between the pre-crisis and crisis periods, tail risk for non-financial firms subsides but remains 12.6% above pre-crisis levels (see Panel B of Table 1.2). A similar but much more pronounced effect is observed for the U.S. banking industry as a whole: tail risk increases by 74.5% between the pre-crisis and crisis periods, and although falling slightly, remains 69.9% higher post-crisis compared to the pre-crisis period (see Panel A of Table 1.2). Thus, consistent with Rubinstein (1994) and what happened following the dot-com crash, there is a permanent increase in tail risk after the GFC for banks as well as non-financial firms.

Table 1.2: Tail risk around crises

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

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

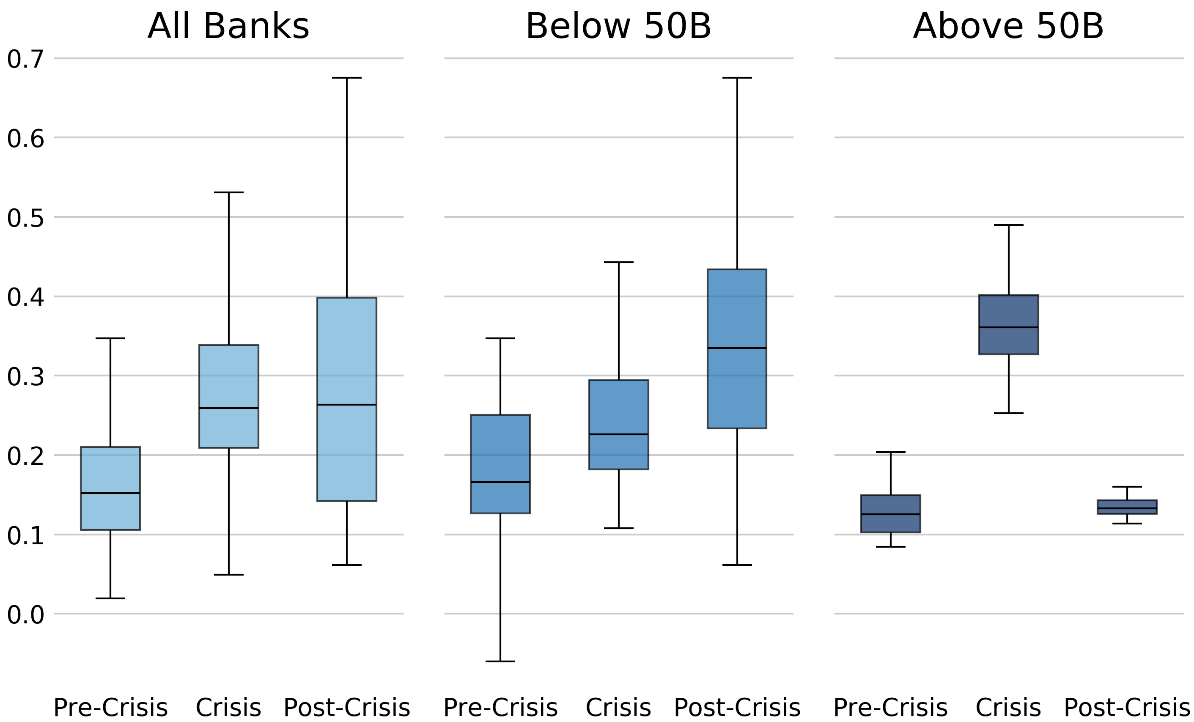
*** p<0.01, ** p<0.05, * p<0.1

Systemically Important Banks

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

Figure 1.2 shows the distribution of quarterly tail risk for all U.S. banks, and below and above 50B banks, for the pre-crisis, crisis, and post-crisis time periods. As men-

Figure 1.2: Tail risk for above and below $50 billion banks
This figure shows the distribution of quarterly tail risk for all U.S. banks, banks with less than $50 billion in assets (Below 50B), and banks with assets equal or greater than $50 billion (Above 50B), for the pre-crisis, crisis, and post-crisis time periods. Pre-crisis corresponds to the time period 2001-2007, crisis to the period 2008-2009, and post-crisis to 2010-2017.



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

Large vs Small Firms

A natural question is whether these differential changes in tail risk according to bank size are an artifact of options markets. For instance, one could argue that large firms have option markets that are inherently more liquid and subject to lower transaction costs, and that these market characteristics produce relative flatter smiles (i.e.

lower tail risk) especially during distress states. If this were the case, we would expect to observe different tail-risk averages for firms of varying sizes following a major market downturn, not just for banks. I investigate, and rule out this possibility, by studying the tail-risk dynamics for (1) non-financial firms of varying size around the GFC; and (2) technology stocks of varying size around the dot-com crash.

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

Table 1.2 presents average tail-risk changes for the pre and post-crisis period for small and large firms separately. Panel A shows the numbers for banks, and Panel B presents the numbers for non-financials. Unlike banks, post-crisis tail risk increases for both small and large firms by 13.6% and 6.6%, respectively. These changes are significantly lower compared to the 64.4% surge observed for below 50B banks – which is to be expected given the nature of the crisis. This table also confirms that the tail risk for above 50B banks did not change post-crisis (in fact, it is marginally lower, though the change is insignificant). The observed increase in tail risk for non-financials can also be attributed to a surge in investors' expectations of future crash-like events caused by the GFC and its spillover effects onto other industries. These findings, however, are qualitatively different from the size tail-risk differences reported for banks.

Next, I examine the tail-risk behaviour for large and small technology firms around the dot-com crash. I define firms with total assets in the top quartile, as of 2000Q1, as large, and all other firms as small. Panel C of Table 1.2 presents changes in tail risk for large and small technology firms. Unlike banks, both size groups depict a substantial

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

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

increase in tail risk post-crisis, 132.6% and 45.5% for small and large firms, respectively.

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

1.4 Potential Explanations

1.4.1 Implicit Guarantees

My central claim is that the series of bailouts targeted at large banks during the financial crisis, and the subsequent designation of above 50B banks as systemically important by the Dodd-Frank Act, reinforced the TBTF status of large financial institutions. This raised expectations of future bailouts for large banks and led market participants to lower expectations of large price declines in the post-crisis period, resulting in a flatter post-crisis smile for above 50B banks (i.e. lower tail risk) relative to small banks. For small banks below the $50B systemically-important threshold, the crisis, however, raised investors' concerns about the possibility of future failures, thus steepening the left-tail segment of the smile for this group – as shown in Table 1.2. I refer to this as the *implicit guarantee* hypothesis.[18]

[18]Note that this explanation does not require large banks to be inherently less risky. Provided that investors perceive large banks to be more likely to receive government assistance in future distress states,

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

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

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

Consistent with this, Gandhi and Lustig (2015) show that the largest bank stocks have significantly lower risk-adjusted returns than smaller banks' stocks, even though large banks are significantly more levered. They interpret this evidence as consistent with the existence of implicit government guarantees that protect shareholders of large U.S. banks in disaster states.

it follows that they will perceive large banks to be less exposed to downside risk, which will be reflected in lower tail-risk levels relative to small banks.

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

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

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

The AIG bailout

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

To examine the effect of the bailout on AIG's perceived exposure to downside risk, I follow Section 1.3 and estimate monthly tail-risk averages around the time of the rescue plan. For comparison purposes, I also estimate tail-risk averages for two qualitatively

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

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

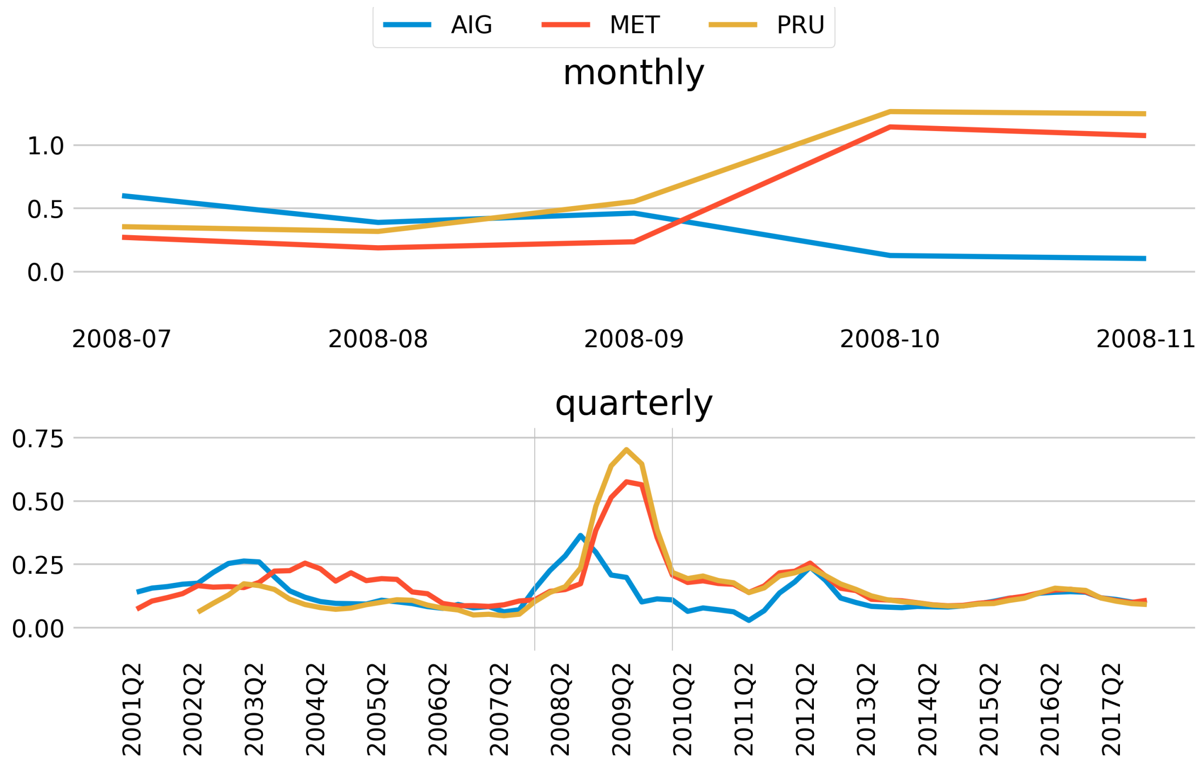
similar insurance companies, namely MetLife and Prudential Financial.[23]

The top panel of Figure 1.3 shows monthly tail-risk averages for these firms between July and November 2008. For AIG, its average tail risk experienced a sharp decline (72.5%) in the month immediately after its bailout. For the other two insurers, however, tail risk surges by 385.1% (MetLife) and 128.3% (Prudential Financial) and remained high for most of the crisis period. Despite being on the brink of bankruptcy, once the U.S. government became a significant shareholder in AIG, its perceived exposure to downside risk fell drastically and remained low for the entire crisis period.[24] I argue that 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 behaviour of AIG. The bottom panel of Figure 1.3 expands the window before and after the AIG bailout and presents quarterly tail-risk averages. We can see that, before the crisis, the variation in tail risk for these three firms was similar and only changed after AIG's bailout. Moreover, average tail risk converges for the three insurers in the post-crisis period. As with banks, this only occurs after the Financial Stability Oversight Council (FSOC) designated these three institutions as systemically important, that is, firms whose failure could pose a threat to the U.S. financial stability.[25] I argue that these designations contributed to increase investors' expectations of future bailouts and thus, reduce these firms' exposure to tail-type events.

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

Figure 1.3: Tail risk for insurance firms

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



1.4.2 An Alternative Explanation: Effective Regulation

A tighter regulatory regime for large banks is another salient characteristic of the U.S. banking industry in the post-crisis period. This, I hypothesise, could also explain the size-based tail-risk differences documented in Figure 1.2.[26]

The Dodd-Frank Act was first introduced in the U.S. House of Representatives in December 2009 and subsequently enacted into law in July 2010. It was a direct response to the multiple regulatory concerns around financial stability raised by the GFC. At its core, Dodd-Frank was specifically designed to end the TBTF problem, and to protect taxpayers by eliminating bailouts. To achieve this, Dodd-Frank effectively established

[26]It is possible that direct assistance by the government through support programs such as the Troubled Asset Relief Program (TARP), the Term Auction Facility (TAF), the Primary Dealer Credit Facility (PDCF), and the Term Securities Lending Facility (TSLF), had a direct effect on banks' exposure to significant price drops. However, most of these programs ended during the first quarter of 2010 and therefore they cannot explain the size-based tail-risk differences documented in Figure 1.2.

– and/or empowered banking regulators to establish – size-based regulatory requirements. For instance, banks with more than \$10 billion in assets were required to establish a risk committee and conduct stress tests to assess their financial resilience to adverse conditions.[27] In addition, banks with more than \$50 billion in assets were designated as systemically important and subjected to enhanced supervisory standards such as stringent liquidity requirements, periodic resolution plans, and concentration limits. Table 1.3 presents a summary of the different size-based regulatory requirements for U.S. banks originated with Dodd-Frank.[28]

Table 1.3: Size-based regulation

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

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

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

It is evident from Table 1.3 that Dodd-Frank established a direct relationship between bank size and regulation stringency. In this sense, the relatively lower tail-risk levels of above 50B banks documented above may simply reflect the more stringent regulatory requirements imposed on them relative to smaller banks. After all, the main of

[27] 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).

[28] 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.

objective of Dodd-Frank was to address the financial stability deficiencies unveiled by the GFC and put an end to the TBTF problem. I refer to this alternative explanation as the *effective regulation* hypothesis. There is some recent evidence consistent with this explanation including Balasubramnian and Cyree (2014) who show Dodd-Frank has been effective in reducing the TBTF discounts on yield spreads in the market for subordinated debt.

In the remainder of the chapter I conduct a series of tests to differentiate between these two competing hypotheses. Overall, I show that the evidence favours the existence of implicit government guarantees as the main source for the cross-sectional difference in tail risk between above and below 50B banks observed after the GFC.

1.5 Empirical Findings

I have shown that the cross-sectional difference in tail risk between small and large banks is starkly higher in the post-crisis period: the average tail risk of below 50B banks is considerably higher than that of above 50B banks. In this section, I first show that this result is robust to controlling for bank and option market characteristics. I then conduct a series of tests to show that this difference in tail risk after the GFC is consistent with an increase in bailout expectations for large banks vis-a-vis small banks (i.e. implicit guarantee hypothesis).

1.5.1 Baseline Results

I start by validating the stylised facts presented Section 1.3 in a regression framework that also accounts for other covariates likely correlated with bank tail risk. Specifically, I employ a difference-in-differences (DiD) model of the form:

$$
\begin{aligned}
\textit{Tail-Risk}_{i,t} = {} & \alpha_1 \textit{Post-Crisis}_t + \alpha_2 \textit{Above-}50B_i \\
& + \alpha_3 \textit{Post-Crisis}_t \times \textit{Above-}50B_i \\
& + \sum_{k=1}^{n} \beta_k X_{i,k,t} + T_t + \varepsilon_{i,t}
\end{aligned}
\tag{1.2}
$$

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

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

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

In addition, I control for quarterly estimates of bank *systematic* and *unsystematic* risk. These are obtained by decomposing total return variance into systematic variance and unsystematic variance. Systematic risk (systematic variance) is then defined as $\beta\sigma_{market}$ ($\beta^2\sigma^2_{market}$), where β represents bank return sensitivity to changes in the market portfolio returns, and σ_{market} the market return volatility.[29] Whereas, unsystematic risk is defined as the square root of the difference between total return variance and systematic variance. Daily bank return data for the construction of these risk estimates is from the Center for Research in Security Prices (CRSP).[30]

Table 1.4: Summary statistics

This table 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 January 2001 - December 2017.

	Obs.	Average	Standard Deviation	Min	Median	Max
Tail Risk	4,173	0.253	0.266	-2.011	0.179	2.578
Return Volatility	4,141	0.024	0.056	0.005	0.016	2.075
Beta	4,055	1.298	0.821	-31.343	1.229	12.452
Systematic Risk	4,055	0.014	0.013	-0.256	0.010	0.102
Unsystematic Risk	4,055	0.018	0.055	0.004	0.012	2.074
Total Loans/Total Deposits	4,173	0.899	0.299	0.064	0.911	3.737
Exposure to FIs	4,173	0.021	0.058	0.000	0.001	0.454
Short-Term Wholesale/Total Liabilities	4,173	0.224	0.152	0.000	0.187	0.919
Non-Performing-Loans/Total Loans	4,173	0.019	0.023	0.000	0.011	0.203
Net Charge-Offs/Total Loans	4,173	0.019	0.032	-0.008	0.007	0.358
Z-Score	4,173	25.572	11.389	1.040	26.155	86.660
Tier1 Capital/Total Assets	4,137	0.101	0.061	0.040	0.093	0.763
Tier1 Capital/RWA	4,137	0.137	0.085	0.066	0.122	1.078
Total Capital/RWA	4,137	0.157	0.081	0.086	0.142	1.079
RWA/Total Assets	4,137	0.731	0.144	0.262	0.744	1.235
ROA	4,173	0.025	0.050	-0.686	0.022	0.771
ROE	4,173	0.196	0.458	-13.199	0.195	2.474
Net Interest Margin/Earning Assets	4,173	0.084	0.048	-0.003	0.077	0.345
Options Volume	4,173	4.030	19.608	0.000	0.027	469.805
Options Bid-Ask Spread	4,173	0.987	1.198	-0.705	0.493	10.000
Total Assets (billions)	4,173	159.448	423.409	1.499	17.546	2,609.785

I also control for specific market characteristics of the OTM put options used in the construction of tail risk. These include bid-ask spreads and volume estimates also

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

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

obtained from OptionMetrics.[31] Table 1.4 shows summary statistics for these bank and market characteristics for a sample of 85 bank holding companies (see Table 1.1) observed quarterly over the period January 2001 - December 2017. Average bank tail risk is positive over the sample period, denoting the downward sloping smile characteristic of equity assets. Also, bank total assets range between \$1.5 and \$2,609.8 billions.

Table 1.5 presents coefficients estimates for the DiD model shown in Equation 1.2. 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.[32] Relative to banks with less than \$50 billion in assets, the average tail risk of larger banks is significantly lower post-crisis. In particular, the average tail-risk difference between below and above 50B banks is more than five times larger in the post-crisis period compared to pre-crisis.

These findings corroborate the stylised facts documented in Section 1.3. In the post-crisis period, markets perceive above 50B banks as significantly less exposed to downside risk. Another important insight from this test is the relevance the leverage ratio has in reducing tail risk. On average, banks with higher levels of Tier 1 capital, as a proportion of total assets, are associated with lower tail-risk exposures (i.e. lower exposure to significant price drops). Specifically, a one standard deviation increase in a bank's leverage ratio is associated with a 6% reduction (relative to the mean) in tail risk.

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

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

Table 1.5: Baseline model

This table presents coefficient estimates for the specification model in Equation 1.2. Above 50B is a dummy variable which takes 1 for banks with assets equal or greater than $50 billion as of 2009Q3, and 0 otherwise. Post-Crisis takes 1 for the period 2010-2017, and 0 otherwise. Column (2) includes a series of financial ratios as controls, Column (3) accounts for market estimates of systematic and unsystematic risk, and Column (4) controls for market characteristics of the put options used in the construction of the tail-risk measure. An unbalanced panel of 85 banks observed quarterly over the period 2001-2017 is used. Regressions include year-quarter fixed effects to control for aggregate time trends that are common to all banks in the sample. Standard errors are clustered at the bank level to allow for error correlation within each panel.

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

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

1.5.2 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 1.3 outlines the different regulatory standards faced by banks in these various regulatory size buckets. Other than the $50 billion threshold for enhanced standards, these regulatory groups are defined using two additional regulatory thresholds conceived after the GFC. These include the $10 billion regulatory threshold for stress tests – also established in the Dodd-Frank Act – and the $250 billion threshold at which banks become subjected to Basel III additional regulatory requirements for advanced approaches banks.

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

To test this, I classify banks into one of the four size-based regulatory groups and then, using the DiD model outlined in Equation 1.2, I explore tail-risk differences between adjacent regulatory groups (two at a time). If stricter regulation does in fact reduce bank tail risk I expect greater regulatory stringency to be associated with lower tail risk. Hence, the effective regulation hypothesis predicts α_3 in Equation 1.2 to be negative for all cases in which the reference regulatory group corresponds to banks of smaller size relative to the larger treatment group. Any departure from this would be inconsistent with the idea that a stricter regulatory regime for larger banks is what explains the post-crisis tail-risk differences documented above.

Table 1.6 shows results for these between-group tests. Column (1) presents point estimates for a sample comprising banks in Group 1 and Group 2. Similarly, in Column (2) the sample is restricted to banks in Group 2 and Group 3, and in Column (3) to banks in Group 3 and Group 4. In all cases, the smaller regulatory group – of the two being compared – is used as the reference group. In addition, Column (4) shows estimates for the same model in Column (3) but with the post-crisis dummy redefined to equal one for the period after 2013Q3 and zero otherwise. I do this to account for the actual time the U.S. adopted Basel III advanced approaches for banks with at least $250 billion in assets (i.e. July 2013). All specifications include year-quarter fixed effects to account for aggregate time trends, and standard errors are clustered at the bank level.

Only in Column (2) is the coefficient on the interaction term negative and statistically significant, suggesting a post-crisis decline in the tail risk for above 50B banks relative to banks between $10B and $50B. On the contrary, results for the other two comparisons (i.e. Columns (1), (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, I observe no differences in tail risk around these other size thresholds.

Interestingly, I only observe a sharp decline in tail risk at one point: when banks cross-over the $50B threshold and are designated systemically important. Overall, these results are inconsistent with the effective regulation hypothesis. On the other hand,

Table 1.6: Other salient regulatory thresholds

This table presents coefficient estimates for the specification model in Equation 1.2 with observations restricted to adjacent regulatory groups. Treatment group is a dummy which takes 1 for banks in the stricter regulatory group (larger banks) and 0 otherwise. Post-Crisis takes 1 for the period 2010-2017, and 0 otherwise. Column (1) shows estimates where the two regulatory groups analysed are "less than $10B" (the reference group) and "between $10B and $50B". Column (2) presents coefficients for regulatory groups "between $10B and $50B" (the reference group) and "between $50B and $250B", and Column (3) for groups "between $50B and $250B" (the reference group) and "more than $250B". Column (4) shows estimates for the same model in Column (3) but with the Post-Crisis dummy redefined to 1 for the period after 2013Q3 and 0 otherwise. All regressions include the series of control variables in Table 1.5 Column (4), as well as year-quarter fixed effects. Standard errors are clustered at the bank level.

DEPENDENT VARIABLE: Tail Risk	(1)	(2)	(3)	(4)
Treatment Group	0.017	-0.043	-0.025	-0.012
	(0.432)	(-1.061)	(-1.399)	(-0.947)
Treatment Group × Post-Crisis	-0.049	-0.102***	0.025	-0.013
	(-1.078)	(-2.945)	(1.047)	(-0.948)
Observations	2,749	1,954	1,356	1,356
Controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj R-squared	0.132	0.274	0.701	0.700

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

the findings in Table 1.6 are compatible with implicit guarantees as the explanation for the lower tail risk of above 50B banks following the GFC. These banks correspond to those that were explicitly designated by Dodd-Frank as institutions whose failure could threaten the financial stability of the U.S. economy, and are the same banks which benefited the most from government assistance during the GFC. Since the systemically important status applied equally to all banks with more than $50 billion in assets (i.e. banks in Group 3 and Group 4), the implicit guarantee hypothesis predicts no extra tail-risk reduction for banks above the $250 billion mark. Consistent with this, I show in Table 1.6, Columns (3) and (4), that the tail risk of Group 3 and Group 4 are not statistically different in the post-crisis period. I argue that the designation of banks above 50B as systemically important reduced the ambiguity for investors about which banks are considered TBTF by the government leading to higher bailout expectations for this group. Similar findings have been documented by Moenninghoff et al. (2015) who show positive wealth effects upon the designation of certain large banks as globally systemically important banks (GSIBs).

1.5.3 Wealth Effects

To further understand the source of the tail-risk differences between small and large banks, I analyse the stock market reaction to the announcement of changes in bank regulation related to the passage of the Dodd-Frank Act. As elaborated in Section 1.4, the two competing hypotheses have starkly different implications for the impact of Dodd-Frank on shareholder welfare. Dodd-Frank introduced a stricter set of regulatory requirements for above 50B banks, but at the same time explicitly designated them as systemically important.

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

On the other hand, the implicit guarantee hypothesis argues that the official designation of above 50B banks as systemically important reinforced the TBTF problem for this group of banks and so predicts positive wealth effects for shareholders. Consistent with this, recent work by Moenninghoff et al. (2015) documents positive wealth effects for shareholders upon the announcement of large banks as globally systemically important (GSIBs). Further evidence of positive market reactions to the designation of banks as 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 (implicit guarantee hypothesis). Accordingly, any evidence of positive wealth effects around the passage of Dodd-Frank for above 50B banks would be consistent with the implicit guarantee hypothesis. That is, despite a larger regulatory burden, a net benefit to the shareholders of large banks could be interpreted as a reinforcement of the TBTF status of these institutions.

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

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

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

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

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

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

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

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

Following Bouwman et al. (2018), for each date I employ a two-day event window $[-1, 0]$ with $t = 0$ as the date of interest. The estimation window corresponds to the 200 trading days spanning the time period $[-211, -11)$. The estimation also includes a 10 day trading gap between the estimation and event windows. A market model is used to calculate daily expected returns following Equation 1.3.

$$R_{i,t} = a_i + b_i R_{M,t} + e_{i,t} \tag{1.3}$$

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.[33] For a given bank, daily abnormal returns (AR) are then calculated as:

$$AR_{i,t} = R_{i,t} - \hat{a}_i - \hat{b}_i R_{M,t} \tag{1.4}$$

with $\hat{a}_i$ and $\hat{b}_i$ corresponding to OLS estimates of Equation 1.3 over the estimation period.

Because the events of interest are the same for all banks, abnormal returns are prone to cross-sectional correlation and event-induced variance inflation. Both, have been shown to lead to over-rejections of the null hypothesis of zero abnormal returns. To account for these effects, I employ the test statistic proposed by Kolari and Pynnönen (2010) in all of my tests.[34]

Table 1.7 reports cumulative abnormal returns (CARs), and corresponding test statistics, for below 50B and above 50B banks. This table presents evidence of positive abnormal returns (5.2%) for above 50B banks around the date the U.S. Senate passed the Dodd-Frank bill. I also find a significantly positive reaction (1.4%) for above 50B banks on the date the House agreed to the final version of the Dodd-Frank bill negotiated between the two chambers via conference committee. There are no significant market reactions on other dates for above 50B banks. For these banks, markets seem to interpret the development of Dodd-Frank as net-positive news: despite the additional regulatory burden Dodd-Frank imposed on above 50B banks, the designation of these banks as systemically important brought with it the perceived benefit of future government support in distress states.

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

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

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

Table 1.7: Wealth effects

This table 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 or greater than $50 billion as of 2009Q3. For each date, a two-day event window $[-1, 0]$ is used with $t = 0$ as the date of interest. The estimation window corresponds to the 200 trading days spanning the time period $[-211, 11)$. The estimation also includes a 10 day trading gap between the estimation and event windows. For each bank, a market model is used to calculate daily expected returns. The reported test statistic corresponds to the one proposed by Kolari and Pynnönen (2010), which accounts for cross-sectional correlation and event-induced variance inflation.

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

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

can be interpreted as the markets expectation of higher regulatory costs for some these banks following the passage of Dodd-Frank.

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

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

Table 1.8: Cross-sectional wealth effects

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

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

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

Dodd-Frank bill), I run a cross-sectional regression of banks' CARs on an indicator for above 50B banks and a series of bank characteristics as of 2009Q4. Table 1.8 shows coefficients estimates for this specification. 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. Moreover, larger CARs on this date are associated with higher exposure to other financial institutions (i.e. interconnectedness) and higher systemic risk. Both of these factors are key characteristics of systemically important institutions. These results add weight to the notion that an increase in bailout expectations for above 50B banks, post-crisis, is the ultimate source of their lower-tail risk.

1.5.4 U.S. Credit-Rating Downgrade

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

In this section, I exploit Standard & Poor's (S&P) decision to downgrade the U.S. credit rating on August 5, 2011 as a shock to the government's creditworthiness.[35] I then examine the effect of this change on the tail risk of both, systemically important (above 50B) and smaller banks (below 50B).

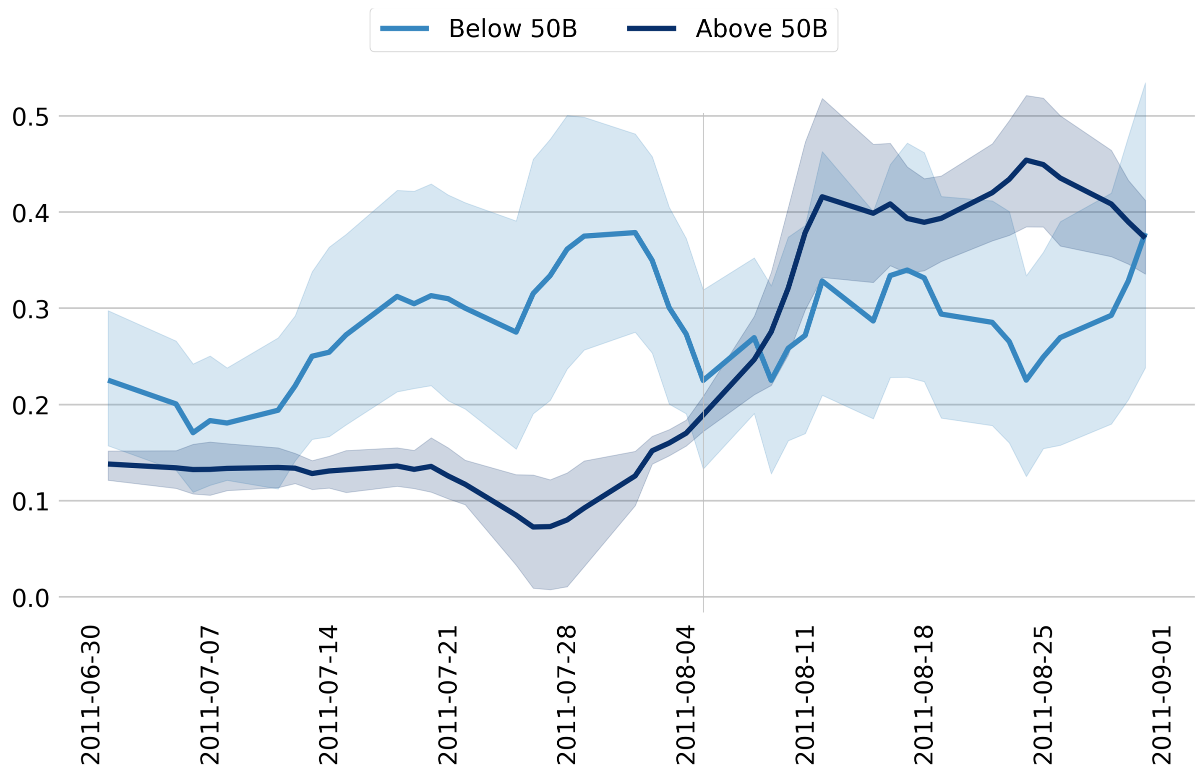
Under the implicit guarantee hypothesis, systemically important banks are perceived as less prone to significant price drops (i.e. tail risk) because markets expect them to receive government assistance in future distress states. Hence, a reduction in the government's ability to fulfil its implicit commitment,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

To test this, I employ Equation 1.1 to construct daily tail-risk estimates for both, systemically important and non-systemically important banks over the entire months

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

Figure 1.4: Tail risk around the U.S. credit-rating downgrade

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



of July and August 2011. That is, approximately one month before and after the U.S. credit-rating downgrade.

Figure 1.4 shows five-day moving averages for the tail risk of systemically important banks and non-systemically important banks before and after the downgrade. This figure presents a marked change in the average tail risk of large banks around the U.S. credit-rating downgrade. In particular, the average tail risk of systemically important banks experiences a three-fold increase following the downgrade, relative to the average tail risk in the previous month.[36] On the contrary, the average tail risk of non-systemically important banks remains relatively constant between July and August 2011.

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

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

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

Specifically, I use the specification model in Equation 1.2 restricted to the sample period July-August 2011 and with the variable $Post\text{-}Crisis_t$ replaced by $Post\text{-}Downgrade_t$. The latter corresponds to a dummy variable which takes one for the period after the credit-rating downgrade, and zero otherwise. Moreover, the dependent variable corresponds to a five-day moving average of each bank's daily tail risk. Also, this specification includes the variable *U.S. Treasury Holdings* as a control. For each bank, this covariate measures the proportion of U.S. Treasury securities held in relation to total assets.[37] 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.

Table 1.9 presents coefficient estimates for this model. Column (1) shows the re-

[37]This and other bank characteristics are estimated using the Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) filed with the Federal Reserve as of 2011Q3 (see Section 1.5.1).

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

Table 1.9: U.S. credit-rating downgrade

This table presents coefficient estimates for the specification model in Equation 1.2 restricted to the sample period July-August 2011 and with the variable $Post\text{-}Crisis_t$ replaced by $Post\text{-}Downgrade_t$. The latter corresponds to a dummy variable which takes 1 for the period after the U.S. credit-rating was downgraded on August 5 2011, and 0 otherwise. The dependent variable corresponds to a five-day moving average of each bank's daily tail risk. Above 50B is a dummy variable which takes 1 for banks with assets equal or greater than $50 billion as of 2009Q3, and 0 otherwise. Column (2) includes the variable *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 Table 1.5 Column (4). Regressions include time fixed effects and standard errors are clustered at the bank level.

DEPENDENT VARIABLE: Tail Risk	(1)	(2)	(3)
Above 50B	-0.152***	-0.150***	-0.064
	(-3.759)	(-3.711)	(-0.764)
Above 50B × Post-Downgrade	0.240***	0.240***	0.238***
	(4.666)	(4.667)	(4.623)
US Treasury Holdings		-1.227	-2.309**
		(-1.392)	(-2.213)
Observations	3,193	3,193	3,193
Controls	No	No	Yes
Quarter fixed effects	Yes	Yes	Yes
Adj R-squared	0.0387	0.0423	0.123

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

Overall, these findings provide further evidence in support of the implicit guarantee hypothesis as the main cause of the cross-sectional differences in tail risk observed in the post-crisis period. The tail risk of banks that benefit from government guarantees (i.e. TBTF banks) is largely affected by a deterioration of the governments' creditworthiness. For smaller banks, the impact of the U.S. downgrade is negligible. In addition, no regulatory change of interest occurred during this time that can explain the differential tail-risk behaviour documented in this section.[38]

[38] In an additional specification, I added a triple interaction term between the variables "Low U.S.

1.5.5 Risk-Taking Differences

In this section I analyse the actual risk-taking behaviour of large and small banks in the post-crisis period. The two alternative explanations make differing predictions regarding banks risk taking. The implicit guarantee hypothesis predicts that, due to moral hazard generated by government guarantees (see Duchin and Sosyura, 2014; Kane, 2009; 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, I define three categories of risk measures: business or operational risk, market-based measures of risk, and regulatory (capital adequacy) measures of risk. To construct these measures, I employ consolidated financial statements filed with the Federal Reserve and historical stock performance data from CRSP. Next, I contrast above and below 50B banks across these various dimensions of risk and test for differences in their average risk taking, before and after the crisis. Table 1.10 reports results for these tests. Columns (1) and (3) show above 50B-*minus*-below 50B mean differences for the pre and post-crisis periods, respectively.[39] In addition, Column (5) reports difference-in-differences estimates obtained by subtracting the mean differences in Column (3) from Column (1).

Market Risk

In regard to market risk, I use four measures: total return volatility, Beta (i.e. quantity of market risk), systematic risk (i.e. $\beta\sigma_{market}$) and unsystematic risk (i.e. total return

Treasury Holdings $\times$ Above 50B $\times$ Post-Downgrade", where "Low U.S. 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. The coefficient on this triple-interaction term (not reported) is not statistically different from zero.

[39] Pre-crisis comprises the time period 2001-2007, whereas post-crisis the period 2010-2017.

Table 1.10: Risk-taking differences

This table 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 (two-tailed) of the test statistic under the null hypothesis of equal means. Pre-crisis corresponds to the time period 2001-2007 and post-crisis to the period 2010-2017.

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

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

volatility less systematic risk).[40] One can see that the difference-in-differences estimates on total, systematic, and unsystematic risk, in Panel A, are all insignificant. Interestingly, the tests do reveal that the Beta coefficient with respect to the market is significantly larger for above 50B banks post-crisis, suggesting that large banks' exposure to market risk has increased relative to smaller banks.

Business Risk

Similarly, I use the following variables to capture business risk: reliance on short-term wholesale funding (liquidity risk), non-performing loans (credit risk), z-score (insolvency risk), and exposure to other financial institutions (interconnectedness).[41] Panel B 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 being 10.3% *lower* pre-crisis (relative to below 50B banks) to 20.4% higher after the GFC.[42]

Finally, above 50B banks' exposure to other financial institutions (relative to below 50B banks) surges more than four times in the post-crisis period. That is, above 50B banks become much more interconnected, which is consistent with their "systemically important" status. It is worth noting that a higher degree of interconnectedness can exacerbate investors' perception that large banks are more likely to receive government protection. Highly interconnected financial institutions are said to accelerate the

[40] See Section 1.5.1 for a detailed description of these variables.

[41] See Section 1.5.1 for a detailed description of these variables.

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

transmission of financial shocks and to increase systemic risk (see Bluhm and Krahnen, 2014; Paltalidis et al., 2015). Hence, analogous to the TBTF problem, if large banks are considered "too-interconnected" markets may increase their expectations of future bailouts for the entire group – a feature known as the "too-many-to-fail" problem (see Acharya and Yorulmazer, 2007; Brown and Dinç, 2011).

The findings from the above analysis show that above 50B banks are more risky compared to below 50B banks in the post-crisis period – a reality that has also been exposed by Sarin and Summers (2016) – which is consistent with the implicit guarantee hypothesis: the series of bank bailouts targeted at large institutions, and the designation of banks above the $50B threshold as systemically important, reinforced the TBTF status for this group resulting in relatively lower tail risk post-crisis. This, in spite of fact that their actual risk exposure increased relative to banks of smaller size.[43]

Capital Adequacy

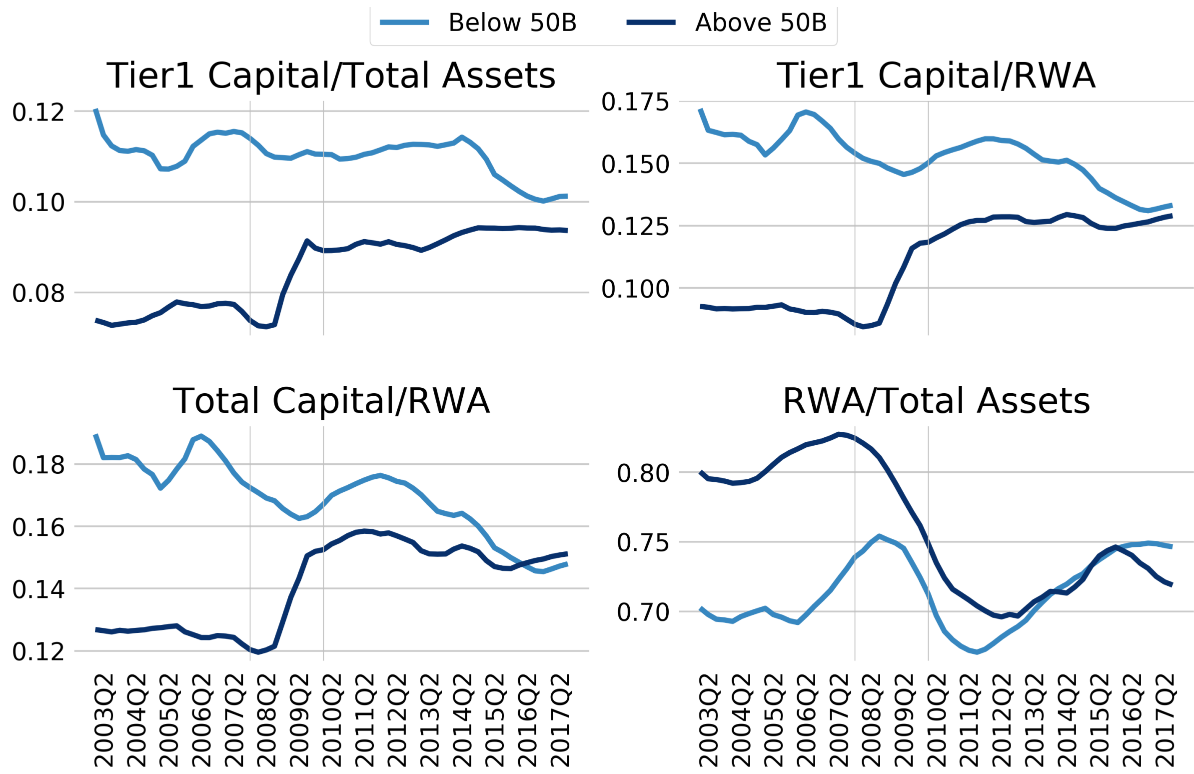
But did enhanced capital regulation for larger banks achieve its intended goal of increasing the capital ratios for large banks by more than that of smaller banks? To answer this question, I examine the evolution of four regulatory ratios using the same approach as above. Panel C of Table 1.10 shows that the new post-crisis regulatory environment led to an increase in regulatory capital and a reduction in risk-weighted assets for above 50B banks relative to smaller banks. Nonetheless, these capital adequacy ratios remain, on average, below those of small banks.

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 1.5. This can be partly explained by the capital injections the U.S. government made in large financial institutions under the Capital Purchase Program (CPP) component of TARP. Of the $205 billion CPP package allocated to enhance the capital ratios of

[43]It can be argued that differences in stress-tests application can also explain the cross-sectional tail-risk differences reported in this chapter. However, provided that stress testing has its intended impact of changing banks' exposure to risk (e.g. liquidity, credit, insolvency), the findings in this section make that possibility unlikely

Figure 1.5: Capital adequacy measures

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



financial institutions, $168 billion (82%) was directed to banks above the $50B threshold.[44]

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

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

1.5.6 Market Discipline

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

For both, below and above 50B banks, I regress bank tail risk on each bank risk-taking measure used in Section 1.5.5 along with an interaction term between the risk measure and a time dummy that identifies the post-crisis period. These interaction terms are the variables of interest, which describe how the sensitivity of tail risk – to changes in bank risk taking – varies in the post-crisis period. Table 1.11 presents results for this test. Columns (1) and (2) show coefficient estimates for below and above 50B banks, respectively.

Two results are worth discussing. For above 50 banks, tail-risk sensitivity to changes in credit risk (non-performing loans) drops almost 100% post-crisis. Similarly, the interaction between the z-score and the crisis indicator is positive and significant, which implies a significant weakening of the tail-risk sensitivity to insolvency risk. Both of these findings are consistent with the implicit guarantee hypothesis. Due to heightened bailout expectations, markets perceive large banks to be less exposed to tail events. This in turn leads to a deterioration of market discipline, weakening the link between large banks tail risk and their actual risk-taking behaviour.[45]

[45]Survivorship bias may also impact the tail-risk averages of below and above 50B banks differently. If bank failures are observed in the below 50B group only – as it was mostly the case – then the post-crisis average tail risk for this group would reflect the perceived exposure to downside risk of those banks which survived. However, this survivorship bias effect acts against the results documented in this study.

Table 1.11: Market discipline

This table shows coefficient estimates from regressing tail risk on a series of market and business risk measures interacted with a post-crisis dummy, which takes 1 for observations in the time period 2010-2017, and 0 for the period 2001-2007. Columns (1) and (2) show estimates for 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), respectively. Both specifications include controls for all other bank and market characteristics in Table 1.5 Column (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.

DEPENDENT VARIABLE: Tail Risk	Below 50B	Above 50B
Systematic Risk	-2.705	4.829***
	(-0.799)	(2.900)
Post-Crisis × Systematic Risk	1.172	0.008
	(0.371)	(0.002)
Unsystematic Risk	-0.803	-0.841**
	(-0.658)	(-2.308)
Post-Crisis × Unsystematic Risk	0.762	0.465
	(0.612)	(0.983)
Exposure to FIs	0.588	-0.117
	(1.134)	(-0.954)
Post-Crisis × Exposure to FIs	2.306	-0.193
	(1.559)	(-0.756)
Short-Term Wholesale	-0.004	0.080
	(-0.025)	(1.601)
Post-Crisis × Short-Term Wholesale	-0.106	0.052
	(-0.366)	(0.642)
Non-Performing Loans	2.271	3.403**
	(0.774)	(2.268)
Post-Crisis × Non-Performing Loans	-2.842	-3.410**
	(-1.078)	(-2.121)
Z-Score	0.002	-0.002
	(0.453)	(-1.237)
Post-Crisis × Z-Score	0.004	0.005***
	(0.846)	(2.750)
Observations	891	1050
Controls	Yes	Yes
Bank fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adj R-squared	0.0452	0.1584

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

1.6 Conclusion

I employ option prices to construct a forward-looking measure of bank exposure to significant price drops (i.e. tail risk) and explore cross-sectional differences between large banks identified as systemically important – banks with at least $50 billion in assets – and smaller banks. I document a permanent 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. I argue that the stark post-crisis difference in tail risk for banks above and below the $50B threshold is consistent with the notion that the TBTF status of above 50B banks was reinforced by the series of bailouts targeted at them during the crisis, and by their subsequent designation as systemically important by the Dodd-Frank Act. This, in turn, raised investor expectations of future bailouts for above 50B banks and reduced their perceived exposure to downside risk as captured by the tail-risk measure.

Overall, the evidence documented in this chapter supports 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. Moreover, 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. I show no significant changes in tail-risk around other salient regulatory size thresholds, even though regulatory stringency varies substantially around these thresholds. I also document positive wealth effects accruing only to above 50B banks around the passage of Dodd-Frank. In addition, I show that a deterioration in the U.S. governments' creditworthiness leads to a sharp tail-risk increase for systemically important banks, which is in line with the notion that these banks are perceived as benefiting from implicit government guarantees. Finally, *actual* risk taking for above 50B banks increases relative to smaller

By construction, the average tail risk of those banks that survived was lower than those which failed. Once the failed banks drop out of the sample, average tail risk would tend to decrease and dampen the size-based tail-risk differences reported here.

banks in the post-crisis period.

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

Chapter 2

The Two Sides of Deposit Insurance: Evidence from the 2005 FDI Reform Act

2.1 Introduction

In most developed countries, deposits are insured by government-sponsored schemes. These schemes are implemented to increase bank stability and to reduce banks' exposure to runs and their resulting perverse economic consequences. However, they can also generate a moral hazard problem by distorting banks' incentives and encouraging risk-taking behaviour. From an empirical standpoint, these two potential sides of deposit insurance have challenged attempts to objectively determine the true consequences of such insurance schemes.

Despite its convincing theoretical rationale (see Diamond and Dybvig, 1983) and wide global implementation, evidence on the professed stabilising effects of deposit insurance is rather mixed. This is not surprising due to the lack of a proper counterfactual to determine the positive effects of government guarantees. In an ideal setting, we would measure the stabilising effects of deposit insurance by contrasting outcomes in a state of the world where deposit insurance has been implemented against its counterfactual, that is, an *unobserved* state of the world where these special guarantees do not exist.

By comparing these two states we would then estimate the number of bank runs, and perhaps banking crises, prevented by the implementation of deposit insurance. Nevertheless, attempts have been made to estimate the stabilising effect of deposit insurance by looking at cross-country variation between banking systems with and without this explicit guarantee. For instance, Anginer et al. (2014) show standalone bank risk and systemic risk during the Global Financial Crisis (GFC) of 2008 were lower in countries with an existing deposit insurance scheme.

In relation to the potential detrimental effects of deposit insurance, there exists a vast literature investigating the impact of such government-sponsored guarantees on banks' risk characteristics. Theoretical models have shown that banks are incentivised to take on more risks when their liabilities are explicitly guaranteed by an insurance scheme that is not actuarially fair.[1] The moral hazard problem that arises as a result has also been studied empirically, with most papers presenting results consistent with the idea that banks take greater risks when a government-sponsored deposit insurance scheme is in place (see Anginer et al., 2014; Barth et al., 2004; Chernykh and Cole, 2011; Demirgüç-Kunt and Detragiache, 2002; Grossman, 1992; Ioannidou and Penas, 2010).

Yet, the identification strategies used within empirical studies have limitations, for several salient reasons. For instance, studies that contrast the probability of banking crises in countries with and without deposit insurance are challenged by endogeneity bias concerns. Similarly, papers that analyse deposit insurance schemes that were set in place gradually, and in a voluntary form, are confronted by self-selection bias issues. In addition, studies that exploit recent implementations of deposit insurance in developing economies may not necessarily reflect the insurance schemes of economies where the government's creditworthiness plays a key role in determining the effects of the deposit guarantee.

This chapter investigates the *moral-hazard* vs *stability* trade-off of deposit insurance

[1] That is, premiums paid by banks do not correspond to their probability of insolvency and the amount of liabilities insured.

by presenting a novel approach that circumvents some of the empirical challenges previous studies have encountered when studying the economic implications of this explicit government guarantee. Specifically, I focus on a sample of more than 8,000 U.S. commercial banks and investigate the impact of the Federal Deposit Insurance Reform Act of 2005 on banks' risk characteristics. Under this Act, the insurance coverage limit for individual retirement accounts (IRAs) more than doubled. I argue that this effectively caused a new set of bank liabilities – those exceeding, or expected to exceed the previous coverage limit – to become insured by the government. Thus, I use this reform as a shock to the insured liabilities and measure changes in the risk-taking behaviour of banks that benefit more (i.e. those with higher ex-ante IRA balances) from extending the government guarantee.

Despite the fact that this reform affected banks differently – based on their ex-ante IRA balances – it is possible that IRA balances and risk taking are both determined by unobserved bank characteristics such as each bank's idiosyncratic business model. I address this potential endogeneity problem with an instrumental variables approach. Specifically, I instrument the variable of interest (i.e. IRA balances per bank) with an original *Senior Index*. This index is an average of the number of seniors living in U.S. counties where a bank has a presence, weighted by the bank's total amount of deposits per county. The validity of this approach is founded on the fact that seniors in the U.S. are consistently the age group with the largest balances for both traditional deposits and IRAs. Thus, this index is highly correlated with banks' IRA holdings. At the same time, and because of its demographic nature, this index is likely to satisfy the exclusion restriction (i.e. uncorrelated with bank-risk characteristics).

Using this approach I show that, after the reform was effected, those banks more reliant on retirement accounts for funding increased their risk-taking behaviour in the form of higher leverage and lower liquidity ratios. This, I argue, constitutes first-hand evidence supporting the existence of a moral hazard problem caused by deposit insurance. Importantly, the evidence presented is aligned with the *leverage* and *asset sub-*

stitution channels of the moral hazard problem identified in the theoretical literature. However, unlike the moral hazard evidence outlined in previous studies – which suggests banks initiate riskier loans after the implementation of deposit insurance – the asset substitution effect reported in this study occurs across assets classes, in the form of a reduction in banks' liquid asset holdings.

In addition, I exploit the chain of events that followed the 2005 deposit insurance reform to explore the impact of this reform on banks' propensity to fail or require government assistance during the GFC. With this, I aim at determining the potential stabilising effect of deposit insurance by exploiting cross-sectional differences in IRA funding amongst U.S banks. I design a logistic classification model that allows for the estimation of banks' probability of financial distress conditional on their reliance on IRA funding. I show that the ex-ante level of a bank's IRA funding is an important determinant of its probability of financial distress during the GFC. Specifically, I show that banks more reliant on IRA deposits experienced a 38 percentage points lower probability of failure, or need for government aid, during the crisis. I interpret these results as evidence of the marginal stabilising effect of extending a deposit insurance scheme.

The contribution of this study is twofold. First, it advances the current literature on government guarantees and bank risk-taking behaviour through a quasi-experimental design, which overcomes some of the most prominent identification challenges. I not only conclude that a moral hazard problem exists, but also present evidence supporting two very specific economic channels with regard to how banks' risk-taking behaviour is influenced by insurance schemes. Moreover, I measure the stabilising effect of extending the government guarantee and its economic significance. Despite the relative importance of individual retirement accounts within the pension funds market and as a source of funding for banks, to my knowledge this is the first study to explicitly analyse the coverage limit increase for IRAs under the Federal Deposit Insurance 2005 Reform Act.

Second, this chapter presents direct evidence as to how financial intermediaries may respond to policies that increase their reliance on government-insured liabilities. The implementation of the Net Stable Funding Ratio (NSFR) under Basel III is likely to be one of these policies because it requires banks to fund their assets with stable sources and considers deposits as the most stable external source of funding.[2] Despite being created to reduce the likelihood of liquidity dry-ups, it is possible this new ratio could have unintended moral hazard consequences given the aforementioned evidence on deposit insurance.

The rest of this chapter is organised as follows. Section 2.2 provides a brief recount of the existing theoretical and empirical literature on deposit insurance and its potential effects. Section 2.3 describes the empirical approach used and explains the key aspects of the methodology. A description of the sample and data sources follows in Section 2.4. Section 2.5 reports the main results, and Section 2.6 presents a series of robustness checks that support the existence of both a moral hazard and a stabilising effect caused by deposit insurance. Finally, Section 2.7 concludes by describing the main implications of my findings.

2.2 Related Literature

Bank Stability

The short-funded nature of a bank's balance sheet exposes it to bank runs. These sudden surges in deposit withdrawals may be well founded on negative information about the bank's risk exposures. In this case, withdrawals become the ultimate form of market discipline, or as Bliss (2012) calls it, "destructive market discipline". Alternatively, these withdrawals could be based on unfounded expectations about the bank's probability of insolvency, or the belief that other depositors consider a bank insolvent. In any case, the depositors' optimal decision may be to run on the bank anticipating

[2]The second most stable source of funding after regulatory capital (Bank for International Settlements, 2014).

that others will also choose the same course of action.

To prevent panicking depositors from running on solvent banks, as it happened in the 1920s and early 1930s, in 1933 the U.S. government created the Federal Deposit Insurance Corporation (FDIC) under the Glass-Steagall Act. The FDIC constituted the first U.S. central-government backed deposit insurance scheme.[3] In their seminal paper, Diamond and Dybvig (1983) support the existence of government deposit insurance, which, they argue, allows banks to perform their liquidity creation and asset transformation roles without being exposed to runs. They show that in the absence of a credible deposit insurance scheme, a bank run is an equilibrium outcome that reduces social welfare by interrupting production and destroying risk sharing among depositors.[4]

However, presenting evidence in favour of the stabilising effect of deposit insurance has been challenging. One approach to tease out any marginal stabilising effect would be to compare the propensity to bank runs between economies with and without the insurance scheme. However, the results from this approach are deficient in supporting the existence of a stabilising effect when we consider previous studies have, in fact, shown a higher propensity to banking crises in countries with these guarantees (see Demirgüç-Kunt and Detragiache, 2002).

Anginer et al. (2014) present recent evidence of the expected stabilising effect of deposit insurance. They use a dataset on publicly traded banks across different countries, and various measures of individual bank risk, to investigate the effect of these guarantees during the GFC. They show standalone and systemic risk are lower in countries with deposit insurance during this crisis. However, they also report the existence of a destabilising moral hazard effect during the period leading up to the crisis.

[3]The FDIC was created by the U.S. Congress with the main purpose of protecting depositors from losses, maintaining trust on the country's financial system, and promoting financial stability. Since its inception "no depositor has ever lost a penny of insured deposits" (FDIC, 2014).

[4]Friedman and Schwartz (1963) present empirical evidence of the significant detrimental effects the 1930s bank runs had on the U.S. economy.

Moral hazard

Despite increasing bank stability and reducing the probability of bank runs, there is also a dark side to deposit insurance as a type of government guarantee. Deposit insurance is said to create a classic moral hazard problem. When banks have their main source of funding insured by a third party, they are incentivised to increase their risk-taking behaviour. Merton (1977) notes that the pay-off structure of deposit insurance is identical to that of a put option on bank assets with the nominal value of the insured deposits as its strike price. He argues that when deposit insurance is unfairly priced, a bank can maximise the value of this additional financial claim (i.e. put option) by increasing the riskiness of its asset portfolio, thus generating a moral hazard problem.

Similarly, Dreyfus et al. (1994), in a theoretical model of regulatory forbearance and deposit insurance, define moral hazard as the incentive to liquidate less risky assets and replace them with riskier ones so as to increase the value of the bank's deposit insurance put option. I will refer to this form of moral hazard as the *asset substitution effect* of deposit insurance. This moral hazard effect is said to be magnified the closer a bank is to insolvency, in which case "gambling for resurrection" is the optimal choice from the perspective of the bank's shareholders (see Merton, 1978). Another form of asset substitution may arise if banks reduce their liquid holdings and substitute them with less liquid, and hence riskier loans (see Bhattacharya et al., 1998). This type of asset substitution does not necessarily imply that banks increase their credit risk (e.g. lower loan standards) but that liquid assets are replaced with illiquid ones.

Using the same framework first introduced by Merton (1977), other theoretical models have focused on financial leverage as the source of banks' higher risk-taking behaviour. For instance, Pennacchi (1987) shows that flat insurance premiums, and mergers as resolution mechanisms for bank failures, increase risk-taking incentives in the form of more leverage. Similarly, Buser et al. (1981) describe a bank's charter value as an increasing function of leverage due to unfairly priced insurance premiums. In this study, I refer to this form of moral hazard as the *financial leverage effect* of deposit insurance.

These two forms of excessive risk taking – that is, replacing safer assets with risky ones or increasing leverage – can be deterred if depositors push for higher interest rates on their holdings or simply exercise their early withdrawal rights.[5] However, this is exactly the form of market discipline deposit insurance is said to destroy (see Karas et al., 2013). If deposits' safety is unaffected by banks' risk-taking behaviour, depositors have less (or no) incentive to gather relevant information and monitor bank activities. Although, regulation and supervision are intended to act as substitutes for depositors' market discipline, several studies suggest banks tend to take on more risks in the presence of deposit insurance schemes.

One of the first studies to attempt to tease out the moral hazard effect of deposit insurance was produced by Grossman (1992).[6] Using balance sheet data on U.S. thrifts, and foreclosures as a measure of risk, Grossman shows how newly insured thrifts became less risky initially and that the problem of moral hazard emerged over time. Unlike commercial banks, not every thrift was initially insured. Thrifts had to apply for deposit insurance and the insurer granted it on the basis of a thorough examination.[7] The voluntary nature of this deposit insurance scheme challenged Grossman's analysis with self-selection bias issues.

In the same vein, Demirgüç-Kunt and Detragiache (2002) use cross-sectional variation in the regulatory framework of 61 countries to conclude that deposit insurance reduces bank stability. They do this by exploring how the nature of deposit insurance can influence the probability of a banking crisis. Using a similar approach and a richer dataset, Barth et al. (2004) also find deposit insurance deteriorates bank stability and exacerbates moral hazard. With this empirical strategy, the moral hazard effect of de-

[5]See Calomiris and Kahn (1991) for a theoretical treatment of how depositors discipline banks given private signals, and Saunders and Wilson (1994) for empirical evidence supporting the existence of informed depositors disciplining banks during the Great Depression.

[6]See also Barth et al. (1989).

[7]The extinguished Federal Savings and Loan Insurance Corporation (FSLIC) administered deposit insurance for thrifts until 1989 when this responsibility was transferred to the FDIC.

posit insurance is identified at the country level based on the probability of banking crises occurring in countries with and without deposit insurance schemes. The number of regulatory environments used under this approach makes it challenging to control for all factors influencing the probability of a banking crisis. Furthermore, the fact that countries self-select to introduce deposit insurance in their regulatory system – and that (in many cases) deposit insurance schemes originated as a response to financial crises – difficults the identification of a moral hazard problem with this methodology.[8]

Other studies have used bank-level data and the introduction of explicit deposit insurance in developing countries as a quasi-natural experiment to investigate its impact on bank risk. For instance, Ioannidou and Penas (2010) use borrower credit ratings at origination for a sample of Bolivian banks and show that, after the introduction of deposit insurance, banks were more likely to lend to riskier borrowers. Similarly, Chernykh and Cole (2011) focus on the gradual implementation of government-sponsored deposit insurance in Russia. They conclude that banks that applied for and were granted deposit insurance increased their reliance on deposits and became more leveraged compared to banks that did not enter into the deposit insurance system.[9] Despite overcoming previous empirical issues, the datasets used in these and similar approaches hinder the identification of any moral hazard problem. This since the creditworthiness of the states issuing these guarantees is a necessary condition to justify any increase in banks' risk-taking behaviour.

More recently, Calomiris and Jaremski (2019) exploit differences in the adoption of deposit insurance laws across U.S. states in the early 20th century to present evidence of the moral hazard effect of deposit insurance. Because these laws applied only to a subsample of the depository institutions in a given state, the authors contrast the risk-taking behaviour of insured and uninsured banks within the same locality, which circumvents some of the aforementioned identification challenges.

[8]The authors acknowledge these important issues and use different techniques to try to circumvent them.

[9]As in Grossman (1992), the voluntary nature of this deposit insurance scheme generates self-selection bias issues.

Finally, and contrary to what most empirical studies have suggested, Gropp and Vesala (2004) argue that the existence of explicit deposit insurance may in fact reduce banks' risk-taking behaviour. Their argument is that in the absence of explicit guarantees, it is "implicitly" expected that all bank liabilities are to be insured by the government. Thus, the introduction of explicit deposit insurance limits the coverage of the government guarantee by credibly excluding some bank creditors from the public safety net. However, the empirical evidence of this study also relies on cross-sectional data from European banks operating under different regulatory regimes and is thus subject to the same aforementioned problems.

2.3 Empirical Strategy

In order to circumvent some of the identification challenges faced in previous studies, in this chapter I design an empirical strategy that exploits the effect of the Federal Deposit Insurance Reform Act of 2005 on U.S. banks' risk-taking behaviour.[10] On February 8, 2006, the Federal Deposit Insurance Reform Act was enacted. This piece of legislation increased the coverage limit for individual retirement accounts (IRAs) from USD 100,000 to USD 250,000, effectively expanding the existing U.S. deposit insurance scheme at the time.[11]

Individual retirement accounts are special accounts depositors establish with a financial service company, such as a commercial bank, to set aside funds for retirement.[12] This special type of retirement accounts were created in 1974 by the U.S. Congress to encourage retirement savings. IRAs offer significant tax benefits in the form of tax deferrals and tax exemptions, and in some cases they also impose important restrictions

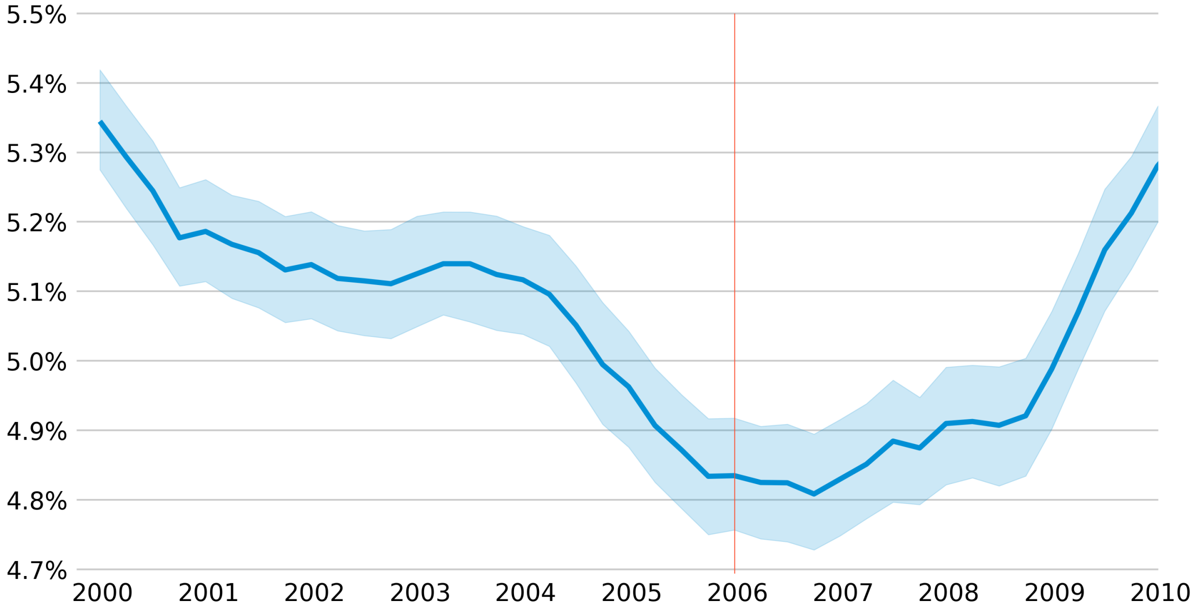
[10]These empirical challenges include controlling for all possible explanatory variables when comparing different regulatory systems, identifying moral hazard at the bank-level, self-selection bias due to voluntary implementation of insurance schemes, and data reliability.

[11]This change was made effective on 1 April, 2006.

[12]The Employee Retirement Income Security Act (ERISA) of 1974 created individual retirement accounts (IRAs).

Figure 2.1: IRA holdings 2000-2010

This figure shows average Individual Retirement Accounts (IRA) holdings, scaled by total deposits, held with commercial banks between 2000 and 2010. The vertical line indicates the date on which the deposit coverage limit for IRAs was increased from USD 100,000 to USD 250,000.



on early withdrawals (FINRA, 2017).[13] Figure 2.1 shows the average IRA holdings, scaled by total deposits, held with U.S. commercial banks between 2000 and 2010. For commercial banks, the average reliance on IRAs increased approximately 12% between the enactment of the 2005 Reform Act and 2010.

Since changes in coverage limits only applied to IRAs, my goal is to capture the bank-level effects of extending the deposit insurance scheme for these accounts.[14] I argue that increasing the coverage limit for individual retirement accounts effectively caused a new set of bank liabilities – those exceeding, or expected to exceed the previous coverage limit – to become suddenly insured by the FDIC. Thus, raising the coverage limit

[13]There are two main types of IRAs: Traditional and Roth. In a Traditional IRA contributions are typically tax deductible and taxes on earnings are deferred until retirement. Traditional IRAs also impose a 10% Federal penalty on early withdrawals.

[14]For deposit insurance purposes, IRAs are treated separately and do not add up to the overall insurance limit of other types of deposits. For instance, in 2007 an individual with USD 50,000 deposited in a transactions account and USD 250,000 saved in an IRA account, both with the same financial institution, would have had all her deposits covered by the deposit insurance system.

for IRAs should (in theory) generate a marginal stabilising and/or moral hazard effect. On this point, for instance, Diamond and Dybvig (1983) argue that when explicit deposit insurance is in place, deposits above the insured amount are still exposed to runs. Similarly, Demirgüç-Kunt and Detragiache (2002) show that the negative impact of deposit insurance tends to be stronger the more extensive the coverage in place. Hence, I hypothesise that U.S. commercial banks that relied more on IRAs ex-ante saw their risk-taking behaviour incentives distorted after the implementation of the 2005 Reform Act.

2.3.1 Moral Hazard Effect

Given the relative importance of retirement savings and restrictions imposed on early withdrawals, IRA holders are expected to exert higher levels of monitoring on bank activities compared to other types of depositors, especially for those IRA balances exceeding the established coverage limit. Hence, I argue that when new IRA balances became insured, banks with a higher reliance on these accounts increased their risk-taking behaviour. To test this and investigate the causal effect of the 2005 reform, I estimate a quasi-experimental model of the following form:

$$\begin{aligned} Bank\_Risk_{i,t} = \alpha_0 + \alpha_1 FDIC\_2005_t + \alpha_2 IRA_{i,t-1} + \alpha_3 (FDIC\_2005_t \times IRA_{i,t-1}) \\ + \sum_{k=1}^{n} \beta_k X_{i,t-1} + T_t + B_i + \varepsilon_{i,t} \end{aligned} \tag{2.1}$$

This model permits to contrast the risk-taking behaviour of banks with higher and lower reliance on IRAs, before and after the Federal Deposit Insurance Reform Act of 2005. I use five different measures for bank risk:

i **Liquidity:** defined as total liquid assets scaled by total assets. I use the definition of liquid assets given by Berger and Bouwman (2009). This includes cash and due from other institutions, securities, Fed funds sold, and trading assets. This ratio is intended to capture banks' ability to fund assets and meet financial obligations.

ii **Off-balance sheet liquidity:** measured by subtracting banks' unused balance of loan commitments issued from their holdings of liquid assets, and then scaling this difference by total assets. This serves as a liquidity risk measure arising from draw-downs of committed lines of credit.

iii **Leverage:** calculated by dividing the book value of total liabilities by total assets. A higher leverage ratio exposes banks to a higher probability of insolvency and agency costs.

iv **Regulatory Capital:** the capital adequacy ratio established by the Basel Committee on Banking Supervision. This ratio is calculated by adding Tier 1 and Tier 2 capital and dividing by risk-weighted assets (RWA).[15] The lower this ratio the higher the bank's exposure to regulatory risk.

v **Z-Score:** I construct a time-varying Z-Score for each bank by following the approach suggested by Lepetit and Strobel (2013). For each time period and bank, I add its capital-asset ratio to its historical mean return on assets (ROA) and divide this by the standard deviation of ROA. This score is inversely related to a bank's probability of insolvency and thus larger values reflect a lower probability of insolvency.

The explanatory variable of interest is the interaction term between $FDIC\_2005$ and IRA. $FDIC\_2005$ is an indicator that takes one for the period after the implementation of the deposit insurance reform, and zero otherwise. IRA measures banks' ex-ante IRA holdings scaled by total deposits.

Furthermore, I control for bank characteristics that can potentially affect bank risk. Specifically, I control for *bank size*, measured as the natural logarithm of total assets; *profitability*, defined as net earnings over assets; *loan quality*, calculated as the dollar value

[15]Under Basel III, banks must maintain a ratio of at least 8% of their risk-weighted assets.

of 90 days past due loans over assets; and *funding structure*, measured as the amount of wholesale funding scaled by total liabilities. All these control variables are lagged to address reverse causality concerns.[16]

I include bank fixed effects to control for time-invariant bank characteristics that can explain mean differences across banks. I also include time 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, and at the time level to control for potential error correlation within the time dimension.[17]

2.3.2 Stabilising Effect

The events that followed the implementation of the Federal Deposit Insurance Reform Act of 2005 are greatly advantageous to an analysis of a stabilising effect (if any) attributable to the insurance scheme. Between 2008 and 2010, the GFC took a huge toll on the U.S. banking sector. More than 300 banks failed during that period and hundreds more received government assistance through initiatives such as the Troubled Asset Relief Program (TARP).[18] In contrast, between 2000 and 2007 the FDIC reported 27 total bank failures only.

This particular setting allows us to investigate the relationship between the deposit insurance coverage limit increase of 2005 and the propensity of banks to fail during the GFC. If deposit insurance does generate a stabilising effect, I argue that those banks that benefited the most from the coverage limit increase (i.e. banks with higher IRA balances) would be deemed safer by other market participants during times of crisis,

[16] These controls are commonly used in the literature as potential determinants of bank risk (see Chernykh and Cole, 2011; Ioannidou and Penas, 2010; Khan et al., 2017).

[17] Not doing this could reduce standard errors, and thus increase the likelihood of getting significant coefficients.

[18] A list of all bank failures since 2000 can be accessed at `www.fdic.gov/bank/individual/failed/banklist.html`. Similarly, a list of all financial and non-financial institutions that received taxpayer money, under programs designed to overcome the crisis, can be found here `https://projects.propublica.org/bailout/list`.

and hence would be less prone to experience financial distress.[19] Therefore, I hypothesise that banks with larger IRA holdings, ex-ante, were less prone to fail or require government assistance between 2008 and 2010.[20] I test this hypothesis by first using a logistic classification model of the form:

$$\log\left(\frac{\Pr(Y_i = 1 \mid \{X_1, \ldots, X_n\})}{1 - \Pr(Y_i = 1 \mid \{X_1, \ldots, X_n\})}\right) = \gamma_0 + \gamma_1 IRA\_2005_i + \sum_{k=1}^{n} \beta_k X_i \tag{2.2}$$

where:

i $\Pr(Y_i = 1 \mid \{X_1, \ldots, X_n\})$ corresponds to the probability of failing or requiring government support for bank i between 2008 and 2010, conditional on the bank's set of specific characteristics $\{X_1, \ldots, X_n\}$.

ii IRA_2005_i measures the reliance of bank i on IRA funding before the implementation of the 2005 Reform Act. I estimate this by calculating a two-year average of banks' IRA holdings for the period immediately preceding the reform.

I also include variables that are likely to influence a bank's propensity to experience financial distress. This includes *size*, *wholesale funding*, *liquidity ratio*, and *leverage*. To avoid reverse causality concerns and guarantee prediction power, all these additional variables are calculated as bank-specific averages over the three-year period immediately before the GFC.

Of a total sample of more than 8,000 U.S. commercial banks, approximately 400 suffered financial distress during the GFC. This means that if I were to use the entire sample of commercial banks, I could easily obtain a model correctly classifying 95% of banks.

[19] This since a higher insurance coverage is expected to further reduce banks' exposure to runs (see Diamond and Dybvig, 1983).

[20] This 3-year window 2008-2010 is defined in order to i) consider banks that failed as direct consequence of the economic turmoil during the GFC, and ii) restrict the analysis to a time period before both IRAs and other deposits had the same insurance coverage.

To see this, consider a naïve model that predicts that no bank failed or required government assistance. Such a model would classify 7,600 banks properly and misclassify 400, that is, a 5% level of false negatives.

To overcome this potential issue, I randomly select 400 banks out of the banks that did not experience financial distress, and complement this sample with the roughly 400 banks that failed or accessed taxpayer funds. I estimate the model's coefficients and statistical significance employing 80% of this even sample of banks to next test the prediction accuracy of the model with the remaining 20% (i.e. the hold-out sample). I then repeat this process 100 times and average coefficients across the different models.

2.3.3 Endogeneity

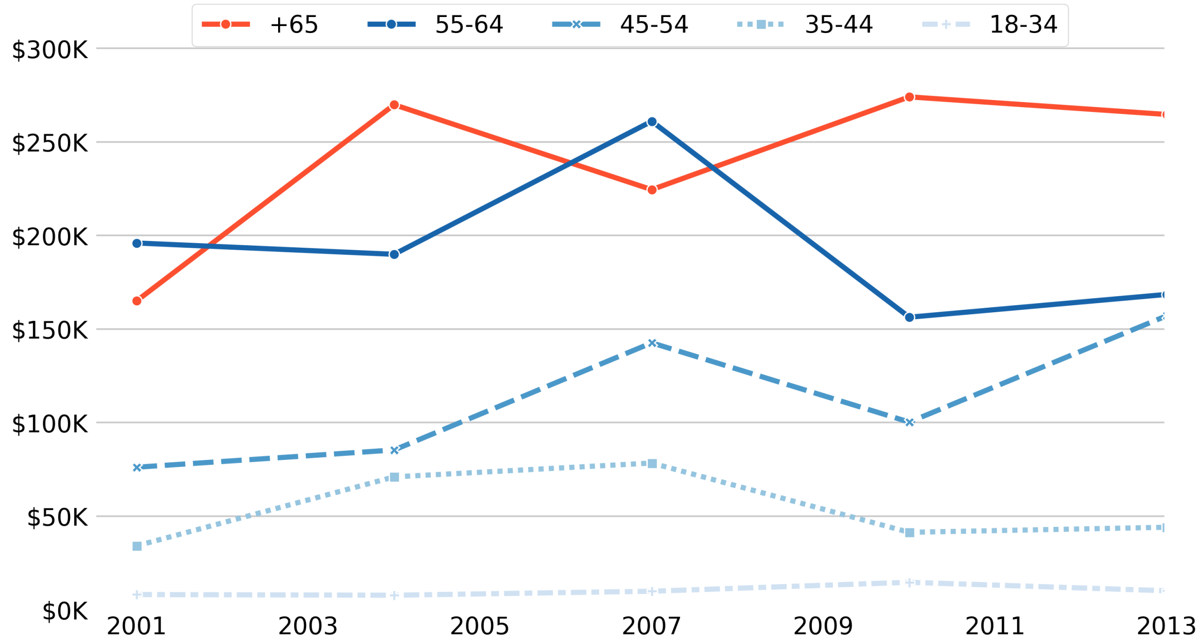
It is possible that unobserved bank characteristics, such as their business model, define both their appetite for long-term stable deposits, such as IRAs, and their risk structure. If this is the case, any difference in the risk-taking behaviour of banks with distinct IRA balances could be attributed to differences in their overall business model. In order to address this endogeneity concern, I use the fraction of seniors living in U.S. counties where a bank has a presence as an instrument for its IRA holdings. This approach allows me to tease out the exogenous variation of IRA holdings across banks and control for other unobserved bank characteristics correlated with both the dependent variable (i.e. bank risk) and IRA balances.

According to the Survey of Consumer Finances (SCF), seniors have the highest portfolio allocations to deposits of any age group.[21] Figure 2.2 presents the average bank deposit holdings in the U.S. by age between 2001 and 2013. This figure exhibits individuals 65 years or older as the age group with the largest deposits holdings over time.

Similarly, the Investment Company Institute (2016) depicts seniors as the age group with the largest holdings of traditional IRAs within the mutual fund and insurance in-

[21] The SCF is a triannual survey run by the Federal Reserve Board and the U.S. Treasury.

Figure 2.2: Deposits holdings by age
This figure presents the average bank deposit holdings in the U.S. by age group, between 2001 and 2013.



dustries (p. 24).[22] Therefore, I argue that it is reasonable to consider the fraction of seniors in a specific geographic area as having a positive effect on banks' IRA holdings. Furthermore, given its demographic nature, this instrument is likely to satisfy the exclusion restriction, which requires the fraction of seniors not to have any effect on individual bank risk other than through banks' IRA holdings.

Exploiting the geographic variation in the proportion of seniors to instrument for bank deposits is not a new approach. Becker (2007) uses the fraction of seniors in the metropolitan statistical area (MSA) where the bank is headquartered as an instrument for bank deposit supply. However, this method ignores the fact that a bank can have several branches located throughout different geographical regions. To address this issue, I construct a *Seniors Index* that accounts for each bank's geographical distribution to determine its exposure to the senior population, and thus the bank's expected reliance

[22]The IRA Investor Database contains information on IRA accounts within the mutual fund and insurance industries compiled by the Investment Company Institute (ICI).

on IRAs. This index is estimated as follows:

$$Seniors\_Index_i = \sum_{b=1}^{N} \frac{Deposits_b}{Total\_Deposits_i} \times Seniors\_Fraction_b \tag{2.3}$$

The *Seniors Index* of bank i is a weighted average of the fraction of seniors in each of the counties where bank i has a branch b. The weights are determined by the proportion of deposits that bank i obtains from each of its N branches. This index can then be interpreted as the total geographical exposure bank i has to the senior population in the U.S.

2.4 Data and Sample

In order to test the model described in Equation 2.1, I construct a dataset consisting of quarterly panel data for 8,297 U.S. commercial banks for the period September 2004 - December 2007. This corresponds to roughly 109,000 total observations.[23] As the Federal Deposit Insurance Reform Act was made effective in April 2006, I include the seven quarters after the implementation of this reform up to December 2007, and the seven quarters corresponding to the period before the reform was made effective. I restrict the time period to these 14 quarters in order to minimise any potential confounding effect stemming from the GFC.

Individual bank data is obtained from quarterly condition and income reports (Call Reports) filed by all U.S. commercial banks with the FDIC. I collect branch location data and deposits distribution per branch from the annual Summary of Deposits Survey (SOD) conducted by the FDIC.[24]

Data on the U.S. senior population and their geographic distribution is gathered from the U.S. Administration for Community Living, an institution adjunct to the U.S.

[23] After removing duplicates and observations with zero total assets.

[24] This survey is a compulsory requirement for all insured financial institutions.

Department of Health and Human Services.[25] Other relevant information in regard to seniors' demographics and their use of financial institutions comes from the triennial Survey of Consumer Finances (SCF) run by the Federal Reserve Board and the Treasury Department.

Table 2.1 shows descriptive statistics for selected bank financial characteristics, as well as for the *Seniors Index*, and bank location. From Panel A, individual retirement accounts correspond, on average, to 4.3% of banks' liabilities, and 4.7% of total deposits. This average reliance on IRAs for funding is significant compared to other external sources such as wholesale funding (6.9%). For some banks, IRAs represent more than 10% of their total external funding. Also, the average bank leverage is 89%, the percentage of bank liquid holdings is 26.2%, and regulatory capital has an average of 17% (above the 8% minimum capital adequacy ratio established by the Basel Accords). None of these reported variables seems to be significantly skewed judging from mean-median differences.

In Panel B, I report the average *Seniors Index* (18.9%) and its standard deviation (4.3%). For each bank, the time-series variation in this index is generated by i) shifts in the geographical distribution of the seniors population across counties, ii) changes in the bank's deposit market share across locations. Figure 2.3 shows the average geographical distribution for the seniors population over the sample period. For each location, the seniors population is defined as the ratio between individuals over 60 years old living in a particular county, and the total population of that county. As of 2007, this ratio ranges from 5.58% (Chattahoochee, GA) to 42.81% (McIntosh, ND). At the state level, Alaska (10.70%), Utah (11.83%), and Texas (12.10%) possess the lowest fraction of seniors. On the other hand, Florida (21.26%), West Virginia (20.93%), and Pennsylvania (19.88%) are the states with the highest fraction of seniors.

In addition, the average number of branches per bank is 11, however, this measure is

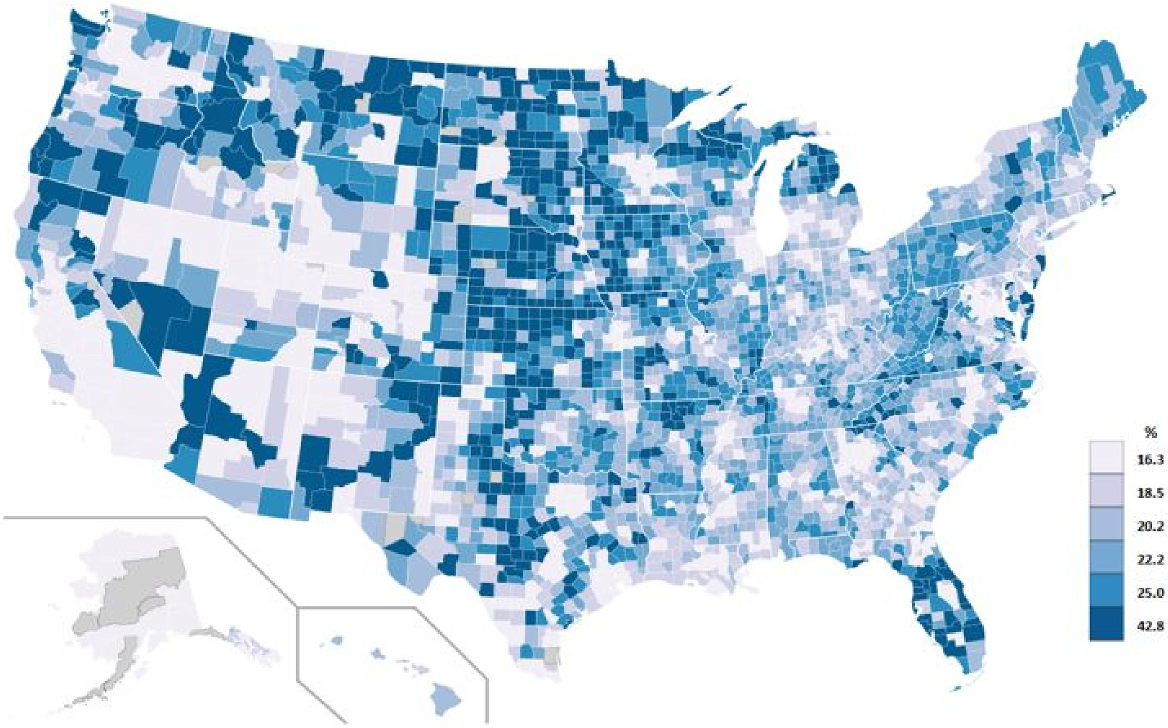
[25] This data is compiled by the U.S. Administration on Aging (AoA) based on population estimates from the U.S. Census Bureau.

Table 2.1: Summary statistics

This table reports summary statistics for selected bank financial characteristics observed quarterly over the period September 2004 - December 2009 (Panel A), as well as for the instrument *Seniors Index*, and bank location (Panel B). Panel C reports summary statistics for a sample of banks that failed or required government assistance over the period 2008-2010 (*Failed/TARP Banks*), and those banks that did not experience financial distress over the same period (*Non-failed/Non-TARP Banks*). All continuous variables are winsorized at the 5th and 95th percentile to mitigate the effect of outliers.

	Obs.	Average	Standard Deviation	Min	Median	Max
(A) Bank Characteristics						
IRA Deposits/Liabilities	109,680	0.043	0.028	0.000	0.040	0.102
IRA Deposits/Deposits	109,680	0.047	0.029	0.001	0.044	0.106
Z-Score	109,564	68.785	28.246	27.061	62.391	132.952
ROA	109,680	0.002	0.002	-0.004	0.003	0.006
Liabilities/Assets	109,680	0.890	0.036	0.789	0.901	0.929
(Tier 1 + Tier 2)/RWA	109,680	0.170	0.069	0.104	0.146	0.361
Liquid Assets/Assets	109,680	0.262	0.141	0.059	0.237	0.566
Wholesale/Liabilities	109,680	0.069	0.063	0.004	0.051	0.194
Log(Assets)	109,680	11.738	1.103	9.296	11.682	13.701
Past-due Loans/Assets	109,680	0.001	0.002	0.000	0.000	0.008
Int. Wholesale/Wholesale	101,191	0.007	0.005	0.000	0.008	0.015
Int. Deposits/Deposits	101,191	0.006	0.002	0.002	0.006	0.010
(B) Location						
Seniors Index	109,680	0.189	0.043	0.001	0.185	0.428
Branches per bank	109,680	11	101	1	3	5909
Counties per bank	109,680	4	19	1	2	733
States per bank	109,680	2	2	1	1	35
(C) GFC Analysis						
Failed/TARP Banks						
IRA Deposits/Deposits	400	0.030	0.024	0.001	0.026	0.106
Log(Assets)	400	12.227	1.069	9.371	12.211	13.701
Wholesale/Liabilities	400	0.079	0.059	0.004	0.069	0.194
Liabilities/Assets	400	0.892	0.034	0.789	0.904	0.929
Liquid Assets/Assets	400	0.173	0.096	0.059	0.154	0.566
(Tier 1 + Tier 2)/RWA	400	0.142	0.057	0.094	0.121	0.361
Non-failed/Non-TARP Banks						
IRA Deposits/Deposits	7,963	0.047	0.029	0.001	0.044	0.106
Log(Assets)	7,963	11.721	1.092	9.296	11.661	13.701
Wholesale/Liabilities	7,963	0.070	0.059	0.004	0.054	0.194
Liabilities/Assets	7,963	0.890	0.033	0.789	0.900	0.929
Liquid Assets/Assets	7,963	0.265	0.136	0.059	0.243	0.566
(Tier 1 + Tier 2)/RWA	7,963	0.166	0.067	0.094	0.144	0.361

Figure 2.3: Geographical distribution of seniors
This figure depicts the geographical variation of the fraction of seniors across U.S. counties in 2007. The seniors fraction is defined as the ratio between individuals over 60 years old living in a particular county and the total population of that county.



positively skewed by the existence of large banks with up to 5,909 branches. Similarly, the number of counties and states where a bank has presence are also positively skewed with averages of 4 and 2, and medians of 2 and 1, respectively.

In Table 2.2, I further present p-values from a difference in means t-test between banks with above median (4.4%) IRA holdings, and banks with below median holdings for the entire time period considered (14 quarters in total). Over this period, banks with higher IRA holdings are more leveraged, more liquid, and possess higher levels of regulatory capital. In addition, banks with a higher IRA reliance are smaller: by total assets and by geographical distribution. Note also that banks with above median IRA holdings have a higher average *Seniors Index*. This further supports the validity of the instrument as having a positive effect on banks' IRA holdings.

In regard to the specification model described in Equation 2.2, I collect data on U.S.

Table 2.2: Difference in means t-test

This table shows p-values from a difference in means t-test between banks with above median IRA Deposits/Deposits ratios (High), and banks with below median IRA Deposits/Deposits ratios (Low). All continuous variables are winsorized at the 5th and 95th percentile to mitigate the effect of outliers.

Reliance on IRA Deposits:	Low	High	t-statistic	p-value
(A) Bank Characteristics				
IRA Deposits/Liabilities	0.021	0.066	449.969	0.000
IRA Deposits/Deposits	0.022	0.071	470.562	0.000
Z-Score	61.768	75.788	84.800	0.000
ROA	0.002	0.003	13.844	0.000
Liabilities/Assets	0.890	0.891	6.990	0.000
(Tier 1 + Tier 2)/RWA	0.167	0.172	14.040	0.000
Liquid Assets/Assets	0.245	0.278	39.530	0.000
Wholesale/Liabilities	0.069	0.070	0.803	0.422
Log(Assets)	11.784	11.692	-13.775	0.000
Past-due Loans/Assets	0.001	0.001	30.244	0.000
Int. Wholesale/Wholesale	0.007	0.007	9.813	0.000
Int. Deposits/Deposits	0.006	0.006	9.813	0.000
(B) Demographics and Location				
Seniors Index	0.181	0.197	62.066	0.000
Branches per bank	14	8	-11.256	0.000
Counties per bank	5	3	-12.776	0.000
States per bank	2	2	-17.393	0.000

commercial bank failures from the official list of failed banks published by the FDIC. Similarly, I construct a dataset on TARP money recipients from ProPublica, a non-profit newsroom that has made extensive efforts to track taxpayer money expenditure in the aftermath of the GFC. Panel C of Table 2.1 presents descriptive statistics for a sample of 400 banks that either failed or received government assistance under TARP (i.e. experienced financial distress) between 2008 and 2010. Similarly, I present statistics for banks that do not fit the definition of financial distress. Individual bank data in these two samples is aggregated over the period 2004-2007. Financially distressed banks present, on average, lower levels of regulatory capital and liquidity. Moreover, the average bank in this group seems to be slightly more leveraged and larger than healthy institutions.

2.5 Results

Using the experimental design described in Section 2.3, in this section I present evidence consistent with both an asset substitution and a leverage effect of deposit insurance. I find that, on average, banks that relied more on IRAs for funding: i) substituted liquid assets for less liquid loans, and ii) increased their financial leverage after the 2005 Federal Deposit Insurance Reform was made effective. In addition, I also show that banks with higher IRA balances before the 2005 Act were less likely to fail or require government support during the financial crisis of 2008.

These results are robust to different specifications and to the use of the constructed *Seniors Index* as an instrument for banks' reliance on individual retirement accounts. Since the model in Equation 2.1 has two potential endogenous variables, namely IRA and the interaction term between $FDIC\_2005$ and IRA, the instruments used are *Seniors Index* and $FDIC\_2005 \times$ *Seniors Index*. Table 2.3 presents first-stage results for each endogenous variable. In Column (1) the dependent variable is IRA, and in Column (2) the dependent variable is the interaction term between $FDIC\_2005$ and IRA. Both instruments have the expected signs and are significant regressors of the variables being instrumented suggesting a strong and positive correlation between banks' IRA holdings and the instrument *Senior Index*.[26] Also, the F-statistic is significant and above 10.

2.5.1 Moral Hazard Effect

Asset Substitution

First, I examine the impact of the 2005 Federal Deposit Insurance Reform Act on banks' liquidity. Table 2.4 presents coefficients estimates for the specification model

[26]For instance, a one standard deviation increase in the *Seniors Index* (0.043) corresponds to a 0.16 percentage points increase in IRA holdings.

Table 2.3: First-stage regressions

This table reports first-stage regressions of IRA holdings per bank on the main instrument *Seniors Index*. In Column (1) the dependent variable is IRA/Deposits, and in Column (2) the dependent variable is FDIC 2005 × IRA/Deposits. *Seniors Index* is defined in Equation 2.3. FDIC 2005 is a dummy variable that takes 1 for the period after the implementation of the FDIC 2005 reform, and 0 otherwise. An unbalanced panel of 8,297 banks observed quarterly over the period September 2004 to December 2007 is used. This regression includes specific lagged bank characteristics as controls, as well as bank fixed-effects and time-fixed effects. Standard errors are clustered at the bank level to allow for error correlation within-bank, and at the quarter level to control for potential error correlation within time. All continuous variables are winsorized at the 5th and 95th percentile to mitigate the effect of outliers.

VARIABLES	(1) IRA/Deposits	(2) FDIC 2005 × IRA/Deposits
Seniors Index	0.037**	0.024
	(2.580)	(0.618)
FDIC 2005 × Seniors Index	0.003	0.121***
	(1.030)	(14.128)
Log(Assets)	0.002***	-0.018***
	(3.325)	(-10.023)
ROA	-0.009	-0.335***
	(-0.208)	(-4.021)
Past-due loans/Assets	0.068**	-0.002
	(2.963)	(-0.030)
Wholesale/Liabilities	0.004**	-0.005
	(2.458)	(-0.898)
Liquid Assets/Assets	0.003	-0.010**
	(1.732)	(-2.616)
Liabilities/Assets	-0.006	0.048***
	(-1.044)	(5.084)
Constant	0.018**	0.184***
	(2.337)	(8.035)
Observations	100,171	100,171
Bank fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Adj R-squared	0.952	0.784

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

presented in Equation 2.1 using banks' liquid asset composition as the dependent variable. In Columns (1) and (2), I use banks' IRA holdings, scaled by deposits, to account for their reliance on these accounts. Column (1) uses a continuous measure of IRA holdings, whereas in Column (2) I use a dummy variable that takes one for banks with above median IRA holdings and zero otherwise. In both cases, the negative and significant coefficient on the interaction term ($FDIC\_2005 \times IRA$) suggests banks with higher reliance on IRAs (i.e. higher treatment intensity) reduced liquid assets holdings after the implementation of the 2005 reform.

In Column (3), I use the same specification model as in Columns (1) and (2), however, here I replace banks' IRA balances with their corresponding *Seniors Index* (see Equation 2.3) as a proxy for banks' *expected* reliance on individual retirement accounts. Results from this specification also suggest that banks with a higher expected reliance on IRAs reduced their liquid asset holdings after the implementation of the reform.

To address endogeneity issues with the treatment variable (i.e. IRA holdings), in Column (4) I report point estimates for the instrumental variable approach (see Section 2.3.3). Similarly, the coefficient on the interaction term $FDIC\_2005 \times IRA$ is negative and statistically significant. These results further show this liquidity moral hazard effect of deposit insurance is not driven by other unobserved (i.e. omitted) bank characteristics potentially correlated with both IRA balances and bank liquidity risk.

I also explore the suggested asset substitution channel (see Ioannidou and Penas, 2010) which states banks initiate riskier loans after the implementation of deposit insurance. I investigate whether banks with higher holdings of IRAs deteriorated their loan portfolios following the implementation of the 2005 reform. I do not find (and do not report) evidence of an asset substitution channel involving a shift towards more risky loans for banks with larger IRAs holdings. However, this can be the result of the backward-looking nature of the data used to measure loan deterioration (e.g. non-performing loans, loan provisions, and write-offs). Ideally, I would need to observe whether banks granted loans to riskier borrowers after the 2005 reform. Unfortunately,

Table 2.4: Liquidity risk

This table presents coefficients estimates for the specification model presented in Equation 2.1 using liquidity risk (Liquid Assets/Assets) as dependent variable. Column (1) uses a continuous measure of IRA Deposits/Deposits as treatment, whereas in Column (2) I use a dummy variable that equals 1 for banks with above median IRA Deposits/Deposits, and 0 otherwise. In Column (3), IRA Deposits/Deposits is replaced with the *Seniors Index* defined in Equation 2.3. In Column (4), the *Seniors Index* is used to instrument IRA Deposits/Deposits. FDIC 2005 is a dummy variable that takes 1 for the period after the implementation of the 2005 reform, and 0 otherwise. An unbalanced panel of 8,297 banks observed quarterly over the period September 2004 to December 2007 is used. Regressions include specific lagged bank characteristics as controls, as well as bank fixed effects and time fixed effects. Standard errors are clustered at the bank level to allow for error correlation within bank, and at the quarter level to control for potential error correlation within time. All continuous variables are winsorized at the 5th and 95th percentile to mitigate the effect of outliers.

DEPENDENT VARIABLE: Liquidity	(1)	(2)	(3)	(4)
Treatment	IRA/Deposits	IRA Dummy	Seniors Index	Instrumented IRA
IRA/Deposits	0.094**			-0.734
	(2.027)			(-0.617)
FDIC 2005 × IRA/Deposits	-0.088***			-0.559***
	(-4.268)			(-4.246)
IRA Dummy		0.038***		
		(12.629)		
FDIC 2005 × IRA Dummy		-0.004***		
		(-3.738)		
Seniors Index			-0.118	
			(-1.345)	
FDIC 2005 × Seniors Index			-0.074***	
			(-5.423)	
Log(Assets)	-0.022***	-0.022***	-0.021***	-0.030***
	(-5.183)	(-7.513)	(-4.969)	(-5.177)
ROA	-0.342	-0.278	-0.333	-0.519**
	(-1.589)	(-1.308)	(-1.533)	(-2.316)
Past-due Loans/Assets	-0.365***	-0.410***	-0.352***	-0.292*
	(-2.954)	(-3.309)	(-2.838)	(-1.837)
Wholesale/Liabilities	-0.065***	-0.068***	-0.063***	-0.047*
	(-5.103)	(-5.531)	(-4.960)	(-1.913)
Liabilities/Assets	0.247***	0.216***	0.245***	0.247***
	(6.620)	(6.327)	(6.533)	(4.861)
Observations	100,171	100,171	100,171	100,171
Bank fixed Effects	Yes	No	Yes	Yes
Quarter fixed Effects	Yes	Yes	Yes	Yes
Adj R-squared	0.931	0.0487	0.931	0.840
Number of Banks	8,297	8,297	8,297	8,297

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

data on loan origination at the bank level is not publicly available.

Overall, these results are in line with the asset substitution effect of deposit insurance. Banks with a high reliance on IRAs seem to have swapped liquid (less risky) investments for illiquid (more risky) assets – such as loans – after the increase in the insurance limit. Unlike the loan deterioration described in previous studies as evidence of a moral hazard problem, the substitution effect reported here occurs across assets classes. Extending deposit insurance seems to cause a reduction in banks' liquid asset holdings. Given the experimental design used, these findings can be interpreted as direct evidence of a moral hazard problem caused by changes in the coverage limit for retirement accounts.

Finally, I investigate a potential increase in banks' liquidity risk arising from credit operations recorded off-balance sheet (OBS), such as lines of credit and loan commitments. In Column (1) of Table 2.5, I report coefficient estimates for the model in Equation 2.1 where the dependent variable is measured by subtracting unused loan commitments from liquid asset holdings, and scaling this difference by total assets. The *Seniors Index* is also used to instrument the treatment variable (i.e. IRA holdings). The negative and significant coefficient for the interaction term suggests banks with larger IRA holdings became more exposed to asset-side runs after the implementation of the FDIC 2005 Act.[27]

Leverage

Likewise, I search for a potential leverage effect of deposit insurance. Under this moral hazard channel, banks are said to increase their reliance on external funding in the presence of government-sponsored guarantees. Column (2) in Table 2.5 presents results for the specification model defined in Equation 2.1 using bank leverage as a measure of risk and the instrumented version of IRA bank holdings. As predicted, the coefficient on the interaction term $FDIC\_2005 \times IRA$ is positive and significant denot-

[27] This could also be interpreted as an enhancement to banks' ability to generate OBS liquidity.

Table 2.5: Other risk measures

This table presents coefficients estimates for the specification model presented in Equation 2.1 using the following dependent variables: OBS Liquidity Risk in Column (1), Liabilities/Assets in Column (2), Capital Adequacy Ratio in Column (3), and Z-Score in Column (4). In all regressions the treatment variable, IRA Deposits/Deposits, is instrumented using the *Seniors Index* defined in Equation 2.3. FDIC 2005 is a dummy variable that takes 1 for the period after the implementation of the 2005 reform, and 0 otherwise. An unbalanced panel of 8,297 banks observed quarterly over the period September 2004 to December 2007 is used. Regressions include specific lagged bank characteristics as controls, as well as bank-fixed effects and time-fixed effects. Standard errors are clustered at the bank level to allow for error correlation within bank, and at the quarter level to control for potential error correlation within time. All continuous variables are winsorized at the 5th and 95th percentile to mitigate the effect of outliers.

VARIABLES	(1) OBS Liquidity Risk	(2) Insolvency Risk	(3) Regulatory Capital	(4) Z-Score
Instrumented IRA	10.264**	-0.349	-0.836	153.196
	(2.109)	(-0.480)	(-0.764)	(0.531)
FDIC 2005 × Instrumented IRA	-0.697***	0.182***	-0.139**	-80.121***
	(-2.675)	(4.805)	(-2.421)	(-4.663)
Log(Assets)	-0.031**	0.031***	-0.054***	-11.895***
	(-2.483)	(20.738)	(-19.832)	(-18.933)
ROA	-1.611***	0.412***	-0.180	-43.315
	(-3.667)	(4.500)	(-1.362)	(-1.217)
Past-due Loans/Assets	-0.674	-0.004	0.127	-7.774
	(-1.576)	(-0.057)	(1.283)	(-0.299)
Wholesale/Liabilities	-0.233**	0.028*	-0.031	-14.364**
	(-2.284)	(1.917)	(-1.350)	(-2.436)
Liabilities/Assets	0.468***			
	(3.535)			
Liquid Assets/Assets		0.006*	0.098***	-4.874***
		(1.668)	(17.125)	(-3.243)
Observations	100,171	100,171	100,171	100,083
Bank fixed Effects	Yes	Yes	Yes	Yes
Quarter fixed Effects	Yes	Yes	Yes	Yes
Adj R-squared	0.818	0.883	0.929	0.961

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

ing an increase in leverage for banks with higher reliance on retirement accounts. In this case, the moral hazard effect of deposit insurance is captured in the higher exposure to insolvency risk of banks more influenced by the 2005 reform.

Similarly, Column (3) in Table 2.5 sheds evidence supporting, not just an increase in solvency risk, but also a rise in the regulatory risk of banks relying more on IRAs. Here, the dependent variable is the capital adequacy ratio defined by Basel III. In addition to characterising bank leverage, this ratio represents a risk-adjusted measure of banks' capital stance to absorb losses. The negative coefficient on the interaction term between the $FDIC\_2005$ dummy and the instrumented IRA implies highly IRA dependent banks reduced their capital adequacy ratio (and therefore increased insolvency and regulatory risk) after the coverage limit changes in the deposit insurance for IRAs.

Lastly, I use the time-varying Z-Score proposed by Lepetit and Strobel (2013) to measure banks' probability of insolvency. Column (4) in Table 2.5 reports regression outputs for a specification where Z-Score is used as the dependent variable and *IRA* is instrumented using the *Seniors Index*. The interaction term is negative and significant, which, considering Z-Score is inversely related to insolvency risk, suggests an association between larger IRA balances and a higher probability of insolvency in the period following the reform.

The empirical findings presented so far support the existence of a moral hazard effect of deposit insurance and, in particular, support the two channels suggested by theory, that is, an asset substitution channel and a leverage channel (see Buser et al., 1981; Merton, 1977; Pennacchi, 1987). In regard to the denominated asset substitution channel, I report risk-shifting behaviour taking place through the deterioration of banks' liquidity. Furthermore, I find an increase in off-balance sheet liquidity risk and regulatory risk also associated with the implementation of explicit government guarantees. Next, I explore a potential stabilising effect by exploiting the hundreds of bank failures and bailouts during the financial crisis of 2008.

2.5.2 Stabilising Effect

I use the logistic model described in Equation 2.2 to test for a marginal stabilising effect stemming from the 2005 reform. In Table 2.6, I present coefficient estimates for this logistic model where the dependent variable is an indicator variable which takes one for banks that either failed or required government assistance between 2008-2010, and zero otherwise. I use different measures for the variable of interest: IRA_2005. In Column (1), IRA_2005 is represented as a dummy variable that takes one for banks with (pre-2005) above median IRA balances, and zero otherwise. Columns (2) and (3) measure IRA_2005 in tertiles and quintiles, respectively.

In all three models the coefficients associated with IRA_2005 are negative and statistically significant indicating that banks with higher pre-2005 IRA balances had a lower probability of financial distress during the GFC. Similarly, Figure 2.4 plots the distribution of IRA holdings for banks that experienced financial distress during the crisis. This figure denotes an association between larger IRA holdings before 2005 and lower failure cases. I argue these results capture the marginal stabilising effect of extending the insurance guarantee over a particular set of banks, that is, those with higher IRA balances. Hence, I interpret these results as direct evidence of an increase in bank stability caused by deposit insurance.

I further estimate the predictive accuracy of the model by exploiting the sample split described in Section 2.3.2. Table 2.7 shows a classification report for the 20% sample not used in the estimation of the models' coefficients. This report shows that, out of the total number of banks predicted as failures, 74% did indeed fail (precision). Moreover, 78% of banks that experienced financial distress are identified as such by the model (recall).

Lastly, I use coefficient estimates and average values for the set of controls – *size*, *wholesale funding*, *liquidity ratio*, and *leverage* – to calculate the average difference in the probability of financial distress attributable to IRA balances. Using quintiles to measure IRA balances, the predicted probability of financial distress for banks in the bottom

Table 2.6: Stabilising effect during GFC

This table reports point estimates for the specification model presented in Equation 2.2. The dependent variable equals 1 for banks that either failed or required government assistance between 2008-2010, and 0 otherwise. In Column (1), IRA_2005 is as a dummy variable that takes 1 for banks with (pre-2005) above median IRA balances, and 0 otherwise. Columns (2) and (3) measure IRA_2005 in tertiles and quintiles, respectively. A sample of 800 banks observed between 2004 and 2010 is used. Bank characteristics included as controls are calculated as bank-specific averages over the period 2004-2007. Robust standard errors are used to allow for heteroscedasticity. All continuous variables are winsorized at the 5th and 95th percentile to mitigate the effect of outliers.

VARIABLES	(1) Median	(2) Tertiles	(3) Quintiles
IRA_2005	-1.068***	-0.700***	-0.394***
	(-6.245)	(-6.724)	(-6.368)
Log(Assets)	0.414***	0.403***	0.408***
	(4.567)	(4.431)	(4.508)
Wholesale/Liabilities	1.374	1.427	1.333
	(0.841)	(0.870)	(0.809)
Liabilities/Assets	-3.379	-2.644	-2.170
	(-1.165)	(-0.901)	(-0.736)
Liquid Assets/Assets	-6.137***	-6.007***	-5.927***
	(-8.035)	(-7.774)	(-7.700)
Constant	-0.299	-0.726	-1.139
	(-0.122)	(-0.292)	(-0.456)
Observations	800	800	800
Pseudo R-squared	0.188	0.193	0.191

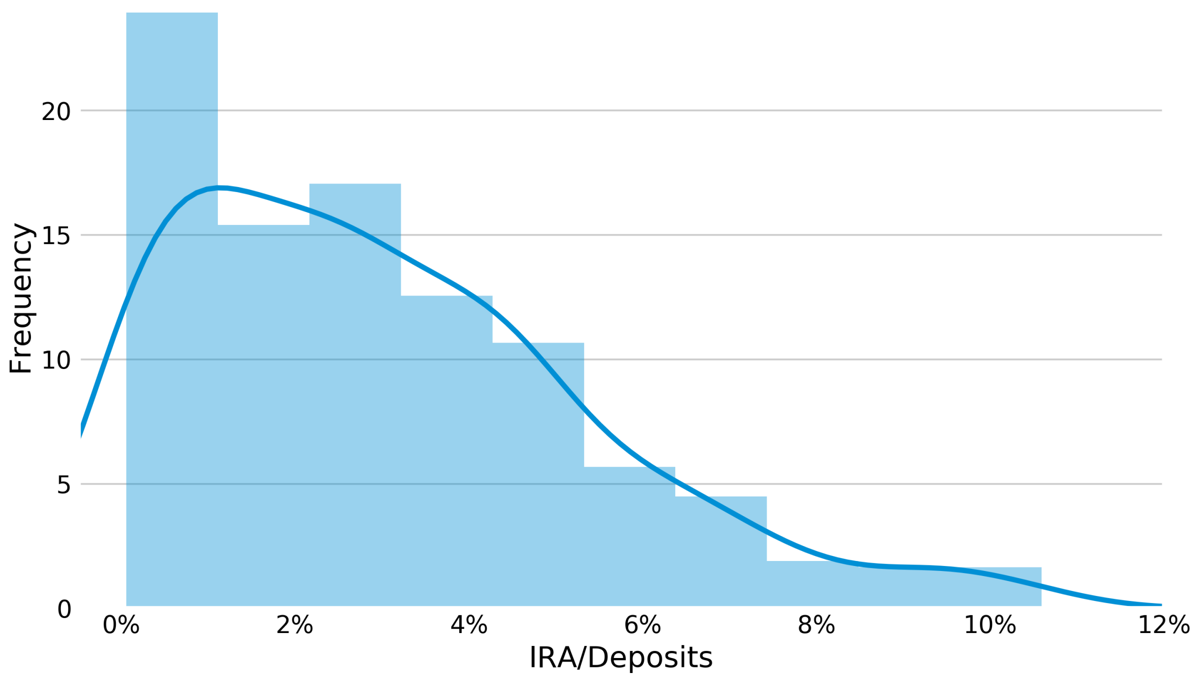
Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

quintile is 57.5%, and 19.9% for the top quintile. This means that, other things being equal, banks with higher IRA balances before 2005 were, on average, 38 percentage points less likely to experience financial distress than those with lower IRA holdings.

In the next section, I address some potential concerns in regard to the true source of the reported stabilising effect of deposit insurance on high IRA dependant banks. Further, I conduct additional tests to minimise concerns as to the validity of the time period chosen, and around the *Seniors Index* used as an instrument for banks' IRA holdings.

Figure 2.4: IRA holdings for distressed banks 2008-2010

This figure shows the distribution of IRA holdings for banks that either failed or required government assistance over the period 2008-2010.



2.6 Robustness

2.6.1 Stabilising Effect: 2010 Reform

The evidence reported so far in regard to the stabilising effect of deposit insurance shows that banks with larger IRA balances were less likely to experience financial distress over the period 2008-2010. One potential caveat with this identification strategy is that it may capture the stabilising effect of relying more on IRA accounts but not the effect that increasing IRAs' insurance limit had on banks' stability. That is, it is possible that banks highly dependent on IRAs were inherently less likely to fail even before any increase in the coverage limit for IRAs.

One way to address this issue would be to run the same model in Equation 2.2 on a period before the reform where both IRAs and other deposits had the same insurance

Table 2.7: Classification report

This table presents a classification report for the model described in Equation 2.2. A 20% hold-out sample (not included in the estimation of the coefficients) is used to test the prediction accuracy of the model. *Non-Failed/Non-TARP* corresponds to banks that neither failed nor required government assistance over the period 2008-2010. *Failed/TARP* corresponds to banks which experienced financial distress over the same period.

Logistic AUC 0.75

	Precision	Recall	F1-score	Support
Non-Failed/Non-TARP	0.76	0.72	0.74	80
Failed/TARP	0.74	0.78	0.76	80
Avg/Total	0.75	0.75	0.75	160

coverage. If the significance of the reported coefficients in Table 2.6 *does* reflect the impact of increasing the coverage limit for IRAs (as I expect), we should not observe IRA balances to have any explanatory power before the 2005 reform when deposit insurance was the same for all accounts. Unfortunately, such a test would lack statistical power considering that between 2000 and 2007 the FDIC only reported 27 bank failures. Instead, I focus on a different period when both IRAs and other deposits enjoy the same coverage limit, but in addition a considerable number of bank failures are observed.

On October 3, 2008, in the midst of the GFC, then U.S. President George W. Bush signed an emergency Act temporarily raising the coverage limit for all insured deposits from USD 100,000 to USD 250,000. This temporary increase was initially intended to be effective until December 31, 2009. However, the increase was made permanent on July 21, 2010 as part of the Dodd-Frank Wall Street Reform and Consumer Protection Act, signed by President Barack Obama.[28] This meant that, after 2010, the FDIC permanently guaranteed all deposits, irrespective of their type, up to USD 250,000. I exploit this fact to explore whether IRA reliance is still significant in predicting the probability of bank failure even when the IRA insurance limit is identical to the broader deposit base. Specifically, I run the following model:

[28]On May 20, 2009, the 2008 temporary increase in coverage was extended through December 31, 2013.

$$\log\left(\frac{\Pr(Y_i = 1 \mid \{X_1, \ldots, X_n\})}{1 - \Pr(Y_i = 1 \mid \{X_1, \ldots, X_n\})}\right) = \gamma_0 + \gamma_1 IRA\_2010_i + \sum_{k=1}^{n} \beta_k X_i \tag{2.4}$$

where:

i $\Pr(Y_i = 1 \mid \{X_1, \ldots, X_n\})$ represents the probability of failure for bank i between 2011 and 2015 conditional on the bank's set of specific characteristics $\{X_1, \ldots, X_n\}$.

ii IRA_2010_i measures the average reliance of bank i on IRA funding over the period 2008-2010, that is, before the insurance limit of all deposits was set to USD 250,000 permanently.

As with the model described in Equation 2.2, I also include variables that are expected to influence banks' probability of failure: *size*, *wholesale funding*, *liquidity ratio*, and *leverage*. For each bank these variables are calculated as averages over the period 2008-2010.

Between 2011 and 2015 the FDIC reported almost 200 bank failures. To mitigate biases stemming from the relative size of the sample of bank failures, I randomly select banks that did not fail over the same time period and estimate the model's coefficients using 80% of this sample. I set aside the remaining 20% to test for prediction accuracy.

Table 2.8 reports coefficient estimates for the logistic model in Equation 2.4. Columns (1), (2) and (3) measure the variable of interest IRA_2010 using median, tertiles and quintiles respectively. Although still negative, the magnitude of the coefficients on the variable IRA_2010 are significantly lower than those reported in Table 2.6. More importantly, none of these coefficients are statistically significant. Similarly, Figure 2.5 presents the distribution of IRA balances within banks that failed between 2011 and 2015. Unlike Figure 2.4, over this period there is no clear relationship between larger IRA balances and more failure cases.

Table 2.8: Stabilising effect around 2010 reform

This table reports point estimates for the specification model presented in Equation 2.4. The dependent variable equals 1 for banks that failed between 2011 and 2015, and 0 otherwise. In Column (1), IRA_2010 is a dummy variable that takes 1 for banks with above median IRA balances over the period 2008-2010, and 0 otherwise. Columns (2) and (3) measure IRA_2010 in tertiles and quintiles, respectively. A sample of 364 banks observed between 2008 and 2015 is used. Bank characteristics included as controls are calculated as bank-specific averages over the period 2008-2010. Robust standard errors are used to allow for heteroscedasticity. All continuous variables are winsorized at the 5th and 95th percentile to mitigate the effect of outliers.

VARIABLES	(1) Median	(2) Tertiles	(3) Quintiles
IRA_2010	-0.435	-0.186	-0.099
	(-1.602)	(-1.068)	(-1.005)
Log(Assets)	-0.456**	-0.448**	-0.447**
	(-2.523)	(-2.494)	(-2.482)
Wholesale/Liabilities	1.708	1.803	1.809
	(0.615)	(0.646)	(0.641)
Liabilities/Assets	93.400***	92.670***	92.767***
	(5.780)	(5.788)	(5.828)
Liquid Assets/Assets	-7.490***	-7.432***	-7.487***
	(-5.723)	(-5.644)	(-5.681)
Constant	-78.146***	-77.433***	-77.589***
	(-5.256)	(-5.251)	(-5.279)
Observations	364	364	364
Pseudo R-squared	0.375	0.373	0.373

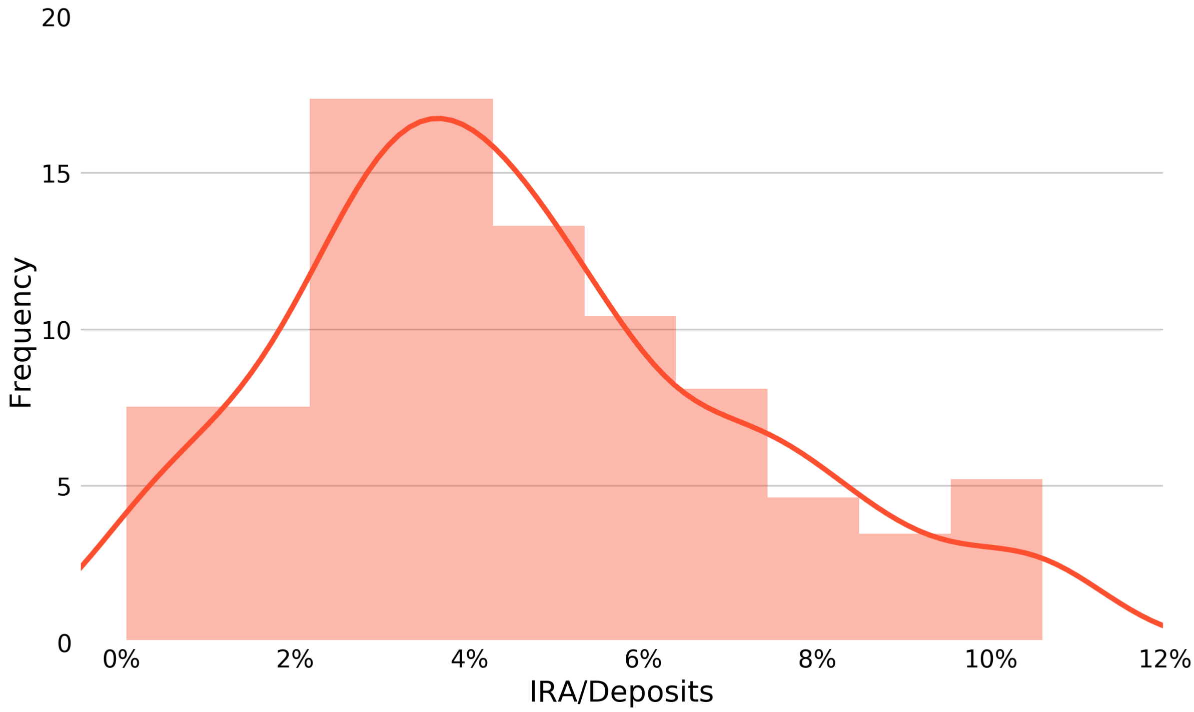
Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

These results suggest that, after the insurance coverage of other types of deposits was matched with that of retirement accounts, there was no extra reduction on a bank's probability of default stemming from holding higher IRA balances. This reduces concerns around the possibility that the stabilising effect of deposit insurance reported in Section 2.5 reflects a higher reliance on IRA accounts and not the marginal effect of increasing the coverage limit for IRAs under the FDIC 2005 Reform Act.

2.6.2 Moral Hazard: Seniors Distribution

The instrument used throughout this chapter (i.e. *Seniors Index*) is defined as the weighted average of the proportion of seniors living in U.S. counties where a bank has a presence, where weights are determined by the amount of deposits generated by each

Figure 2.5: IRA holdings for distressed banks 2011-2015
This figure depicts the distribution of IRA holdings for failed banks over the period 2011-2015.



bank branch. I do this to account for differences in the geographical distribution of banks in the sample. Despite showing this index is significantly correlated with banks' reliance on individual retirement accounts, the fact that some banks have a relatively large geographical distribution (up to 5,909 branches in 733 counties across 35 different states) may raise some concerns about the validity of this index in representing banks' geographical exposures to the seniors population.

To address this concern, I use the same specification model defined in Equation 2.1 on bank subsamples restricted based on their geographical distribution. Specifically, I limit the observations to banks with: i) a single branch; ii) presence in one county only; and iii) presence in a single state. With this, I aim to reduce any potential bias that banks with large geographical distributions could exert on the constructed instrument. For instance, when restricting the sample to banks with one branch or banks located in a single county, the instrument (i.e. *Seniors Index*) becomes the actual fraction of seniors living in the county where the bank is located as opposed to being calculated as a weighted average of the senior population across different counties.

Table 2.9 shows regression outcomes for these subsamples. I explore both an asset substitution and a leverage effect for the insurance coverage increase on IRAs in 2005. Using the most restricted subsample of banks – banks with only one branch – in Columns (1) and (4) I show that banks with higher ex-ante reliance on IRAs reduced liquid assets and increased leverage, respectively, after the implementation of the 2005 reform.[29] Similarly, in Columns (2) and (5) I present similar findings (i.e. lower liquidity and higher leverage) using a sample of commercial banks with presence in a single county. Finally, Columns (3) and (6) report identical results for single-state banks.

This analysis indicates that the empirical evidence presented in this study is not driven by banks with a large geographical distribution and/or the method I use to create the *Seniors Index*. This, to some extent, further confirms the validity of this instrument as a driver of banks' reliance on retirement accounts. These results may also imply that the main findings reported do not differ for banks with different levels of incorporation (federally vs state-chartered banks), and thus subject to the supervision of different regulatory entities.

2.6.3 Alternative Explanations

Besides increasing the insurance coverage limit on individual retirement accounts, the Federal Deposit Insurance Reform Act of 2005 made other amendments that could potentially explain the results reported in this chapter. Specifically, the 2005 reform included a provision that eliminated the 1.25 percent fixed designated reserve ratio (DRR). The DRR in the U.S. is calculated by dividing the Deposit Insurance Funds (DIF) by the total amount of insured deposits. The reform designated the FDIC to set the DRR within a range of 1.15 to 1.50 percent (Federal Register, 2006). If banks expected the FDIC to increase the DRR, they could have anticipated having to pay higher

[29] For this subsample, the number of observations is roughly one fourth of the original sample size.

Table 2.9: Restricted geographical distribution

This table presents coefficients estimates for the specification model presented in Equation 2.1 using Liquid Assets/Assets and Liabilities/Assets as dependent variables. In Columns (1) and (4) observations are restricted to banks with a single branch. Columns (2) and (5) limit observations to banks operating in a single county, and Columns (3) and (6) limit observations to single-state banks. In all regressions, the treatment variable, IRA Deposits/Deposits, is instrumented using the *Seniors Index* defined in Equation 2.3. FDIC 2005 is a dummy variable that takes 1 for the period after the implementation of the 2005 reform, and 0 otherwise. An unbalanced panel of banks observed quarterly over the period September 2004 to December 2007 is used. Regressions include specific lagged bank characteristics as controls, as well as bank-fixed effects and time-fixed effects. Standard errors are clustered at the bank level to allow for error correlation within bank, and at the quarter level to control for potential error correlation within time. All continuous variables are winsorized at the 5th and 95th percentile to mitigate the effect of outliers.

VARIABLES	(1)	(2) Liquidity Risk	(3)	(4)	(5) Insolvency Risk	(6)
Instrumented IRA	0.447	2.192	5.389*	0.525	3.942	-0.650
	(0.205)	(0.179)	(1.689)	(0.732)	(0.483)	(-0.816)
FDIC 2005 × Instrumented IRA	-0.701***	-0.782***	-0.623***	0.207***	0.341*	0.205***
	(-2.696)	(-3.271)	(-3.433)	(2.828)	(1.916)	(4.947)
Log(Assets)	-0.030**	-0.028	-0.025***	0.038***	0.040***	0.033***
	(-2.522)	(-1.340)	(-2.931)	(14.520)	(6.623)	(18.670)
ROA	-1.289***	-1.462***	-0.962***	0.244	0.200	0.444***
	(-3.001)	(-3.700)	(-3.196)	(1.592)	(0.750)	(4.538)
Past-due Loans/Assets	-0.572*	-0.502	-0.780***	-0.070	-0.080	0.013
	(-1.716)	(-1.234)	(-2.811)	(-0.652)	(-0.297)	(0.187)
Wholesale/Liabilities	-0.010	-0.121	-0.190***	0.016	-0.047	0.032*
	(-0.196)	(-0.574)	(-2.771)	(1.015)	(-0.340)	(1.950)
Liabilities/Assets	0.182**	0.230	0.356***			
	(2.459)	(1.023)	(4.009)			
Liquid Assets/Assets				0.005	0.006	0.007*
				(0.913)	(0.677)	(1.765)
Observations	26,112	46,395	92,473	26,112	46,395	92,473
Bank fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.927	0.927	0.876	0.890	0.391	0.876

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

premiums to fund the inflated DRR. This expectation could have incentivised some banks to reduce liquid assets holdings and raise leverage to make up for the higher expected premiums, and thus shelter earnings.

There are two important reasons this alternative explanation is implausible. First, this explanation relies on the assumption that banks expected to pay higher premiums after the reform. However, results show higher post-reform risk-taking behaviour for banks with higher reliance on IRAs. In this regard, there is no evidence to suggest that it was solely banks with larger IRAs' holdings that anticipated the higher premiums, especially since banks with higher IRA balances are less risky on average, even after the implementation of the 2005 reform (see Table 2.2). Another reason to reject this alternative explanation is based on the date when the change to the DRR design was made effective (i.e. January 1, 2007). This is almost one year after the date I use to separate before and after periods in the specification model described in Equation 2.1. This suggests the findings presented are less likely to be driven by this amendment.

2.7 Conclusion

In this chapter, I develop a novel identification strategy to investigate the trade-off posed by a key explicit government guarantee: deposit insurance. I focus on a major reform to the U.S. deposit insurance scheme, and exploit the rich information available on U.S. commercial banks, to show the effect of extending the insurance coverage on banks' risks and probability of failure. Specifically, I investigate the coverage limit increase on individual retirement accounts (IRAs) implemented through the Federal Deposit Insurance Reform Act of 2005.

Based on this approach, I provide supporting evidence of a moral hazard problem caused by deposit insurance. In particular, I show that after the implementation of the 2005 reform, banks with higher funding reliance on IRAs increased their risk-taking behaviour in the form of higher solvency and liquidity risk. That is, I find a within-bank increase in risk-taking behaviour caused by the coverage limit rise on IRAs. These results provide new insight into the specific economic channels through which deposit insurance can create a moral hazard issue. In particular, I report a novel channel by which banks increase their risk exposure by swapping liquid investments such as cash and marketable securities, for illiquid assets such as loans.

In addition, I use the chain of events following the 2005 reform, and in particular the Global Financial Crisis of 2008, to measure differences in banks' probability to fail or require government assistance conditional on their IRA balances. I report cross-sectional differences in the probability of failure between banks with high and low IRA balances during the crisis. Specifically, I show a 38 percentage point lower probability of financial distress for banks with high IRA holdings. Given this large difference in banks' probability of default, the stabilising effect of deposit insurance seems to have played a bigger role in determining banks' risk exposures during the GFC.

Despite the relative importance of individual retirement accounts within the pension fund market and as a source of funding for banks, to my knowledge this is the first study to explicitly analyse the coverage limit increase for IRAs under this reform. Moreover, these results are relevant to the implementation of the latest set of banking standards under Basel III. One of the key reforms in Basel III is the introduction of a liquidity framework which, among other things, encourages banks to rely on insured deposits as a stable source of funding. Therefore, this study offers a glance at how banks may react to policies that increase their reliance on insured liabilities.

Chapter 3

De Facto Bank Bailouts

with Phong Ngo

3.1 Introduction

The events during and after the 2007-2009 financial crisis reminded us of governments' willingness to bail out banks. This has seen renewed interest in understanding the economic trade-offs associated with bank bailouts. In this chapter, we are interested in the costs associated with bank bailouts from the politician's point of view. First, there is the fiscal cost. For example, in 2008 the Trouble Asset Relief Program (TARP), which authorised \$700 billion (about 5% of GDP) in U.S. tax payers money to bailout banks in distress, placed significant strain on federal resources.[1] Several papers now document that bailouts significantly weaken a government's fiscal position and own credit standing (see Acharya et al., 2014; Fratzscher and Rieth, 2019; Mäkinen et al., 2019).

Second, there is the political cost. Using taxpayer money to bail out banks is rarely a popular decision, as former Secretary to the Treasury Tim Giethner put it when referring to the 2008 bailout "we did it to save the economy, but we lost the country doing

[1]Indeed, as the crisis spread around the world, there was an unprecedented wave of bank bailouts globally. Laeven and Valencia (2010) estimate that governments around the world spent (in direct fiscal outlays) an average of 5% of GDP bailing out their banks.

it".[2] The academic literature has also shown that politicians either avoid bailing out banks or take action to delay bank failure altogether when political costs are high (see Bian et al., 2017; Brown and Dinc, 2005; Liu and Ngo, 2014)

Given these costs, are there alternative, subtler ways for the government to prop up troubled banks? To obfuscate a bailout and minimise voter backlash? To reduce the burden on domestic resources? Our central argument is that the U.S. government uses its voting power and political influence to direct IMF loans to defaulting sovereigns where U.S. banks have large exposures to losses from default – a de facto bailout.[3] De facto bailouts not only spread the cost of absorbing bank losses across the IMF membership, but also allow U.S. politicians to obfuscate bailouts, thus minimising public condemnation.

IMF loans reduce losses to U.S. banks through loan conditionality, which typically enforces the payment of external debt arrears from recipient governments. For example, Kentikelenis et al. (2016) examine the conditionality in IMF loan agreements between 1985 and 2014 and show that 28% of all conditions identified relate to the payment of external debt in arrears. Because a significant fraction of U.S. bank foreign exposures are to the public sector, IMF loans can be used to pay down this debt directly.[4]

Using the Bank for International Settlements (BIS) consolidated banking statistics, we construct a measure of U.S. bank exposures to 47 developing countries between 1983 and 2016, covering 269 IMF loans. Our analysis reveals that the likelihood a defaulting sovereign receives an IMF loan increases significantly with U.S. bank exposure to that country. Specifically, a standard deviation increase in U.S. bank exposure increases

[2] From his memoir *Stress Test: Reflections on Financial Crises*.

[3] The U.S. is by far the largest IMF member with 16.52% of the vote share. Moreover, the U.S. has particular control over certain important decisions – like changing quotas and voting power – that are subject to an 85% super-majority rule. We provide a discussion of the institutional details in Section 3.2.

[4] Data from the Federal Financial Institutions Examination Council (FFIEC) show that over our sample period, about 30% of foreign exposures are to the public sector. At its peak in the 1980s, foreign public sector exposures accounted for two-thirds of the total exposure and today the number sits at about 25%. In Section 3.2, we discuss how banks can also benefit *indirectly* from IMF loans to defaulting sovereigns.

the likelihood a defaulting sovereign receives a loan by four times. Moreover, conditional on receiving a loan, the loan is 12% larger. These findings survive a number of robustness tests as well as instrumental variables estimation to address endogeneity.

Next, we investigate how the likelihood of a de facto bailout varies with the relative costs of direct bailouts. As discussed above, research argues that direct bailouts are more costly if political costs are especially high (e.g. during election years) and/or if the government's fiscal position is already weak. Consistent with our expectations, we find that the likelihood of de facto bailouts is higher when the fiscal position of the U.S. government is weaker, and during federal elections years. For example, a standard deviation increase in U.S. bank exposure increases the likelihood a defaulting sovereign receives and IMF loan by over 9 times when the U.S. budget deficit is greater that 5% of GDP.

We then ask whether these observed patterns can be explained by a public interest or a private interest view of government. Our argument is that U.S. politicians are responsive to the special interest pressure from the banking lobby. However, it is possible that politicians, who favour de facto bailouts, act in the public interest if their constituency is reliant on lending from banks who are exposed to sovereign losses. To tease out which view of government is driving our findings, we examine congressional voting patterns relating to IMF funding increases. Funding increases for the IMF expand its capacity to bail out sovereigns, so a vote in favour of an increase is a vote in favour of de facto bailouts. We construct a constituency-level measure for local banks' exposure to sovereign default to capture the public interest view, and use campaign contributions from the finance industry to proxy for the private interest view. We find that our constituency exposure variable cannot explain congressional voting patterns for IMF funding increases. However, campaign contributions significantly increase the likelihood of a "yes" vote: a standard deviation increase in campaign contributions from the finance industry increases the likelihood of a "yes" vote by about 30%.

Finally, we confirm that exposed U.S. banks do indeed benefit from IMF loans to defaulting sovereigns by examining the implications for shareholder wealth. Precisely, we conduct an event study around the dates IMF loans are announced and find that U.S. banks exposed to sovereign default experience, on average, a 5% cumulative abnormal return (CAR) over the event window. Thus, IMF loans, although directed to foreign governments, ultimately reach U.S. banks.

Our study is related to the literature studying the economic trade-offs associated with bank bailouts. On the one hand, bailouts may correct market failures and avoid the negative externalities associated with large bank failures (see Giannetti and Simonov, 2013; Gorton and Huang, 2004). On the other hand, critics argue that bailouts exacerbate moral hazard problems in the banking industry (see Chari and Kehoe, 2016; Dam and Koetter, 2012; Duchin and Sosyura, 2014; Farhi and Tirole, 2012; Gropp et al., 2011). In addition, bank bailouts have been shown to be costly for taxpayers (see Acharya et al., 2014; Fratzscher and Rieth, 2019; Mäkinen et al., 2019), and for politicians running for office (see Bian et al., 2017). We contribute to this literature by identifying an alternative mechanism through which the U.S. government can backstop banking losses, that is, using IMF funds to bailout sovereigns to which U.S. banks are exposed. A de facto bailout. This indirect bailout mechanism reduces both, the amount of domestic resources used as well as the degree of discontent among voters, two highly desirable traits for politicians.

In addition, our work connects to a broader literature on the political economy of banking. Early work demonstrated that lobbying by financial institutions affected the regulatory environment for U.S. thrifts in the 1980s (see Romer and Weingast, 1991), the timing of interstate bank branching law changes (see Kroszner and Strahan, 1999), and U.S. legislation on bankruptcy (see Nunez and Rosenthal, 2004). In the aftermath of the financial crisis, several papers examine how financial industry legislation is affected by the lobbying of special interest groups and voter interests (see McCarty et al., 2010; Mian et al., 2010, 2013). Finally, Agarwal et al. (2018) show that the foreclosure decisions of banks during the crisis reflected banks' political considerations. We show in this study that banking special interests increased the likelihood politicians voted in favour of IMF funding increases, and by doing so, implicitly voted in favour of de facto bailouts.

3.2 Background and Argument

The International Monetary Fund (IMF) is an organisation of 189 member countries that works to support trade, growth, and financial stability by providing assistance to countries facing balance-of-payments problems.

The IMF obtains its financial resources from member country subscriptions, which are known as quotas. Each country's quota broadly represents its relative position in the world economy, calculated using various measures of output and trade. Quotas also play an important role in determining members' voting power and ultimately the IMF's governance. Each member country has 250 basic votes, plus one additional vote for each part of its quota equal to 100,000 Special Drawing Rights (SDR).[5] Since basic votes comprise a trivial fraction of total votes, voting power and control of IMF decisions is significantly tilted in favour of the larger member countries. For example, the U.S. is the largest member with a quota of SDR 82,994.2 million (or about USD 115.2 billion) which buys it 831,407 votes (or 16.52% vote share). By contrast, Vanuatu, for example, has a quota of SDR 23.8 million and meager 1,703 votes (or 0.03% vote share).[6]

With 16.52% of the vote share, the U.S. has particular control over certain important decisions – like changing quotas and voting power – that are subject to an 85% super-majority rule. In these instances, the executive branch of the U.S. government generally has total control of representation at the IMF, with only occasional direct Congressional oversight, such as when seeking to increase the U.S. contribution to the IMF (for ex-

[5]The value of the SDR currency is determined by adding the values, in U.S. dollars, of a basket of five major currencies: the U.S. dollar, Euro, Japanese yen, pound sterling, and the Chinese renminbi.

[6]See here `www.imf.org/external/np/sec/memdir/members.aspx` for current information on quotas and voting power.

ample, in 2015). In these instances, IMF decision making requires approval from U.S. Congress.[7]

U.S. control over IMF decision making places it in a position to direct IMF loans for reasons other than the prevailing economic needs of the recipient countries. Indeed, a growing number of studies now demonstrate that countries tend to get larger loans more frequently (and with fewer conditions) if they are more economically (i.e. trade) or politically connected to the U.S. (see Barro and Lee, 2005; Dreher and Jensen, 2007; Dreher et al., 2009; Stone, 2004; Thacker, 1999)

In this study, we argue that the U.S. bank lobby can also influence IMF decisions via its connection to the White House and Congress. In particular, international lending by U.S. banks exposes them to losses in the event of sovereign default. These losses can be substantial. For example, Huizinga and Sachs (1987) report that during the Latin American debt crisis of the 1980s, total exposure of U.S. banks was almost 120% of capital. Exposure was also highly concentrated in the money centre banks – those with the greatest political clout. The nine largest U.S. money-centre banks held Latin American debt amounting to 176% of their capital. In monetary terms, if we consider just the top four countries (Argentina, Brazil, Mexico and Venezuela), U.S. bank exposure was almost USD 64 billion, of this, 65% was concentrated in the top nine banks. Moreover, sovereign loans (i.e. foreign public sector loans) accounted for two-thirds of the total exposure to these four countries.[8]

Consequently, exposed banks have great incentives to lobby for government support. Unlike a domestic crisis where support can come in the form of a direct bailout, the U.S. government has an alternative leaver to pull when dealing with a foreign sovereign

[7]For most of our sample period, the countries with the greatest vote share, other than the U.S., are Japan, Germany, France, and the United Kingdom (U.K.). These four countries collectively control about another 20% of the votes. In 2015 the IMF, and the U.S. Congress, approved an increase in IMF funding which also saw a significant increase in the voting power of China, India, Russia, and Brazil. All these countries are now in the top 10 countries according to voting power. Of these, China has the greatest vote share with 6.09% making it third overall after the U.S. and Japan.

[8]Data from the Federal Financial Institutions Examination Council (FFIEC) show that over our entire sample period, about 30% of foreign exposures are to the public sector. The remaining is made up of 30% exposure to banks and 40% to other sectors.

crisis: its influence over the allocation of IMF loans to defaulting sovereigns. By propping up countries struggling to make debt payments, the IMF and the U.S. government can indirectly absorb U.S. bank losses – a de facto bailout.

IMF loans reduce losses to U.S. banks through loan conditionality, which typically enforces the payment of external debt arrears from recipient governments. Evidence of this comes from Kentikelenis et al. (2016), who examine the conditionality in IMF loan agreements between 1985 and 2014 and show that 28% of all conditions identified relate to the payment of external debt in arrears. Thus, IMF loans can be used to pay down external debt directly. IMF loans can also benefit U.S. banks indirectly by propping up the local private and banking sector of the recipient country. Indeed, Faccio et al. (2006) show that upon receiving an IMF loan, recipient governments are significantly more likely to bail out local firms in distress. This effect is strengthened by the fact that state ownership of banks is prevalent in developing countries. Thus, IMF money can also filter back to U.S. banks through both, the banking and private sectors.

Why not simply bail out banks directly? We argue that the benefits of de facto bailouts are large. First, using the IMF obfuscates the bailout from the voting public and thus reduces the political costs. Recent evidence from Bian et al. (2017) suggests that politicians systematically avoid bailing out banks when the political costs of doing so are high (e.g. in election years or if political competition is high). As Vaubel (1986, 1991, 1996) would put it: delegating the "dirty work" to international organisations allows governments to avoid political backlash.

Second, there are domestic budgetary considerations. Recent history shows the strain that bank bailouts can place on public finances, so to put it bluntly, when using IMF funds to indirectly bail out U.S. banks, other IMF member countries share in the burden, reducing the impact on domestic resources. Indeed, recent work by Mäkinen et al. (2019) demonstrates that implicit bank guarantees by the state are risky and depend crucially on the government's budget position.

Despite these benefits, there is a trade-off to using the IMF's money: transaction costs increase. Specifically, the U.S. has to leverage its influence in the IMF and convince other members to agree. Thus, a de facto bailout may be a less effective tool when the major IMF shareholders disagree or if bank failure is imminent.

3.3 Data

We gather data on U.S. banks foreign exposures from the Bank for International Settlements (BIS) consolidated banking statistics. For a given country, the BIS provides quarterly information on claims (e.g. loans, deposits, debt, and equity securities) held by a banking industry in a foreign state. We use this information to estimate an annual measure of U.S. banks foreign exposure to a sample of 47 developing countries between 1983 and 2016. U.S. bank exposure is measured as the natural logarithm of all claims U.S. banks have to entities in a foreign country, as a percentage of their total exposure worldwide.[9]

The main benefit of the BIS data is that it allows us to ask whether other major IMF members' bank exposures, e.g. Japan or Germany, also increase the likelihood a defaulting sovereign receives an IMF loan. The Federal Financial Institutions Examination Council (FFIEC) also provides data on international exposures, however, this is only for U.S. banks. We make use of this alternative data source in robustness tests.

For each country in our sample, we identify historical episodes of sovereign debt defaults over the sampling period from the Harvard Business School (HBS) Global Crisis Data.[10] We also collect other country-level macroeconomic data – such as GDP growth, inflation, gross trade with the U.S. (measured as the sum of exports and imports and scaled by U.S. GDP), and population – from the World Bank. Finally, we obtain data on countries' voting similarity with the U.S. at the United Nations (UN) from the Harvard

[9]These claims are estimated in an immediate counterparty basis, that is, allocated to the country of residence of the contract obligor.

[10]See www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/global.aspx

Dataverse, a democracy index (Polity) from the Center for Systemic Peace, and a list of temporary members of the UN Security Council from the UN.

Panel A in Table 3.1 presents summary statistics for selected country-level characteristics employed in this study. In our sample, there are 269 IMF loans made.[11] Detailed information on these loans – such as type, date of arrangement, and amount agreed — is from the IMF's Monitoring of Fund Arrangements (MONA) database. Finally, there are 55 unique sovereign defaults corresponding to 393 country-year observations where the sovereign is considered "in default" by the HBS Global Crisis Data. The average loan amount is just under USD 3 billion. The exposure U.S. banks have to a given country varies from zero to 14% with a mean of 1%. Mean log(population), GDP growth and inflation are 16.78, 3.71%, and 68.25%. Inflation is high due the high inflationary periods of the 1980s and 1990s, the median value is 4.1%.

At the bank level, we estimate foreign exposures to particular countries as a fraction of bank capital. Data on individual U.S. bank holding companies (BHC) foreign exposure is from the DealScan database, which provides detailed historical information on global syndicated loan contracts. Additional bank characteristics are sourced from the Consolidated Financial Statements (FR Y-9C) U.S. BHCs are required to file with the Federal Reserve. Panel B in Table 3.1 shows summary statistics for bank-level variables observed around the dates IMF loans were granted to developing countries (see Section 3.4.3 for further details). We can see that only 1% of banks are exposed to international lending – the money centre banks. Conditional on having foreign exposure, the mean bank exposure amounts to 18% of the bank's capital.

Finally, we collect historical information on U.S. Congress roll-call votes on IMF funding increases from the Congressional Roll-Call Votes Database Voteview.[12] For each member of the U.S. Congress, these data includes whether they support IMF fi-

[11]Two main types of IMF lending programs are included in our sample, General Resources Account (GRA) and Poverty Reduction Growth Trust (PRGT) arrangements.

[12]Broz (2011) provides a comprehensive list of roll-call votes on IMF financing in the U.S. congress between 1944-2009.

Table 3.1: Summary statistics

This table reports summary statistics. Panel A presents selected country characteristics for an unbalanced panel of 47 countries recipients of IMF loans between 1983 and 2016. Panel B presents bank-level statistics around the time of IMF loan announcements. Panel C presents statistics for members of Congress who took part in IMF funding increases votes.

	Obs.	Average	Standard Deviation	Min	Median	Max
(A) Country						
IMF Loan	1,598	0.28	0.45	0.00	0.00	1.00
IMF Loan Amount	269	2,987.84	7,986.80	15.00	300.20	62,388.90
Log IMF Loan Amount	269	6.08	1.85	2.71	5.70	11.04
Sovereign Debt Default	1,529	0.26	0.44	0.00	0.00	1.00
US Banks Exposure	1,598	0.01	0.02	0.00	0.00	0.14
Log US Banks Exposure	1,598	-6.79	2.47	-16.39	-6.71	-1.98
GDP Growth	1,550	3.71	4.43	-36.70	4.10	33.74
Inflation	1,550	68.25	578.48	-27.05	7.28	13,611.63
Log Population	1,598	16.78	1.57	12.38	16.65	21.04
Net Capital Flows	1,598	2.62	4.56	-15.99	1.58	81.69
Trade	1,541	65.78	31.25	11.54	59.32	221.16
External Balance	1,541	-2.28	8.54	-40.29	-2.25	40.82
Economic Openness	1,551	0.54	0.35	0.00	0.61	1.00
Trade with US	1,528	0.11	0.12	0.00	0.07	0.96
Temporary Member	1,598	0.09	0.28	0.00	0.00	1.00
UN Voting Similarity	1,487	0.26	0.14	0.00	0.22	1.00
Polity	1,520	4.20	6.06	-9.00	7.00	10.00
(B) Bank Holding Company						
Exposed	29,309	0.01	0.11	0.00	0.00	1.00
Exposure/Capita | Exposed=1	348	0.18	0.33	0.00	0.04	1.79
Log Assets	29,309	14.64	1.66	12.12	14.29	20.25
ROE	29,309	0.20	0.42	-2.56	0.29	0.67
Tier 1 Capital /RWA	27,088	0.13	0.07	0.05	0.12	1.88
Tier 1 Capital /Assets	27,088	0.09	0.04	0.04	0.09	0.86
Short-term Wholesale/Liabilities	29,309	0.17	0.12	0.00	0.15	0.55
RWA/Assets	27,088	0.72	0.12	0.40	0.72	1.62
Loans/Deposits	29,309	0.88	0.18	0.39	0.87	1.49
(C) Congress						
Finance Contributions	1,222	0.18	0.10	0.00	0.16	0.68
Constituency Exposure	1,126	0.26	0.23	0.00	0.20	0.97
Exports per Capita	1,696	2.63	1.87	0.05	2.11	12.08
GDP per Capita	1,696	36.19	15.74	0.70	33.69	96.65
Ideology	1,696	0.02	0.40	-0.68	-0.02	0.88
Democrat	1,696	0.51	0.50	0.00	1.00	1.00
House	1,696	0.77	0.42	0.00	1.00	1.00

nancing (i.e. a "yes" vote), their ideological position (i.e. NOMINATE score of Poole and Rosenthal (1985)), and party affiliation. Moreover, we gather data on campaign contributions from the finance industry, to individual members of Congress, from the Center for Responsive Politics (OpenSecrets), and use the Survey of Deposits (SOD) dataset – from the Federal Deposit Insurance Corporation (FDIC) – to estimate the deposit market share of foreign-exposed U.S. banks in a member's constituency. The resulting dataset comprises seven IMF-financing votes (three in the House of Representatives and four in the Senate) between 1983 and 2016. Panel C in Table 3.1 presents summary statistics for selected congress-level variables. We have a total of 1,696 votes cast by 1,293 unique members of Congress. The mean value for finance contributions is 0.18, implying that the average politician receives 18% of her campaign contributions from the finance industry, but this number varies from zero to 97%. The mean value of constituency exposure is 0.26 which can be interpreted as the average deposit market share, at the constituency level, of banks with foreign exposure to developing countries.

3.4 Empirical Methodology and Results

Our analysis comprises of three components. First, we show that U.S. bank exposure robustly predicts the likelihood that a defaulting sovereign receives an IMF loan. Second, we examine whether congressional voting patterns for IMF funding increases are responding to the public interest or special (banking) interests. Third, we conduct an event study to examine how U.S. bank stock returns respond to IMF loan announcements.

3.4.1 Baseline Model

We estimate the impact of U.S bank exposure on a country's likelihood of receiving an IMF loan, using the following logistic regression:

$$
\begin{aligned}
g(\textit{IMF Loan}_{i,t}) = {} & \alpha_1 \textit{US Banks Exposure}_{i,t} + \alpha_2 \textit{Sovereign Default}_{i,t} \\
& + \alpha_3 \textit{Sovereign Default}_{i,t} \times \textit{US Banks Exposure}_{i,t} \\
& + \boldsymbol{\beta}' \boldsymbol{X}_{i,t} + I_i + T_t
\end{aligned} \tag{3.1}
$$

where *IMF Loan*$_{i,t}$ is an indicator variable which takes the value of one if country i received an IMF loan in year t, and zero otherwise. *US Banks Exposure*$_{i,t}$ is the natural logarithm of the exposure U.S. banks have to country i as a percentage of their total exposure worldwide in year t.[13] *Sovereign Default*$_{i,t}$ is an indicator that equals one if country i is in default in year t, and zero otherwise. I_i is a country fixed effect and T_t is a time fixed effect which varies by year. Standard errors are clustered at the country level. The vector of control variables, $\boldsymbol{X}_{i,t}$, includes:

i *GDP Growth*, annual GDP growth;

ii *Inflation*, annual inflation;

iii *Log*(*Population*), the natural logarithm of the population;

iv *UN Voting Similarity*, an index measuring how similar a country's UN general assembly voting is with that of the U.S.;

v *Trade with US*, gross trade with the U.S. expressed as a fraction of U.S. GDP;

vi *Polity*, the polity score which is a scale measuring the degree of autocracy-democracy;

vii *Temporary*, an indicator that equals one if a country is currently a temporary member of the UN security council;

Table 3.2: Baseline model

This table presents coefficient estimates for the logistic model in Equation 3.1 using an unbalanced panel of 47 countries between 1983 and 2016. The dependent variable is a dummy which takes 1 for countries that received an IMF loan, and 0 otherwise. The variable US Banks Exposure is the natural logarithm of the exposure U.S. banks have to a given country, as a percentage of their total exposure worldwide. Sovereign Debt Default is a dummy variable which takes 1 if a country's external debt is in default in a given year, and 0 otherwise. Column (2) includes country-specific macroeconomic characteristics as controls: GDP Growth, Inflation, and Log Population. Column (3) controls for whether a country is a temporary member of the United Nations (UN) Security Council. Column (4) accounts for a country's voting similarity with the U.S. voting history in the UN. Column (5) controls for the level of trade relationship with the U.S., and Column (6) accounts for how democratic a country's system of government is. Regressions include country fixed effects to control for unobserved time-invariant characteristics, and year fixed effects to account for aggregate time trends that are common to all countries in the sample. Standard errors are clustered at the country level to allow for error correlation within each panel.

DEPENDENT VARIABLE: IMF Loan	(1)	(2)	(3)	(4)	(5)	(6)
US Banks Exposure	0.06	-0.02	-0.04	-0.06	-0.12	-0.10
	(0.47)	(-0.15)	(-0.28)	(-0.46)	(-0.71)	(-0.58)
Sovereign Debt Default	5.73***	6.15***	6.26***	6.50***	6.67***	6.63***
	(5.24)	(4.94)	(5.00)	(5.31)	(5.13)	(5.10)
Sovereign Debt Default × US Banks Exposure	0.42***	0.46**	0.47**	0.52***	0.56***	0.56***
	(2.76)	(2.51)	(2.57)	(2.78)	(2.84)	(2.79)
GDP Growth		-0.07***	-0.07***	-0.07***	-0.08***	-0.08***
		(-2.70)	(-2.58)	(-2.66)	(-2.81)	(-2.80)
Inflation		-0.00**	-0.00**	-0.00**	-0.00*	-0.00*
		(-2.55)	(-2.50)	(-2.55)	(-1.84)	(-1.73)
Log Population		1.60	1.54	0.37	-0.76	-0.51
		(1.05)	(1.00)	(0.19)	(-0.55)	(-0.32)
Temporary Member			0.55**	0.48	0.66**	0.58**
			(2.07)	(1.60)	(2.43)	(2.16)
UN Voting Similarity				6.79**	5.66*	5.85**
				(2.11)	(1.95)	(1.97)
Trade with US					8.16**	8.06**
					(2.39)	(2.41)
Polity						-0.02
						(-0.52)
Observations	1,495	1,461	1,461	1,366	1,326	1,302
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Our variable of interest is the interaction term *Sovereign Default* $\times$ *US Banks Exposure* and our claim, that the likelihood that a defaulting sovereign receives an IMF loan increases with the exposure of U.S. banks to that country, implies that $\alpha_3 > 0$.

Baseline Estimation Results and Robustness

Table 3.2 presents our baseline results across six columns. Column (1) presents the results of a simple regression without any control variables. Each subsequent column adds additional control variables to the specification. Our most restrictive model is Column (6), which includes all the control variables listed above. We find similar results across all specifications, the coefficient on the interaction term *Sovereign Default* $\times$ *US Banks Exposure* is positive and significant as expected. The economic magnitude is large. The point estimate from Column (6) is 0.56, which implies that, conditional on sovereign default, a standard deviation increase in *US Banks Exposure* increases the likelihood country i receives an IMF loan by almost four times.

Our control variables have the expected signs. Higher GDP Growth and Inflation are negatively correlated with the likelihood of receiving an IMF loan. Being a temporary member on the security council increases the likelihood of receiving a loan, which is consistent with Dreher et al. (2009). Finally, stronger economic and political alignment increases the likelihood of a loan (i.e. positive and significant coefficients on *Trade with US* and *UN Voting Similarity*) which is consistent with papers like Barro and Lee (2005) and Dreher and Jensen (2007). We now perform a series of robustness tests.

Loan size. We investigate whether, conditional on country i receiving a loan, the size of the IMF loan is also increasing with U.S. banks exposure. Using our sample of 269 IMF loans, we regress the natural logarithm of loan size on *US Banks Exposure*, plus the same vector of controls $\boldsymbol{X}$ and year fixed effects. The results are presented in Table 3.3 across six columns with each column adding additional controls. In all cases,

[13] $g(x) = \log\left(\frac{\Pr(x=1)}{1-\Pr(x=1)}\right)$ is the logit function or logarithm of the odds.

Table 3.3: IMF loan size

This table presents coefficient estimates for an OLS regression where the dependent variable is the natural logarithm of the loan amount a country receives from the IMF. The sample consists of 269 loans to 47 countries between 1983 and 2016. The variable US Banks Exposure is the natural logarithm of the exposure U.S. banks have to a given country, as a percentage of their total exposure worldwide. Sovereign Debt Default is a dummy variable which takes 1 if a country's external debt is in default in year t, and 0 otherwise. Column (2) includes country-specific macroeconomic characteristics as controls: GDP Growth, Inflation, and Log Population. Column (3) controls for whether a country is a temporary member of the United Nations (UN) Security Council. Column (4) accounts for a country's voting similarity with the U.S. voting history in the UN. Column (5) controls for the level of trade relationship with the U.S., and Column (6) accounts for how democratic a country's system of government is. Regressions include year fixed effects to account for aggregate time trends that are common to all countries in the sample. Standard errors are clustered at the country level to allow for error correlation within each panel.

DEPENDENT VARIABLE: IMF Loan Size	(1)	(2)	(3)	(4)	(5)	(6)
US Banks Exposure	0.46***	0.29***	0.28***	0.26***	0.29***	0.30***
	(8.08)	(6.31)	(6.34)	(6.09)	(6.97)	(7.04)
GDP Growth		-0.07***	-0.07***	-0.06***	-0.07***	-0.07***
		(-3.87)	(-3.75)	(-3.10)	(-4.02)	(-3.82)
Inflation		-0.00	0.00	0.00	-0.00	-0.00
		(-0.07)	(0.09)	(0.43)	(-0.32)	(-0.18)
Log Population		0.64***	0.63***	0.65***	0.59***	0.59***
		(8.41)	(8.23)	(9.40)	(7.94)	(8.42)
Temporary Member			0.28	0.27	0.16	0.08
			(1.29)	(1.31)	(0.79)	(0.36)
UN Voting Similarity				2.64***	1.90***	1.90**
				(4.21)	(2.79)	(2.69)
Trade with US					-2.14***	-1.98***
					(-3.61)	(-3.25)
Polity						-0.01
						(-0.74)
Constant	9.07***	-2.59*	-2.48*	-3.82***	-2.00	-2.06
	(22.09)	(-1.79)	(-1.72)	(-3.01)	(-1.51)	(-1.67)
Observations	269	264	264	249	238	236
R-squared	0.610	0.762	0.764	0.772	0.794	0.801
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

the coefficient estimate on *US Banks Exposure* is positive and significant. The point estimate from Column (6) is 0.3, which implies that a standard deviation increase in *US Banks Exposure* leads to a 12% increase in loan size.

Other major IMF members. A natural question to ask is whether the foreign bank exposures from the other major IMF members have a similar impact on the likelihood a defaulting sovereign receives an IMF loan. For the majority of our sample, the four other major IMF members are Japan, Germany, France, and the United Kingdom. The advantage of using the BIS data is that we have the ability to calculate similar bank exposure measures for these countries on an individual basis, as well as the group exposure. We estimate models of the same nature as Equation 3.1 replacing *US Banks Exposure* with the exposures for each of the four countries, and the collective exposure of all four countries. The results are presented in Table 3.4. Column (1) presents regression coefficients for Japanese Banks, Column (2) for Germany, Column (3) for France, and Column (4) for the UK. Finally, Column (5) presents estimates for the foreign exposures of these four IMF members as a whole. We do not find much evidence that other major countries' bank exposures matter. The coefficient on the interaction term between *Sovereign Default* and *Banks Exposure* is insignificant for all the countries except Germany. For the German case, the magnitude of the effect is about one-third that of U.S. banks. Importantly, the collective exposure is insignificant in explaining the likelihood of getting an IMF loan.

FFIEC data and linear probability model. U.S. banks have an alternative data source detailing foreign exposures available from the Federal Financial Institutions Examination Council (FFIEC). The FFIEC data come in disaggregated form, with total foreign exposure broken down into public exposures, bank exposures, and other sector exposures. We reestimate Equation 3.1 using these data and, to conserve space, we present the results in Appendix Table B1. Columns (1) to (4) present the results for public, bank, other sector, and total exposures, respectively. While the results are significant in

Table 3.4: Other countries

This table presents coefficient estimates for the logistic model in Equation 3.1 applied to the foreign bank exposures of other IMF members with high voting power. The sample consists of an unbalanced panel of 47 countries between 1983 and 2016. Column (1) presents regression coefficients for Japanese Banks. Column (2) for Germany, Column (3) for France, and Column (4) for the UK. In addition, Column (5) presents estimates for the foreign exposures of these four IMF members as a whole. The dependent variable is a dummy which takes 1 for countries that received an IMF loan, and 0 otherwise. The variable US Banks Exposure is the natural logarithm of the exposure U.S. banks have to a given country, as a percentage of their total exposure worldwide. Sovereign Debt Default is a dummy variable which takes 1 if a country's external debt is in default in a given year, and 0 otherwise. Regressions include all controls used in Table 3.2 Column (6), country fixed effects, and year fixed effects. Standard errors are clustered at the country level.

DEPENDENT VARIABLE: IMF Loan	(1) Japan	(2) Germany	(3) France	(4) UK	(5) Total
Sovereign Debt Default	5.20***	5.31***	4.75***	3.32***	4.62***
	(4.36)	(5.92)	(4.42)	(2.93)	(4.26)
Japanese Banks Exposure	-0.26*				
	(-1.77)				
Sovereign Debt Default × Japanese Banks Exposure	0.17				
	(1.00)				
German Banks Exposure		-0.07			
		(-0.33)			
Sovereign Debt Default × German Banks Exposure		0.21**			
		(2.17)			
French Banks Exposure			-0.26		
			(-1.62)		
Sovereign Debt Default × French Banks Exposure			0.22		
			(1.29)		
UK Banks Exposure				-0.07	
				(-0.50)	
Sovereign Debt Default × UK Banks Exposure				0.01	
				(0.08)	
Total Banks Exposure					-0.16
					(-0.81)
Sovereign Debt Default × Total Banks Exposure					0.19
					(1.22)
Observations	1,084	1,424	1,424	1,424	1,424
Controls	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

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

all cases, the magnitude of the effect is largest for public exposures as expected.

Next, since interaction terms can be problematic in non-linear models (see Ai and Norton, 2003) we replicate Table 3.2 using a linear probability model.[14] The results for this specification, in Appendix Table B2, are qualitatively the same as our main findings above.

Identification

There may be concerns that our results are contaminated by endogeneity. In particular, it may be the case that U.S. banks are able to predict which countries are more likely to receive IMF loans, and so increase their exposures to those countries knowing that there is a safety net in the event of default (i.e. reverse causality). We address this concern in two ways. First, we build a model for predicting which countries are more likely to receive IMF loans, and show that U.S. banks exposures are *not* positively correlated with the predictions from this model. Second, we use an instrumental variables approach to identify causal effects.

A predictive model of IMF loan allocation. Since the concern is that U.S. banks can predict where IMF loans are going and increase their exposures, we build a predictive model using observable information available to banks. Specifically, we estimate the following logit model:

$$g(\textit{IMF Loan}_{i,t}) = \alpha_1 \textit{Sovereign Default}_{i,t} + \boldsymbol{\beta}' \boldsymbol{X}_{i,t} + I_i + T_t \tag{3.2}$$

Where all the variables are the same as before. We then take the predicted values from this regression, $\widehat{\textit{IMF Loan}}$, and relate them to *US Banks Exposure* in the following

[14]Here, the function $g(.)$ in Equation 3.1 takes the form $g(x) = x$.

Table 3.5: Predictive model

This table presents coefficient estimates for the endogeneity test described in Section 3.4.1 using an unbalanced panel of 47 countries between 1983 and 2016. Column (1) shows estimates for a logistic regression in which the dependent variable is a dummy which takes 1 for countries that received an IMF loan, and 0 otherwise. Covariates in this model include Sovereign Debt Default which is a dummy variable that takes 1 if a country's external debt is in default, and 0 otherwise, and controls used in Table 3.2 Column (6). Column (2) presents estimates from an OLS regression in which the dependent variable is US Banks Exposure. This variable is estimated as the natural logarithm of the exposure U.S. banks have to a given country, as a percentage of their total exposure worldwide. The independent variable of interest is $\widehat{\text{IMF Loan}}$, which is the predicted probability of receiving an IMF loan estimated from Column (1). Regressions include controls used in Table 3.2 Column (6), country fixed effects, and year fixed effects. Standard errors are clustered at the country level.

DEPENDENT VARIABLE:	(1) IMF loan	(2) US Banks Exposure
Sovereign Debt Default	2.26***	
	(9.09)	
$\widehat{\text{IMF Loan}}$		-2.85***
		(-5.21)
GDP Growth	-0.06***	-0.00
	(-2.58)	(-0.15)
Inflation	0.00	-0.00
	(0.50)	(-1.45)
Log Population	-0.65	-3.24***
	(-0.47)	(-9.03)
Temporary Member	-0.15	0.15*
	(-0.50)	(1.85)
UN Voting Similarity	5.20**	0.02
	(2.53)	(0.04)
Trade with US	5.25***	1.31***
	(3.23)	(2.89)
Polity	-0.01	0.04***
	(-0.28)	(4.23)
Constant		47.92***
		(7.93)
Observations	1,302	1,281
R-squared		0.883
Country Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Robust z-statistics (Column 1) and t-statistics (Column 2) in parentheses
*** p<0.01, ** p<0.05, * p<0.1

linear regression:

$$\begin{aligned} \textit{US Banks Exposure}_{i,t} = \gamma_1 \textit{Sovereign Default}_{i,t} + \gamma_2 \widehat{\textit{IMF Loan}_{i,t}} \\ + \boldsymbol{\beta}' \boldsymbol{X}_{i,t} + I_i + T_t + \varepsilon_{i,t} \end{aligned} \tag{3.3}$$

If U.S. banks indeed increase exposures to countries they consider more likely to receive IMF loans, then we should find γ_2, in Equation 3.3, to be positive and significant. We estimate Equation 3.2 and Equation 3.3, and present results in Table 3.5. We can see from Column (2) that the coefficient on $\widehat{\textit{IMF Loan}}$ is actually negative, which is inconsistent with the notion that banks increase exposures to countries that are more likely to receive IMF loans.

Instrumental variables. We employ an instrumental variables approach to identify causal effects. Since our main model has two endogenous variables (i.e. *US Banks Exposure* and *Sovereign Default* $\times$ *US Banks Exposure*) we employ two instruments. Our first instrument is the physical distance between the U.S. and each country in our sample. Due to increased informational and transactional frictions, physical distance has been shown to have a negative impact on cross-border banking and equity flows (see Aviat and Coeurdacier, 2007; Buch, 2005; Buch and Lipponer, 2007; Portes and Rey, 2005). As such, we expect it to be negatively related to U.S bank exposure, but, at the same time, physical distance is clearly exogenous. For each country i, our second instrument is the average U.S. bank exposure of all the countries that border it. In this instance, regional trends imply that U.S. banks exposures are likely correlated among neighbouring countries, but it is unlikely that the average exposures of the neighbouring countries to country i are *directly* related to the likelihood that country i receives a loan. We obtain estimates for the geodesic distance between the U.S. and each developing country from the CEPII institute, and information on country borders from `www.geodatasource.com`.

We present the first-stage results for each of the endogenous variables in Table 3.6, Columns (1) and (2). The dependent variable in Column (1) is *US Banks Exposure* and the dependent variable in Column (2) is *Sovereign Default* $\times$ *US Banks Exposure*. We see that the two instruments have the expected signs and are significant. The instruments have a sizeable impact on *US Banks Exposure*: a standard deviation increase in Neighbouring Exposure (Geodesic Distance) leads to a 7.6% (6.8%) increase (decrease) in *US Banks Exposure* relative to the sample mean. We compare the cluster-robust F-statistics from the first-stage to the rule of thumb level in testing weak instruments (i.e. $F \geq 10$).[15] The F statistics are well above 10, which reduces the concern that weak instruments may contaminate our inference.

Importantly, we can see from the second-stage regression that the instrumented variable $\widehat{\textit{Sovereign Default} \times \textit{US Banks Exposure}}$ remains positive and significant. The point estimate is smaller than the main result and implies that a standard deviation increase in *US Banks Exposure* results in a 68% increase in the likelihood that a developing country receives an IMF loan.

The Relative Cost of Direct Bailouts

As argued in Section 3.2, the benefits of de facto bailouts relate to (1) reducing the political costs associated with direct bailouts, for example, Bian et al. (2017) show that bailouts are much less likely to occur in an election year; and (2) reducing the strain on domestic resources, for example, Mäkinen et al. (2019) demonstrate that direct government bailouts are risky and depend crucially on the state of the government's finances. In other words, direct bailouts are less likely when the state is more indebted.

To test these ideas, we estimate Equation 3.1 on the following subsamples: Federal election years vs non-election years; and Budget Deficit > 0.05 vs Budget Deficit < 0.05.[16] The expectation is that IMF loans are more likely in election years when governments are trying to avoid bad press associated with a direct bailout. Likewise, de facto

[15]Note that the system is exactly identified. In this case, we report the Kleibergen-Paap F-statistic, which is equivalent to Montiel Olea-Pflueger effective first-stage F statistic. See Kleibergen and Paap (2006) and Olea and Pflueger (2013) for a detailed discussion.

[16]Federal elections include both Presidential as well as mid-term elections. We find qualitatively similar results using just Presidential elections.

Table 3.6: Instrumental variable

This table presents coefficient estimates for the instrumental variable model described in Section 3.4.1 using an unbalanced panel of 47 countries between 1983 and 2016. Column (1) and Column (2) present estimates for First-Stage regressions where the endogenous variables are US Banks Exposure and Sovereign Debt Default × US Banks Exposure, respectively. The instruments are Neighbouring Exposure and Geodesic Distance. Neighbouring Exposure is calculated as the natural logarithm of the average exposure U.S. banks have (as a percentage of their total exposure) to the neighbouring states of a given country. Geodesic Distance measures the physical distance (in thousands of kilometres) from the U.S. Column (3) shows coefficient estimates for a Second-Stage regression where the dependent variable is a dummy which takes 1 for countries that received an IMF loan, and 0 otherwise. All regressions include controls used in Table 3.2 Column (6). Regressions include year fixed effects, and standard errors are clustered at the country level.

	(1)	(2)	(3)
DEPENDENT VARIABLE:	**First-Stage 1** US Banks Exposure	**First-Stage 2** Sovereign Debt Default × US Banks Exposure	**Second-Stage** IMF Loan
Sovereign Debt Default	-0.57***	-6.71***	1.88***
	(-4.62)	(-63.90)	(3.11)
Neighbouring Exposure	0.23***	0.09***	
	(9.15)	(4.19)	
Geodesic Distance	-0.13***	-0.12***	
	(-7.51)	(-7.89)	
$\widehat{\text{US Banks Exposure}}$			-0.06
			(-1.05)
$\widehat{\text{Sovereign Default} \times \text{US Banks Exposure}}$			0.21**
			(2.17)
Observations	1,048	1,048	1,048
R-squared	0.576	0.850	0.220
F-statistic	80.59	45.10	
Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

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

bailouts will be more likely when government finances are in a bad position.

The results are presented in Table 3.7 across four columns. Columns (1) and (2) are subsamples split by non-election and election years, respectively. We can see that the coefficient on *Sovereign Default* × *US Banks Exposure* is positive in both subsamples and the magnitude effect is 31% larger in the election-years subsample, as expected. However, the between sample differences are not statistically different from each other.

Columns (3) and (4) split the sample by below and above the 75th percentile for

Table 3.7: Bailout cost

This table presents coefficient estimates for the logistic model in Equation 3.1 applied to subsamples based on proxies for political costs and fiscal costs. The sample consists of an unbalanced panel of 47 countries between 1983 and 2016. The variable US Banks Exposure is the natural logarithm of the exposure U.S. banks have to a given country, as a percentage of their total exposure worldwide. Sovereign Debt Default is a dummy variable which takes 1 if a country's external debt is in default in a given year, and 0 otherwise. Columns (1) and (2) present coefficients for non-election and U.S. Federal election years, respectively. Columns (3) and (4) show estimates for years in which the U.S. Budget Deficit (scaled by GDP) was below and above the 75th percentile (i.e. below or above 5% of GDP), respectively. Regressions include controls used in Table 3.2 Column (6), country fixed effects, and year fixed effects. Standard errors are clustered at the country level.

DEPENDENT VARIABLE: IMF Loan	(1) Elections=0	(2) Elections=1	(3) Deficit<0.05	(4) Deficit>0.05
US Banks Exposure	-0.08	-0.11	0.01	-0.47*
	(-0.45)	(-0.50)	(0.03)	(-1.87)
Sovereign Debt Default	6.03***	7.59***	6.10***	10.01***
	(5.13)	(4.67)	(5.39)	(3.93)
Sovereign Debt Default × US Banks Exposure	0.51***	0.67***	0.49***	0.90***
	(3.00)	(2.95)	(2.97)	(2.94)
Observations	618	572	829	308
Controls	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Between-Sample Differences	(1) vs (2)	(3) vs (4)
Sovereign Debt Default × US Banks Exposure	0.16	0.41**

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

U.S. government budget deficit (i.e. below and above a deficit of 5% of GDP). In this instance, we see a stark difference in the size of the effect across the two subsamples: de facto bailouts are much more likely when the U.S. government is in a poorer financial position. Precisely, the coefficient estimates on *Sovereign Default* × *US Banks Exposure* imply that a standard deviation increase in *US Banks Exposure* increases the likelihood a defaulting sovereign receives an IMF loan by 3.4 times when the U.S. budget deficit is below 5% of GDP, compared to 9.2 times when the deficit is above 5% of GDP. The results in this section thus provide some evidence on how the likelihood of a de facto bailout varies with the relative costs of direct versus de facto bailouts.

3.4.2 Public or Private Interest? Congressional Voting on IMF Funding Increases

Proponents of direct bank bailouts argue that bailouts ameliorate the significant negative externalities associated with bank failure – the public interest view of government. In the other camp, the belief is that politicians may follow their own interests when bailing out banks (i.e. special interest pressure) in order to increase their probability of re-election – a private interest view of government.

Our argument is that de facto bailouts occur because U.S. politicians are responding to special interest pressure from the banking lobby, especially those banks exposed to losses from overseas lending. However, it is certainly plausible that politicians are responding in the public interest if losses from overseas lending have negative repercussions for their local constituencies, for example, from a contraction in local lending and real activity.

In this section, we ask the question: Are the patterns we observe above more in line with a public interest or private interest view of government? To do this, we examine roll-call voting data relating to funding increases for the IMF. Funding increases raise the resources available to the IMF to provide assistance to defaulting sovereigns. Hence, politicians who vote in favour of increases are also in favour of de facto bailouts. To tease out whether public or private interest is the motivation for voting yes, we construct a proxy to capture each of these concepts.

To capture the private interest view, we create the variable *Finance Contributions*$_{i,t}$ which is calculated as the total campaign contributions from the finance industry received by member of Congress i, as a percentage of their total contributions, up to roll-call vote t. We are able to construct this variable for the full sample period covering seven IMF-financing roll-call votes between 1983 and 2016.[17] Our proxy for the public interest view is more involved to calculate since we need constituency-level measures

[17] The IMF roll-call votes occurred in 1983, 1991, 1998, 2009, and 2015.

to account for their exposure to foreign lending losses. We proceed as follows.

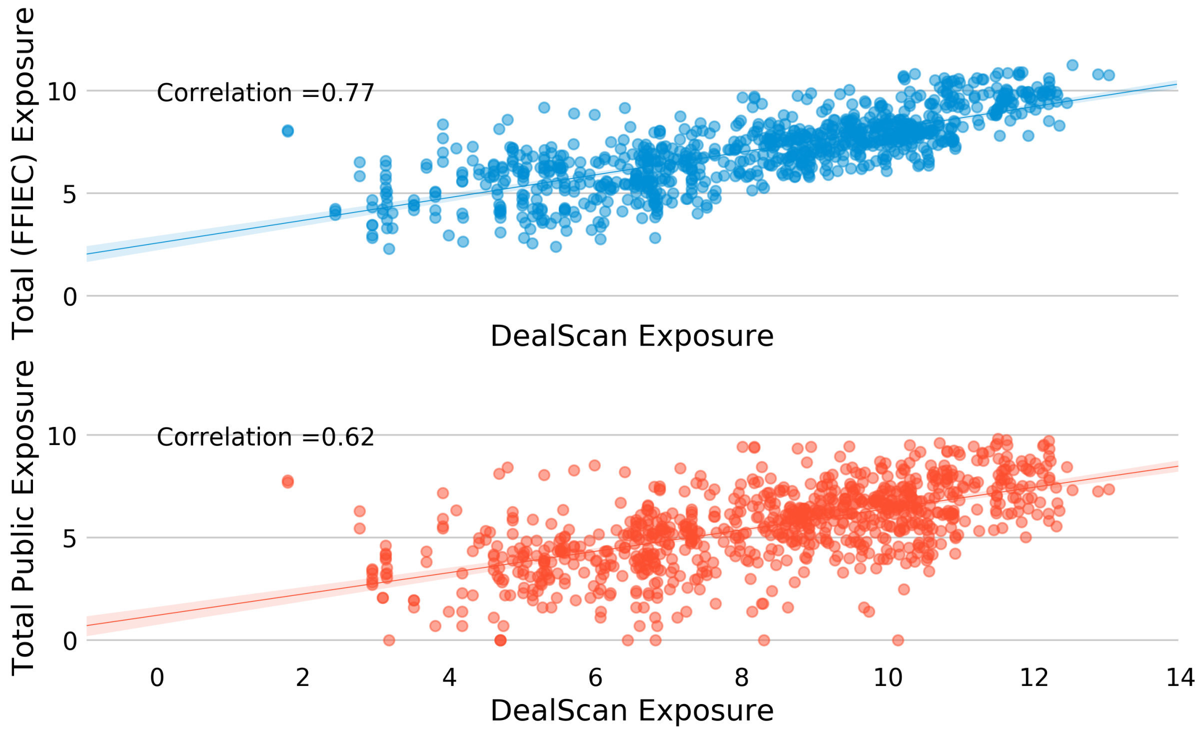
First, we follow the prior literature and use the DealScan database to calculate bank-level exposures to each country that has experienced a sovereign default during our sample period (see Giannetti and Laeven, 2012a,b; James, 1989). The exposure of bank b to country c is simply the ratio of the value of lending to country c to bank capital (i.e. equity). DealScan is a database of syndicated loans to large corporations around the world. Thus, it does not contain non-syndicated lending nor does it contain lending to sovereigns. To ensure that exposure to syndicated corporate loans is a good proxy for bank foreign exposures, in general, we present a scatter plot relating total foreign bank exposures to particular countries – using official data from the FFIEC – to aggregated exposures to those countries obtained from the DealScan database. Figure 3.1 plots the results across two panels. The top panel is the scatter plot of FFIEC total exposures of U.S. banks on DealScan exposures, whereas the bottom panel plots FFIEC public exposures against DealScan exposures. In each case, we can see that there is a strong positive relation between the FFIEC and DealScan exposures (i.e. 0.77 for total exposures and 0.62 for public exposures).

Second, we obtain summary of deposits (SOD) data from the FDIC (available from 1994) to determine the deposit share for each bank in each constituency. We then create the variable $\textit{Constituency Exposure}_{i,t}$, which measures how exposed each constituency is to U.S. banks exposed to foreign countries that experienced a sovereign default during the sample period. For member of Congress i's constituency, this is calculated as the weighted sum of each bank's foreign exposure, where weights are their corresponding deposit market shares.[18] Because of the SOD data limitations, we are able to calculate this variable for five roll-call votes between 1994 and 2016.

We examine the determinants for voting in favour of IMF funding increases in the

[18]For Senators we consider the State they represent as their constituency.

Figure 3.1: Commercial vs public sector foreign exposures
This figure shows the linear relationship between the aggregate foreign exposure of U.S. banks estimated using commercial loan market data from DealScan, and total U.S. banks exposures reported by the Federal Financial Institutions Examination Council (FFIEC) (top panel), and foreign exposures to the public sector (bottom panel). The sample period spans 1983 to 2016.



following logit model:

$$
\begin{aligned}
g(IMF\ Vote_{i,t}) = \beta_1 Finance\ Contributions_{i,t} + \beta_2 Constituency\ Exposure_{i,t} \\
+ \beta_3 Ideology_{i,t} + \beta_4 Democrat_{i,t} + \beta_5 House_{i,t} + T_t
\end{aligned}
\tag{3.4}
$$

where $IMF\ Vote_{i,t}$ corresponds to an indicator that equals one if member of Congress i votes to support an IMF funding increase in roll-call vote t, and zero otherwise. Our control variables include $Ideology_{i,t}$, which is estimated based on historical voting patterns available at www.voteview.com, and serves as a proxy for member of Congress i's political ideology; $Democrat_{i,t}$ is an indicator that takes one if the member is from the Democratic party; $House_{i,t}$ an indicator that equals one if the vote took place in the House of Representatives; and T_t is a roll-call number fixed effect.

Table 3.8: Congressional voting

This table presents coefficient estimates for a logistic regression on a sample of U.S. Congress roll-call votes on IMF funding increases. The dependent variable is a dummy which takes 1 for votes that support IMF financing, and 0 otherwise. Column (1) shows coefficients for a sample of seven IMF-financing roll-call votes between 1983 and 2016, while Column (2) presents estimates for a sample of five roll-call votes between 1998 and 2016. The variable Finance Contributions is the campaign contributions from the finance industry received by each member of Congress, as a percentage of their total contributions received. In Column (2), we control for the variable Constituency Exposure. For a given constituency, this variable measures the total deposit market share of U.S. banks exposed to countries that experienced a sovereign debt crisis. In addition, the model in Column (3) controls for both Finance Contributions and Constituency Exposure. For each member of Congress, additional controls include an ideology index, a dummy variable which takes 1 for Democrats and 0 for Republicans, and a dummy which equals 1 for members of the House of Representatives and 0 for the Senate. Regressions include rollnumber fixed effects and robust standard errors.

DEPENDENT VARIABLE: IMF Vote	(1)	(2)	(3)
Finance Contributions	2.79***		2.66***
	(3.53)		(2.95)
Constituency Exposure		0.44	0.35
		(1.00)	(0.77)
Ideology	-4.63***	-4.13***	-3.91***
	(-8.52)	(-7.31)	(-6.52)
Democrat	-0.96**	-0.52	-0.19
	(-2.30)	(-1.18)	(-0.39)
House	-0.77*	-1.04***	-1.08***
	(-1.71)	(-3.78)	(-2.97)
Constant	0.52	0.92***	0.36
	(1.05)	(2.80)	(0.82)
Observations	1,222	1,126	1,036
Rollnumber Fixed Effects	Yes	Yes	Yes

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

Our results are presented in Table 3.8. Column (1) includes only *Finance Contributions* along with controls. We can see that *Finance Contributions* has a strong positive relation with *IMF Vote*. Specifically, a standard deviation increase in *Finance Contributions* raises the likelihood of voting in favour of an IMF funding increase by over 32%. Next, in Column (2) we replace *Finance Contributions* with *Constituency Exposure* and reestimate the model. Interestingly, we find no significant relation between *Constituency Exposure* and *IMF Vote*.

Finally, in Column (3) we include both *Finance Contributions* and *Constituency Exposure* and once again find that only *Finance Contributions* is positive and significant. Consequently, the results here point toward a private interest view of government: de facto bailouts of U.S. banks appear to be driven by special interests considerations.

3.4.3 U.S. Bank Stock Returns Around IMF Loan Announcements

Since IMF loans are official monies to governments, one may wonder whether any of this money actually reaches U.S. banks. While it is impossible to track where this money goes, we make two observations in this section. First, IMF loan conditionality typically enforces the payment of external debt arrears from recipient governments. For example, Kentikelenis et al. (2016) examine the conditionality in IMF loan agreements between 1985 and 2014, and count a total 55,465 individual conditions. Of these, the most frequently cited condition is related to debt management and the payment of external debt in arrears with a count of 15,407, or 28% of all conditions identified.

Second, we take an indirect approach to confirm that U.S. banks benefit significantly from IMF loans by examining the impact of IMF loan announcements on U.S bank shareholder wealth. To do so, we employ a standard event study approach. First, we calculate the cumulative abnormal returns (CAR) for all U.S. bank holding companies (BHC) for the 20 days around (10 days prior to and 10 days after) the announcement of an IMF loan. Our model for expected returns is the Fama and French three-factor model.[19] We use a longer event window because of the public nature of sovereign defaults and IMF loan allocation. Second, using our bank level exposures estimated via DealScan data (see Section 3.4.2), we classify banks as being exposed or unexposed to a given country at the time the IMF loan is announced. Third, we calculate and compare the average CAR for exposed versus unexposed banks.

The top panel in Table 3.9 presents the univariate results from this comparison. We can see that exposed banks experience an average CAR of 3.4% around the announce-

[19] We find similar results when using a market model instead.

Table 3.9: Univariate event study

This table shows average cumulative abnormal returns (CAR) for US bank holding companies (BHC) around the dates an IMF loan was granted. The sample consists of 269 IMF loans to 47 countries between 1983 and 2016. Exposed refers to the those BHC which, on the event date, were exposed to the recipient country. In Panel A, the sample includes all BHC for which price data is available, whereas Panel B considers a subsample of internationally active BHC (i.e. banks with any foreign exposures).

	(1) CAR	(2) Obs
(A) All BHC		
Exposed	0.034**	54
	(2.30)	
Unexposed	0.001*	35,777
	(1.88)	
(B) Internationally Active BHC		
Exposed	0.034**	54
	(2.30)	
Unexposed	-0.005**	1,764
	(-2.06)	

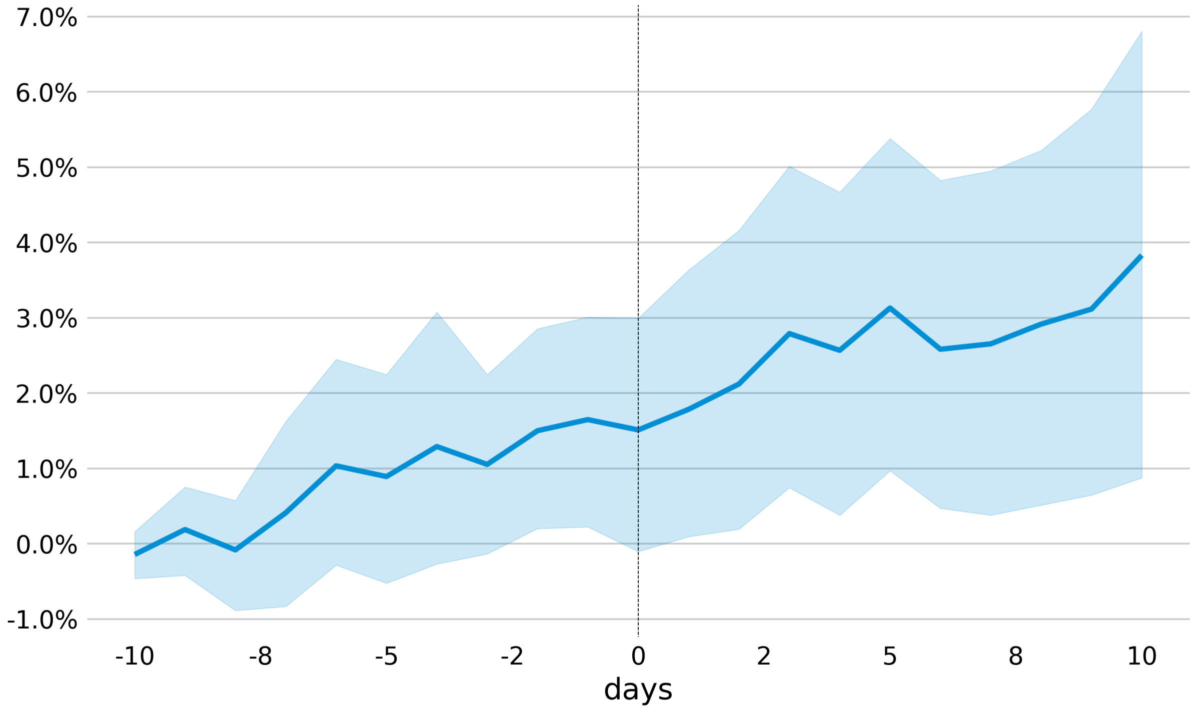
Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

ment of an IMF loan. In contrast, the market response is fairly neutral for unexposed banks, which only experience a 0.1% CAR. Since foreign lending is heavily concentrated in the money-centre banks, most other U.S. banks never report having international exposures. As a result, comparing exposed banks to all other unexposed banks could be misleading. Therefore, in the bottom panel of Table 3.9 we only keep internationally active banks in our sample, that is, banks that at some point in our sample have made a foreign loan. In this instance, the CAR for unexposed banks is marginally negative.

Figure 3.2 summarises these results nicely. It plots the CAR for exposed banks over the 20 day window and shows a clear increase around IMF loan announcements. We observe here how the public nature of IMF bailouts leads to a drift up in CARs in the pre-event period, followed by another jump in CARs post-event.

Since the univariate results are subject to omitted variable bias, we conduct a mul-

Figure 3.2: Wealth effects around IMF loan announcements
This figure shows the average cumulative abnormal returns (CAR) of U.S. banks that were exposed to a country experiencing a sovereign debt crisis, around the date in which the International Monetary Fund (IMF) granted a loan to the sovereign.



tivariate analysis of bank CARs in the following cross-sectional regression:

$$\begin{aligned} CAR_{b,c,t} = {} & \alpha_1 Exposed_{b,c,t} + \alpha_2 Sovereign\ Default_{c,t} \\ & + \alpha_3 Sovereign\ Default_{c,t} \times Exposed_{b,c,t} \\ & + \boldsymbol{\beta}' \boldsymbol{X}_{b,t} + B_b + \varepsilon_{b,t} \end{aligned} \tag{3.5}$$

where $CAR_{b,c,t}$ is the cumulative abnormal return for bank b around the announcement of a loan to country c at time t; $Exposed_{b,c,t}$ is an indicator that equals one if bank b is exposed to country c at time t; $Sovereign\ Default_{c,t}$ is an indicator that takes one if country c defaulted a time t; $\boldsymbol{X}_{b,t}$ is a vector of bank-level controls which include bank size (i.e. natural log of assets), return-on-equity, tier 1 capital to assets ratio, tier 1 capital to risk weighted assets (RWAs), the ratio of short-term wholesale funding to liabilities, the ratio of RWA to assets, and the ratio of loans to deposits; finally, B_b is a bank fixed effect.

Table 3.10: Multivariate event study

This table presents coefficient estimates for an OLS regression model in which the dependent variable is the cumulative abnormal returns (CAR) for US bank holding companies (BHC) on the dates an IMF loan was granted. The sample consists of 269 IMF loans to 47 countries between 1983 and 2016. Exposed is a dummy which takes 1 for those BHC which, on the event date, had commercial exposures to the recipient country. Sovereign Debt Default is a dummy variable which takes 1 if the recipient country's external debt is in default, and 0 otherwise. In Column (1) the sample includes all BHC for which price data is available, whereas Column (2) considers a subsample of internationally active BHC (i.e. banks with foreign exposures). Controls include bank size (i.e. natural log of assets), return on equity, tier 1 capital to assets ratio, tier 1 capital to risk weighted assets (RWAs), the ratio of short-term wholesale funding to liabilities, the ratio of RWA to assets, and the ratio of loans to deposits. Regressions include bank fixed-effects and standard errors are clustered at the bank level.

DEPENDENT VARIABLE: CAR	(1) All Banks	(2) Internationally Active Banks
Exposed	0.02***	0.01**
	(2.88)	(2.14)
Sovereign Debt Default	0.01***	-0.01*
	(4.04)	(-1.84)
Sovereign Debt Default × Exposed	0.03***	0.05***
	(2.75)	(3.29)
Log Assets	0.00	0.01
	(1.18)	(1.50)
ROE	0.00	0.07*
	(0.60)	(1.85)
Tier 1 Capital /RWA	-0.05	0.06
	(-0.72)	(0.15)
Tier 1 Capital /Assets	-0.10	-0.09
	(-0.76)	(-0.14)
Short-term Wholesale/Liabilities	-0.05**	0.01
	(-2.35)	(0.38)
RWA/Assets	-0.03	-0.04
	(-1.34)	(-0.51)
Loans/Deposits	0.00	-0.00
	(1.26)	(-0.03)
Constant	0.00	-0.18*
	(0.15)	(-1.89)
Observations	27,087	1,315
R-squared	0.035	0.032
Bank Fixed Effects	Yes	Yes

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

The results are presented in Table 3.10 across two columns. Column (1) includes all BHCs in our sample, whereas Column (2) restricts the sample to internationally-active banks only. Let us focus on Column (2). We observe that, compared to unexposed banks, exposed banks experience a small (1%) increase in CAR around the announcement of an IMF loan (i.e. positive and significant coefficient on *Exposed*). However, the largest gains are to exposed banks when an IMF loan announcement also coincides with a sovereign default. That is, the coefficient on *Sovereign Default* $\times$ *Exposed* is positive and significant, and the point estimate suggests that banks exposed to sovereign default experience a 5% CAR when an IMF loan is announced. On the other hand, unexposed banks actually experience a slight decline in CAR when the IMF loan announcement relates to a defaulting sovereign. This is perhaps because a defaulting sovereign is the most extreme case of balance-of-payments problems that might require an IMF loan, but at the same time unexposed banks do not stand to benefit from the IMF loan.

In sum, this section demonstrates that IMF loans, although directed to governments, ultimately reach U.S. banks. Moreover, the market appears quite adept at differentiating between the foreign exposures of different banks as well as the severity of the balance-of-payments problems that the loan-recipient countries are facing.

3.5 Conclusion

We argue that the U.S. government uses its voting power and political influence to direct IMF loans to defaulting sovereigns where U.S. banks have large exposures to losses from default. By using IMF loans to prop up countries struggling to make debt payments, the U.S. government can indirectly absorb U.S. bank losses – a de facto bailout. We argue that de facto bailouts reduce the political costs associated with direct bank bailouts (e.g. voter backlash) as well as the burden on domestic resources.

In line with these claims, our analysis reveals that the likelihood a defaulting sovereign receives an IMF loan increases significantly with U.S. bank exposure to that country.

This effect strengthens in federal election years and in years when the government's fiscal position is weak, that is, when the political and fiscal costs of direct bailouts are the greatest. In addition, we show that campaign contributions from the finance industry – but *not* the exposure of a politician's constituency to foreign lending losses – is an important determinant of members of Congress's support for IMF funding increases, and thus de facto bailouts. We interpret this as evidence of special interest pressure from the U.S. banking lobby. Finally, we show de facto bailouts ultimately benefit individual banks by documenting positive wealth effects accruing to U.S. banks exposed to a defaulting sovereign around the time an IMF loan is granted.

Overall, we identify an alternative mechanism through which the U.S. government can backstop the losses of large banks while, at the same time, reducing both the amount of domestic resources used and the degree of discontent among voters.

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Appendices

A Chapter 1 - Appendix

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

$$t_{AR_g} = \frac{\overline{SAR}_g \sqrt{N_g}}{SD_g \sqrt{1 + (N_g - 1)\bar{\rho}_g}} \tag{6}$$

$\overline{SAR}_g$ is the average scaled abnormal return (SAR) for banks in group g on the event day. For each bank, scaled abnormal returns are calculated as $SAR_{i,t} = \frac{AR_{i,t}}{SD_i}$ where SD_i is bank's i sample standard deviation of abnormal returns over the estimation window. N_g corresponds to the number of banks in group g, and $\bar{\rho}_g$ is the average of the sample cross-correlations of scaled abnormal returns for banks in group g over the estimation window. That is:[20]

$$\bar{\rho}_g = \frac{1}{N_g(N_g-1)/2} \sum_{i=2}^{N} \sum_{j=1}^{i-1} \mathbb{1}_{\{i:i \in g\}} \mathbb{1}_{\{j:j \in g\}} \frac{1}{T_1 - T_0} \sum_{t \in [T_0, T_1]} SAR_{i,t} SAR_{j,t} \tag{7}$$

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

$$SD_g^2 = \frac{\frac{1}{N_g - 1} \sum_{i=1}^{N} \mathbb{1}_{\{i:i \in g\}} \left(SAR_i - \overline{SAR}_g \right)^2}{1 - \bar{\rho}_g} \tag{8}$$

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

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

B Chapter 3 - Appendix

Table B1: Other data source

This table presents coefficient estimates for the logistic model in Equation 3.1 using data from the Federal Financial Institutions Examination Council (FFIEC). The sample consists of an unbalanced panel of 47 countries between 1983 and 2016. Column (1) considers banks exposure to the Public Sector, Column (2) exposures to the Banking Sector, Column (3) exposures to Other Sectors, and Column (4) considers the total (FFIEC) exposure. For each type, exposures are measured as the natural logarithm of the exposure to a given country's sector as a percentage of their total exposure worldwide. The dependent variable is a dummy which takes 1 for countries that received an IMF loan, and 0 otherwise. Sovereign Debt Default is a dummy which takes 1 when a country's external debt is in default, and 0 otherwise. Regressions include all controls used in Table 3.2 Column (6), country fixed effects, and year fixed effects. Standard errors are clustered at the country level.

DEPENDENT VARIABLE: IMF Loan	(1) Public	(2) Banks	(3) Other	(4) Total FFIEC
Sovereign Debt Default	7.14***	6.06***	6.22***	6.74***
	(5.06)	(4.44)	(4.65)	(5.22)
Public Sector	-0.08			
	(-0.70)			
Sovereign Debt Default × Public Sector	0.52***			
	(2.82)			
Banking Sector		-0.04		
		(-0.28)		
Sovereign Debt Default × Banking Sector		0.37**		
		(2.37)		
Other Sector			-0.10	
			(-0.75)	
Sovereign Debt Default× Other Sector			0.37**	
			(2.16)	
FFIEC Bank Exposure				-0.04
				(-0.29)
Sovereign Debt Default × FFIEC Bank Exposure				0.54***
				(2.96)
Observations	1,104	1,178	1,178	1,207
Controls	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

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

Table B2: Linear model

This table presents coefficient estimates for an OLS regression where the dependent variable is a dummy which takes 1 for countries that received an IMF loan, and 0 otherwise. The sample consists of an unbalanced panel of 47 countries between 1983 and 2016. The variable U.S. Banks Exposure is the natural logarithm of the exposure U.S. banks have to a given country, as a percentage of their total exposure worldwide. Sovereign Debt Default is a dummy variable which takes 1 if a country's external debt is in default in a given year, and 0 otherwise. Column (2) includes country-specific macroeconomic characteristics as controls: GDP Growth, Inflation, and Log Population. Column (3) controls for whether a country is a temporary member of the United Nations (UN) Security Council. Column (4) accounts for a country's voting similarity with the U.S. voting history in the UN. Column (5) controls for the level of trade relationship with the U.S., and Column (6) accounts for how democratic a country's system of government is. Regressions include country fixed effects to control for unobserved time-invariant characteristics, and year fixed effects to account for aggregate time trends that are common to all countries in the sample. Standard errors are clustered at the country level to allow for error correlation within each panel.

DEPENDENT VARIABLE: IMF Loan	(1)	(2)	(3)	(4)	(5)	(6)
US Banks Exposure	0.00	-0.01	-0.01	-0.01	-0.02	-0.02
	(0.03)	(-0.47)	(-0.55)	(-0.73)	(-1.16)	(-1.02)
Sovereign Debt Default	0.96***	0.96***	0.97***	0.98***	1.00***	1.00***
	(6.50)	(6.48)	(6.50)	(6.60)	(6.64)	(6.68)
Sovereign Debt Default $\times$ US Banks Exposure	0.07***	0.06**	0.06***	0.07***	0.08***	0.07***
	(2.94)	(2.68)	(2.71)	(2.87)	(3.14)	(3.11)
GDP Growth		-0.01**	-0.01**	-0.01**	-0.01**	-0.01**
		(-2.56)	(-2.46)	(-2.34)	(-2.69)	(-2.57)
Inflation		-0.00***	-0.00***	-0.00***	-0.00**	-0.00**
		(-2.85)	(-2.80)	(-2.90)	(-2.53)	(-2.25)
Log Population		0.25	0.24	0.12	0.06	0.12
		(1.32)	(1.28)	(0.56)	(0.31)	(0.59)
Temporary Member			0.07*	0.06	0.07**	0.07**
			(2.01)	(1.60)	(2.39)	(2.25)
UN Voting Similarity				0.61**	0.51*	0.54**
				(2.04)	(1.97)	(2.04)
Trade with US					0.78*	0.79*
					(1.94)	(2.00)
Polity						-0.01
						(-1.19)
Constant	0.17	-3.91	-3.80	-2.09	-1.09	-2.11
	(1.36)	(-1.26)	(-1.23)	(-0.57)	(-0.33)	(-0.60)
Observations	1,529	1,495	1,495	1,391	1,351	1,327
R-squared	0.446	0.473	0.475	0.486	0.496	0.496
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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