

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

Diego L. Puente M.



Australian  
National  
University

January 20, 2020

# Motivation

## Dodd-Frank

- ▶ The series of **bailouts** during the GFC exacerbated the public perception of the Too Big to Fail (TBTF) problem.
- ▶ The U.S. government responded by enacting the **Dodd-Frank Act**.

### An Act

To promote the financial stability of the United States by improving accountability and transparency in the financial system, to end “too big to fail”, to protect the American taxpayer by ending bailouts, to protect consumers from abusive financial services practices, and for other purposes.

- ▶ Dodd-Frank defined \$50 billion as the size **threshold** above which a bank is deemed a large financial institution whose failure could threaten the financial stability of the U.S. **Section 165**
- ▶ Stricter regulatory requirements for **above** 50B banks.



# Motivation

## TBTF post-crisis

Several papers have attempted to determine whether the more **stringent** bank regulation after the crisis resulted in a decline in the TBTF problem.

### **TBTF declined:**

- ▶ Schäfer et al. (2015)
- ▶ Bongini et al. (2015)
- ▶ Atkeson et al. (2019)

### **TBTF has not declined:**

- ▶ Moenninghoff et al. (2015)
- ▶ Sarin and Summers (2016)
- ▶ Duchin and Sosyura (2014)



# Summary

- ▶ Use option prices to construct a **forward-looking** measure of bank tail-risk and explore cross-sectional differences between systemically important banks and smaller banks.
- ▶ **Result 1:** Show a permanent increase in the average tail-risk of the U.S. banking industry after the GFC, **except** for above 50B banks.
- ▶ **Result 2:** Present evidence consistent with the notion that this difference owes to the TBTF **status** of systemically important banks that was reinforced by the Dodd-Frank Act.



# Measuring Tail-Risk

## Implied Volatility Smile

- ▶ In Black-Scholes-Merton (BSM) model implied volatility ( $\sigma_{IV}$ ) is the parameter that makes the model yield the observed market price of an option.

$$P_{BSM}(S, K, \tau, \sigma, r) = Ke^{-r\tau} N(-d_2) - SN(-d_1)$$

$$d_{1,2} = \frac{\ln\left(\frac{S}{K}\right) + \left(r \pm \frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}}$$

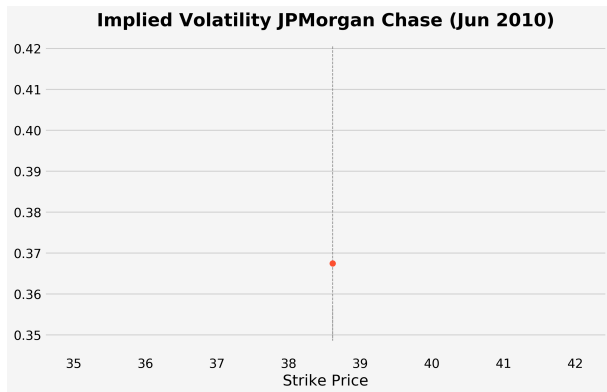
$$P_{BSM}(S, K, \tau, \sigma_{IV}, r) = P_{observed}$$



# Measuring Tail-Risk

## Implied Volatility Smile

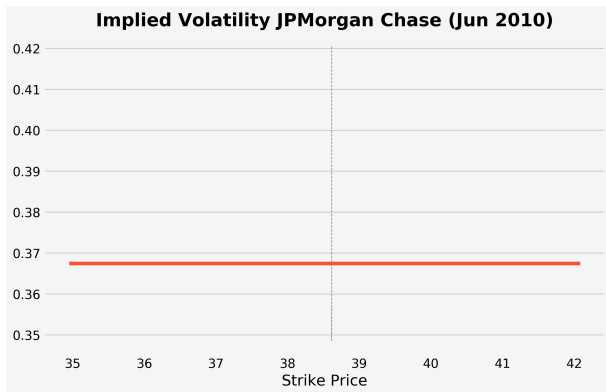
- ▶ If the BSM model described option prices accurately, options of varying **strike** prices written against the same underlying asset should produce the same implied volatilities.



# Measuring Tail-Risk

## Implied Volatility Smile

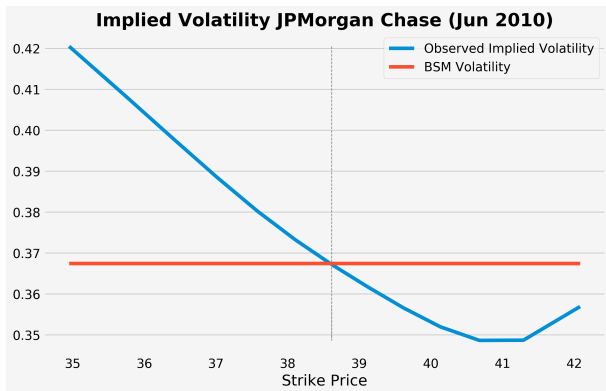
- ▶ If the BSM model described option prices accurately, options of varying **strike** prices written against the same underlying asset should produce the same implied volatilities..



# Measuring Tail-Risk

## Implied Volatility Smile

- ▶ If the BSM model described option prices accurately, options of varying **strike** prices written against the same underlying asset should produce the same implied volatilities.





# Measuring Tail-Risk

## 1987 Market Crash

- ▶ Rubinstein (1994) documented a **structural** change in the shape of the implied volatility curve of S&P 500 index options.
- ▶ He suggested "**crash-o-phobia**" to explain the appearance of a volatility smile.

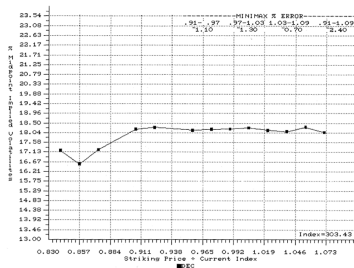


Figure 1. Typical precrash smile. Implied combined volatilities of S&P 500 index options

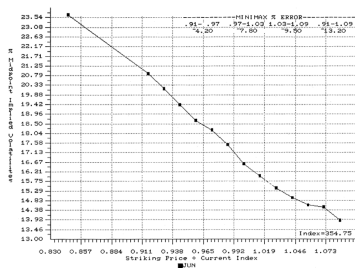


Figure 2. Typical postcrash smile. Implied combined volatilities of S&P 500 index options



# Measuring Tail-Risk

## Volatility Smile and RND Skewness

- ▶ A steeper volatility smile implies investors perceive significant price **drops** as more likely compared to a lognormal distribution.
- ▶ Several papers have used implied volatility slopes as forward-looking measures of the **perceived** exposure of a given asset to significant price drops.
  - Collin-Dufresne et al. (2001)
  - Tang and Yan (2010)
  - Yan (2011)
  - Hett and Schmidt (2017)



# Measuring Tail-Risk

## Bank Tail-Risk

- ▶ I 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).

$$\text{Tail-Risk}_{i,t} = \sum_{\delta \in \Delta} (\sigma_{i,\delta,t} - \sigma_{i,-0.5,t}) \quad (1)$$

$$\Delta := \{-0.45, -0.40, \dots, -0.20\}$$

- ▶ Higher bank **tail-risk** corresponds to larger weights assigned to the probability of downturn events.
- ▶ Data:
  - OptionMetrics
  - 85 Bank Holding Companies (BHC) observed between 2001-2017. [List](#)



# Tail-Risk Around GFC

## Bank Holding Companies

	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

- ▶ Pre-Crisis: 2001-2007
- ▶ Crisis: 2008-2009
- ▶ Post-Crisis: 2010-2017



# Implicit Guarantees Hypothesis

## Main Claim

- ▶ Series of **bailouts** targeted at large banks during the crisis and the subsequent designation of above 50B banks as systemically important by **Dodd-Frank** Act, reinforced the TBTF status of large financial institutions. **AIG**
- ▶ For **systemically important** banks  $\implies$  increase expectations of future bailouts  $\implies$  lower expectations of large price declines in the post-crisis period.
- ▶ For **smaller** banks  $\implies$  raise investors' concerns about the possibility of future failures  $\implies$  increase in post-crisis tail-risk.



# Alternative Explanation

## Effective Regulation Hypothesis

- ▶ Dodd-Frank effectively triggered a **size-based** regulatory requirements.
- ▶ The lower tail-risk levels of large banks after the GFC may simply denote the **effectiveness** of the additional regulatory requirements imposed on them.
  - Balasubramnian and Cyree (2014) report Dodd-Frank has been **effective** in reducing the TBTF discounts on yield spreads in the market for subordinated debt.



### Difference-in-Differences (DiD)

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

- ▶  $Tail-Risk_{i,t}$ : average tail-risk of bank  $i$  in quarter  $t$ .
- ▶  $Post-Crisis_t$ : dummy that takes 1 for the period 2010-2017, and 0 otherwise.
- ▶  $Above-50B_i$ : dummy that takes 1 for banks with more than \$50 billion as of 2009Q3.



# Empirical Findings

## Baseline results

DEPENDENT VARIABLE: Tail-Risk	(1)	(2)	(3)	(4)
Above 50B	-0.009 (-0.565)	0.026 (0.909)	0.025 (0.834)	0.026 (0.842)
Above 50B × Post-Crisis	-0.192*** (-8.633)	-0.185*** (-7.855)	-0.183*** (-7.477)	-0.189*** (-7.488)
Tier1 Capital/Total Assets		-0.211*** (-3.437)	-0.223*** (-3.646)	-0.231*** (-3.541)
ROE		0.019* (1.712)	0.019* (1.863)	0.019* (1.874)
Z-Score		0.001 (1.028)	0.001 (0.928)	0.001 (0.985)
Log(Assets)		-0.015* (-1.700)	-0.016* (-1.854)	-0.018* (-1.734)
Systematic Risk			1.699 (1.440)	1.671 (1.370)
Unsystematic Risk			-0.359 (-1.352)	-0.361 (-1.350)
Options Volume				0.000 (0.112)
Options Bid-Ask Spread				-0.007 (-0.734)
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





# Empirical Findings

## Other Salient Regulatory Thresholds

I exploit the **monotonic** relationship between bank size and regulatory stringency that characterises the post-crisis banking industry in the U.S.

- ▶ **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.



# Empirical Findings

## Other Salient Regulatory Thresholds

- ▶ Banks are classified into one of the four **size-based** regulatory groups.
- ▶ I use the DiD above to explore tail-risk differences between **adjacent 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.
  - Effective regulation hypothesis  $\implies \alpha_3 < 0$



# Empirical Findings

## Other Salient Regulatory Thresholds

DEPENDENT VARIABLE: Tail-Risk	< 10B vs [10B, 50B)	[10B, 50B) vs [50B, 250B)	[50B, 250B) vs >= 250
Treatment Group	0.017 (0.432)	-0.043 (-1.061)	-0.025 (-1.399)
Treatment Group $\times$ Post-Crisis	-0.049 (-1.078)	-0.102*** (-2.945)	0.025 (1.047)
Observations	2,749	1,954	1,356
Time fixed effects	Yes	Yes	Yes
Adj R-squared	0.132	0.274	0.701



# Empirical Findings

## Wealth Effects

Analyse the stock market reaction to the announcement of **changes** to bank regulation related to Dodd-Frank.

- ▶ Stricter regulation and higher compliance costs  $\implies$  negative wealth effects.
  - Bongini et al. (2015) report evidence of **negative** wealth effects to the announcement of tighter regulation for SIFIs by the FSB.
- ▶ The explicit designation of systemically important banks reduces ambiguity  $\implies$  positive wealth effects.
  - Moenninghoff et al. (2015) document **positive** wealth effects upon the release of a list of G-SIB banks.
  - O'hara and Shaw (1990).



# Empirical Findings

## Wealth Effects

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.
- ▶ 11/12/2009 - The Dodd-Frank bill is **passed** by the House.
- ▶ 15/04/2010 - Dodd-Frank is **introduced** in the U.S. Senate.
- ▶ 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 **agreed** to conference report.
- ▶ 21/07/2010 - Dodd-Frank is **signed** into law by the U.S. president.



# Empirical Findings

## Wealth Effects

Cumulative abnormal returns (**CAR**) for each date are estimated using:

- ▶ Two-day  $[-1,0]$  **window**.
- ▶ Market **model** for expected returns.
- ▶ Kolari and Pynnönen (2010) test **statistic** to account for cross-sectional correlation of abnormal returns and event-induced variance inflation.



# Empirical Findings

## Wealth Effects

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



# Empirical Findings

## Wealth Effects

DEPENDENT VARIABLE: CAR	(1)	(2)
Above 50B	0.035*** (5.630)	0.032*** (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*** (6.002)	0.027 (1.329)
Observations	82	82
Adj R-squared	0.321	0.316





# Empirical Findings

## U.S. credit-rating downgrade

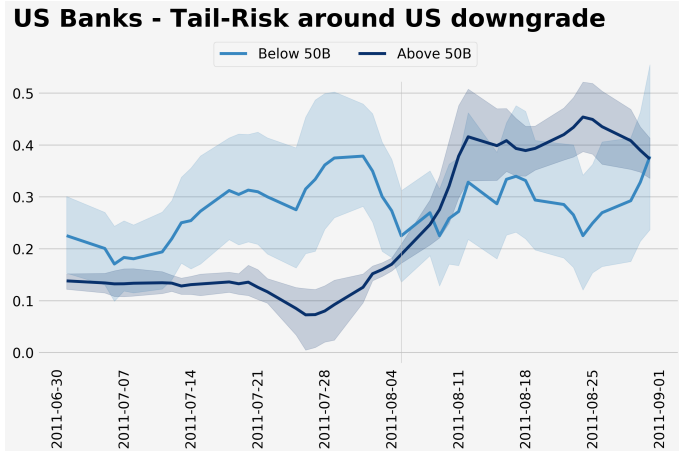
I exploit Standard & Poor's (S&P) decision to **downgrade** the U.S. credit rating on August 5, 2011 as a shock to the government's creditworthiness.

- ▶ The existence of implicit government guarantees is predicated on the government's ability to provide **assistance** to large banks in distress.
- ▶ 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.
- ▶ For systemically important banks:
  - Reduction in government's ability to provide assistance  $\implies$  lower bailout expectations  $\implies$  increase in tail-risk.



# Empirical Findings

U.S. credit-rating downgrade



Australian National University

# Empirical Findings

## U.S. credit-rating downgrade

DEPENDENT VARIABLE: Tail-Risk	(1)	(2)	(3)
Above 50B	-0.152*** (-3.759)	-0.150*** (-3.711)	-0.064 (-0.764)
Above 50B × Post-Downgrade	0.240*** (4.666)	0.240*** (4.667)	0.238*** (4.623)
U.S Treasury Holdings		-1.227 (-1.392)	-2.309** (-2.213)
Tier1 Capital/Total Assets			0.087 (0.240)
ROE			0.075 (1.074)
Log(Assets)			-0.044 (-1.335)
Systematic Risk			3.817 (0.958)
Unsystematic Risk			-4.193** (-2.014)
Options Volume			0.001*** (2.808)
Options Bid-Ask Spread			-0.025 (-1.108)
Observations	3,193	3,193	3,193
Quarter fixed effects	Yes	Yes	Yes
Adj R-squared	0.0387	0.0423	0.123



# Empirical Findings

## Risk-Taking Differences

I analyse the actual **risk-taking** behaviour of large and small banks in the post-crisis period.

- ▶ implicit guarantee hypothesis  $\implies$  moral hazard  $\implies$  **higher** risk taking.
  - Duchin and Sosyura (2014), Kaufman (2014), and Kane (2009).
- ▶ effective regulation hypothesis  $\implies$  tighter regulatory standards  $\implies$  **lower** risk taking.



# Empirical Findings

## Risk-Taking Differences

	(1)	(2)	(3)
	Pre-crisis: Above - Below	Post-crisis: Above - Below	Diff-in-Diff
<b>(A) Market Risk</b>			
Return Volatility	-0.001**	-0.004*	-0.003
Systematic Risk	0.000	0.001**	0.000
Unsystematic Risk	-0.002***	-0.005**	-0.003
<b>(B) Business Risk</b>			
Exposure to Fls	0.011***	0.051***	0.041***
Short-Term Wholesale/Total Liabilities	0.030***	0.102***	0.072***
Non-Performing Loans/Total Loans	0.002***	0.002**	-0.000
Z-Score	1.147*	-2.484***	-3.631***
<b>(C) Capital Adequacy</b>			
Tier1 Capital/Total Assets	-0.041***	-0.016***	0.025***
Tier1 Capital/RWA	-0.075***	-0.020***	0.055***
Total Capital/RWA	-0.059***	-0.008***	0.051***
RWA/Total Assets	0.104***	0.002	-0.101***

time-series



Australian  
National  
University

# Empirical Findings

## Risk-Taking Differences

- ▶ Although regulatory ratios for SIFIs improve relative to smaller banks, their **risk-taking** increases in the post-crisis period.
- ▶ SIFIs risk-taking higher post-crisis..
  - Duchin and Sosyura (2014): Safer ratios, riskier portfolios.
  - Sarin and Summers (2016): higher risk exposure post-crisis.
- ▶ These findings are **inconsistent** with the effective regulation hypothesis and add weight to a reinforcement of the TBTF status of banks above the 50B threshold.



# Conclusion

- ▶ I document a permanent increase in the average tail-risk of the U.S. banking industry following the GFC, **except** for SIFIs.
- ▶ I attribute this to a reinforcement of the **TBTF status** of SIFI banks caused by:
  - The series of **bailouts** targeted at them during the crisis.
  - The explicit **designation** as SIFIs by Dodd-Frank.
- ▶ I find unlikely the possibility these results are due to the **stricter** regulatory regime large banks face under Dodd-Frank.
  - No significant changes in tail-risk around other salient regulatory size **thresholds**.
  - Positive **wealth** effects accruing to SIFIs around Dodd-Frank.
  - Tail-risk changes following the U.S. **downgrade**.
  - SIFIs' actual **risk taking** increases post-crisis.



# Thank you!



Australian  
National  
University



# Appendix

## Section 165 – Dodd-Frank

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 ... "

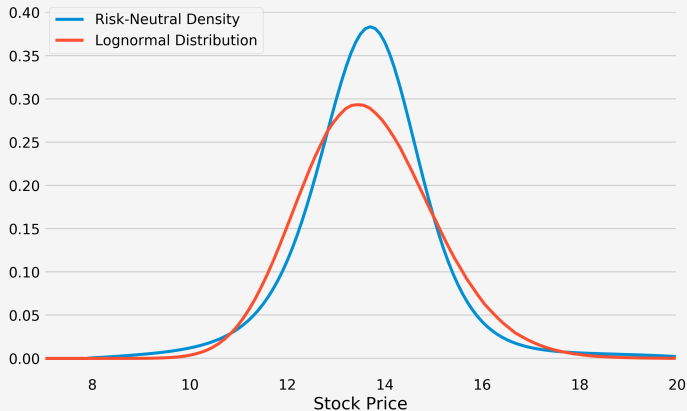
[back](#)



# Appendix

## RND vs Lognormal Distribution

### Risk-Neutral-Density Sterling Bancorp - Dec 2014



back



Australian  
National  
University

# Appendix

## BHC list

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

back



Australian  
National  
University

# Appendix

## Large vs. Small firms

<b>(A) Banks</b>					
	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>(B) Non-Financials</b>					
	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

<b>(C) Technology Firms</b>					
	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

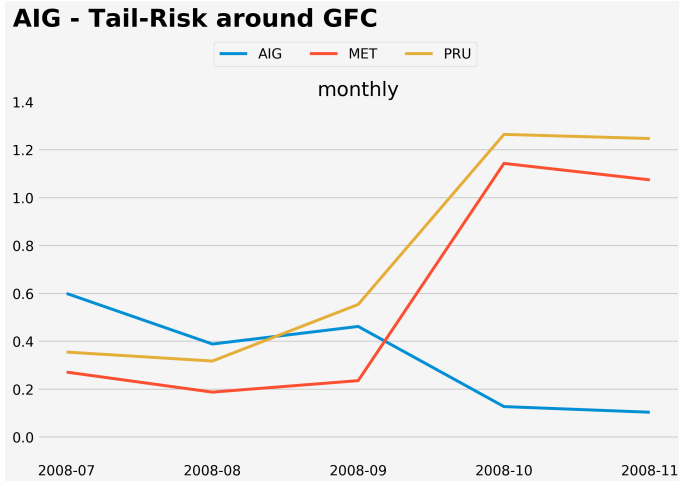
back



Australian  
National  
University

# Implicit Guarantees Hypothesis

The AIG bailout

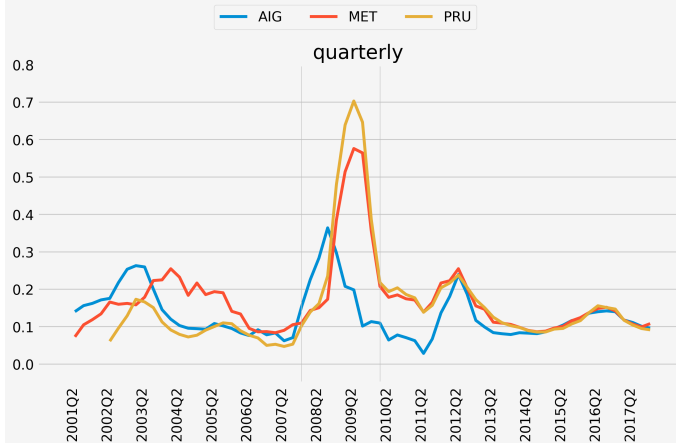


Australian National University

# Appendix

## The AIG bailout

### AIG - Tail-Risk around GFC



back

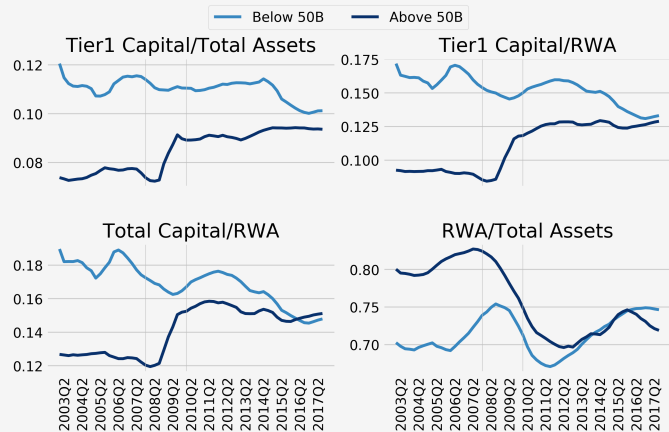


Australian  
National  
University

# Empirical Findings

## Risk-Taking Differences

### US Banks - Capital Adequacy



back



Australian  
National  
University

# Appendix

## Implicit guarantees and asset prices

Implicit guarantees are reflected in asset prices.

- ▶ Völz and Wedow (2011) report distortions in CDS prices for banks considered too-big-to-fail.
- ▶ Kelly et al. (2016) document a four-fold increase in the cost difference between a basket of OTM put options for individual banks and OTM puts on the financial sector index during the GFC.
- ▶ Gandhi and Lustig (2015) present evidence of size anomalies in bank stock returns consistent with the existence of implicit government guarantees that protect shareholders of large banks in disaster states.





Atkeson, A. G., d'Avernas, A., Eisfeldt, A. L., and Weill, P.-O. (2019). Government guarantees and the valuation of American banks. *NBER Macroeconomics Annual*, 33(1):81–145.

Bakshi, G., Kapadia, N., and Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *The Review of Financial Studies*, 16(1):101–143.

Balasubramnian, B. and Cyree, K. B. (2014). Has market discipline on banks improved after the Dodd–Frank Act? *Journal of Banking & Finance*, 41:155–166.

Bongini, P., Nieri, L., and Pelagatti, M. (2015). The importance of being systemically important financial institutions. *Journal of Banking & Finance*, 50:562–574.

Collin-Dufresne, P., Goldstein, R. S., and Martin, J. S. (2001). The determinants of credit spread changes. *The Journal of Finance*, 56(6):2177–2207.

Duchin, R. and Sosyura, D. (2014). Safer ratios, riskier portfolios: Banks' response to government aid. *Journal of Financial Economics*, 113(1):1–28.

Gandhi, P. and Lustig, H. (2015). Size anomalies in US bank stock returns. *The Journal of Finance*, 70(2):733–768.

Hett, F. and Schmidt, A. (2017). Bank rescues and bailout expectations: The erosion of market discipline during the financial crisis. *Journal of Financial Economics*, 126(3):635–651.



- Kane, E. J. (2009). Extracting nontransparent safety net subsidies by strategically expanding and contracting a financial institution's accounting balance sheet. *Journal of Financial Services Research*, 36(2-3):161.
- Kaufman, G. G. (2014). Too big to fail in banking: What does it mean? *Journal of Financial Stability*, 13:214–223.
- Kelly, B., Lustig, H., and Van Nieuwerburgh, S. (2016). Too-systemic-to-fail: What option markets imply about sector-wide government guarantees. *American Economic Review*, 106(6):1278–1319.
- Kolari, J. W. and Pynnönen, S. (2010). Event study testing with cross-sectional correlation of abnormal returns. *The Review of Financial Studies*, 23(11):3996–4025.
- Moeninghoff, S. C., Ongena, S., and Wieandt, A. (2015). The perennial challenge to counter too-big-to-fail in banking: Empirical evidence from the new international regulation dealing with global systemically important banks. *Journal of Banking & Finance*, 61:221–236.
- O'hara, M. and Shaw, W. (1990). Deposit insurance and wealth effects: the value of being “too big to fail”. *The Journal of Finance*, 45(5):1587–1600.
- Rubinstein, M. (1994). Implied binomial trees. *The Journal of Finance*, 49(3):771–818.



- Sarin, N. and Summers, L. H. (2016). *Have big banks gotten safer?* Brookings Institution.
- Schäfer, A., Schnabel, I., and Weder di Mauro, B. (2015). Financial sector reform after the subprime crisis: Has anything happened? *Review of Finance*, 20(1):77–125.
- Stern, G. H. and Feldman, R. J. (2004). *Too big to fail: The hazards of bank bailouts*. Brookings Institution Press.
- Tang, D. Y. and Yan, H. (2010). Market conditions, default risk and credit spreads. *Journal of Banking & Finance*, 34(4):743–753.
- Völz, M. and Wedow, M. (2011). Market discipline and too-big-to-fail in the CDS market: Does banks' size reduce market discipline? *Journal of Empirical Finance*, 18(2):195–210.
- Yan, S. (2011). Jump risk, stock returns, and slope of implied volatility smile. *Journal of Financial Economics*, 99(1):216–233.



# Discussion

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

by Diego Puento

Discussant  
Patricio Valenzuela

Lima 2020

# This paper

- Constructs a forward-looking measure of bank exposure (i.e, tail risk).
- Explores cross-sectional differences between large and small banks.
- TBTF status of SIFIs that was reinforced by the Dodd-Frank Act.
- Effective Regulation Hypothesis versus Implicit Guarantee Hypothesis
- Increase in the tail-risk of the U.S. banking industry following the GFC, except for banks above the \$50B size threshold.
- Results are consistent with the TBTF status and investor expectations of future bailouts for above 50B banks.

# Comments

- Empirical strategy
- Downgrade analysis
- Potential non-linear effects
- Short term versus Long term
- Different types of banks
- Minor suggestions

# Empirical strategy

- Discontinuity at 50 billion in assets (Sharp RDD)

*Above 50B x Post – Crisis*

*Log(Assets)x Post – Crisis*

- Paralell trends and placebo test

- Sub-Sample: 2001-2010

*Above 50B x I(2002); Above 50B x I(2003)...; Above 50B x I(2010)*

# Downgrade analysis

- Sovereign credit risk is likely to affect large banks (TBTF hypothesis).
- Downgrades should affect more banks that invest more heavily in Treasury securities.

$$\begin{aligned} \text{Tail Risk} = & \alpha_1 \text{Above 50B} + \alpha_2 \text{Above 50B} \times \text{Downgrade} + \alpha_3 \text{Treasury Holdings} \\ & + \alpha_4 \text{Treasury Holdings} \times \text{Downgrade} + \varepsilon \end{aligned}$$



# Potential non-linear effects

*Above 50B x Post – Crisis*

```
graph TD; A["Above 50B x Post – Crisis"] --> B["ROE x Post – Crisis"]; A --> C["Above 50B x Systemic risk"]; B --> D["Leverage x Post – Crisis"]; B --> E["Z – score x Post – Crisis"]; B --> F["ST funding x Post – Crisis"]; C --> G["Above 50B x Unsystematic Risk"]; C --> H["Above 50B x Bid – ask spread"]; C --> I["Above 50B x Options volume"];
```

*ROE x Post – Crisis*

*Above 50B x Systemic risk*

*Leverage x Post – Crisis*

*Above 50B x Unsystematic Risk*

*Z – score x Post – Crisis*

*Above 50B x Bid – ask spread*

*ST funding x Post – Crisis*

*Above 50B x Options volume*

# Short term versus Long term

*Above 50B x Post – Crisis*

Short-term: *Above 50B x I(2011 – 2013)*

Medium term: *Above 50B x I(2014 – 2015)*

Long term: *Above 50B x I(2016 – 2017)*

# Different types of banks

- Commercial Banks versus Investment Banks
- Domestic Banks versus Global Banks

# Additional comments

- Equation 1: Eliminate Post-Crisis
- Table 6: Eliminate column 3
- Table 6: Eliminate clustering by bank of column 4 (few banks)
- Table 11: One interaction at the time
- Policy implications

# Conclusion

- Very interesting paper
- Nice empirical strategy
- Comprehensive set of results consistent with the implicit guarantee hypothesis
- Very important implications for financial markets regulators

# Discussion

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

by Diego Puente

Discussant  
Patricio Valenzuela

Lima 2020