Essays in Financial Systemic Risk

Dissertation

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

Hieu Vu Dang, M.A.

Graduate Program in Economics

The Ohio State University

2020

Dissertation Committee:

Pok-Sang Lam, Advisor

Robert Martin de Jong

Thien Tung Nguyen

Abstract

In this dissertation, I study the financial systemic risk from firm-level perspectives. Chapter 1 investigates a breakdown of the total financial system risk into individual contributors and sources. Chapter 2 studies a theoretical model about the active balance sheet management of individual bank in securitization. Chapter 3 and 4 present empirical evidence about securitization asset choices of banks when they face different constraints. Chapter 5 provides a brief summary of findings in this dissertation.

In chapter 1, I propose a novel systemic importance (SI) index that tracks the contribution of a financial institution to the total financial system risk. That risk measure can be decomposed into idiosyncratic and spillover risk contribution to further study the risk characteristics of each firm. Using equity return data from 1965 to 2018, I find two important results. First, the spillover risk can account for approximately 80% of the aggregate financial system risk, which emphasizes the importance of contagion risk as a major amplification mechanism of shocks during a systemic event. Second, a portfolio of the top 20 most systemically important financial institutions (SIFIs), ranked by SI index, earns a significantly lower risk-adjusted return than their counterparts. This substantial equity funding cost advantage of approximately 4% per year on average implies that the ex-ante implicit government guarantee for the "too-important-to-fail" is priced by the market.

In chapter 2, I develop a theoretical model that features two benefits of securitization. First, banks can reduce idiosyncratic risks and enhance risk-absorbing capacity by converting a fraction of their risky investments into securitized assets.

Second, securitized assets require less regulatory capital, helping banks obtain a higher leverage without breaking the regulation. This chapter studies effects of the two motives above, namely risk-transferring and regulatory arbitrage, on bank portfolio choices. My analytical results predict that banks would securitize safer loans and retain only higher-risk, higher-return assets that justify their regulatory capital cost.

In chapter 3, I analyze new data points in the recently revamped HMDA data to examine mortgage securitization decision choices and motives of all non-exempt banks in the US. Combining with the bank-level data from Call Reports, I find that capital-constrained banks retain riskier loans and involve more in the securitization market to optimize return on capital and keep regulatory ratios in control. On the other hand, risk-constrained banks use securitization mainly for the purpose of risk and liquidity improvement. When putting together, risk transferring seems to dominate regulatory arbitrage as the main reason banks engage in securitization.

Chapter 4 serves as a complementary case study to Chapter 3, in which I investigate the mortgage loan approval and securitization decision of PNC Bank. There are three interesting findings: First, the bank uses third-party automated underwriting systems to originate over 90% of its conforming residential mortgage loans and then sell more than 70% of them. Second, the bank retains safer loans on balance sheet, which emphasizes the role of securitization as a risk-transferring mechanism. Third, compared to a non-depository financial institution (shadow bank), a traditional commercial bank like PNC behaves differently and shows a clear presence of active securitization management. With a stable deposit funding channel, PNC is able to originate jumbo loans at a higher approval rate, retain more loans on balance sheet, and selectively choose to sell off riskier loans.

Dedication

To Mom and Dad,

who offered me unlimited support

and encouraged me to go on every adventure,

especially this one

Acknowledgments

I would like to thank my advisor, Professor Pok-Sang Lam, for his enormous guidance, support, and encouragement throughout my years in the graduate school. Without his numerous feedback and comments, this dissertation could not have been completed.

I also want to sincerely thank Professor Robert de Jong and Professor Thien Nguyen for their invaluable suggestions and advice. Discussions with them have significantly improved the quality of my work.

Vita

2015..............................Bachelor of Science in Mathematics, Wittenberg University

2015..............................Bachelor of Arts in Economics, Wittenberg University

2016..............................Master of Arts in Economics, The Ohio State University

2016 to present.............Graduate Teaching Associate, Department of Economics, The Ohio State University

Fields of Study

Major Field: Economics

Table of Contents

List of Tables

List of Figures

Chapter 1

Measuring Financial Systemic Importance and Asset Pricing Implications

1.1 Introduction

Since the global financial crisis of 2008, systemic risk and financial stability have been rising as a focal point of research and policy in the macro-finance literature. According to Freixas et al. (2015), the term "macroprudential" only produces 639 hits on Google search prior to 2000. However, as of today (June 2020), that keyword generates over one million search results. Similarly, the term "systemic risk" has only four thousand Google hits before 2000, but over two million today.

There are clear distinctions in objectives between microprudential and macroprudential policy. On the one hand, microprudential regulation mainly concerns about the individual bankruptcy risk, so its main objective is to strengthen the resiliency of financial institutions (e.g. internal risk model) and to limit the social costs of a bank failure (e.g capital requirement). On the other hand, macroprudential policy focuses on limiting systemwide risks in the financial system. Since systemic risk is usually invisible in individual risk model and in normal time, macroprudential policy must address two specific dimensions of systemic risk: the time dimension and the cross-sectional dimension.

In this chapter, I present a unified framework to measure and monitor in real time the overall levels of financial system risk and a breakdown into its sources and contributors. Along the time dimension, my proposed methodology is able to track and forecast the evolution path of financial system volatility, and its decomposition into different risk characteristics. At a given point of time, it can measure the potential risk contribution of each financial institution and hence provide a quick cross-section rankings of systemic importance. Moreover, by design, the measure of total risk contribution can be further decomposed to study how much a firm's risk contribution comes from its idiosyncratic risk and how much can be accounted for by the potential spillover risk due to its linkages to other financial institutions in the industry.

In my definition, a financial institution is highly important and possesses large systemic risk when its idiosyncratic shocks could significantly raise the volatility of the financial system. That interpretation of systemically important financial institutions (SIFIs) closely follows the definition from the Financial Stability Board, an international organization established after the G20 London summit in 2009 to monitor and make recommendations about the global financial system. In their framework, systemically important financial institutions are defined as "institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system".

My measure of systemic importance (SI) has three key ingredients: idiosyncratic risk, size, and the level of connectedness. A financial institution would score higher in SI index when it is large, suffers highly volatile idiosyncratic shocks, and has deep connections to other large financial firms. That makes sense since failures of a few small regional banks may not trigger a systemic crisis, but a single collapse of a well-known name on Wall Street such as Lehman Brothers in 2008 can definitely cause a severe damage to the system.

In the empirical analysis, I extract a firm's idiosyncratic shocks by removing common risk factors from its equity returns. That practice aims to reduce the time-series dependence (cointegration) displayed in cross-sectional stock returns, which is crucial in estimating connectedness. I follow the idiosyncratic volatility literature and utilize the Fama and French (1993) three factors for the task[1]. Then, given the firm's series of idiosyncratic shocks, I use GARCH (1,1) model (Engle, 1982; Bollerslev, 1986) to forecast its idiosyncratic volatility in the next period. The GARCH framework is widely used in risk management to capture the risk dynamics. Instead of assuming equal weight to return innovations as in realized volatility, the GARCH model estimates different weights assigned to long-run volatility, past volatilities, and past innovations. The use of GARCH(1,1) implicitly assumes that investors continuously update their forecast of a firm idiosyncratic risk as a weighted average of the long-run average variance, the variance predicted for last period, and the newly revealed surprises in last period's returns. To estimate connectedness level of a firm, I use the Constant Conditional Correlation framework (Bollerslev et al., 1990). Though the CCC model does not allow us to analyze the interrelation of variance - covariance and the direction of volatility spillover, it solves the curse of dimensionality problem in modeling the conditional covariance matrix, which is crucial for a big-data project like this.

Then, I compute the total risk of the system by aggregating individual idiosyncratic risk and spillover risk. My empirical results show a dynamic evolution of the total financial risk over time. During all major recessions, the financial system

[1] Herskovic et al. (2016) show that a richer set of common factors would not much differ the pairwise correlation of idiosyncratic returns

becomes highly volatile and more connected. The US subprime mortgage crisis in 2008 and the subsequent European sovereign debt crisis in 2010 record highest spikes in the financial system volatility. Moreover, based on my estimation, the aggregate spillover risk is four times as large as the aggregate idiosyncratic risk on average. To the best of my knowledge, it is the first analysis that directly compares the share of idiosyncratic and contagion risk contribution to the total financial system risk. That result emphasizes the importance of the cross-sectional dimension in the systemic risk literature.

Using my novel Systemic Importance Index, I find that the most systemically important financial institutions enjoy a huge advantage in equity funding cost. Controlling for all common risk factors, and also exposure to systemic risk, the top 20 financial institutions in the U.S receive a risk subsidy of approximately 4 percent annually over a long period from 1970 to 2018. Breaking up the sample into two subperiods, I find that the equity funding advantage of top SIFIs is larger over the most recent period 1995-2018 (over 4.5%), compared to that in the further period 1970-1995 (about 2.5%). The results imply that market participants place a risk discount on the "too-important-to-fail" status of the most systemically important financial institutions. Ex ante, investors anticipate some forms of government bailouts would be granted to the top SIFIs in case of a systemic event, and therefore require less returns from them than from their peers. However, one may argue that top SIFIs are actually safer due to their better risk management or stricter regulations imposed on them. I show that this argument is not supported by data. The top 20 and top 20-40 SIFIs have insignificant differences in equity loss during the 2008 financial crisis, but their long-run average risk-adjusted returns spread is huge, almost 4 percent annually. In addition, I show that systemic importance, not size, is the main factor of the spread between large and small financial institutions.

This chapter contributes to the macroprudential policy literature in three ways. First, my risk measures provide regulators a tool to quickly determine (1) which financial institutions are contributing the most to the riskiness of the system, and (2) whether a firm's specific shocks may contribute to the system risk by its changes in idiosyncratic risk or potential spillover risk. Financial industry lies at the heart of the economy and so being able to track and identify the sources of financial sector volatility is crucial to understanding the macroeconomy. For example, Giglio et al. (2016) show that the average equity volatility of the largest 20 financial institutions is the most useful individual predictor of macroeconomic downturns. In contrast, equity volatility in the non-financial sector appears to have little, if any, predictive power.

Second, my results that connectedness risk is the main driver of the financial system total risk provide empirical support for the ongoing debate about stricter regulations in the cross-sectional dimension. Strengthening the financial system as a whole and mitigating the risk of cascading failures always stay as the main objectives of macroprudential policies. In addition to time-varying regulations such as countercyclical capital/liquidity buffers aiming to reduce excessive risk built up in peace time, cross-sectional regulations that make the system more transparent and control linkages among financial institutions are much needed.

Lastly, my empirical findings contribute to the growing literature in estimating the "too-big-to-fail" funding advantage. During the 2008 financial crisis, an unprecedented amount of government bailouts was spent to rescue some of the most important financial institutions in the industry, which actually materialized what is expected by the market. Though government bailouts can be ex-post efficient under some circumstances (Acharya and Yorulmazer, 2008), that ex-ante distortion in funding costs may give systemically important firms incentives to take excessive risk, creating negative externalities that require government interventions.

The rest of this paper is organized as follows. Section 1.2 briefly reviews related literature. A detailed construction of systemic importance measure is presented in Section 1.3. Section 1.4 discusses some time-series properties of the risk measures, while Section 1.5 presents their asset pricing implications. Section 1.6 concludes.

1.2 Related Literature

My paper is closely related to at least three strands of literature: cross-sectional dimension of systemic risk, measuring financial systemic importance, and "too big to fail" externalities.

First, a major part of the theoretical systemic risk literature aims at finding contagion and amplification mechanisms to explain why idiosyncratic shocks to a small group of financial institutions can turn into large losses that affect the whole system. This strand of literature can be traced back to Allen and Gale (2000) seminal paper that rationalizes the existence of interbank markets. In their framework, banks optimally choose to hold interbank deposit claims to cope with idiosyncratic liquidity risk. That risk-sharing mechanism reduces the probability of individual default, at the cost of contagion risk. They show that under certain conditions, a complete financial network, in which all banks in the system are linked to each other, is more robust than an incomplete structure, as the initial impact of a shock to a bank may be spread equally and attenuated. The trade-off between risk-sharing and contagion risk is further studied in Acemoglu et al. (2015). When the magnitude of negative shocks is relatively small, a complete market structure minimizes the number of individual defaults and improves the resiliency of the financial system. However, when the magnitude of negative shocks surpasses certain thresholds, a more interconnected network facilitates financial contagion and creates a more fragile system. The reason for such a sharp difference is that, under large negative shocks, the excess liquidity in the market is not sufficient to absorb the losses; hence, in that case, a less diversified lending pattern may contain losses and defaults within a small group of senior creditors without spreading to the whole system.

Not only does interconnected financial network serve as a source of contagion risk, but it also acts as a mechanism to amplify idiosyncratic shocks. For example, when asset prices drop in the market, some financial intermediaries need to liquidate their positions to meet funding and collateral constraints (i.e. "margin call"). These sales further put pressure on asset prices, and lower asset prices force firms to liquidate even more of their assets, leading to "fire sale" spillover. Brunnermeier and Pedersen (2008) formalize that amplification effect as an interaction between a "loss spiral" and a "margin spiral" which quickly evaporate liquidity in the market in case of systemic events.

My empirical results emphasize the importance of the cross-sectional dimension of systemic risk. On average, the aggregate spillover risk due to the connectedness of the financial system is four times as large as the aggregate idiosyncratic risk contributed by individual institutions. That spillover risk is the main driver of the total volatility in the financial industry and always spikes up during recessions over business cycles.

The second field of relevant literature involves measuring and ranking systemic risk importance of financial institutions. In this literature, there exist two main approaches: measures based on fundamentals, and measures based on market data.

In the first realm, the Basel Committee on Banking Supervision (BCBS 2011, 2013) proposed a framework to identify global systemically important banks (G-SIBs). Based on the annual disclosures of bank activities (e.g. Form FR Y-15 in the US), the BCBS framework creates a set of twelve measures over five categories and assigns a systemic score to each bank. The five major risk categories include size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity.

Though the BCBS methodology is widely used by regulators in the world, it faces several criticisms. The first critique is that all twelve risk indicators are directly related to size of the bank. For example, the interconnectedness category includes measurements of a bank's total claims on the financial system, its total liabilities to the financial system, and the total value of debt and equity securities issued by a bank; the substitutability is measured by a bank's payments activity, assets under custody at the bank, and the bank's total underwriting transactions; three indicators measuring complexity include a bank's amount of OTC derivatives, total amount of trading, and total illiquid assets. Those indicators are measured as the share of a bank in each activity total value, so larger banks usually dominate in all categories. A bigger drawback of this methodology is that it assigns equal weight of 20% to each category, and equal weight to each indicator within a category. Following this approach is similar to saying that OTC derivatives, or illiquid assets have the same meaning as payments activity or custodian assets in calculating systemic risk. In practice, to avoid overestimating the systemic importance of some small but specialized banks such as BNY Mellon and State Street who dominate the custodian services, the US applies a cap of 5% to the score of substitutability indicators.

Since size alone is not always a good proxy for systemic importance (Office of Financial Research Viewpoint, 2017), some regulators also look at other systemic risk measures in the literature using market data. Some of the most prominent include $CoVaR$ (Adrian and Brunnermeier, 2016), SES (Acharya et al., 2017), and SRISK (Brownlees and Engle, 2016). These three measures share the same idea in studying the pairwise relationship between individual institutions and the financial market in case of a systemic event. However, due to the differences in estimation strategy, each measure attempts to quantify a different part of systemic risk. In particular, $CoVaR$ measures the Value at Risk (VaR) of the market return conditional on some events observed for an individual firm. Using $\triangle CoVaR$ defined as the difference between the VaR of the financial system when a company is distressed and the VaR of the system when the firm is in its regular state, Adrian and Brunnermeier are able to study what would happen to the market when a financial institution becomes distressed. Hence, firms with higher $\triangle CoVaR$ score are more systemically important. On the other hand, SES and SRISK answer a reverse question: what would happen to an individual financial institution when the market falls below a certain threshold? Specifically, the systemic expected shortfall (SES) captures a firm's propensity to be undercapitalized when the overall financial system is in distress. The idea is quite intuitive: a financial institution will more likely generate stronger negative externalities due to spillover effect if it experiences capital shortfall when the whole market is weak and other financial institutions are also undercapitalized. (Brownlees and Engle, 2016) proposes a different variation of the SES measure to take into account both the liabilities and the size of a financial institution. Their systemic risk measure, SRISK, corresponds to the forward-looking expected capital shortfall of a given financial institution in case of a downturn in the market. Hence, firms with the largest SRISK are assumed to contribute the most liquidity spillover externality to the market and deemed to be the most systemically risky.

Though $CoVaR$, SES and SRISK provide useful frameworks to analyze the co-movements of financial firms and the market in the tail of the return distribution, they do not explicitly model the interconnectedness among financial institutions in the industry. To fill this gap in the literature, Billio et al. (2012) use principal components analysis and pairwise Granger - causality to derive a measure of connectedness. They show that linkages within and across hedge funds, banks, broker/dealers, and insurance companies are highly dynamic and tend to rise when the market goes down. Moreover, their empirical results show that financial institutions with a high level of interconectedness are more likely to suffer greater losses in the 2008 financial crisis. On the other hand, Diebold and Yılmaz (2014) measure interconnectedness among financial intermediaries by decomposing the forecast error variance of returns through a VAR framework and assign a fraction of that total prediction error variability to shocks contributed by each firm in the system. Their empirical results also suggest that the volatility of large US financial institutions has a high degree of interconnectedness and that interconnectedness increases in periods of distress.

My paper proposes a unified framework to study the financial system risk both from time-series and cross-sectional perspectives. The measure of aggregate total risk decomposes additively into each bank's contribution as well as into different risk characteristics. Using the GARCH framework to forecast conditional volatility, my risk measures attempt to answer two important questions: (1) Which financial intermediaries are contributing the most to the riskiness of the system, and (2) Whether that risk contribution comes from the firm's idiosyncratic risk or potential spillover risk due to its linkages with others. Since my measures can be implemented in real time using high-frequency market data, they can detect certain abnormal changes in the financial industry, and are useful for macroprudential supervision and regulation.

My paper is related to the studies that deal with measuring the "too-big-to-fail" funding advantage. Acharya et al. (2016) compute the credit spreads on bonds issued by major US financial institutions as the difference between the yield on its bonds and the corresponding maturity-matched Treasury bond. They use various measures of size as an indicator of systemic importance and find that there is a negative relationship between firm's size and its credit spreads. The estimated annual funding cost that large financial institutions earn is approximately 30 basis points over the 1990 - 2012 period, which translates to about $30 billion per year on average.

Using credit default swap (CDS) data for 73 banks in 21 countries from 2005 to 2011, Barth and Schnabel (2013) find that CDS spreads are negatively correlated with the firm's systemic importance, measured by $CoVaR$. The empirical results show that the difference between the mean and the max systemic importance is approximately 20-50 bps in CDS spreads. More interestingly, size measures are not statistically significant after controlling for $CoVaR$.

In the stock market, Gandhi and Lustig (2015) find that risk-adjusted returns on the portfolio of largest commercial banks in the US are approximately 7% per year lower than risk-adjusted returns on the portfolio of smallest banks. They decompose the difference into a 3.1 percent subsidy to the largest banks and a 3.25 percent disaster tax on the smallest banks. This translates into an annual advantage to the largest commercial banks of $4.71 billion per bank in 2005 dollars.

My empirical results are consistent with other findings that the most systemically important financial institutions enjoy advantages in funding cost. Using the equity return data from 1965 to 2018, I find that the estimated subsidy to the highest risk contributors is about 4 percent annually. There are several differences between my approach and Gandhi and Lustig (2015). First, I choose to include all financial firms in the market, rather than a smaller subset of only commercial banks. My sample covers important sectors in the financial industry such as insurance and investment banks, which proved to be key trouble makers during the 2008 financial crisis. Moreover, my risk contribution measure captures both size and connectedness, so the results can be interpreted as "too-important-to-fail" subsidy, which is broader than "too-big-to-fail" or "too-connected-to-fail" premium in the literature. Lastly, I show that controlling for size, the risk-adjusted equity return spread between the largest and the smallest risk contributors is statistically significant, while the converse is not true. Controlling for risk contribution, the spread between the biggest and the smallest financial institutions based on market capitalization becomes positive and insignificant.

1.3 Measuring Systemic Importance Index

In this section, I present a novel measure of systemic importance that captures all key factors of SIFIs according to the FSB's definition. Intuitively, financial institutions score high in SI index when they are large, have highly volatile idiosyncratic shocks, and being well connected to other top firms in the financial industry. There are two crucial components of SI index: the measure of a firm's idiosyncratic volatility and its connectedness. In Subsection 1.3.1, I introduce the construction of the SI index and its decomposition based on idiosyncratic and spillover risk. Subsection 1.3.2 discusses the volatility measure using the GARCH framework, while Subsection 1.3.3 specifies a measure of connectedness using the Constant Conditional Correlation (CCC) model, which is the simplest in the multivariate GARCH family.

1.3.1 SI Index Construction

A financial institution can be classified as systemically important when its idiosyncratic shocks could threaten the stability of the financial system. There are several theoretical channels for such a seemingly isolated shock to propagate throughout the market, such as contagion (Allen and Gale, 2000; Acemoglu et al., 2015), liquidity spirals (Brunnermeier and Pedersen, 2008), and fire-sale spillover (Duarte and Eisenbach, 2018). However, all of those amplification mechanisms share a premise that the shocks need to take place in a considerably large and well connected financial institution. For example, failures of a few small regional banks may not trigger a systemic crisis as their losses can be easily absorbed by the market, but a single collapse of a well-known name on Wall Street such as Lehman Brothers in 2008 can definitely cause severe damages to the system. Therefore, size and connectedness should be the key features in determining the importance of a financial institution to the system, as recognized by the Financial Stability Board.

To incorporate the size and connectedness simultaneously in the measure of systemic importance, I first consider the financial system as a collection of interconnected institutions. In particular, the whole financial industry return R^s can be expressed as the weighted sum of each individual institution's return R^i, that is, $R^s = \sum_i \omega_i R^i$, where ω_i is the weight of each firm i in the system. Then, I further decompose individual return into two components: expected return μ_i and idiosyncratic shock ϵ_i. From the definition of conditional variance, a forecast of the financial system risk in terms of individual risk can be written as

$$Var(R^s_{t+1}|\Omega_t) = Var(\sum_i \omega_i R^i_{t+1}|\Omega_t) \tag{1.1}$$

$$= Var(\sum_i \omega_i \mu_{i,t+1} + \sum_i \omega_i \epsilon_{i,t+1}|\Omega_t) \tag{1.2}$$

where Ω_t is the information set known at time t.

Since the conditional expectation return of firm i is known at time t, the conditional variance of the financial system can be rewritten as

$$Var(R^s_{t+1}|\Omega_t) = Var(\sum_i \omega_i \epsilon_{i,t+1}|\Omega_t) \tag{1.3}$$

$$= \sum_i \omega_i^2 Var(\epsilon_{i,t+1}|\Omega_t) + \sum_i \sum_{j \neq i} \omega_i \omega_j Cov(\epsilon_{i,t+1}, \epsilon_{j,t+1}|\Omega_t) \tag{1.4}$$

Equation 1.4 decomposes the total system risk into two main drivers: individual idiosyncratic risk and connectedness risk. The first part, $\sum_i \omega_i^2 Var(\epsilon_i|\Omega_t)$ can be interpreted as a measure of total individual idiosyncratic risk. Apparently, the financial system risk would be larger when each individual firm became riskier. The second part, $\sum_i \sum_{j \neq i} \omega_i \omega_j Cov(\epsilon_{i,t+1}, \epsilon_{j,t+1}|\Omega_t)$ is a measure of the system total connectedness.

There are certain concerns about using equity data to reveal true risks and relationship of financial institutions. For example, Beatty and Liao (2014) argue that there exists an information asymmetry between bank managers and outside equity and debt holders. As a result, the market's perception of risk reflected by stock returns might not describe the true underlying risk of the bank. However, to obtain high-frequency estimates of financial institution true idiosyncratic and connectedness risk, we need high-frequency balance sheet data and other internal information, which is generally unavailable. Therefore, the reliance on the assumption of the efficient market is a standard in the literature of estimating systemic risk using market data. As Diebold and Yılmaz (2014) argue, stock market returns and return volatilities "reflect forward-looking assessments of many thousands of smart, strategic and often privately-informed agents as regards precisely the relevant sorts of connections". Hence, in a reasonably efficient financial market, we would expect the pairwise covariance between innovations in stock returns of two institutions to reflect the degree of their linkages.

Using the weights of each individual firm (ω_i, ω_j) in the derivation of the total system risk makes sense because the impact on the financial system vulnerability would vary widely when a big player like JP Morgan rather than a regional small bank suffers a large loss, or when a group of large financial intermediaries become more interconnected, which certainly raises the contagion risk.

In addition to the decomposition of total system risk based on two main risk characteristics, we can also estimate the risk contribution of each individual firm in the industry. Specifically, let $SI_{i,t}$ denote the systemic importance/risk contribution of firm i to the total industry risk at time t, then

$$SI_{i,t} = \frac{\omega_i^2 \sigma_{i,t+1}^2 + \sum_{j \neq i} \omega_i \omega_j \sigma_{ij,t+1}}{\sigma_{s,t+1}^2} \tag{1.5}$$

where

- $\sigma_{i,t+1}^2 = Var(\epsilon_{i,t+1}|\Omega_t)$, representing firm i's expected idiosyncratic risk,
- $\sigma_{ij,t+1} = Cov(\epsilon_{i,t+1}, \epsilon_{j,t+1}|\Omega_t)$, representing firm i and j degree of expected connectedness,
- $\sigma_{s,t+1}^2 = Var(R_{t+1}^s|\Omega_t)$, representing the expected total system risk at time t, and ω_i, ω_j are the weights of firm i and j, respectively.

Equation 1.5 then implies that an individual institution contributes a larger share to the total system risk when it becomes larger (higher ω_i), more volatile (higher $\sigma_{i,t+1}$), and more connected (higher $\sigma_{ij,t+1}$). Note that the denominator $\sigma_{s,t+1}^2$ acts as a scale factor to track the systemic importance evolution of firm i over time, but it does not change firm i's contemporaneous rank order, which we later use to test cross-sectional asset pricing implications.

Furthermore, we can study by which channel a firm contributes to the total system risk. To see that, we can break up the systemic importance index into the contribution by idiosyncratic risk, $IdioRisk_{i,t}$ and by contagion risk, $Spillover_{i,t}$ according to

$$IdioRisk_{i,t} = \frac{\omega_i^2 \sigma_{i,t+1}^2}{\sigma_{s,t+1}^2} \tag{1.6}$$

and

$$Spillover_{i,t} = \frac{\sum_{j \neq i} \omega_i \omega_j \sigma_{ij,t+1}}{\sigma_{s,t}^2} \tag{1.7}$$

This decomposition emphasizes that controlled for size, a financial institution can be highly important and pose a significant threat to the system either because it is extremely risky, or because it is extremely well-connected.

Compared to other systemic risk measures using market data such as SES (Acharya et al., 2017), SRISK (Brownlees and Engle, 2016), and CoVaR (Adrian and Brunnermeier, 2016), the Systemic Importance Index is different in many aspects. First, the SI index measures the risk contribution of each financial institution to the total industry risk directly and unconditionally, instead of conditioning on extreme losses. This approach therefore provides a different dynamics in gauging the importance of each firm over time, especially during non-crisis periods, when correlations among financial institutions remain low. Second, the SI index can be further decomposed into idiosyncratic and spillover risks, which then track different risk characteristics of a firm in the financial sector. Moreover, this methodology allows to estimate the importance of financial firms in real time using high-frequency market data, thus providing regulators a tool to quickly determine which financial intermediates are contributing the most to the riskiness of the system.

The next two subsections will detail the estimate of individual idiosyncratic risk and the conditional covariance among financial institutions.

1.3.2 Idiosyncratic Risk Estimation

Idiosyncratic risk is defined as the risk unique to a specific firm, so it is independent of the common movement of the market. Following the common practice in the idiosyncratic volatility literature (Ang et al., 2006, 2009; Fu, 2009), I define idiosyncratic shocks to firm i as residuals from the regression of firm i's excess returns on Fama and French (1993, 1996) three common factors: (i) MKT, the excess return of the value-weighted market portfolio, which captures the market risk; (ii) SMB, the excess return on a portfolio of small stocks over a portfolio of big stocks, which captures the size premium; and (iii) HML, the excess return on a portfolio of high book-to-market stocks over a portfolio of low book-to-market stocks, which captures the value premium. The regression can be described as follows:

$$R_t^i - R_t^f = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + \epsilon_{i,t} \tag{1.8}$$

where

- $R_t^i - R_t^f$ is the excess return of firm i at time t,
- MKT_t, SMB_t, HML_t are market, size, and value premium at time t, respectively,
- b_i, s_i, h_i are firm i's risk premium sensitivity,
- α_i is the portion of excess return left unexplained by the model,
- and ϵ_{it} is the firm-specific shock.

In the empirical analysis, I use a rolling window of 60 months from $t - 59$ to t to derive a series idiosyncratic shocks and forecast the expected volatility for each financial institution in the sample. For the volatility forecasting purpose, I resort to the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) (1,1) model (Engle, 1982; Bollerslev, 1986) to capture the dynamics of firm-specific risk. The use of GARCH(1,1) implicitly assumes that investors continuously update their forecast of a firm idiosyncratic risk as a weighted average of the long-run average variance, the variance predicted for last period, and the newly revealed surprises in last period's returns. The weight of each component is optimally chosen to maximize the likelihood function assuming the errors follow a Gaussian process.

In particular, the residuals ϵ_{it} from equation 1.8 is modeled following a GARCH(1,1) process:

$$\epsilon_{it} = \sigma_{it} z \tag{1.9}$$

where $z \sim N(0,1)$ and

$$\sigma_{it+1}^2 = \omega_i + a_i \epsilon_{it}^2 + b_i \sigma_{it}^2 \tag{1.10}$$

Here, ω_i, a_i and b_i are three constants that need to be estimated using the maximum likelihood procedure.

1.3.3 Conditional Covariance Estimation

In the world of multivariate GARCH literature, there are two main approaches in modeling the conditional covariance matrix. In the first realm, econometricians attempt to directly estimate each term in the covariance matrix, allowing a flexible model for volatilities and conditional covariances to be interrelated. However, the empirical implementation of this approach is limited because of the curse of dimensionality, i.e. the number of coefficients grows much faster than the number of observations.

For example, consider the original VECH model, proposed by Bollerslev et al. (1988) with two stocks and one lag. That is, we want to model the conditional covariance matrix $\Sigma_{t+1} = \begin{bmatrix} \sigma_{11,t+1} & \sigma_{21,t+1} \\ \sigma_{12,t+1} & \sigma_{22,t+1} \end{bmatrix}$ based on the past squared residuals matrix $\epsilon_t \epsilon_t'$ and the past conditional covariance Σ_t. Since Σ_{t+1} is symmetric, we need to care only about its lower triangular component. The unrestricted specification of the model can be written as

$$\begin{bmatrix} \sigma_{11,t+1} \\ \sigma_{12,t+1} \\ \sigma_{22,t+1} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t}\epsilon_{1,t} \\ \epsilon_{1,t}\epsilon_{2,t} \\ \epsilon_{2,t}\epsilon_{2,t} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} \sigma_{11,t} \\ \sigma_{12,t} \\ \sigma_{22,t} \end{bmatrix} \tag{1.11}$$

As a result, for a parsimonious model with two stocks and one lag, we have 20 free parameters to estimate. In general, for a model with N stocks, p ARCH terms and q GARCH terms, the total number of parameters in an unrestricted specification is $(p+q+1) \times [N(N+1)/2]^2 = O(N^4)$. In subsequent studies, many authors use more restrictive specifications to reduce the number of free parameters. For example, in the DVECH model, if we ignore the cross-volatility and cross-covariance feedback effects and use a diagonal matrix $A = diag(a_{11}, a_{22}, a_{33})$ and $B = diag(b_{11}, b_{22}, b_{33})$ instead of the full matrix as in 1.11, then the total number of parameters of the model is reduced to $O(N^2)$, which is still infeasible when we have a large number of stocks but small number of observations.

To overcome the curse of dimensionality while maintaining a certain level of flexibility, I need a different approach in modeling the conditional covariance matrix. Following Bollerslev et al. (1990), the conditional covariance is specified as the product of conditional variances and their pairwise correlation, according to

$$\sigma_{ij,t+1} = \sigma_{it+1} \cdot \rho_{ij} \cdot \sigma_{jt+1} \tag{1.12}$$

where $\rho_{ij} = corr(\epsilon_i, \epsilon_j)$, and in a matrix form,

$$\Sigma_{t+1} = D_{t+1}^{1/2} R D_{t+1}^{1/2} \tag{1.13}$$

where Σ_{t+1} is a $N \times N$ conditional covariance matrix of N firms in the system, $D_{t+1} = diag(\sigma^2_{1t+1}, ..., \sigma^2_{Nt+1})$ is a diagonal matrix with N conditional variances as diagonal elements and R is a $N \times N$ constant correlation matrix of N residuals series from equation 1.8.

In a nutshell, the whole procedure in calculating the Systemic Importance Index involves three steps. First, I extract for each firm the idiosyncratic shocks by regressing its excess returns on the three factors specified in 1.8. Second, I form a forecast of idiosyncratic risk for each firm using residuals from the first step and the GARCH(1,1) process following equation 1.9 and 1.10. Lastly, under the assumption that the correlation coefficient between two banks is unchanged over a specific time window, I compute the conditional covariance matrix as in 1.13.

The total number of parameters using this Constant Conditional Correlation framework is $O(N)$, as we need to estimate three parameters (ω, a, b) in each GARCH(1,1) process for a total of $3N$ parameters. Bauwens et al. (2006) show that parameters of the CCC-GARCH model estimated in multiple steps are still consistent and asymptotically normal under the assumption that errors follow a Gaussian process.

1.4 Empirical Analysis

In this section, I implement the measures defined in Section 1.3 using equity market data on the financial institutions ranked top 200 in market capitalization in the U.S from Jan-1965 to June-2018. Subsection 1.4.1 elaborates on the data selection process, while Subsection 1.4.2 provides time-series properties of the risk measures. Subsections 1.4.3 compares the rankings of financial institutions using different risk measures, and Subsection 1.4.4 reports the performance of the SI index in predicting equity losses of financial firms during the 2008 financial crisis.

1.4.1 Data Description

I use monthly stock data from the Center for Research in Security Prices (CRSP) and track the stock by its permanent unique id number (PERMNO) from Jan-1965 to June-2018. Similar to Gandhi and Lustig (2015), my sample periods do not start in July 1963, which is the conventional start-date in the empirical asset pricing literature. The reason is that only a small number (less than 50) of financial firms listed on the stock market prior to 1965. Since I use a rolling window of 60 months in the empirical work, the first reported result is in January 1970 and the last one is in May 2018, for a total of 581 months.

Following the empirical finance literature, I select only U.S. common stocks with share codes 10 and 11 and listed on NYSE, AMEX, and NASDAQ. The whole stock market is then classified into 12 industries based the four-digit Standard Industrial Classification code, following Kenneth French's industry definitions. For example, financial institutions are selected as companies with SIC codes from 6000 to 6799. For each month in the sample period, I form a portfolio of top 200 firms based on their average market capitalization over the previous 60 months for the analysis. The portfolio of top 200 financial stocks is a good representative of the financial sector as it covers about 75% of the total industry capitalization and explains about 98% of its fluctuations. A bigger sample that includes more small firms would not change the order of financial institutions in their systemic importance, as the bottom 10% of this portfolio already has less than 0.5% value weight on average and contribute less than 0.1% in the total risk. Factors data are downloaded from Kenneth French's online library.

Table 1.1: Descriptive Statistics for Financial Industry Aggregate Risks (Jan 1970 - May 2018)

This table summarizes the time-series statistics of the financial industry aggregate risk and its decomposition into idiosyncratic and spillover risk contribution. In every month, excess returns on each individual financial institution in the sample over the past 60 months are regressed on the monthly Fama-French three factors: MKT, SMB, and HML. Then the GARCH(1,1) model is applied to compute the conditional variance of residuals from the factor regression. Idiosyncratic risk is defined as the product of the squared value weight and the conditional variance and spillover risk is the value weighted sum of conditional covariances derived from the CCC model. Individual idiosyncratic and spillover risk are then aggregated each month to achieve the industry level. The aggregate total risk is the sum of aggregate idiosyncratic and spillover risk. The last column reports the standard deviation of each risk measure over 581 months from Jan-1970 to May-2018.

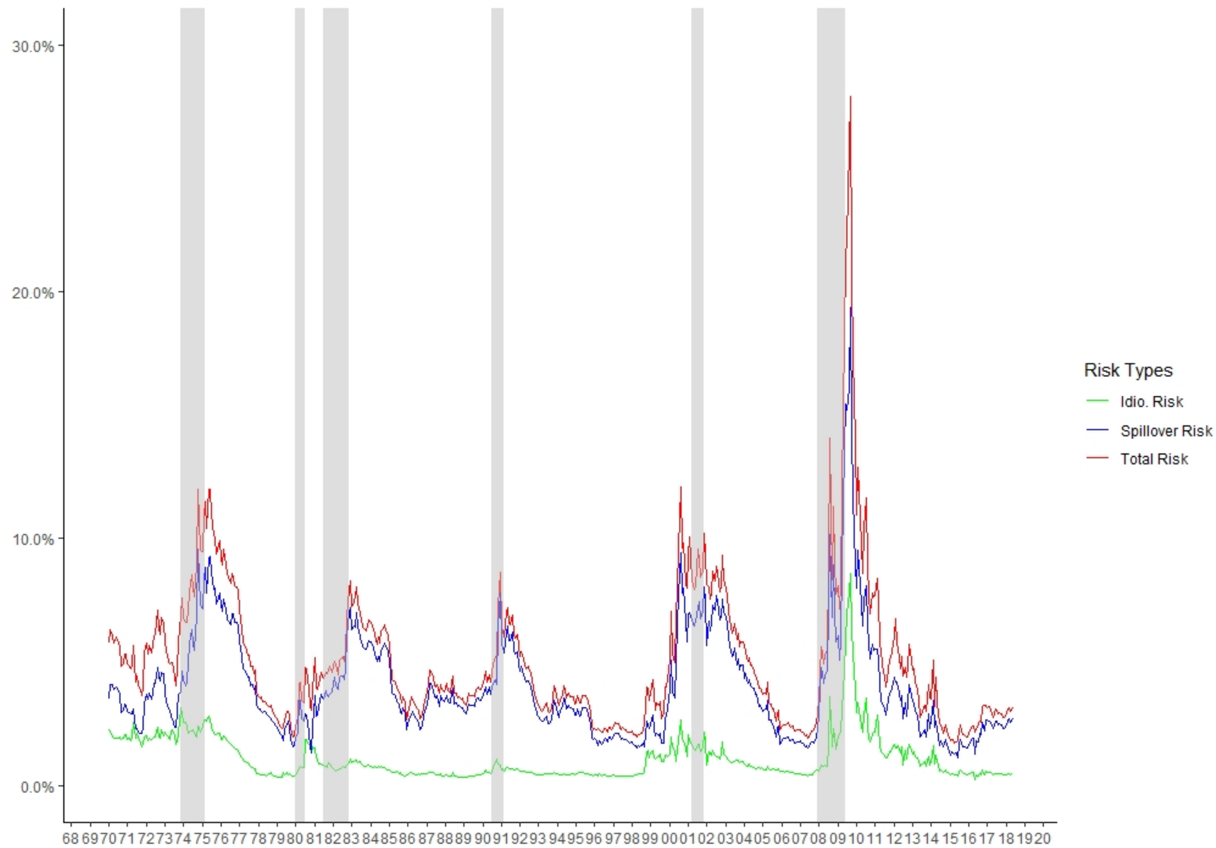
	Min	Q1	Median	Mean	Q3.	Max.	SD
Total Risk	0.339	2.749	3.885	4.913	6.343	27.775	3.381
Idiosyncratic Risk	0.249	0.467	0.722	1.074	1.463	8.577	0.923
Spillover Risk	1.107	2.452	3.392	3.991	5.020	19.371	2.253

1.4.2 Time-series Property of Financial System Risk

Table 1.1 presents the time-series property of the financial industry aggregate total risk and its two components: idiosyncratic and spillover risk. In every month, I form a portfolio of top 200 firms based on their average market capitalization over the previous 60 months. The monthly excess returns on each institution are regressed on the monthly Fama-French three factors: MKT, SMB, and HML. Then, I use the GARCH(1,1) model to forecast the conditional variance of the the firm idiosyncratic shocks. The idiosyncratic risk contribution to the total risk is then calculated as the product of the firm value weight squared and the idiosyncratic conditional variance. Individual spillover risk contribution is estimated as the value weighted sum of the firm's covariances. The industry-level measures are then aggregated across all firms in the sample. The industry total risk is calculated as the sum of aggregate idiosyncratic and aggregate spillover risk. In the appendix, I show that the time-series properties of the financial industry total risk do not differ much when we use the value-weighted top-200 portfolio or industry return.

Figure 1.1: Financial Industry Aggregate Risk (Jan 1970 - May 2018)

This figure presents the time-series dynamics of the financial industry aggregate risk, and the contribution from idiosyncratic and spillover components. The shaded areas represent NBER-defined recessions for the U.S. economy. By definition, the sum of idiosyncratic and spillover risk equals to the total risk in every month.



Over 581 months from Jan-1970 to May-2018, the mean percentage contribution of spillover risk is approximately 79, which is four times as large as the idiosyncratic risk contribution to the total financial industry risk. This empirical evidence further highlights the importance of contagion risk in the financial sector, which as shown in the theoretical systemic risk literature is one of the major propagation and amplification channels of idiosyncratic risk.

Moreover, that connectedness is the main driver of the financial system risk also points to the need to include a measure of linkages among individual firms in estimating systemic risk. In the existing literature, many systemic risk measures using market data solely focus on the pairwise relationship between a financial institution and the market in extreme events. Though they are all useful measures, they may greatly underestimate the systemic risk that a firm poses to the market and other individuals if the interconnections among financial institutions are not directly modeled.

Figure 1 presents the dynamics of financial industry aggregate risk from January 1970 to May 2018. We can observe two important results directly.

First, financial aggregate total risk shows a clear counter-cyclical pattern and the "volatility clustering" phenomenon. That is, financial system volatilities tend to rise up in recessions and remain high for a while before returning to the long-run mean. However, the magnitude of volatility spikes differs across recessions. It seems that the two latest recessions, dot-com bubble 2000 - 2002 and financial crisis 2008-2009, which are closely related to the financial industry, witnessed the largest increases in the total risk of the financial sector. Moreover, in each episode, the volatility clustering effects last for about four years, longer than any previous recession.

Second, except in the period 2008-2009, the aggregate idiosyncratic risk remains relatively flat, and the main driver of the total risk is the spillover counterpart. That is understandable, as the collapse of an isolated bank, insurance, or real estate company, regardless of its size, could not trigger a systemic event. The real issue differentiating the financial industry to other industries is that a big financial institution with a large balance sheet usually have deep connections to others in the industry. On the other hand, it is also hard to imagine that the collapse of a small financial firm, regardless of how well-connected it is, could lead to a cascade of failures, since the market can easily absorb that whole loss without much damage. Hence, a financial institution that has the potential to trigger a systemic event must be large and is deeply connected to the financial system. These two key features, size and connectedness, are well captured by my novel measure of systemic importance.

1.4.3 Rankings of the most Systemically Important Financial Institutions

Table 1.2: Top 20 Financial Institutions by Systemic Importance Index (2017 average)

This table presents the top 20 financial institutions ranked by the systemic importance index using the average monthly data in 2017. The first column, ”SI Ranking” indicates the systemic importance order based on the total risk contribution to the financial system risk. The next three columns show names, standard industrial classification codes, and business services of the top 20. ”Total Contribution” reveals the percent of total system risk contributed by each financial institution in the list, while ”Size”, ”Idiosyncratic”, and ”Spillover” columns display market capitalization in billions, contribution by idiosyncratic risk, and contribution by spillover risk, respectively. The number in parenthesis indicates their rankings in each category.

SI Ranking	Name	SICCD	Services	Total Contribution (%)	Size ($B)	Idiosyncratic (%)	Spillover (%)
1	BANK OF AMERICA	6021	Bank	14.04	254.4 (3)	3.76 (1)	10.27 (1)
2	WELLS FARGO	6021	Bank	12.19	275.3 (2)	2.95 (2)	9.24 (3)
3	JPMORGAN CHASE	6021	Bank	12.12	327.8 (1)	2.61 (3)	9.51 (2)
4	CITIGROUP	6021	Bank	7.93	180.0 (6)	1.35 (4)	6.58 (4)
5	MORGAN STANLEY	6211	Brokers	3.12	85.2 (9)	0.27 (7)	2.85 (6)
6	GOLDMAN SACHS	6211	Brokers	3.10	90.8 (7)	0.25 (8)	2.85 (5)
7	SCHWAB CHARLES	6221	Brokers	3.01	57.3 (14)	0.22 (9)	2.79 (7)
8	UNITEDHEALTH	6324	Insurance	2.46	182.5 (5)	1.01 (5)	1.45 (12)
9	PNC	6021	Bank	2.07	61.8 (12)	0.09 (19)	1.98 (8)
10	US BANCORP	6021	Bank	2.01	88.7 (8)	0.10 (17)	1.91 (9)
11	BNY MELLON	6022	Bank	1.78	51.9 (16)	0.09 (18)	1.69 (10)
12	METLIFE	6311	Insurance	1.73	56.2 (15)	0.12 (16)	1.61 (11)
13	AMERICAN EXPRESS	6029	Bank	1.46	76.5 (10)	0.22 (10)	1.24 (14)
14	PRUDENTIAL	6311	Insurance	1.43	46.5 (19)	0.05 (23)	1.38 (13)
15	BERKSHIRE HATHAWAY	6371	Funds	1.36	233.2 (4)	0.68 (6)	0.68 (31)
16	CIGNA	6324	Insurance	1.13	43.8 (20)	0.12 (15)	1.01 (17)
17	BB & T	6712	Bank	1.12	37.4 (25)	0.03 (30)	1.09 (15)
18	ANTHEM	6324	Insurance	1.09	49.6 (18)	0.14 (12)	0.95 (19)
19	STATE STREET	6022	Bank	1.07	33.1 (28)	0.05 (25)	1.02 (16)
20	AMERIPRISE	6282	Brokers	1.02	21.0 (37)	0.05 (24)	0.97 (18)

Table 1.2 reports the list of top 20 financial institutions ranked by their 2017 average systemic importance index. Though there is a slight difference in ranking order, all eight U.S. global systemically important banks (G-SIBs) reported in the FSB list show up in my top 20. Based on the assessment methodology designed by the Basel Committee on Banking Supervision, the FSB names JP Morgan Chase the only bank in their highest bucket of G-SIBs, followed by Citigroup in the second bucket. Bank of America, Goldman Sachs, and Wells Fargo fall in the same third bucket. The last US banks to make the cut are BNY Mellon, Morgan Stanley, and State Street.

In my ranking, it is no surprise that the big four commercial and top two investment banks take the six top spots. However, the difference in risk and size ranking order shows that my Systemic Importance measure does not simply sort financial institutions based on their size alone. For example, Bank of America has average market cap ranked third in the list, but it is the most systemically important bank due to its huge risk contribution to the financial system. We can further decompose the 14.04% of total financial risk contributed by Bank of America as 3.76% due to its idiosyncratic risk and 10.27% due to its spillover risk. Some investment banks such as Goldman Sachs and Morgan Stanley have much lower market cap than some of their peers (rank 7 and 9 in size, respectively), but they are highly systemic important because of their spillover risk to other big banks. Some firms well-known for their conservative investment strategy and seemingly isolated from others such as Berkshire Hathaway do not pose as much systemic risk as other medium-size brokers or banks, such as Schwab Charles and PNC.

Overall, my systemic risk measure seems able to provide a broader picture of financial systemic risk as it covers the whole financial sector, and can indicate different types of risk contribution. More importantly, the SI index can be updated using higher frequency data to track systemic risk contributors on a real-time basis.

1.4.4 Early Warning Signals

Following Billio et al. (2012), I calculate the maximum percentage market capital loss suffered by each of the financial institutions in my sample during the crisis period from July 2007 to December 2008. The percentage loss, Max%Loss is defined as the difference between the market capitalization of the institution at the end of June 2007 and the minimum market capitalization during the period from July 2007 to December 2008 divided by the market capitalization of the institution at the end of June 2007. Then, I run a simple regression of Max%Loss rankings on the institutions' Systemic Index, IdioRisk, Spillover and Size rankings based on the average measure over three samples: January 2007-June 2007, July 2004-June 2007, and October 2002-September 2005. Table 1.3 provides results for the top 200 financial institutions, while Table 1.4 restricts the sample to only banks (SIC code 6000 to 6199).

Compared to results in Billio et al. (2012), my risk measure rankings provide a better and consistent early warning signals than all of their financial connectedness measures using principle components and Granger causality. First, my results in predicting equity losses of financial firms during the 2008 crisis are robust using data in all sample periods, while Billio et al.'s results are statistically significant for only measures calculated in the subperiod (2002-2005), which seems quite counterintuitive. Second, unlike their results, the correlation between my risk measures and financial firm's equity losses shows a consistent pattern over time, in the sense that measures calculated in more distant periods to the 2008 crisis have less predictive power. However, the difference is quite small because systemically important financial institutions

Table 1.3: Predictive power of different risk measures (All Firms)

This table reports regression coefficients, t-statistics, p-values, and Kendall τ rank-correlation coefficients for regressions of Max%Loss rankings on rankings ordered by Systemic Importance Index, Idiosyncratic Risk Contribution, Spillover Risk Contribution, and Market Capitalization. The risk measures are calculated as the averages over three samples: January 2007-June 2007, July 2004-June 2007, and October 2002-September 2005. The maximum percentage loss (Max%Loss) for a financial institution is the difference between the market equity at the end of June 2007 and its minimum during the period from July 2007 to December 2008 divided by the market equity at the end of June 2007. The sample includes all top-200 financial firms in the market.

	Max%Loss			
Measure	Coeff	t-Stat	p-value	Kendall τ
Panel A: January 2007 - June 2007				
Systemic Rank	0.240	3.623	0.000	0.172
IdioRisk Rank	0.306	4.783	0.000	0.231
Spillover Rank	0.261	3.946	0.000	0.185
Size Rank	0.260	3.967	0.000	0.193
Panel B: July 2004 - June 2007				
Systemic Rank	0.228	3.986	0.000	0.189
IdioRisk Rank	0.277	5.037	0.000	0.236
Spillover Rank	0.229	3.988	0.000	0.189
Size Rank	0.251	4.443	0.000	0.210
Panel C: October 2002 - September 2005				
Systemic Rank	0.200	3.456	0.001	0.178
IdioRisk Rank	0.254	4.466	0.000	0.222
Spillover Rank	0.199	3.439	0.001	0.179
Size Rank	0.212	3.613	0.000	0.184

usually retain their status and rankings quite persistently, despite the volatile market return data.

My results are also consistent with Gandhi and Lustig (2015) in that size is also an important indicator of systemic risk exposure. Bigger financial institutions tend to lose more during the 2008 crisis. However, when the sample is restricted to include only banks, my risk measures better forecast losses than using size alone. In particular, Table 1.4 reports results for firms with SIC code from 6000 to 6199, which cover Depository Institutions (60) and Non-Depository Credit Institutions (61)[2]. The correlation between my risk measures and financial institution's equity losses are stronger in the restricted sample with only banks, compared to the full sample with all top financial firms. That makes sense because banks are supposed to

[2]Banking industry is the largest sector in my sample of biggest financial institutions. Out of 200 top financial firms by market cap during the 2008 financial crisis, there are almost 100 banks.

have higher exposure to financial systemic risk than other sectors such as real estate and brokers/dealers. As a result, banks that have higher risk rankings tend to suffer bigger loss during the financial crisis.

There is also evidence that risk measures calculated in the first six months of 2007, right before the crisis, have a better predictive power than risk measures calculated using data from 2002 to 2005, which is quite distant from the crisis period. Moreover, within the banks sample, size rankings seem to be less correlated with Max%Loss, compared to other risk measures using conditional volatility and covariance. The results imply that my risk measures certainly provide quite a different picture of financial systemic risk and better prediction of financial firms' capital losses in the 2008 crisis than both Billio et al. (2012)'s connectedness measures and Gandhi and Lustig (2015)'s simple size measure.

1.5 Asset Pricing Implications

In this section, I present some asset pricing implications of my systemic importance measure. Subsection 1.5.1 shows that the most systemically important financial institutions enjoy advantages in equity cost of approximately 4% per year. The lower risk-adjusted returns from top SIFIs imply that market participants price a risk discount on the "too-important-to-fail" status. Subsection 1.5.2 confirms that the risk discount comes from the systemic importance, rather than the size of the financial institution. Subsection 1.5.3 provides a robustness check by breaking up the whole sample into two subperiods.

Table 1.4: Predictive power of different risk measures (Banks Only)

This table reports regression coefficients, t-statistics, p-values, and Kendall τ rank-correlation coefficients for regressions of Max%Loss rankings on rankings ordered by Systemic Importance Index, Idiosyncratic Risk Contribution, Spillover Risk Contribution, and Market Capitalization. The risk measures are calculated as the averages over three samples: January 2007-June 2007, July 2004-June 2007, and October 2002-September 2005. The maximum percentage loss (Max%Loss) for a financial institution is the difference between the market equity at the end of June 2007 and its minimum during the period from July 2007 to December 2008 divided by the market equity at the end of June 2007. The sample includes only (approx. 90) banks that are in the portfolio of top-200 financial firms in the market.

	Max%Loss			
Measure	Coeff	t-Stat	p-value	Kendall τ
Panel A: January 2007 - June 2007				
Systemic Rank	0.320	3.278	0.001	0.213
IdioRisk Rank	0.378	3.954	0.000	0.253
Spillover Rank	0.315	3.216	0.002	0.209
Size Rank	0.304	3.095	0.003	0.204
Panel B: July 2004 - June 2007				
Systemic Rank	0.309	3.031	0.003	0.207
IdioRisk Rank	0.385	3.893	0.000	0.266
Spillover Rank	0.308	3.017	0.003	0.207
Size Rank	0.285	2.770	0.007	0.191
Panel C: October 2002 - September 2005				
Systemic Rank	0.296	2.939	0.004	0.195
IdioRisk Rank	0.375	3.841	0.000	0.253
Spillover Rank	0.293	2.904	0.005	0.193
Size Rank	0.291	2.883	0.005	0.194

1.5.1 Anomalies in SIFIs Stock Returns

If the market is efficient, any dimension of risk, including exposure to a rare event like systemic disaster should be priced by the market. In other words, financial institutions that are exposed more to systemic risk must compensate investors with higher returns. However, that relationship between risk and return is not linear, as largest financial institutions usually receive an implicit government guarantee due to their "too-important-to-fail" status. For example, two financial institutions with equal exposures to all kinds of risk may still have different equity costs ex ante, if investors consider one is more systemically important and would be saved by the government in case of a rare disaster. Government bailouts of some or all failed banks can be ex-post efficient to avoid continuation losses if the number of impacted banks is sufficiently large (Acharya and Yorulmazer, 2008). However, that ex ante implicit guarantee can cause a huge moral hazard problem and distortions in the capital market. There have been a few articles attempting to measure the funding cost advantage of large financial institutions using bonds spread (Acharya et al., 2016), credit default swap (Barth and Schnabel, 2013), and equity returns (Gandhi and Lustig, 2015).

My paper is closely related to Gandhi and Lustig (2015). In their paper, they show that the top decile portfolio of commercial banks sorted by size earn much lower risk-adjusted returns (7.35% per year on average) than the bottom decile portfolio, and this anomaly is not observed in non-financial stocks. My findings are consistent with their results. However, there are some crucial differences in methodology between my paper and Gandhi and Lustig (2015). First, I choose to include all financial firms (SIC codes 6000-6799), instead of only commercial banks (header SIC codes 60 or 67). My extended sample covers many important companies deemed to be trouble makers during the financial crisis, such as Freddie Mac, Fannie

Mae (SIC 6122), AIG (SIC 6711), and Merrill Lynch (SIC 6211). Hence, my systemic importance measure provides a broader picture about the whole financial sector, instead of banking industry alone. Second, Gandhi and Lustig use only size as a measure of systemic importance, but my SI index implies that both riskiness and connectedness are important determinants of systemic importance in addition to size, which is closer to the definition of a systemically important financial institution (SIFI). For example, a relatively small firm may pose more threat to the system if it holds more risky assets (idiosyncratic risk) and have large exposure to other banks (contagion risk).

Table 1.5: Portfolios of top financial institutions formed on Systemic Index (1970 - 2018)

This table reports estimates from OLS regression of monthly value-weighted (Panel A) and equal-weighted (Panel B) excess returns on each Systemic Index sorted portfolio of top financial firms on the three Fama and French (1993) risk factors. The whole sample period includes 581 months from January 1970 to May 2018. At the beginning of each month t, Systemic Index is calculated using market data in the previous 60 months from $t-60$ to $t-1$. The top 200 financial institutions are then sorted into ten deciles from Low to High based on the SI index. The last two columns present results for long-short portfolios. Excess returns and alphas are annualized by multiplying by 12 and expressed in percentages.

Panel C presents the average Max%Loss in each portfolio sorted on SI over the 2008 financial crisis using measures calculated in the first six months of 2017. *StdErr* reports the standard errors of each portfolio average Max%Loss. $*$, $**$, $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Low	2	3	4	5	6	7	8	9	High	Hi-Lo	Hi-9
						Panel A: Value-Weighted Excess Returns						
vwret	8.59***	7.65***	8.53***	9.39***	9.63***	10.31***	8.20***	8.82***	8.91***	5.08*	−3.51**	−3.83***
α	−1.19	−2.39	−1.10	0.08	−1.51	−1.07	−2.72*	−1.56	−1.39	−5.25***	−4.06*	−3.86***
MKT	1.08***	0.94***	0.92***	0.89***	1.02***	1.11***	1.14***	1.14***	1.20***	1.28***	0.20***	0.08**
SMB	0.16***	0.38***	0.38***	0.35***	0.39***	0.27***	0.12***	0.06	−0.13***	−0.33***	−0.49***	−0.20***
HML	0.50***	0.68***	0.61***	0.60***	0.81***	0.79***	0.70***	0.60***	0.58***	0.56***	0.07	−0.02
R^2	60.91	65.16	64.72	62.44	68.08	70.99	71.30	68.24	76.42	74.51	8.61	4.94
						Panel B: Equal-Weighted Excess Returns						
eqret	8.73***	7.73**	8.69***	9.96***	9.33***	10.94***	8.25***	9.33***	8.44***	5.83**	−2.90**	−2.61***
α	−2.26	−3.70**	−2.40	−1.01	−2.58	−0.77	−3.74**	−2.20	−2.81*	−5.28***	−3.03*	−2.48**
MKT	1.08***	0.98***	0.94***	0.95***	1.05***	1.10***	1.19***	1.21***	1.26***	1.33***	0.25***	0.07**
SMB	0.45***	0.64***	0.66***	0.59***	0.49***	0.36***	0.24***	0.12***	−0.06	−0.29***	−0.74***	−0.23***
HML	0.64***	0.81***	0.78***	0.78***	0.89***	0.83***	0.81***	0.74***	0.68***	0.65***	0.01	−0.03
R^2	66.37	65.84	67.35	66.02	68.59	70.77	71.76	72.06	75.83	74.77	20.55	7.04
						Panel C: Average Max%Loss						
Avg.Loss	46.2	35.8	35.1	39.6	48.7	66.9	41.2	57.3	54.6	65.8	19.6	11.2
StdErr	7.03***	5.74***	6.01***	5.36***	5.75***	6.46***	7.65***	6.29***	5.97***	6.88***	9.49**	8.98

Panel A and B in Table 1.5 report estimates from OLS regression of monthly value-weighted (Panel A) and equal-weighted (Panel B) excess returns on each Systemic Index sorted portfolio of top financial firms on the three Fama and French (1993) risk factors. The sample period includes 581 months from January 1970 to May 2018. At the beginning of each month t, Systemic Index is calculated using market data in the previous 60 months from $t - 60$ to $t - 1$. The top 200 financial institutions are then sorted into ten equal-sized portfolios based on SI index. Then, I match individual returns at the end of month t to stocks in ten deciles to calculate portfolio returns. Factor premia in month t are aligned with portfolio returns to run regressions and extract risk-adjusted returns (α).

The humped shape in excess returns and risk-adjusted returns generated by portfolios formed on SI index is quite interesting. On the one hand, we would expect that larger systemic risk contributors are more exposed to this dimension of risk, so that investors would demand higher returns for those institutions. Hence, all else equal, systemic importance measure and excess returns should have a positive relationship, which is shown in the first six deciles. However, not all financial institutions are treated equally. Ex ante, investors understand that top financial institutions would be saved by the government with a high probability in case of a systemic crisis. As a result, most systemically important financial institutions are deemed relatively safer than their small and medium peers. Indeed, that risk discount is priced well by the market as shown by the decline in returns on the top four portfolios sorted by SI index.

The difference in value-weighted and equal-weighted returns between the highest and the lowest decile is 3.51% and 2.9%, on average, respectively. Both are statistically significant at the 5% level. However, the difference in mean returns does not tell all the stories, as firms with different levels of systemic importance may have very different risk characteristics. For example, financial institutions in the first decile are much smaller than those in the last decile; or they have different exposure to aggregate risk. Indeed, looking at the factor loadings of each portfolio gives us a glimpse about risk characteristics of firms in that portfolio. A higher market coefficient means that the portfolio is more sensitive to aggregate risk. A positive size factor loading tells us that the portfolio behaves quite similar to a portfolio of small stocks; and vice versa, a large negative SMB coefficient implies that the portfolio is tilted toward big-cap stocks. The value (HML) loadings tell us whether the portfolio behaves like stocks with high book-to-market ratio (positive coefficient), or like stocks with low book-to-market ratio (negative coefficient).

Factor loadings in Table 1.5 are exactly what we expect about risk characteristics of firms in each decile. Since systemic risk and aggregate risk should have a positive relationship, firms with higher systemic risk exposure tend to be more sensitive to the market risk, which is shown by a (nearly) monotonic increase in market-beta from the lowest to the highest decile in the univariate SI-sort. Similarly, the SMB coefficient decreases almost linearly across the ten portfolios. Since financial firms usually have higher leverage than firms in non-financial industries, the value factor loadings are positive and quite large for all portfolios. One explanation for the difference in the risk characteristics of lowest decile is that some firms in this portfolio have a negative risk contribution, i.e. they are risk absorbers in the market. Hence, it is harder to predict the risk profile of this portfolio.

A long-short portfolio that goes long \$1 in the highest value-weighted (equal-weighted) decile and short \$1 in the lowest value-weighted (equal-weighted) decile loses 4.06% (3.03%) over the entire sample. Though the long-short portfolio is a good way to control for industry-specific risks, and regressing against Fama-French 3 factors is a good way to control for market, size, and value premium, it is not possible to distinguish between effects of systemic risk exposure and “too-big-to-fail” implicit bailout risk subsidy. Firms that are deemed most systemically important arguably have a higher exposure to systemic risk, hence requiring higher returns. However, on the other hand, investors also expect that government would not let those important institutions fail in case of a systemic event. Due to that ex-ante expectation of implicit guarantee, investors grant top SIFIs a risk discount and demand lower returns from them.

To control for systemic risk exposure and derive a better estimate of SIFIs equity funding advantage, I attempt to build a long-short portfolio that goes long in a portfolio of the top 20 most important institutions (the 10th decile), and short in a portfolio of firms between top 20-40 in SI rankings (the 9th decile). The rationale for that practice is as follows. First, only the very top financial institutions may earn the “too-big-to-fail”, or in this case, “too-important-to-fail” status and risk subsidy. The financial crisis in 2008 has shown that the government is willing to let such a big name like Lehman Brothers and many other medium size banks go bankrupt, but save other arguably more important firms such as AIG, Freddie and Fannie. In my 2007 systemic importance ranking, Lehman Brothers stays at 18th, while AIG is ranked 4th, and both Freddie and Fannie are inside the top 10.

Second, the top two deciles have a very similar exposure to systemic risk. If we consider the equity losses in the 2008 financial crisis as a rough proxy to systemic risk exposure, Panel C in Table 1.5 shows that the difference between the highest and lowest SI-sorted portfolios (using data in the first six months of 2007) is very large, nearly 20% and statistically significant at the 5% level. However, the difference between the top two deciles is much lower, about 10%, and not statistically significant (t-stat = 1.25). Hence, the long-short “Hi-9” portfolio is an ideal candidate to study the “too-important-to-fail” risk subsidy, as it can control for different exposures to industry, market, size, value, and systemic risk, while leave out the effect of being systemically important. The spread in risk-adjusted returns on that long-short portfolio, which can be interpreted as the "too-important-to-fail" risk subsidy, is 3.86%.

In the next section, I attempt to separate the effects of size and systemic importance on cross-section returns by forming double-sorted portfolios.

1.5.2 Double Sorts

In this subsection, I form portfolios by double sorting size and systemic importance index to distinguish their effects on equity returns of top financial firms. The result is that the spread between the most and least systemically important firms is negative and significant at the 5% level, after controlling for the size effect. However, when controlled for systemic importance, a portfolio that long largest firms and short smallest firms earn a positive but not significant return. In other words, the size effect is subdued by the systemic importance effect even though the two measures are highly correlated.

Panel A in Table 1.6 reports results when the size effect is controlled for. Specifically, I first sort firms into five quintiles based on their market capitalization, and then, within each quintile, sort firms into quintiles based on their systemic importance. Finally, I collapse the double-sort back to a single-sort by combining all stocks in the five size quintiles with the same SI rank number. The main objective of this practice is to have firms with all sizes in each SI quintile, so that the size effect would be equally divided and neutralized across five portfolios with different SI rankings.

Similarly, in Panel B, I report results from portfolios with different firm sizes but the systemic importance is controlled. In particular, I first form five quintiles sorted on systemic importance index, then within each SI quintile, I sort firms into quintiles

Table 1.6: Portfolios of top financial institutions formed on double sorting Size and Systemic Index (1970 - 2018)

This table reports annualized average value-weighted excess returns on portfolios double sorted by size and SI, and estimates from Fama-French 3-factor regressions. In Panel A, I first sort firms into quintiles based on their market capitalization, and then, within each quintile, sort firms into quintiles based on their systemic importance. For each SI quintile, I combine all stocks in the five size quintiles with the same SI rank number, collapsing the double-sort back to a single-sort. The main objective of that exercise is to form portfolios that are controlled for size effects. In Panel B, the double-sorting order is reversed to control for systemic importance effects. $Avg(ME)$ and $Avg(SI)$ are the portfolio average market capitalization and average total risk contribution, respectively. Excess returns and alphas are annualized by multiplying by 12 and expressed in percentages. $*$, $**$, $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Low	Q2	Q3	Q4	High	Hi-Lo
Panel A: Controlled for Size						
$vwret$	8.28***	9.48***	8.16***	7.32***	5.04***	−3.24*
α	−1.08	−0.60	−1.92	−2.76*	−5.88***	−4.80**
MKT	1.09***	1.10***	1.17***	1.20***	1.31***	0.21***
SMB	−0.02	0.00	−0.11*	−0.19***	−0.24***	−0.22***
HML	0.46***	0.63***	0.58***	0.57***	0.61***	0.15***
R^2	72.9	76.2	73.5	73.0	71.6	5.6
$Avg(ME)$	3.64	3.62	4.30	6.12	12.28	NA
$Avg(SI)$	0.03	0.26	0.42	0.66	1.63	NA
Panel B: Controlled for Systemic Index						
$vwret$	7.32***	9.11***	9.08***	7.29***	5.55***	−1.77
α	−5.71***	-2.33	-1.67	−2.91**	−4.00**	1.71
MKT	1.35***	1.22***	1.18***	1.20***	1.19***	−0.16***
SMB	0.14**	0.03	−0.11**	−0.10**	−0.25***	−0.39***
HML	0.86***	0.74***	0.71***	0.54***	0.48***	−0.38***
R^2	68.9	74.4	75.0	79.0	77.6	18.2
$Avg(ME)$	1.5	2.56	3.79	6.27	15.89	NA
$Avg(SI)$	0.28	0.34	0.43	0.60	1.32	NA

based on their market capitalizations. After that, for each size quintile, I combine all stocks in the five SI quintiles with the same size rank to form portfolios controlled for systemic importance.

One reason that we do not have completely equal average market value across all portfolios in Panel A is that size and systemic importance are highly correlated. In fact, size is explicitly included in the calculation of systemic importance in equation 1.5. Within each size-sorted quintile, firms that score higher in systemic index also tend to be bigger. However, the last two rows of each panel show that the average size and average systemic index behave exactly as we expect. For instance, when controlled for size in Panel A, the first three quintiles show very similar average market capitalization, and the range between Q1 and Q5 is much smaller than that in Panel B. On the contrary, the differences in average SI across portfolios in Panel A is much steeper than that in Panel B, where we attempt to control for SI. That implies the double-sorting approach can distinguish the effects of size and systemic importance on cross-sectional stock returns.

Interestingly, my empirical results show that the size anomaly in financial stocks documented by Gandhi and Lustig (2015) completely vanishes after controlling for my measure of systemic importance (Panel B). The risk-adjusted return on a position that long the largest firms and short the smallest firms is positive (1.71%), but is not significant. However, as shown in Panel A, the spread between the most and the least important financial institutions after controlling for the size effect is -3.24%, and 4.8% after controlling for other common risk factors such as market, size, and value.

1.5.3 Robustness Check

In this subsection, I divide the whole sample period (1970-2018) into two subperiods, 1970-1995 and 1995-2018. The main result is that the risk subsidy to top SIFIs seems to be larger in the period 1995-2018 than the period 1970-1995. One of the possible explanations for that difference may be changes in market expectation of government implicit bailout due to the savings and loans crisis in the 1980s and 1990s.

Between 1980 and 1994, over 1,600 out of 3,234 savings and loans associations insured by the FDIC were closed or received FDIC financial assistance. However, none of the top banks went bankrupt, and only 1 percent of failed institutions from 1986 to 1994 had more than $5 billion in assets (FDIC, 1997). Most notably, in 1984, the FDIC infused $1 billion in new capital to rescue Continental Illinois Corporation, which is the seventh largest bank at that time. According to C. T. Conover, the Comptroller of the Currency from 1981 to 1985, the reason for Continental's bailout was the concerns about systemic risk and "the continued operation of such a bank is essential to provide adequate banking service in the community" (Barth and Prabha, 2014). For a comparison, the largest bank in 1981 was Bank of America, with total assets of $118.54 billion, while Continental Illinois had $45.15 billion in total assets. The largest banks that went bankrupt in the 1980s banking crisis such as Gibraltar Savings (1989), Bank of New England (1991), Home Fed Bank (1992), Southeast Bank (1991), and City Savings (1989) had total assets ranging from $9.8 to $13.4 billion.

Table 1.7: Risk-Adjusted Returns on Portfolios of top Financial Institutions Sorted by Systemic Index - Robustness Check

This table provides replicated results from table 1.5 over two sub-periods: 1970 - 1995 and 1995 - 2018. Panel A (B) reports value-weighted (equal-weighted) annualized excess returns and estimates from Fama-French 3-factor regressions over period 1970 - 1995. Panel C and D reports results over period 1995 - 2018. Excess returns and alphas are annualized by multiplying by 12 and expressed in percentages. $*$, $**$, $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Low	2	3	4	5	6	7	8	9	High	Hi-Lo	Hi-9
					Panel A: Value-Weighted Excess Returns, 1970 - 1995							
$vwret$	6.85*	7.33*	7.19*	8.37**	10.05**	9.82**	6.34	7.78*	8.07**	4.14	−2.71	−3.93**
α	−2.47	−2.36	−2.06	−0.08	−1.40	−2.01	−4.59**	−2.05	−1.36	−4.12**	−1.65	−2.76*
MKT	1.12***	0.90***	0.94***	0.85***	1.03***	1.15***	1.17***	1.16***	1.21***	1.23***	0.11	0.02
SMB	0.41***	0.71***	0.62***	0.67***	0.76***	0.58***	0.38***	0.32***	-0.02	−0.33***	−0.74***	−0.31***
HML	0.31***	0.52***	0.43***	0.37***	0.67***	0.65***	0.53***	0.38***	0.35***	0.22***	−0.09	−0.13*
R^2	69.70	70.11	69.33	66.16	71.37	74.29	75.66	71.05	77.01	73.97	15.70	10.56
					Panel B: Equal-Weighted Excess Returns, 1970 - 1995							
$eqret$	5.58	6.64	6.87*	10.52**	9.27**	10.70**	6.55	8.01*	7.48*	4.73	−0.85	−2.75
α	−3.82*	−4.68*	−3.95*	−0.33	−3.18	−1.57	−5.49**	−2.91	−2.65	−4.22*	−0.40	−1.57
MKT	1.01***	0.91***	0.95***	0.96***	1.08***	1.17***	1.24***	1.22***	1.26***	1.26***	0.25***	0.00
SMB	0.74***	1.03***	0.89***	0.92***	0.85***	0.65***	0.53***	0.35***	0.07	−0.27***	−1.01***	−0.34***
HML	0.35***	0.70***	0.60***	0.60***	0.76***	0.69***	0.61***	0.49***	0.40***	0.29***	−0.06	−0.11*
R^2	75.07	71.53	69.85	70.02	72.05	75.72	76.33	75.00	76.24	71.61	28.61	13.30
					Panel C: Value-Weighted Excess Returns, 1995 - 2018							
$vwret$	10.98***	8.98**	11.26***	11.33***	9.92***	11.74***	11.56***	10.88***	11.00***	7.56*	−3.42*	−3.44**
α	1.57	−0.65	2.24	2.36	−0.07	1.60	1.33	0.87	0.40	−4.15**	−5.73*	−4.56***
MKT	0.97***	0.92***	0.83***	0.85***	0.94***	0.99***	1.04***	1.04***	1.13***	1.27***	0.30***	0.14***
SMB	−0.05	0.11**	0.18***	0.09*	0.07	0.00	−0.10*	−0.15***	−0.21***	−0.29***	−0.24***	−0.08
HML	0.65***	0.78***	0.75***	0.75***	0.90***	0.89***	0.82***	0.77***	0.77***	0.84***	0.19**	0.06
R^2	55.84	65.95	65.04	66.48	72.81	74.78	71.95	71.88	79.61	79.01	8.25	5.47
					Panel D: Equal-Weighted Excess Returns, 1995 - 2018							
$eqret$	13.11***	9.72**	11.71***	10.27***	10.21**	12.16***	11.43***	11.78***	10.72**	8.52*	−4.59**	−2.20*
α	1.81	−1.23	1.34	0.30	−0.30	1.96	0.47	0.68	−0.79	−4.01**	−5.82**	−3.22*
MKT	1.07***	1.00***	0.87***	0.87***	0.95***	0.94***	1.06***	1.10***	1.19***	1.34***	0.27***	0.15***
SMB	0.22***	0.31***	0.47***	0.32***	0.18***	0.11***	0.00	−0.06	−0.16***	−0.28***	−0.50***	−0.12***
HML	0.84***	0.86***	0.91***	0.90***	0.98***	0.95***	0.96***	0.94***	0.90***	0.93***	0.09	0.03
R^2	63.14	65.40	68.95	68.49	72.42	72.19	73.19	74.85	79.88	81.85	15.48	7.73

The belief that the government is willing to let medium but not most systemically important financial institutions fail seems to hold true throughout the history. That market ex-ante anticipation of government implicit fail-proof guarantee explains the large and negative risk-adjusted returns on the portfolio of the most important firms, which is approximately -4 percent across sub-samples and portfolio weighting approaches. However, when controlled for systemic risk exposure and other common risk factors, the risk subsidy that top SIFIs earn is 2.76 percent over the period 1970 - 1995, but jumps to 4.56% over the period 1995 - 2018. The results imply that despite all the new regulations to mitigate the impact of the "too-big-to-fail" status after the banking crisis in the 1980s, the stock market still grants top SIFIs a favor in equity funding costs. That ex-ante distortion encourages top SIFIs to take excessive risk, creating negative externalities which demand government intervention. In reality, one of the regulations proposed by the Basel committee after the 2008 financial crisis to address this issue is the capital surcharge imposed on banks classified as global systemically important (G-SIB). All else equal, the higher capital requirement leads to less earnings per share, which suppresses demand from investors. It would be very interesting to see how the SIFIs risk subsidy changes in the future as a consequence of the additional capital charge.

1.6 Concluding Remarks

In this chapter, I present a different approach to measure the systemic importance of all financial institutions using market data. A firm is deemed systemically important when its idiosyncratic shocks could significantly raise the volatility of the financial system. Using modeling techniques in the multivariate GARCH framework, I estimate the expected volatility and covariance of each firm in the sample, then aggregate them to obtain an estimate of the financial system risk. Then, systemic importance index is defined as the risk contribution of each individual firm to the total system risk. Using this estimation strategy, I can track the sources and contributors of the financial system risk in real time without private data.

My empirical results show that the potential spillover risk due to system connectedness is the main driver of the total risk. More precisely, the aggregate connectedness risk can account for approximately 80% of the total financial system risk. That result emphasizes the importance of the cross-sectional dimension in the systemic risk literature. In addition, I show that my systemic importance index describes a broader picture of the financial risk and provides better predictions about equity losses of the top financial institutions during the 2008 financial crisis, compared to other systemic risk measures.

The second finding of my paper is that systemic importance, instead of size, is the main factor account for the risk subsidy that top financial institutions receive from the equity market. That funding advantage is roughly 4 percent annually over a long period from 1970 to 2018. Interestingly, the "too-important-to-fail" risk subsidy seems to increase after the banking crisis in the 1980s despite more regulations imposed to address the moral hazard concerns about big banks. This finding hence strongly supports a rising call in the literature for more comprehensive macroprudential policies, instead of focusing only on the strength of individual financial institution.

In my future works, I would like to dig deeper into balance sheet and asset holdings data to further study risk the characteristics of each individual financial institution. The framework I present in this paper is flexible enough to accommodate this task. For example, instead of using the market capitalization, we could use market shares of specific assets and their risk indices to derive a risk-adjusted value weight for each firm to estimate its risk contribution. By doing so, a firm that holds more risky assets would receive a boost in the systemic importance ranking. However, there are several serious challenges in executing this approach. For instances, how do we estimate the risk index of each asset class? How should we incorporate high-frequency market and low-frequency balance sheet data to have a hybrid model? Though I do not have clear answers for those questions right now, the literature in measuring systemic risk seems to be still in an early stage and has a lot of promises.

Chapter 1 References

Daron Acemoglu, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608, 2015.

Viral V Acharya and Tanju Yorulmazer. Information contagion and bank herding. *Journal of money, credit and Banking*, 40(1):215–231, 2008.

Viral V Acharya, Deniz Anginer, and A Joseph Warburton. The end of market discipline? investor expectations of implicit government guarantees. 2016.

Viral V Acharya, Lasse H Pedersen, Thomas Philippon, and Matthew Richardson. Measuring systemic risk. *The Review of Financial Studies*, 30(1):2–47, 2017.

Tobias Adrian and Markus K. Brunnermeier. Covar. *American Economic Review*, 106(7):1705–41, July 2016.

Franklin Allen and Douglas Gale. Financial contagion. *Journal of political economy*, 108(1):1–33, 2000.

Andrew Ang, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang. The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1):259–299, 2006.

Andrew Ang, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang. High idiosyncratic volatility and low returns: International and further us evidence. *Journal of Financial Economics*, 91(1):1–23, 2009.

Andreas Barth and Isabel Schnabel. Why banks are not too big to fail–evidence from the cds market. *Economic Policy*, 28(74):335–369, 2013.

James R Barth and Apanard Penny Prabha. An analysis of resolving too-big-to-fail banks throughout the united states. *Journal of Regional Analysis and Policy*, 44 (1100-2016-90137):1, 2014.

Luc Bauwens, Sébastien Laurent, and Jeroen VK Rombouts. Multivariate garch models: a survey. *Journal of applied econometrics*, 21(1):79–109, 2006.

Anne Beatty and Scott Liao. Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, 58(2-3):339–383, 2014.

Monica Billio, Mila Getmansky, Andrew W Lo, and Loriana Pelizzon. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics*, 104(3):535–559, 2012.

Tim Bollerslev. Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3):307–327, 1986.

Tim Bollerslev, Robert F Engle, and Jeffrey M Wooldridge. A capital asset pricing model with time-varying covariances. *Journal of political Economy*, 96(1):116–131, 1988.

Tim Bollerslev et al. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized arch model. *Review of Economics and statistics*, 72(3): 498–505, 1990.

Christian Brownlees and Robert F Engle. Srisk: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies*, 30(1):48–79, 2016.

Markus K Brunnermeier and Lasse Heje Pedersen. Market liquidity and funding liquidity. *The review of financial studies*, 22(6):2201–2238, 2008.

Francis X Diebold and Kamil Yılmaz. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134, 2014.

Fernando Duarte and Thomas M Eisenbach. Fire-sale spillovers and systemic risk. *FRB of New York Staff Report*, (645), 2018.

Robert F Engle. Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, pages 987–1007, 1982.

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1):3–56, 1993.

Eugene F Fama and Kenneth R French. Multifactor explanations of asset pricing anomalies. *The journal of finance*, 51(1):55–84, 1996.

FDIC. *History of the Eighties: Lessons for the Future. Vol. 1, An Examination of the Banking Crises of the 1980s and Early 1990s*. Federal Deposit Insurance Corporation (FDIC), 1997.

Xavier Freixas, Luc Laeven, and José-Luis Peydró. *Systemic Risk, Crises, and Macroprudential Regulation*. Mit Press, 2015. ISBN 9780262028691. URL `http://www.jstor.org/stable/j.ctt17kk82g`.

Fangjian Fu. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of financial Economics*, 91(1):24–37, 2009.

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

Stefano Giglio, Bryan Kelly, and Seth Pruitt. Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, 119(3):457–471, 2016.

Bernard Herskovic, Bryan Kelly, Hanno Lustig, and Stijn Van Nieuwerburgh. The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics*, 119(2):249–283, 2016.

OFR Viewpoint. *Size Alone is Not Sufficient to Identify Systemically Important Banks*. Number 17-04 in Viewpoint Papers. Office of Financial Research, US Department of the Treasury, 2017.

Chapter 2

Risk-transferring, Regulatory Arbitrage and Portfolio Choices under Securitization

2.1 Introduction

Securitization is one of the most innovative financial practices in the banking industry over the last four decades. A traditional lending model would describe banks as a financial intermediary that uses deposits to fund loans which are kept until maturity. However, with the evolution of securitization, modern banks nowadays have an option to syndicate a fraction of loans they originate into a pool,[1] which then issues claims to the interest payments from the underlying assets. These claims can be called "asset–backed securities" (ABS) or "mortgage-backed securities" (MBS) depending on the structure of the pool.

Historically, at its birth in the 1970s, securitization was strictly confined to mortgage loans. At the first glance, it seems to be a brilliant innovation. Since mortgage

[1] a pool of loans can be held either by government-sponsored enterprises such as Fannie Mae and Freddie Mac, or by the bank's own special purpose entities.

loans are usually a long-term contract that requires a good chunk of initial capital, by converting a pool of illiquid assets into tradable claims, securitization process provides a substantial amount of liquidity to the banking and housing market, lowering funding costs and helping banks economize on equity. On the other hand, due to the intrinsic diversification benefits of assets pooling, securitization also offers outside investors an additional channel of safe investments. However, securitization has evolved over time from a simple practice into an extremely complex process that involves a long chain of highly specialized intermediaries, known as the shadow banking system (Pozsar et al., 2013). Since the 1990s, not only mortgage loans, but credit card receivables, auto loans, and other forms of debt have been securitized through private markets. As a result, securitization has become a major funding channel in the U.S. economy. In 2005, for the first time, the U.S. non-mortgage private securitization issuance exceeded U.S. corporate bond issuance; and as of April 2011, the total outstanding securitized assets reached \$11 trillion in value to be the largest bond market, surpassing the size of all outstanding marketable U.S. Treasury securities (Gorton and Metrick, 2013).

This chapter proposes a theoretical model to analyze bank's balance sheet behaviors when engaging in securitization. In this model economy, a large number of risk-neutral banks actively choose a portfolio to maximize its expected return subject to the regulatory capital requirement and bank internal risk management constraints. To highlight the role of securitization in bank portfolio choices, I study two environments in which only one allows banks to convert a fraction of their risky assets into securitized claims. Banks are assumed to have different idiosyncratic risks. When securitization is absent, there exists a risk threshold that safer banks are constrained by the capital regulation, while riskier banks are constrained by the internal risk governance.

There are two incentives that motivate banks to participate in securitization. The first one is risk-transferring channel. By converting a portion of risky investments into fully diversified assets, a bank can reduce its idiosyncratic risks and lower the extreme-case loan loss provision (Value at Risk). However, lower VaR then allows the bank to take more risk by originating more new loans. Thus, at the end of the day, the total bank risk exposure is not lower, even though securitization is designed to be a risk-transferring instrument. The second motive of securitization is regulatory capital arbitrage. Considered safer, securitized assets require a less capital charge by regulators. Banks then can exploit differences in regulatory costs and expected returns between different asset classes to have a higher actual leverage and fully economize on equity. Since this paper looks at securitization exclusively from the bank's perspective, it does not address the safety net abuse aspect of regulatory arbitrage. On the contrary, this paper considers securitization as an efficient contracting mechanism that helps banks more closely align regulatory measures of risk (represented by the capital charge) to the true economic risk of the asset.

The main result is that banks retain assets only if their expected return is high enough to justify their price in regulatory capital, and securitize assets whose returns do not uphold their high capital need. In other words, assets with high risk weights must have truly high risk premium to be worth keeping on the book. Moreover, the motives of securitization also vary according to the type of banks. For capital-constrained banks, regulatory arbitrage is the dominant incentive. There is a certain situation that a bank would be indifferent in holding risky and securitized assets. On the other hand, risk management is the main motive for risk-constrained banks, as they gain more by having a diversified portfolio that fully utilizes capital. Regarding the asset choices, capital-constrained banks retain relatively high risk assets, while risk-constrained banks have relatively high securitization rate.

This paper contributes to the literature of asset choices and capital structure of securitization. In particular, the model results have implications for the following questions:

1. Do banks retain riskier or safer assets on their balance sheet?

   In theory, the "lemons market" problem (Akerlof, 1970) implies that the originators can use inside information to selectively sell riskier loans to the market while keep safer ones for themselves. This view also fits the conventional wisdom that securitization is a risk-transferring instrument. On the other hand, the optimal security design literature (e.g., DeMarzo and Duffie, 1999) suggests that since investors are concerned with the adverse selection issue, to avoid "lemon's premium", the originators should sell only the least information-sensitive (i.e., lower risk) loans into the pool.

   The empirical literature also offers mixed results. For example, using a large mortgage loans data from a single major U.S. bank from 1995 to 1997, Ambrose et al. (2005) show that "lenders do indeed retain higher-risk loans for their portfolio while selling lower-risk loans into the secondary market". However, Krainer and Laderman (2014) find a quite opposite result using California mortgages data from 2000 to 2007. Particularly, they stated that "lenders appear to have sold loans through private-label securitizations that were in many ways observably riskier than the loans they retained in their portfolios."

   The prediction from this model favors the view that banks tend to securitize safer loans but only if they are in the same risk-weight category. The intuition is simple. For the same capital buffer, safer loans are more likely to generate lower returns, and thus for some banks that are not at the risk limit, they should keep the riskier ones.

2. Why is there no market for the equity tranche? Why do banks seem to issue as much highly rated securities as possible from the underlying assets in the pool? In the first step of the private securitization process, the originator (usually a bank) sells a pool of loans to its own special purpose vehicle (SPV). Then claims to the payoff are divided into different tranches based on seniority. The most senior classes get paid first and thus stay insulated from default risk and receive a higher rating. The equity tranche is the leftover claims held by the originator who receives the residual cash flow and absorbs the first loss in case of any defaults. Gorton and Metrick (2013) argue that since there is no tax advantages and no bankruptcy costs associated with the SPV, capital structure for the SPV would be indeterminate under the assumptions of the Modigliani and Miller theorem. However, it "remains a puzzle" that the originator seems to preferably fund the most risk-concentrated tranches, while offer the market mostly low-risk securities. Some may argue that it is because of a high demand for safe assets, but this paper offers a different view on this capital structure. In particular, if the risk weight of mortgage loans is too high, the bank can use this funding structure to save regulatory capital. For example, instead of holding regulatory capital for the whole pool of loans on its book, the bank can sell off most of the pool in forms of low-risk, low-return claims and keep a small portion of the most risky but highest expected return assets that nicely compensate their regulatory cost.

The rest of the paper is organized as follows. Section 2.2 studies an environment when securitization is absent, while Section 2.3 allows banks to engage in securitization. In each section, I will present the bank's balance sheet, the portfolio expected payoff, the risk measure used in the bank risk management constraint, and the bank's optimization problem. Section 2.4 concludes.

2.2 The "Originate-to-Hold" Model

Following Adrian and Shin (2010), the model is set in a one period asset market in which there are a large number of risk-neutral banks actively choosing asset holdings to maximize their expected returns. However, to motivate the regulatory capital arbitrage channel of securitization, the model departs in two ways:

i) banks are heterogeneous in their riskiness, and

ii) in addition to the internal risk constraint, banks are subject to the regulatory capital requirement.

The next subsections will describe an environment where securitization is absent, which can be interpreted as a traditional lending practice, i.e., the "originate-to-hold" model. In this economy, banks do not have any means to reduce their idiosyncratic risks. Hence, since banks vary in payoff uncertainties, some riskier banks might hit the internal risk governance limit and could not expand investments even if regulators allowed them to. On the other hand, some safer banks might not take more risks to create wealth for their shareholders, as they are constrained by the regulatory capital requirement. Whether a bank faces the internal risk limit or regulatory capital limit depends on the magnitude of bank's idiosyncratic risk and the regulatory measure of risk.

2.2.1 Bank's Portfolio

Suppose that each bank comes into period 0 with an initial equity e_i, which remains fixed during the period. The assumption that firms do not finance their investments by raising equity is common in the corporate finance literature, starting from the pecking order theory first appeared in Myers and Majluf (1984). Moreover,

Table 2.1: Bank balance sheet when securitization is not allowed

Assets	Liabilities
Risky assets, pa_i^r	Equity, e_i Deposits, $pa_i^r - e_i$

empirically, Adrian and Shin (2013) provide support for this argument in the banking industry by showing that most of changes in banks' assets can be accounted for by changes in debt, while equity is unchanged throughout the business cycles.

Given the endowed equity, the next (and last) source of funding for banks is deposit, d_i. For simplicity, we assume that banks can raise deposits at the risk-free rate r^f. This assumption can be thought of as there exists an implicit deposit insurance from the government. Hence, even though banks have a small possibility of default, households are willing to supply deposits inelastically (Diamond and Dybvig, 1983).

Now turn to the asset side of banks' balance sheet. Since securitization is not allowed, we consider only one class of asset. A claim to the risky asset is traded at market price p, which banks take as given. The total risky investments of the bank is denoted as a_i^r. This risky asset can be interpreted as either bank loans granted to ultimate borrowers or corporate bonds held by banks, where there is a default risk from borrowers. The heterogeneity in bank riskiness is modeled in a simple way. Each bank draws its risky payoff, w_i from a unique normal distribution $N(q, \sigma_i^2)$, where q is the expected payoff similar for all banks, and σ_i is bank i's idiosyncratic risk. The bank's balance sheet without securitization can be described as below:

2.2.2 Expected Payoff

For a bank with equity e_i holding a_i^r units of risky asset and $pa_i^r - e^i$ units of deposit debt, the portfolio random payoff W_i^p can be written as

$$W_i^p = a_i^r w_i - r^f (pa_i^r - e_i) \tag{2.1}$$

where w_i is the risky asset random payoff.

The bank's expected payoff is

$$E(W_i^p) = \left(q - r^f p\right) a_i^r + r^f e_i \tag{2.2}$$

where q is the risky asset expected payoff.

The first term, $\left(q - r^f p\right) a_i^r$ can be interpreted as the expected excess return for holding a_i^r. For the bank to hold any claim of the risky asset, we need to assume that $q > r^f p$, or in other words, the risky asset price p must be less than its expected discounted payoff q/r^f .

The second term, $r^f e_i$, can be interpreted as the risk-free return on equity, or in other words, the shareholders' opportunity cost of investing in the bank.

2.2.3 Value at Risk

Let L_i denote the possible economic loss of bank i's stockholders, which can be calculated by subtracting the portfolio payoff from the shareholder's outside option value

$$\begin{aligned} L_i &= r^f e_i - W_i^p \\ &= \left(r^f p - w_i\right) a_i^r \end{aligned} \tag{2.3}$$

Intuitively, $L_i > 0$ implies that the portfolio payoff is below the risk-free return that the bank's stockholders would have received had they deposited e^i to other banks (i.e. opportunity cost). However, since the expected excess return of risky asset $\left(q - r^f p\right)$ is positive, and bank's stockholders are risk neutral, they would not hold the safe deposit claims issued from other banks ex ante. In other words, we can think of the loss function as the difference between the net debt payment $r^f p a_i^r$ and the payoff from risky investment $w_i a_i^r$.

In the spirit of Stulz (2016), the role of bank's risk management is not to minimize the overall amount of risk, but to ensure that the bank's risk remains within predetermined limits based on its risk appetite. That idea can be well captured in the model by the use of a Value at Risk constraint. Generally, the $\alpha - VaR$ indicates the maximum loss that cannot be exceeded at the confidence level α. For example, if the 95%-VaR of a portfolio is \$100, then we expect the portfolio will lose \$100 or less with a probability of 95%, and lose \$100 or more with a probability of only 5%.

To make the model more tractable, we assume that all banks share the same risk appetite. Specifically, banks in the model choose the same confidence level α when measuring their value at risk. Though this assumption is quite strong, since banks with a different level of riskiness or different risk appetite might find a different optimal risk strategy, the use of a standardized risk measure is not entirely inappropriate. First, for regulatory purposes, banks are required to report their 99%-VaR over a 10-day time horizon, as well as one-day 95%-VaR in the Form 10-K (annual report) and Form 10-Q (quarterly report). Moreover, based on the data from eight largest banks in the U.S from 1994 to 2012, Adrian and Shin (2013) show that banks seem to maintain just enough equity to cover their value at risk and keep the probability of failure at a constant level over time.

Given the bank's risk appetite α, let VaR_i denote the Value at Risk of bank i. Since the risky payoff w_i is distributed as $N(q, \sigma_i^2)$, bank i's VaR can be written as the extreme loss when the risky payoff reaches the tail end of its distribution, or

$$\begin{aligned} VaR_i &= E(L_i) - Std(L_i) \cdot \Phi^{-1}(1-\alpha) \\ &= \left(r^f p + z\sigma_i - q\right) a_i^r \end{aligned} \tag{2.4}$$

where $z = |\Phi^{-1}(1-\alpha)| = \Phi^{-1}(\alpha)$. For example, $z = 1.96$ when $\alpha = 95\%$.

To have a meaningful risk measure, I assume that all banks suffer a true loss, $r^f p + z\sigma_i - q > 0$ when they receive a bad draw in the $1-\alpha$ tail end of the payoff distribution. In other words, the cost of funding to finance a unit of risky asset $r^f p$ is greater than the worst-case discounted payoff $q - z\sigma_i$ for all i.

The internal risk management constraint thus means that the bank needs its capital cushion e^i to be greater than VaR^i to maintain the risk of default below the $1-\alpha$ probability mark. The next subsection will explain the bank's optimization problem under capital and risk constraints.

2.2.4 The Bank's Problem

Endowed with the initial equity e_i, bank i takes the risky asset price p and the deposit risk-free rate r^f as given, then chooses its risky investment a_i^r to maximize the portfolio expected return $E(W_i^p)$ subject to capital and risk constraints.

Particularly, let $V_n(e_i)$ denote bank i's value function where no other funding source except deposit is allowed. The bank's problem can be written as

$$V_n(e_i) = \max_{a_i^r} E(W_i^p) \tag{2.5}$$

subject to the regulatory capital requirement

$$\omega p a_i^r \leq e_i \tag{2.6}$$

where ω is the regulatory capital charge against the risky asset. In this case, since there is only one asset, ω can also be interpreted as the capital adequacy ratio (e.g., 8% under Basel III).

The bank is also constrained by its internal risk governance, given by

$$VaR_i \leq e_i \tag{2.7}$$

where VaR_i is bank i's Value at Risk as defined in eq. 2.7.

There are two important notes regarding to the bank's choice of asset holdings:

1. The portfolio expected return, $E(W_i^p) = \left(q - r^f p\right) a_i^r + r^f e_i$ increases in the amount of risky asset holdings, as the expected excess return on risky investment is positive. The implication is that banks that do not meet any binding constraint would want to originate new loans, or invest in risky assets as much as possible.

2. The market value of bank's asset pa_i^r and its Value-at-Risk $VaR_i = \left(r^f p + z\sigma_i - q\right) a_i^r$ also increase in risky asset holdings, so the bank cannot expand its investments to infinity even though it has a risk-neutral preference.

However, since there is simply one class of asset available in this "origination" model, but the bank faces two constraints, it turns out that only one of the two is binding in optimum. Which constraint the bank faces depends on its idiosyncratic risk σ_i and the regulatory capital charge requirement ω. The relationship between bank's risk and regulatory measure of risk will be described below.

First, suppose that the bank is constrained by the regulatory capital requirement. In this case, even though the bank still has available risk-taking capacity to cover a larger value at risk, it cannot reach the desirable risk level due to regulations. We can interpret this situation as the bank's true risk is lower than the regulatory measure of risk.

Second, suppose that the bank is constrained by its internal risk management. In this case, since the bank has just enough capital to cover the current value at risk, without any means of diversification, it cannot expand its business even though regulators allow it to do so. We can interpret this situation as the bank's true risk is higher than the regulatory measure of risk.

In the regulator's perspective, if they consider the market is too risky, then they can request banks to hold more capital buffer by raising the capital adequacy ratio to avoid more bank failures. Ceteris paribus, this action would raise the number of banks that hit the regulatory requirement and stay further from their risk target. Hence, the risk threshold that makes banks switching between being constrained by the regulatory requirement and being constrained by the internal risk management can be interpreted as a regulatory measure of risk. In this simple model, that measure is a linear function of the adequacy capital ratio and can be derived from eq. 2.6 and eq. 2.7.

Specifically, let $\bar{\sigma} = \dfrac{q - r^f p + \omega p}{z}$ denote the regulatory measure of risk[2], there are two scenarios:

1. If $\sigma_i < \bar{\sigma}$, then $\omega p a_i^r = e_i > VaR_i$ implying that the bank is constrained by the regulatory capital requirement, or "capital-constrained" for short. From the

[2]See Appendix A.1 for the detailed derivation and more discussion of the risk threshold

binding constraint eq. 2.6, its risky asset holding can be derived as

$$a_i^r = \frac{e_i}{\omega p} \tag{2.8}$$

which is a function of the risky asset price, the regulatory risk weight, and the bank's equity.

The value function of the capital-constrained bank can be written as

$$V_n(e_i) = e_i \left(r^f + \frac{q - r^f p}{\omega p} \right) \tag{2.9}$$

2. If $\sigma_i > \bar{\sigma}$, then $VaR_i = e_i > \omega p a_i^r$ implying that the bank is constrained by the internal risk management, or "risk-constrained" bank for short. From the binding constraint eq. 2.7, its risky asset holding can be derived as

$$a_i^r = \frac{e_i}{z\sigma_i + r^f p - q} \tag{2.10}$$

which is a function of the bank's idiosyncratic risk in addition to the risky asset price and bank's equity.

The value function of the risk-constrained bank can be written as

$$V_n(e_i) = e_i \left(r^f + \frac{q - r^f p}{z\sigma_i + r^f p - q} \right) \tag{2.11}$$

As will be shown in the next section, the regulatory measure of risk plays a vital role in the effect of securitization on bank portfolio choices. For instance, when securitization is allowed, banks can have another funding source to finance their additional investment in risky assets while keeping the capital and risk constraints under control.

However, due to their different motives in using securitization, capital-constrained and risk-constrained banks behave differently under different pricing scenarios.

2.3 The "Originate-to-Distribute" Model

In this section, I extend the "origination" model by allowing banks to participate in the securitization market. Following Barattieri et al. (2016) and Shleifer and Vishny (2010), securitization is simply modeled as a true sale of a fraction ϕ_i of bank's risky asset holding a_i^r. The leftover $(1 - \phi_i)$ can be interpreted as the bank's "skin in the game" which is endogenously chosen by the bank. Banks who engage in securitization can sell risky assets and purchase securitized claims at the market-clearing price p_s. To simplify the notation and algebra of the bank's problem, I assume that the securitization process is implemented under the direct swap program, in which bank i receives a_i^s units of claims in the pool of securitized assets for selling/swapping $\phi_i a_i^r$ units of its own risky assets.

Since a large number of atomistic banks pool their risky payoffs together, the risk of securitized asset payoff goes to zero. This captures the conventional view of securitization as an effective instrument for financial intermediaries to diversify and reduce their idiosyncratic risks. However, in aggregate, the total market aggregate risk does not vanish, as pooling does not alter the underlying risk of individual assets brought to the market[3]. Therefore, even though banks treat the pooled securities as a perfectly safe asset ex ante, regulators still require them to hold a certain level of capital against this class of asset. For example, AAA-rated privately issued asset-backed-securities carry a 20% risk weight (i.e. 1.6% regulatory capital charge under Basel III), despite its near-zero default rate (S&P Global Ratings Report). Nevertheless, the fact that different classes of assets bear different risk weights and

[3]See Appendix A.2 for more details

returns offers banks opportunities to arbitrage on regulatory capital. The next subsection will describe a bank's balance sheet in more details.

2.3.1 Bank's Portfolio

Bank's assets now contain two types of assets, risky and securitized assets. Bank i originates a_r^i units of risky loans and sell $\phi_i a_r^i$ units of them to the securitization pool. Since securitization is a true sale, the bank effectively keeps only $(1-\phi^i)a_r^i$ units of risky asset and a_s^i units of securitized claim on its balance sheet.

On the liabilities side, in addition to deposits d_i and bank's own equity e_i, securitization is another source of funding for banks. With the assumption that securitization occurs under the direct swap mechanism, the level of deposits that the bank i needs to raise is then $d_i = (1-\phi_i)pa_i^r - e^i$. This strictly follows the pecking order theory of capital structure that internal funding (sale of risky asset) is a preferable method to raising debt. However, to avoid the arbitrage opportunity between the two funding methods, I assume that the securitization process has a linear cost function $c(\phi_i a_i^r) = r^f p\phi_i a_i^r$.

As shown in Appendix A.2, the expected return of securitized asset $E(w_s) = E(w_i) = q$ and its variance $Var(w_s) = 0$ when bank i's market share $\left(\frac{\phi_i a_i^r}{\sum_i \phi_i a_i^r}\right) \to 0$. Hence, I need to add two additional assumptions about the pricing structure of the securitized asset: First, for any bank to hold some of this class of asset, its discounted expected payoff must be higher than its price, i.e. $\frac{q}{r^f} > p_s$. Second, since the securitized bond is safer, it is obvious that its price is higher than that of risky asset, i.e., $p_s > p$.

The table below depicts the bank's balance sheet when securitization is allowed:

Table 2.2: Bank balance sheet when securitization is allowed

Assets	Liabilities
Risky assets, $(1-\phi_i)pa_i^r$	Equity, e_i
Securitized assets, $p_s a_i^s$	Asset sale, $p_s\phi_i a_i^r$
	Deposits, $(1-\phi_i)pa_i^r - e^i$

2.3.2 Expected Payoff

For a bank with equity e_i holding $(1-\phi_i)a_i^r$ units of risky asset, a_i^s units of securitized asset, and d_i units of deposit debt, the portfolio random payoff W_i^p can be written as

$$W_i^p = (1-\phi_i)a_i^r w_i + a_i^s w_s - r^f((1-\phi_i)pa_i^r - e^i) - c(\phi_i a_r^i) \tag{2.12}$$

and its expected payoff is

$$E(W_i^p) = \left(q - r^f p\right) a_r^i + r^f e_i \tag{2.13}$$

Given the assumptions that there is no arbitrage opportunity in funding source, and securitization mechanism is a direct swap, the bank's expected payoff under this distribution model (eq. 2.13) is completely similar to that under the origination model (eq. 2.2). This feature emphasizes the main business model of traditional banks as a spread earner, which is vastly different from a shadow bank, whose major income stream comes from non-interest activities. In this economy environment, banks earn exactly the same if they invest in the same amount of risky asset, regardless of which funding sources (asset sale or deposit), and asset management styles (origination or distribution model) that they choose. This model could be an oversimplified version of the reality, but it helps to highlight the differences in banks' choices and motives of securitization. In particular, banks benefit from securitization in two ways:

First, securitization helps banks to optimize the regulatory capital charge. For example, banks can reduce the risk-weighted total asset by selling a fraction of risky assets that carry a higher regulatory risk weight and investing in securitized assets that have a lower capital buffer requirement. By doing so, banks can manipulate the regulatory capital ratio, which is defined as tier 1 capital over risk-weighted total asset to their desired level without the need to shrink balance sheet too much. As a result, individual banks could appear to be safer and have better capital ratios, even though the whole industry aggregate ratios could be even worse. This portfolio shifting to minimize the capital charge can be described as the regulatory capital arbitrage motive of securitization.

Second, securitization helps banks to grow balance sheet without the need of raising risk absorbing capacity. Based on its risk appetite, a bank needs to hold a certain amount of capital to cover its value at risk. By securitizing some of its risky assets, the bank can lower its idiosyncratic risk and hence be able to reduce its needed capital buffer. However, the total risk exposure banks keep on balance sheet may not be lower, since it is optimal to utilize all of the risk-taking capacity by increasing risky investments. At the aggregate level, the shift from bank exposure to idiosyncratic risk to exposure to the more elusive connectedness risk via the securitization mechanism could be devastating when the market is under a systemic shock. This motive can be named as the risk-taking channel of securitization.

The next subsection will describe the bank's Value-at-Risk, which is the risk measure playing a vital role in the bank's risk governance.

2.3.3 Value at Risk

Similar to the previous section, the bank's economic loss function can be simply written as

$$L_i = r^f e_i - W_i^p$$

where W_i^p is the portfolio payoff variable.

Let VaR_i denote bank i's Value-at-Risk under its desirable risk target, $1 - \alpha$. Using the definition of portfolio payoff in eq. 2.12 and eq. 2.13, VaR_i can be derived as

$$\begin{aligned} VaR_i &= E(L_i) - Std(L_i) \cdot \Phi^{-1}(1-\alpha) \\ &= a_i^r \left[r^f p + z\sigma_i - q - \phi_i z \sigma_i \right] \end{aligned} \tag{2.14}$$

where $z = |\Phi^{-1}(1-\alpha)| = \Phi^{-1}(\alpha)$.

The only difference between the Value at Risk measure in eq. 2.14 (securitization allowed) and in eq. 2.7 (no securitization) is the reduction in extreme loss provision due to the true sale of risky asset, $z\sigma_i\phi_i a_r^i$. This feature asserts the important role of securitization as a risk management instrument for financial institutions. However, as shown later, the total risk exposure of individual bank is not reduced, but even upsurges in some cases (e.g. capital-constrained banks) due to the increase in total loan origination.

The next subsection will illustrate the bank's problem and analytical solution.

2.3.4 The Bank's Problem

Given the definition of expected portfolio payoff in eq. 2.13, bank i chooses how much to invest in risky assets (or originate risky loans), and the proportion of risky assets to be securitized (a_i^r and ϕ_i, respectively). Let $V_s(e_i)$ denote bank i's value function when securitization is allowed, the optimization problem can be written as

$$V_s(e_i) = \max_{a_i^r, \phi_i} E(W_i^p) \tag{2.15}$$

subject to the regulatory capital requirement

$$\omega p(1 - \phi_i)a_i^r + \omega_s p_s a_i^s \leq e_i \tag{2.16}$$

where ω and ω_s is the regulatory capital charge against risky and securitized assets, respectively.

The bank's risk governance constraint can be written as

$$VaR_i \leq e_i \tag{2.17}$$

where VaR_i is bank i's Value at Risk as defined in eq. 2.14.

The capital constraint in eq. 2.16 captures the accounting standard that if securitization is a true sale, the originator can remove the transferred assets from its balance sheet, eliminating the regulatory capital charge for these. On the other hand, the VaR constraint captures the risk transferring aspect of securitization. By converting risky assets to relatively safer claims to the securitization pool of assets, banks can free up the loan loss provision and hence reduce the capital buffer needed for the portfolio. However, in this environment without aggregate uncertainty, holding unused capital is costly and not efficient due to its opportunity cost. Banks could maximize return on equity by either reducing deposit debt, originating new loans, or investing in more securitized claims. As shown in Proposition 1 below, securitization provides banks a mechanism to utilize all of their regulatory required equity, regardless of their initial conditions before participating in the securitization market (i.e., whether eq. 2.6 or eq. 2.7 is a binding constraint).

Proposition 1. *When securitization is allowed, the regulatory capital constraint is always binding at the optimum.*

A full proof is provided in Appendix A.3.

Intuitively, since risky assets earn positive excess return ($q - r^f p > 0$), a risk-neutral bank would increase its risky holding as long as there is available room in both capital and risk constraint. In the origination model mentioned in the previous section, due to the lack of diversification and risk management mechanism, banks cannot have both binding constraints. However, in the distribution model, banks can use securitization to align the regulatory measure of risk and the true risk of the investment. As a result, both types of banks can fully utilize their available regulatory capital by originating new loans and converting them to securitized claims without breaking the risk limit. This result implies that the total risky assets in the market would increase when securitization is allowed, even though individual banks have unchanged total assets on the risk-weighted basis.

Given the binding capital constraint, and under the assumption that securitization is a direct swap, the risky asset holding can be derived as

$$a_i^r = \frac{e_i}{\omega p - \phi_i(\omega p - \omega_s p_s)} \tag{2.18}$$

Since the bank's expected payoff increases in the total risky asset origination, banks will only originate more loans when securitization is allowed, compared to their initial level in the origination model (eq. 2.8 for capital-constrained banks and eq. 2.10 for risk-constrained banks). However, there exists a threshold that makes some banks not getting benefit from securitization and prefer retaining all risky assets and opting out of the securitization market. This threshold can be derived as the ratios of expected regulatory-adjusted return between risky and securitized assets. Proposition 2 illustrates this result.

Proposition 2. *For capital-constrained banks, regulatory capital arbitrage is the main motive of securitization. They retain the risky asset if its expected regulatory-adjusted returns is equal or greater than that of securitized assets, i.e.*

$$\begin{cases} \phi = 1 & \textit{if } \dfrac{\pi}{\omega} < \dfrac{\pi_s}{\omega_s} \\ \phi = 0 & \textit{otherwise} \end{cases}$$

where ϕ is the securitization rate, $\pi = q/p, \pi_s = q/p_s$ are expected returns of risky and securitized assets, respectively, and ω, ω_s are the regulatory risk weight of the two assets.

A full proof is provided in Appendix A.4.

Intuitively, since capital-constrained banks have available risk absorbing capacity even when securitization is not allowed (as in the origination model), risk reduction is not the main motive of this type of banks when engaging in the securitization market. As a result, capital-constrained banks would only swap risky assets for securitized claims if they can earn more without altering their regulatory capital ratio. To make that happen, securitized claims must have greater expected regulatory-adjusted returns[4]. For example, suppose there are two assets: a mortgage loan that has expected return of 5% with risk weight of 50% and a mortgage-backed security that has expected return of 2% with risk weight of 20%, a bank without the need

[4]Securitized claims always have lower expected return, as they are safer. However, since its risk weight is also lower, the ratio of expected return over risk weight of securitized assets can be higher than that of risky assets

to reduce the loan loss provision would be indifferent between the two assets, since a portfolio of 1 unit of mortgage loan or 2.5 units of MBS would yield exactly equal expected return and risk-weighted total asset calculation. Hence, given the expected return and risk weight of the risky asset and its securitized version, capital-constrained banks have a binary choice whether they want to completely retain or securitize that risky asset.

Under the efficient market hypothesis, this result also implies that capital- constrained banks retain riskier assets that yield higher expected returns and securitize relatively safer ones. That makes sense because for this type of bank, regulatory capital is relatively more expensive, and hence they need to keep the riskier assets with higher expected return justify their high regulatory costs. The next proposition presents the asset choices of risk-constrained banks.

Proposition 3. *For risk-constrained banks, risk transferring is the main motive of securitization. They always have a positive securitization rate and riskier banks securitize more*

$$\begin{cases} \phi = 1 & \textit{if } \frac{\pi}{\omega} < \frac{\pi_s}{\omega_s} \\ \phi > 0 & \textit{otherwise} \end{cases}$$

and

$$\frac{\partial \phi}{\partial \sigma_i} > 0$$

A full proof is provided in Appendix A.5.

Table 2.3: Capital-constrained versus Risk-constrained banks when securitization is allowed

		$\frac{\pi}{\omega} < \frac{\pi_s}{\omega_s}$	$\frac{\pi}{\omega} = \frac{\pi_s}{\omega_s}$	$\frac{\pi}{\omega} > \frac{\pi_s}{\omega_s}$
Capital-constrained: $\sigma_i < \bar{\sigma}, a_{i0}^r = \frac{e_i}{\omega p}$	Loan origination	$a_i^r > a_{i0}^r$	$a_i^r = a_{i0}^r$	$a_i^r = a_{i0}^r$
	Securitization rate	$\phi_i = 1$	$\phi_i = 0$	$\phi_i = 0$
Risk-constrained: $\sigma_i > \bar{\sigma}, a_{i0}^r = \frac{e_i}{z(\sigma_i - \bar{\sigma}) + \omega p}$	Loan origination	$a_i^r > a_{i0}^r$	$a_i^r > a_{i0}^r$	$a_i^r > a_{i0}^r$
	Securitization rate	$\phi_i = 1$	$\phi_i = \frac{z(\sigma_i - \bar{\sigma})}{z\sigma_i} > 0$	$\phi_i = \frac{z(\sigma_i - \bar{\sigma})}{z\sigma_i + (\omega_s p_s - \omega p)} > 0$

Intuitively, risk-constrained banks need to reduce their value at risk first, by converting some of their risky assets into securitized claims, before originating new loans to reach the maximum risk-weighted total assets allowed by regulators (i.e. binding capital constraint). As a result, risk-constrained banks always participate in securitization, regardless of the expected return of the securitized assets. This further highlights the incentive of riskier banks in using securitization as a risk management tool. However, how much a bank chooses to securitize depends on its intrinsic riskiness, σ_i. The riskier banks benefit more from reducing their value at risk and therefore more willing to forgo higher-risk assets. The following table presents analytical results about the differences between capital-constrained and risk-constrained banks in the total loan origination and securitization rate under three scenarios.

The first column shows the bank riskiness level, σ_i and its initial loan origination, a_{i0}^r when securitization is not allowed. As shown in the previous section, $\bar{\sigma}$ is the threshold that determines whether banks meet the capital or risk constraint. The first row states three scenarios that compare the expected regulatory-adjusted return of risky assets to their securitized version. In the first scenario where the risky expected regulatory-adjusted return is lower than the securitized expected regulatory-adjusted return, both types of banks sell off all of their originated assets and hold only securitized assets in their portfolio. That is because banks in this model consider securitized assets as riskless and do not need to have loan loss provision for them.

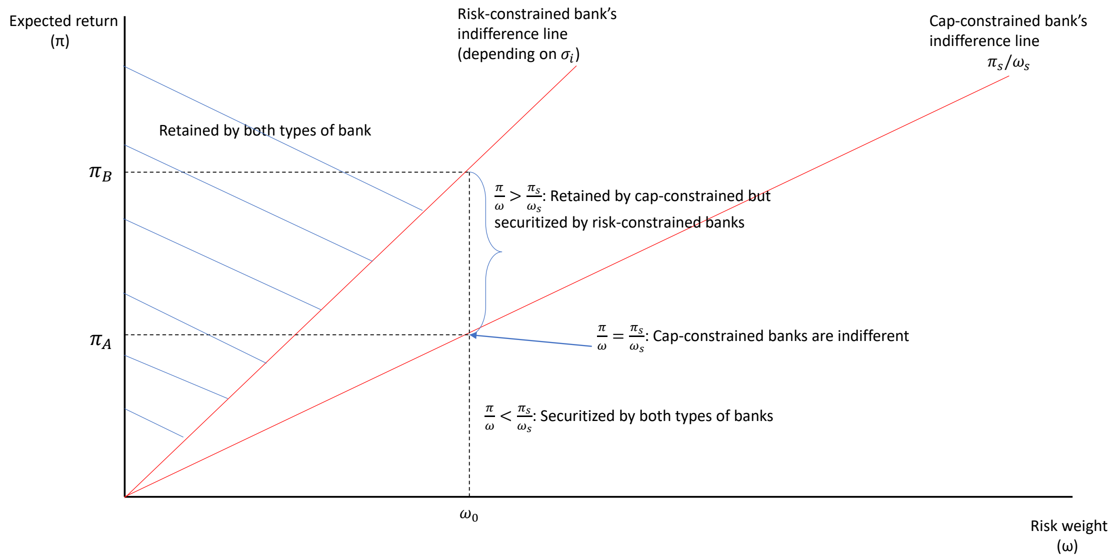
Moreover, securitized assets also have a lower risk weight and require lower regulatory capital. As a result, if its expected return after adjusting for the regulatory risk weight could surpass that of risky asset, banks would strictly prefer swapping risky assets for securitized claims. In the second and last scenarios, things are more interesting as now banks need to evaluate the tradeoff between the two types of assets. Banks need to decide whether they want to retain riskier assets with higher expected return based on their characteristics. Since capital-constrained banks have available risk-absorbing capacity, they prefer holding riskier assets on balance sheet. On the other hand, since risk-constrained banks need to enhance their risk position, they are willing to sell higher return but riskier assets and hold relatively safer assets. Additionally, risk-constrained banks benefit more from securitization when they are riskier, and so their securitization rate is higher.

The differences between two types of banks in asset choices can be visualized as in Figure 2.1. Assume that all risky assets with different pair of expected return and risk weight (π, ω) can be securitized to a pool that issues claims with expected return π_s with risk weight ω_s. Then, there exists an indifference line for each bank. If the risky asset falls above that line, it is worth retaining on the balance sheet, while if it lies below the line, the bank is better off securitizing that asset.

There are several interesting implications from these results:

1. Capital-constrained banks retain relatively riskier loans than risk-constrained banks. As shown in the figure, both capital-constrained and risk-constrained banks sell off risky assets falling in the corner right region where $\pi/\omega < \pi_s/\omega_s$, as these assets do not have high enough expected return to justify their regulatory cost. Banks are better off by holding securitized claims of these underlying assets. However, there is also a region (between two indifference lines) where capital-constrained banks choose to retain the risky asset, while risk-constrained

Figure 2.1: Capital-constrained versus Risk-constrained asset choices



banks choose to sell it off. The reason is that capital-constrained banks have better risk-absorbing capacity, and prefer to keep riskier assets with higher payoff to maximize its return on equity. On the other hand, risk-constrained banks prefer to sell it off and hold a relatively safer securitized assets to enhance their risk position.

2. Riskier banks tend to engage more in the securitization market. This is consistent with the result found in Gorton and Souleles (2007). The intuition is that risk-constrained banks find additional advantages of securitization in the risk-transferring channel, compared to capital-constrained banks who use securitization solely for the regulatory capital arbitrage motive. Moreover, as discussed previously, this extra risk-transferring benefit becomes larger for banks that have higher idiosyncratic risks.

3. The originators tend to carry more risk-concentrated security tranches, and supply mostly low-risk, high-rating securities to the market. This phenomenon

already has several possible explanations in the literature such as the reputation hypothesis or signaling mechanism, but it can also be explained by the interaction of risk-transferring and regulatory arbitrage motives proposed in this paper. For example, a bank can pool different loans in the same risk-weight category and divide the pool payoff into different tranches, where the most senior claims earn highest ratings. Then, since low-risk securities demand lower rate of return, the bank would like to sell them off, and keep only highly risk-concentrated tranches to maximize returns on its regulatory capital. In other words, the originator attempts to create different tranches of securities to squeeze out the most risk and return from the pool into a small portion that is kept on the book. Now, instead of the need to hold regulatory capital for the whole pool, the originator is required to prepare capital buffer for the small portion of the riskiest, highest expected return assets.[5] Visually, we can describe this simple pooling and tranching mechanisms by drawing a vertical line on the figure. Then, the lower end below the indifference line represents low risk premium synthetic assets (e.g., AAA rated securities) that the originator offers in the market, while the portion above the indifference line represents the most risky assets (e.g., the equity tranche) that the bank wants to keep on its balance sheet (or its SPV with implicit recourse).

2.4 Concluding Remarks

This chapter looks at the risk-transferring and regulatory capital arbitrage motives of securitization to study bank balance sheet behaviors. In the model, a risk-neutral bank chooses a portfolio to maximize its expected return subject to the regulatory

[5]though the original mortgage loans and equity tranche have a different risk weight, it is still possible to save regulatory capital by keeping the equity tranche instead of the whole pool

capital requirement and the bank internal risk governance. Securitization gives the bank an opportunity to fully utilize its risk-taking capacity allowed by regulators and have a more efficient portfolio. The main result is that a bank chooses to keep on its balance sheet only assets that justify their regulatory cost. In other words, assets with high risk weights must have truly high risk premium to be worth keeping on the book. For capital-constrained banks, regulatory arbitrage is the central motive of securitization. The bank would be indifferent in holding risky and securitized assets if their relative regulatory capital charges are correctly priced by the market. This supports the view in the regulatory arbitrage literature that securitization is an efficient contracting mechanism that helps banks align the regulatory calculation of risks to the true asset risks. On the other hand, risk-constrained banks gain additional benefit from securitization in addition to regulatory arbitrage. This risk-transferring benefit is larger for riskier banks, which makes them engage more heavily in the securitization market. With these theoretical results and their implications, this chapter attempts to offer a different view on the asset choices and capital structure of securitization.

In my future work, there are questions that may be worth further considerations. The first one involves designing an empirical framework to test whether the market evaluation of risks fully reflects the regulatory measures of risks. As predicted by this chapter, if the regulatory arbitrage is the sole motive of securitization, then we would expect equal expected returns after adjusting for risk weights across different asset classes. However, if securitization is a method for banks to take more risk as suggested by the safety net abuse view of the implicit recourse literature, then the assets that banks keep on balance sheet would have a relatively higher risk premium, while securitized/safer assets would have a lower risk premium. On the other hand, if risk-transferring is the dominant motive of securitization, then we would see banks sell off lower-quality, higher-risk assets to the securitization market, as suggested by the adverse selection literature.

Whether banks retain safer or riskier assets plays an important role in making sound regulations. For example, the regulatory arbitrage channel implies that banks engage in securitization to obtain a more efficient portfolio and be able to increase credit supply in the market, stimulating higher growth during normal time. However, since banks do not need to carry equity buffer for assets they securitize, if the risk is not truly transferred to outside investors as pointed out in Acharya et al. (2013), then the whole financial system may suffer a capital shortage when adverse exogenous shocks deteriorate the value of underlying assets in the pool. That possibility of systemic risk raise questions about the importance of capital regulations and operation standards in the securitization market.

Chapter 2 References

Viral V Acharya, Philipp Schnabl, and Gustavo Suarez. Securitization without risk transfer. *Journal of Financial Economics*, 107(3):515–536, 2013.

Tobias Adrian and Hyun Song Shin. Financial intermediaries and monetary economics. In *Handbook of monetary economics*, volume 3, pages 601–650. Elsevier, 2010.

Tobias Adrian and Hyun Song Shin. Procyclical leverage and value-at-risk. *The Review of Financial Studies*, 27(2):373–403, 2013.

Geokge A Akerlof. The market for ”lemons”: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500, 1970.

Brent W Ambrose, Michael LaCour-Little, and Anthony B Sanders. Does regulatory capital arbitrage, reputation, or asymmetric information drive securitization? *Journal of Financial Services Research*, 28(1-3):113–133, 2005.

Alessandro Barattieri, Laura Moretti, Vincenzo Quadrini, et al. Banks interconnectivity and leverage. Technical report, CEPR Discussion Papers, 2016.

Peter DeMarzo and Darrell Duffie. A liquidity-based model of security design. *Econometrica*, 67(1):65–99, 1999.

Douglas W Diamond and Philip H Dybvig. Bank runs, deposit insurance, and liquidity. *Journal of political economy*, 91(3):401–419, 1983.

Gary Gorton and Andrew Metrick. *Securitization*, volume 2 of *Handbook of the Economics of Finance*, chapter 0, pages 1–70. Elsevier, 2013. doi: 10.1016/B978-0-44-453594-. URL `https://ideas.repec.org/h/eee/finchp/2-a-1-70.html`.

Gary B Gorton and Nicholas S Souleles. Special purpose vehicles and securitization. In *The risks of financial institutions*, pages 549–602. University of Chicago Press, 2007.

John Krainer and Elizabeth Laderman. Mortgage loan securitization and relative loan performance. *Journal of Financial Services Research*, 45(1):39–66, 2014.

Stewart C Myers and Nicholas S Majluf. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, 13(2):187–221, 1984.

Zoltan Pozsar, Tobias Adrian, Adam B Ashcraft, and Hayley Boesky. Shadow banking. *Economic Policy Review*, (Dec):1–16, 2013.

Andrei Shleifer and Robert W Vishny. Unstable banking. *Journal of financial economics*, 97(3):306–318, 2010.

Rene M Stulz. Risk management, governance, culture, and risk taking in banks. *Economic Policy Review*, (Aug):43–60, 2016.

Chapter 3

Bank's Securitization Behavior - New Evidence from the 2018 HMDA Data

3.1 Introduction

Securitization has become a spotlight in many debates among academic researchers and policy makers since the 2008 financial crisis. Once considered one of the most important financial innovations in the modern banking history that helped reallocating risk and liquidity efficiently, securitization then earned negative reputation as a major troublemaker that amplified the severity of initial shocks in the mortgage market in the last downturn.

On the one hand, many criticize financial institutions engaging in securitization as displaying opportunistic behavior by lowering underwriting standards and transferring lower quality collateralized assets to the secondary market (Keys et al. (2010), Acharya et al. (2013)). However, on the contrary, Hanson and Sunderam (2013) argue that securitization markets collapsed because lenders provide too many safe, sometimes nearly riskless securities in good times, which reduces investor's incentives in building infrastructure needed to analyze a product as complex as asset-backed securities.

A seemingly simple and naive question about lenders behavior in securitization decision, such as whether they retain riskier or safer assets, turned out to be a surprisingly intensive debate in both theoretical and empirical literature, spanning several decades (see Ambrose et al., 2005; An et al., 2009; Calomiris and Mason, 2004; Duffie, 2008; among others). The real challenge in finding a conclusive answer to the question lies on the lack of granular loan-level data and full understanding of securitization motives.

In this chapter, I analyze the bank choices in securitization using the completely revamped Home Mortgage Disclosure Act (HMDA) database from the Federal Financial Institutions Examination Council (FFIEC). The full database is published in August, 2019 and includes more than two dozens of entirely new data points that reveal a glimpse of transaction-level characteristics of mortgage loans that originators choose to hold on balance sheet or sell to the secondary market. To the best of my knowledge, it is the first time we have a public dataset at that level of comprehension and granularity. Combining the HMDA data with the popular Call Reports, I can obtain unique bank-loan observations to test three hypotheses:

First, banks that are constrained by the capital regulation are more likely to retain riskier loans and have a higher securitization rate. Intuitively, since all residential mortgage loans require banks to hold the same amount of capital for every dollar they originate regardless of the loan intrinsic credit risk, capital-constrained banks would prefer to keep high-risk-premium loans on their book to maximize return on their scarce capital. Moreover, banks closer to the binding regulatory constraint would need to improve their capital ratio. There are two ways to do that, either issuing more capital or reducing risk-weighted total assets. Typically, the first approach is not adopted to avoid diluting current shareholders (Myers and Majluf, 1984) and manipulating the risk-weighted asset calculation is much more favorable. As a result, those banks tend to have a higher securitization rate since they need to swap more of their own originated loans that bear a higher risk weight for lower risk weight assets such as agency mortgage-backed securities and T-bill. In short, capital-constrained banks exploit securitization as an instrument to utilize their limited capital and manipulate the regulatory capital ratio.

Second, riskier banks are more likely to retain low-risk-premium loans and safer banks are more likely to retain shorter-term loans. Apparently, securitization is a mechanism for banks to off-load credit risk and create liquidity by transferring claims of the loan future cash flows to a third party. This practice incentivizes banks to change their lending business from the traditional "originate-to-hold" to the "originate-to-distribute" model (Bord and Santos, 2012). As banks have more information about borrowers, they can "cherry-pick" to retain loans that fit their risk appetite and liquidity need. As a result, banks that have a higher riskiness level would prioritize in reducing their total risk by selling high-risk-premium loans. On the other hand, safer banks may find more attractive but riskier investments from the mortgage market and improve their liquidity position by selling longer-term loans. In a nutshell, banks may have different strategies and actively manage their mortgage loan portfolio.

Third, risk transferring dominates regulatory capital arbitrage as the main interest of banks in securitization. There are two possible explanations for this hypothesis. First, as Stulz (2016) argues, since risk management is the practice of using a large set of rigid procedures and limits to keep a bank's total risk below some pre-determined level (i.e. risk appetite), risk measurement can never be perfect and sometimes inappropriately inflexible. As a result, increases in risk exposure are frequently prohibited even when taking more risk would be manageable and profitable to the bank. In other words, it is totally rational for banks to be more conservative in choosing which loans to retain and which to unload off the balance sheet. Second, all banks in 2018 were deeply well capitalized. Hence, only a small number of banks in the sample may find the need to manipulate their capital ratios to accommodate the stress test conducted by the FED. Subsequently, bias toward low-risk-premium assets and abundant capital make banks seemingly engage in securitization as a channel to enhance their risk and liquidity management.

My empirical findings show clear distinctions in behaviors and motives in securitization when banks meet different constraints.

In particular, banks having lowest tier 1 capital ratio retain significantly riskier loans, which are on average 14 basis points (or about 30%) higher in risk premium than loans they sell to the secondary market. Moreover, capital-constrained banks securitize more than 70% of their total originated mortgage loans, which is much higher than the market average of 65%. The securitization rate of banks in the group of highest capital ratio is also much lower, merely 48%. These results provide evidence for the literature viewing securitization as a possible way for banks to legally bypass the regulatory capital requirement.

On the other hand, the group of riskiest banks, measured by the charge-off rate, retain loans that earn significantly less (10 basis points) in risk premium, compared to the loans they sell to third-party buyers. In addition, though the average lengths of retained and sold loans originated by riskier banks are indistinguishable (about 320 months), safer banks choose to keep shorter term loans (about 287 months) and unload loans with much longer maturity (about 330 months). These results provide evidence for the literature featuring asymmetric information in bank securitization behaviors.

In a counterfactual exercise where each of the bank constraint is removed, I see a much bigger change in the securitization rate when the risk constraint is removed than when capital constraint is removed. Particularly, when no banks meet the risk limit, they lose incentives in transferring risk via securitization, yielding a drop of 2.64% in the conditional securitization probability from the actual level of 65.9%. On the other hand, when capital-constrained banks become overly capitalized, they lose incentives in holding riskier loans to utilize their required capital buffer, resulting in more loans being sold off and an increase in securitization rate. However, the increase is quite small, only 0.21%, and completely disappears when both constraints are removed, suggesting that risk transferring, not capital arbitrage is the dominant motive of securitization.

The rest of the paper is organized as follows. In Section 3.2, I offer a brief review of related literature. Section 3.3 describes the data used in the empirical analysis. Section 3.4 provides a summary of the overall characteristics of loans originated, retained, and sold by banks in the sample. Section 3.5 presents the different behaviors of capital and risk-constrained banks participating in securitization. Section 3.6 contains the analysis of a simple securitization decision rule. Section 3.7 demonstrates a counterfactual exercise to quantify the impact of the capital and risk constraint. Section 3.8 concludes.

3.2 Related Literature

This paper contributes to at least three different tranches in the securitization literature.

First, there have been theoretical debates about the role of securitization in bank asset choices. On the one hand, the "lemon market" problem (Akerlof, 1970) implies that mortgage originators know more about their borrowers and can use this informational advantage to selectively sell riskier loans to the market while keeping safer ones for themselves. That leads to a secondary market that is populated with lower-quality assets and more prone to shocks in the downturn. In this perspective, securitization is an instrument for individual banks to convert idiosyncratic credit risk to more elusive systemic risk that only materializes in extreme scenarios (Acharya et al., 2013; Gorton and Souleles, 2007; Pozsar et al., 2013). However, on the other hand, the optimal security design literature (DeMarzo and Duffie, 1999; Dang et al., 2012) suggests that since investors are also concerned with the adverse selection issue, originators can avoid the "lemon's premium" by maintaining their reputation and selling only the least information-sensitive and safe loans into the pool. From this point of view, the secondary market can have a suboptimal and inefficient amount of safe securities in good times, resulting in the lack of information infrastructure which can be harmful when the market goes south (Hanson and Sunderam, 2013). My results present a clear contrast in asset choices between banks facing different constraints. This suggests that we need a more complex theoretical model involving bank heterogeneity to study bank behavior in securitization, which is a crucial task to improve the stability and resiliency of the financial market.

Second, there have also been mixed empirical results regarding the characteristics of loans that banks retain on balance sheet. For example, using a large mortgage loans data from a single major U.S. bank from 1995 to 1997, Ambrose et al. (2005) show that lenders do indeed retain higher-risk loans for their portfolio while selling lower-risk loans to the secondary market. However, Krainer and Laderman (2014) find a quite opposite result using California mortgage data from 2000 to 2007. Particularly, they report "lenders appear to have sold loans through private-label securitizations that were in many ways observably riskier than the loans they retained in their portfolios". As both studies use private and confidential loan-level data either from a single bank or from banks in the same geographic location, a clear limitation is the possible sample selection bias due to the lack of comprehensive cross-sectional variations in securitization behavior of banks with different characteristics. My paper attempts to shed light on this issue by using a unique combination of the revamped HMDA and Call Reports that covers more than five hundred banks and millions of mortgage loans originated by them.

Lastly, my results provide some important implications for financial systemic risk regulations. For instance, since capital-constrained banks tend to hold riskier assets on balance sheet to increase returns without breaching the regulatory capital requirement. The tendency could cause troubles during a downturn when banks need to increase loan loss reserve and hence put more stress on the bank capital ratios. In that scenario, though counter-intuitive, banks would shift their portfolio toward riskier but fairly priced assets, given the bank risk appetite is unchanged and assets are in the same class with fixed risk weights. As a result, bank capital ratios may still look good, but the underlying risk exposure may not be as sound as it appears. There have been several proposals by the BIS to more closely align the regulatory calculation of risks with the true asset risk. One of the most promising regulations that may come up in the next Basel capital framework is the introduction of different risk weights for residential mortgage loans that have different risk characteristics. Moreover, in addition to imposing capital and liquidity regulations based on the size of bank total assets as in the current updated framework, we might also need more regulations based on finer bank characteristics such as net-charge-off or delinquency rates.

3.3 Data

There are two main data sources used for this research: loan-level data from HMDA, and bank-level data from Call Reports. The following subsections will provide a brief description of those data sets.

3.3.1 Home Mortgage Disclosure Act

The Home Mortgage Disclosure Act was enacted in 1975 to address the public concern over the discrimination in mortgage loan approval for certain ethnics, genders, and neighborhoods. Prior to 2018, all financial institutions covered under the HMDA are required to report the application decision, the loan type, purpose, and amount, the borrower's race, income, and gender, among other things. Nevertheless, since the original purpose of the HMDA is to identify possible discriminatory lending patterns, the collected data lack many variables related to the loan risk and liquidity characteristics, which are the main determinants of bank's securitization decisions.

However, the Dodd-Frank Act enacted in 2010 after the subprime mortgage crisis has significantly changed the amount of information related to mortgage lending transactions that financial institutions have to disclose. In particular, the 2018 HMDA data released in August, 2019[1] include a total of 25 brand-new and 14 modified variables revealing formerly non-public information about characteristics of mortgage loan applications. Hence, for the first time, we can study the differences between loans that banks choose to retain on balance sheet and loans that banks sell off in the secondary market.

All 48 existing and new variables in the 2018 HMDA data can be grouped into 4 major categories:

[1]Technically, the 2018 data is firstly available in April, 2019, but the public aggregate dataset is not downloadable until August, 2019

1. Loan Characteristics: Loan amount, loan term, loan purpose, loan type, application date, open-end line of credit flag, reserve mortgage flag, non-amortizing features, intro rate period, prepayment penalty term, application channel, conforming loan flag, type of purchaser, lien status, legal entity identifier of issuer.

2. Applicant Characteristics: Debt-to-Income ratio, loan-to-value ratio, age, race, sex, HOEPE status.

3. Property Characteristics: Occupancy type, property value, manufactured home secured property type, manufactured home land property interest, number of units, property location, construction method.

4. Pricing Outcome and Components: action taken, rate spread, interest rate, total loan costs, discount points and lender credits, origination charges, reason for denial.

3.3.2 Call Reports

To study whether regulatory arbitrage or risk transferring is the main motive of bank's securitization choice, I need to match loan characteristics to their originator's conditions. Since mortgage loans in the HMDA data are originated by both depository (banks) and non-depository (shadow banks) financial institutions, the first step is to separate lenders into two groups. I classify mortgage originators as banks if they are FDIC-insured financial institutions who have records in the Federal Reserve's Consolidated Report of Condition and Income (Call Reports). Particularly, from the Call Schedule ENT, I obtain the financial institution's Legal Entity Identifier (LEI) that is used to identify banks in the HMDA data. Mortgage lenders existing in the HMDA data without LEI from the Call reports are classified as shadow banks.

Bank capital ratios such as total risk-based capital and tier 1 capital ratio are chosen to identify "capital-constrained" banks. On the other hand, I use the charge off rate defined as total charge-offs over total outstanding loans as a proxy for bank risk. To match with the loan origination date in the HMDA data, I use the December 2018 Call Reports for bank-level statistics.

3.4 Differences in Loan Characteristics between Sold and Retained Loans

This section reports characteristics of conforming residential mortgage loans originated by all of 540 FDIC-insured financial institutions that have non-exempt records in HMDA data set[2]. For fair comparison, I select only a subset of loans that are easily resalable for the analysis. As a result, all non-conforming, for-commercial-purpose loans and open-ended line of credit are excluded. I classify a loan as "sold" if it is associated with a purchaser and as "retained" otherwise. Though government-sponsored enterprises such as Fannie Mae, Ginnie Mae, and Freddie Mac are dominant buyers in the secondary mortgage market (more than 75% of total conforming loans sold), other types of purchaser reported in the HMDA data include Farmer Mac (less than 0.1%), Private securitizer (0.3%), Commercial banks or savings associations (9.25%), Credit unions or finance companies (8.03%), Life insurance companies (0.12%), and Others (6.5%).

Overall, more than sixty five percent of total number of conforming loans originated by banks in 2018 are eventually sold in the secondary market. Those loans also have distinguishable characteristics compared to loans banks retain on balance

[2]The new HMDA however exempts insured depository institutions or insured credit unions if they originated fewer than 500 closed-end mortgage loans in each of the two preceding calendar years.

sheet (Table 3.1). In particular, securitized loans seem to be more risky as they have higher average loan-to-value ratio (73.8% vs 71.4%), lower borrower average gross annual income (105k vs 124k), and longer term (326 vs 311 months). Due to their higher risk, securitized loans have slightly higher average rate spread (0.449% vs 0.458%) and higher average origination charges ($1,417 vs $1,360). These results are consistent with previous findings in the literature suggesting that securitization is an instrument for financial institutions to offload idiosyncratic risk and improve their liquidity management.

Table 3.1: Loan Characteristics between Sold and Retained Loans

	Originated	Retained	Sold
Count	801,565	273,303	528,262
Volume ($B)	184.08	67.77	116.31
LTV Ratio (%)	72.97	71.40	73.78
Borrower Income ($T)	111.47	124.04	104.96
Loan Amount ($T)	229.65	247.98	220.17
Loan Term (months)	320.88	311.06	325.96
Rate spread (%)	0.455	0.448	0.458
Origination Charges ($)	1,398	1,360	1,417

However, the average statistics of all banks obscure the complexity of their securitization choices. In the next section, I will further study banks' heterogeneous securitizing decisions by combining loan characteristics from HMDA and bank profiles from Call Reports.

3.5 Securitization Motives

After originating a mortgage loan, banks need to decide whether to sell it off in the secondary market (securitization) or to hold it on balance sheet till maturity (retention). Banks participate in the secondary market for a number of reaons. First of all, regardless of securitization channels, securitization increases liquidity position of the originator. When loan issuers accept the sale agreement, they receive a liquid asset in the form of either mortgage-backed securities (under the agency swap program) or T-bill (under the cash program), which are frequently traded in the bond market. As a result, thanks to its liquidity transformation function, securitization is an important funding source for creditors, especially those who do not have a large capital or great ability to raise deposit. Moreover, securitization helps mortgage lenders reduce credit risk. Since the buyer of the loan owns the legal right to collect all subsequent payments from the mortgage, the loan originator is unscathed in case of default. Lastly, securitization can be used to improve the bank's regulatory ratios. Under the current capital rules, mortgage loans have a risk weight of 50 percent, whereas agency MBS and US Treasury bonds have a risk weight of 20 and 0 percent, respectively. By converting higher risk weight assets to lower ones, banks can manipulate their total risk-weighted assets and hence regulatory capital ratio as desired.

In this section, I show that whether riskier or safer loans are securitized depends on the bank's capital and risk position. Specifically, capital-constrained banks sell off safer loans and retain riskier loans that earn higher risk premium. They also securitize a much larger proportion than the least capital-constrained banks. These findings imply that regulatory arbitrage and capital optimization are important motives of securitization for this type of banks. On the other hand, risk-constrained banks keep safer loans on balance sheet, implying securitization is used mainly as a financial instrument to cut down credit risk.

3.5.1 Capital-constrained Banks

In this subsection, I use the tier 1 capital ratio (i.e. tier 1 capital divided by total risk weighted assets) as a proxy measure of regulatory capital constraint. I sort all non-exempt depository institutions in the HMDA dataset into 5 quintiles based on their tier 1 capital ratio. I classify the bottom 20% quintile as "capital-constrained" banks and compare them to the top 20%, which is the group of banks least likely being constrained by the regulatory capital requirement[3].

One important note is that all banks in my sample well surpass the Basel III tier 1 capital ratio requirement of 8%, so none of them in reality face a binding regulatory capital constraint[4]. However, banks tend to have a higher internal target for their actual capital ratios, as most of banks need to conduct annual stress tests, in which they must prove to be able to maintain required capital ratios under a "severely adverse" scenario employed by the FED. Since the bank target depends on its asset portfolio and internal strategy, it is not possible to have a clear threshold of banks being constrained by their regulatory capital level. Nevertheless, banks with lower regulatory capital ratios are more likely to be constrained. They need to implement specific strategies to maintain their ratios to avoid penalties from the FED. Therefore, for those banks, regulatory capital is relatively expensive and plays an important role in their securitization decision.

Assuming all mortgage loans are originated under a fair pricing structure, the rate spread between the covered loan's annual percentage rate (APR) and the average prime offer rate (APOR) indicates the risk premium required to compensate for the difference in the loan riskiness. In other words, if the bank's pricing model and the market are efficient, then ex-ante, loans with riskier characteristics must be charged a higher interest rate and thus higher rate spread. Prior to 2018, mortgage lenders need to report rate spread of only "higher-priced" mortgage loans (rate spread greater than 1.5% for first-lien, and 3.5% for subordinate-lien mortgages). However, the new

[3]Banks in the bottom quintile have the tier 1 capital ratio less than 11.1%, whereas banks in the top quintile have that ratio greater than 13.89%. There are 108 banks in each quintile.

[4]The Equitable Bank in Milwaukee has the lowest tier 1 capital ratio at 8.29%.

rule implemented in the 2018 HMDA requires loan originators report rate spread of all mortgage loans. Therefore, it is the first time we can have a clear picture about the risk and pricing of loans sold and retained by banks.

Table 3.2 reports the difference in mortgage loan securitization decision between banks with the lowest tier 1 capital ratio (Bottom 20%) and those with the highest ratio (Top 20%)[5]. Overall, the average rate spreads of mortgage loans originated by the two groups show very little difference, less than one basis point. That makes sense since I restrict the loan sample to include only conforming closed-end residential mortgages[6]. Regardless of banks' capital level, they can originate loans and sell back to a third-party agency as long as the loans satisfy certain agency purchasing requirements. By doing so, banks can earn origination charges without holding regulatory capital against the loan. As a result, banks have little incentive to reject a qualified borrower, making mortgage loans appear drawn from a similar population despite the two groups differentiating in capital ratios and securitization behavior.

Table 3.2: Risk premium and Banks sorted on tier 1 capital ratio

Loan Status	Bottom 20%	Top 20%	Top - Bottom	t-stat
All	0.484	0.476	-0.008	-2.377
Sold	0.443	0.506	0.063	19.637
Retained	0.587	0.448	-0.139	-22.897

Despite the similarity in loan origination, the securitization choices of the top and bottom banks are apparently different. Capital-constrained banks show a clear regulatory arbitrage and capital optimization behavior. They have a significantly higher securitization rate (72%, Table 3.3), and the loans they choose to retain are

[5]To attenuate the impact of outliers and typos, we exclude the 0.5% lowest and highest loans along five variables: rate spread, income, loan amount, loan-to-value ratio, and origination charges.

[6]Mortgage loans reported in HMDA can be either open-end or closed-end line of credit, conforming or non-conforming, residential or commercial loans.

significantly riskier (14 basis points spread between sold and retained loans, Table 3.2). Intuitively, since all residential mortgage loans have a constant risk weight of fifty percent in the regulatory risk-weighted assets calculation, banks need to hold the same amount of capital for every dollar they originate to satisfy the regulatory requirement, even though the loans may vary in credit risk. For banks closer to the binding regulatory constraint, capital is relatively more expensive, and as a result, they choose to swap more of the originated loans for lower risk weight assets (MBS or T-bill) and retain higher-risk higher-return loans that justify the high cost of regulatory capital. This finding supports the view of securitization as an efficient contracting mechanism that helps banks more closely align regulatory measures of risk (represented by the capital charge) with the true economic risk of the asset (Calomiris and Mason, 2004).

Table 3.3: Securitization rate and Banks sorted on tier 1 capital ratio

Quintile	Tier 1 Cap Ratio	Charge-off Rate (%)	Total Count	Total Amount ($B)	Securitization Rate (count)	Securitization Rate (volume)
Bottom	10.58%	0.39	196878	42.23	71.92%	69.83%
2	11.73%	0.22	94742	19.28	64.93%	63.75%
3	12.62%	0.39	296569	71.4	66.21%	61.51%
4	14.23%	0.24	147937	36.72	65.63%	64.12%
Top	20.22%	0.17	65439	14.45	48.45%	48.86%

On the other hand, banks with the highest level of capital ratio use secrutization as an instrument to enhance credit risk management and earn origination charges on high-risk loans. Table 3.3 shows that those bank securitize only 48% of their originated loans, much less than the rest. Moreover, Table 3.2 indicates that they choose to keep relatively safer loans on the balance sheet (the spread is 6 basis points). Apparently, since the main source of income for banks is the spread between deposits and loans they issue, keeping too high a capital ratio is not always optimal (DeAngelo and Stulz, 2015). Banks in the highest quintile of capital ratio can certainly originate more loans without worries of violating the FED's regulatory capital requirement. However, for some reasons, those banks cannot expand the asset side of their balance sheet. They therefore choose to keep more of their originated loans on balance sheet, which explains why they have such a low securitization rate.

Table 3.4 reports additional characteristics of retained and securitized loans for both groups of banks. Interestingly, capital-constrained banks have indistinguishable origination charges for both loans retained on balance sheet and loans eventually sold-off, implying that regulatory arbitrage and capital optimization are more important motives than earning origination fee. In contrast, banks with the highest capital ratios charge much higher origination fees for loans that they ultimately sell off, compared to loans they keep on balance sheet. Given that loans they sell on the secondary market have higher risk premium, banks in this group appear to originate loans to riskier borrowers who are willing to pay a higher fee, and then use securitization market remove them.

In short, banks facing regulatory capital constraint tend to be more active in the secondary market and use securitization to arbitrage and optimize regulatory capital. On the flip side, banks that are safely far from the regulatory capital requirement tend to use securitization to screen out high-risk loans and earn almost risk-free origination charges.

3.5.2 Risk-constrained Banks

In this subsection, I use the charge-off rate as a proxy of the bank riskiness level. To calculate the charge-off rate, I use the total charged-off loans reported on Schedule RI-B and the total outstanding loans on Schedule RC of the Call Reports. Then,

Table 3.4: Other loan characteristics - Sorted on tier 1 capital ratio

Loan Status	Quintile	Risk Premium	Loan Amount ($T)	Loan Term (months)	Origination Charges ($)	Borrower Income ($T)	Loan-to-Value Ratio (%)
Sold	Bottom	0.443	208.3	327.2	1,351	102.4	75.8
Sold	Top	0.506	222.7	329.8	1,705	104.2	74.2
Retained	Bottom	0.587	230.5	310.6	1,220	120.7	75.4
Retained	Top	0.448	219.1	299.0	1,254	118.3	70.7

similarly, all non-exempt depository institutions in the HMDA dataset are sorted into 5 quintiles. The bottom 20% represents banks that have the lowest charge-off rates in 2018 and are considered the least risky banks. At the other end, the top 20% are classified as "risk-constrained" banks.

Table 3.5 reports the average rate spread of mortgage loans originated by the least and most risky banks measured by charge-off rate. At the first glance, banks having the highest charge-off rates seem to be cautious in originating new loans. The average rate spread of loans underwritten by the top 20% riskiest banks is three basis points lower than the bottom 20% and the difference is highly significant. Moreover, risk-constrained banks keep much safer loans on balance sheet. The difference in risk premium between the loans they sell and those they retain is almost ten basis points. On the other hand, the least risky banks keep high-risk-high-return loans in their portfolio, but the spread between retained and sold loans is less than five basis points, which is half of the difference in the top quintile.

Table 3.5: Risk premium and Banks sorted on charge-off rate

Loan Status	Bottom 20%	Top 20%	Top - Bottom	t-stat
All	0.457	0.429	-0.028	-11.044
Sold	0.437	0.462	0.025	11.654
Retained	0.486	0.365	-0.121	-22.717

These findings provide empirical support for the literature arguing for the presence of asymmetric information in the securitization market. Since the lenders know the characteristics of their borrowers, they may be able to make optimal securitization decision that suits their risk and capital conditions. As shown previously, capital-constrained banks have a higher securitization rate because they need to swap assets that take more space in the risk-weighted assets calculation for less costly ones. The loans that they remove from balance sheet also have lower risk premium. In contrast, risk-constrained banks use securitization mainly to reduce credit risk, as they offload loans of much higher risk premium than the ones they retain.

In addition, there are two interesting patterns that can be drawn from Table 3.6 and Table 3.7.

First, both the least and the most risky banks share quite similar securitization rate, approximately 62%. That is quite surprising because the riskiest banks supposedly have higher incentives to remove loans from their balance sheet to reduce the loan loss reserve. As a result, riskier banks are expected to more actively engage in the securitization practice. However, it is not what the data show. The next section by estimating securitization rule will address this observation. Banks with different riskiness may have similar unconditional securitization rate, but that rate may differ after controlling for other characteristics of the loan and the bank.

Table 3.6: Securitization rate and Banks sorted on charge-off rate

Quintile	Tier 1 Cap Ratio	Charge-off Rate (%)	Total Count	Total Amount ($B)	Securitization Rate (count)	Securitization Rate (volume)
Bottom	15.73%	0.02	56358	14.35	62.77%	61.63%
2	14.06%	0.06	81059	17.98	58.18%	58.64%
3	13.18%	0.10	84933	18.96	72.65%	74.56%
4	12.31%	0.20	99877	22.38	66.04%	65.34%
Top	12.49%	0.47	479338	110.40	66.35%	61.73%

Second, the fact that safe banks choose to retain shorter term loans is also interesting. A possible explanation for this phenomenon is that the banks with lower charge-off-rate may find investing in riskier class of assets out of the mortgage market more attractive. As a result, they engage in securitization mainly to raise fund to finance other investments.

In summary, banks with different level of riskiness differ greatly in securitization behavior and incentive. Riskier banks tend to retain relatively safer loans while safer banks tend to retain relatively riskier but shorter term loans.

Table 3.7: Other loan characteristics - Sorted on charge-off rate

Loan Status	Quintile	Risk Premium	Loan Amount ($T)	Loan Term (months)	Origination Charges ($)	Borrower Income ($T)	Loan-to-Value Ratio (%)
Sold	Bottom	0.437	223.5	330.3	1,393	109.6	75.6
Sold	Top	0.462	214.3	320.8	1,361	103.8	72.3
Retained	Bottom	0.486	219.3	287.5	1,308	121.4	71.4
Retained	Top	0.365	261.9	322.3	1,421	124.1	71.1

In the next section, I will put both capital and risk constraints together to study the bank's securitization decision rule.

3.6 Securitization Decision Rule

Now turn to the main question of this paper: Do banks securitize riskier or safer loans? In the previous section, I have shown different securitization choices of banks given their capital and risk position separately. Using rate spreads as a proxy of loan risk, I find that banks more likely being constrained by the regulatory capital requirement have a higher securitization rate and keep high-risk high-return loans. On the other hand, riskier banks retain safer and less profitable loans.

In this section, I study the probability of a loan being sold based on its risk premium and the constraint its originator is more likely to face. In particular, I create two dummy variables, Cap_Constrained and Risk_Constrained to denote the capital and risk status of the bank. The first indicator, Cap_Constrained equals 1 if the loan originator belongs to the bottom 20% of banks sorted by the tier 1 capital ratio. In a similar manner, the second indicator, Risk_Constrained equals 1 if the loan originator is in the top 20% of banks having the highest charge-off rate.

Table 3.8 reports results on two specifications of the securitization decision rule. In the first column, I specify the probability of securitization as a function of risk premium and its interaction terms with bank risk and capital status. Using a logistic regression, the log odds of securitization is written as:

$$\begin{aligned}\log\left(\frac{p}{1-p}\right) &= \beta_0 + \beta_1 \cdot \text{Cap\_Constrained} + \beta_2 \cdot \text{Risk\_Constrained} \\ &+ \beta_3 \cdot \text{Risk\_Premium} + \beta_4 \cdot \text{Risk\_Premium}\times\text{Cap\_Constrained} \\ &+ \beta_5 \cdot \text{Risk\_Premium}\times\text{Risk\_Constrained}\end{aligned} \tag{3.1}$$

where

p is the probability of a loan being sold off.

Risk_Premium is the spread between the loan interest rate and the prime rate.

Cap_Constrained and Cap_Constrained are two dummy variables indicating the capital and risk constraint of the loan originator.

All of the estimated coefficients fall in line with what we expected. Specifically, the negative coefficient of the risk premium implies that when both constraints are not binding, banks are more likely to keep riskier loans, which earn higher premium and are thus more profitable. For banks that are constrained by the capital requirement but have not reached the risk limit, the tendency of retaining

Table 3.8: Securitization Decision Rule

	Dependent variable:	
	Securitized	
	(1)	(2)
Intercept	0.673***	0.263***
	(0.005)	(0.056)
Cap_Constrained	0.735***	0.692***
	(0.008)	(0.008)
Risk_Constrained	−0.320***	−0.279***
	(0.006)	(0.009)
Risk_Premium	−0.196***	−0.163***
	(0.006)	(0.007)
Risk_Premium × Cap_Constrained	−0.781***	−0.756***
	(0.011)	(0.011)
Risk_Premium × Risk_Constrained	0.753***	0.734***
	(0.009)	(0.009)
log(Total_Capital)		−0.006***
		(0.001)
Loan_Term		0.002***
		(0.00004)
log(Loan_Amount)		0.104***
		(0.005)
Loan_to_Value_Ratio		0.004***
		(0.0001)
log(Borrower_Income)		−0.365***
		(0.005)
Observations	801,565	801,546
Log Likelihood	−506,512.900	−499,316.800
Accuracy Rate	74.7%	76.3%
Note:		*p<0.1; **p<0.05; ***p<0.01

riskier loans is even stronger. Since banks are required to hold the same amount of capital buffer against all mortgage loans regardless of the risk level, it is optimal to retain higher risk, more profitable loans, given the risk constraint is not breached. Interestingly, the large positive coefficient of the risk premium and risk constraint interaction term exceeds the sum of the coefficients of risk premium and its interaction term with capital constraint. It implies that when banks hit the risk limit, regardless of the capital status, banks are more likely to securitize the riskier loans. As a result, risk transferring seems to dominate regulatory arbitrage as the main motive of securitization.

The second column of Table 3.8 serves as a robustness check of the decision rule presented in equation 3.1. In that specification, I control for bank size, measured by log of total capital, loan liquidity, by loan term and loan amount, and loan risk, by loan-to-value ratio and log of borrower income. The signs of coefficients of all variables in equation 3.1 remain unchanged. Moreover, the estimated coefficients of control variables are consistent with other findings in the literature. In particular, all else equal, bigger banks with a larger capital level are more likely to retain their originated assets, implying securitization is a more important funding channel for small banks and non-depository institutions, i.e. shadow banks (Buchak et al., 2018). My results also show that loans that have a longer term and larger amount are more likely to be sold, implying that banks involve in securitization to get more liquidity (Casu et al., 2013).

Table 3.9 provides a summary of the securitization rule. For a typical bank that does not meet any constraint, riskier loans have a lower probability of being sold. This effect is stronger for banks that are constrained by the regulatory capital requirement but have available space in risk allowance, as they need to keep more profitable but riskier loans to maximize return on the scarce capital. On the other hand, riskier loans originated by banks facing a binding risk limit are more likely to be securitized. When both constraints are binding, the risk transferring motive wins.

Table 3.9: Securitization decision rule summary

Capital Constraint	Risk Constraint	Risk Premium Coeff	Implication
Non-Binding	Non-Binding	Negative	Risk $\uparrow \rightarrow$ Securitization $\downarrow$
Non-Binding	Binding	Positive	Risk $\uparrow \rightarrow$ Securitization $\uparrow\uparrow$
Binding	Non-Binding	Negative	Risk $\uparrow \rightarrow$ Securitization $\downarrow\downarrow$
Binding	Binding	Positive	Risk $\uparrow \rightarrow$ Securitization $\uparrow$

3.7 Counterfactuals

In this section, I will quantify the impact of capital and risk constraints on the probability of securitization conditional on the loan risk. Specifically, I use the coefficient estimates of equation 3.1 to compute the average conditional probability of securitization when each of the two constraints is removed by setting its indicator to zero. Table 3.10 reports these counterfactual results.

Table 3.10: Conditional Probability of Securitization Counterfactuals

Capital Constraint	Risk Constraint	Cond. Probability (%)	Change (%)
Not removed	Not removed	65.90	N/A
Removed	Not removed	66.11	+0.21
Not removed	Removed	63.26	-2.64
Removed	Removed	63.48	-2.42

Overall, the simple model predicts that on average, a mortgage loan has a probability of 65.90% of being sold off, conditional on its risk premium. This conditional probability increases by merely 0.21% when we relax the capital constraint. It increases because banks lose the incentive to hold riskier loans to optimize their regulatory capacity. On the other hand, relaxing the risk constraint yields a much bigger change in the securitization probability. When no bank needs to reduce risk via securitization, the securitization rate drops 2.64% in this counterfactual scenario. In the last scenario when both constraints are relaxed, the result reconfirms the dominance of risk management over capital optimization as the main motive of securitization.

3.8 Concluding Remarks

What constitutes the main motive of banks in participating in the securitization market and whether banks retain safer or riskier loans has been under intensive debate, even more so after the 2008 financial crisis. Finding the right answer is not an easy task, mainly due to the lack of data. In this chapter, I use the recently overhauled HMDA data to discover the bank securitization behavior. Using the spread between loan interest rate and the prime rate as a measure of risk, I find that banks with lower tier 1 capital ratio securitize safer loans and retain higher risk, higher return loans on balance sheet. Along with the high securitization rate of this group of banks, there is evidence that capital-constrained banks securitize to arbitrage and optimize their capital. On the other hand, banks that have higher charge-off rate tend to prioritize on risk reduction when participating in securitization. Overall, since all banks are well capitalized in 2018, risk transfer dominates regulatory arbitrage as the motive of securitization, resulting in slightly higher average risk premium of sold loans compared loans retained on balance sheet.

Chapter 3 References

Viral V Acharya, Philipp Schnabl, and Gustavo Suarez. Securitization without risk transfer. *Journal of Financial Economics*, 107(3):515–536, 2013.

Geokge A Akerlof. The market for ”lemons”: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500, 1970.

Brent W Ambrose, Michael LaCour-Little, and Anthony B Sanders. Does regulatory capital arbitrage, reputation, or asymmetric information drive securitization? *Journal of Financial Services Research*, 28(1-3):113–133, 2005.

Xudong An, Yongheng Deng, and Stuart A Gabriel. Value creation through securitization: evidence from the cmbs market. *The Journal of Real Estate Finance and Economics*, 38(3):302–326, 2009.

Vitaly M Bord and Joao AC Santos. The rise of the originate-to-distribute model and the role of banks in financial intermediation. *Federal Reserve Bank of New York Economic Policy Review*, page 21, 2012.

Greg Buchak, Gregor Matvos, Tomasz Piskorski, and Amit Seru. Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130(3): 453–483, 2018.

Charles W Calomiris and Joseph R Mason. Credit card securitization and regulatory arbitrage. *Journal of Financial Services Research*, 26(1):5–27, 2004.

Barbara Casu, Andrew Clare, Anna Sarkisyan, and Stephen Thomas. Securitization and bank performance. *Journal of Money, Credit and Banking*, 45(8):1617–1658, 2013.

Tri Vi Dang, Gary Gorton, and Bengt Holmström. Ignorance, debt and financial crises. *Yale University and Massachusetts Institute of technology, working paper*, 17, 2012.

Harry DeAngelo and Rene M Stulz. Liquid-claim production, risk management, and bank capital structure: Why high leverage is optimal for banks. *Journal of Financial Economics*, 116(2):219–236, 2015.

Peter DeMarzo and Darrell Duffie. A liquidity-based model of security design. *Econometrica*, 67(1):65–99, 1999.

Darrell Duffie. Innovations in credit risk transfer: implications for financial stability. Technical report, Bank for International Settlements, 2008.

Gary B Gorton and Nicholas S Souleles. Special purpose vehicles and securitization. In *The risks of financial institutions*, pages 549–602. University of Chicago Press, 2007.

Samuel G Hanson and Adi Sunderam. Are there too many safe securities? securitization and the incentives for information production. *Journal of Financial Economics*, 108(3):565–584, 2013.

Benjamin J Keys, Tanmoy Mukherjee, Amit Seru, and Vikrant Vig. Did securitization lead to lax screening? evidence from subprime loans. *The Quarterly journal of economics*, 125(1):307–362, 2010.

John Krainer and Elizabeth Laderman. Mortgage loan securitization and relative loan performance. *Journal of Financial Services Research*, 45(1):39–66, 2014.

Stewart C Myers and Nicholas S Majluf. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, 13(2):187–221, 1984.

Zoltan Pozsar, Tobias Adrian, Adam B Ashcraft, and Hayley Boesky. Shadow banking. *Economic Policy Review*, (Dec):1–16, 2013.

Rene M Stulz. Risk management, governance, culture, and risk taking in banks. *Economic Policy Review*, (Aug):43–60, 2016.

Chapter 4

Case Study: PNC Bank

4.1 Introduction

PNC is a super-regional commercial bank headquartered in Pittsburgh, Pennsylvania and operates in 19 states with 2,459 branches. With total assets of 410 billion dollars (as of December, 2019), PNC is the 9th largest bank in the US. The banks has three core business lines - Retail Banking, Corporate and Institutional banking, and the Asset Management Group. In 2019, the Retail Banking business including consumer lending, residential mortgage and consumer services leads the whole group in total revenue with 8.17 billion dollars, of which 32% is from non-interest income. However, the retail sector is only second in terms of total assets with 93 billion dollars on balance sheet, which is behind the Corporate and Institutional Banking division at 164 billion dollars. The numbers truly reflect the focus of PNC as a bank specialized in commercial lending. The C&I business is also the second largest revenue stream of PNC with the total revenue of 6.25 billion dollars, of which 41% comes from non-interest services. Lastly, the Asset Management Group contributes 1.3 billion dollars to PNC's total revenue, the majority of which is non-interest income (77%).

In this case study, I focus on the residential mortgage origination and securitization decision of PNC. Particularly, I use the individual-level mortgage loan application data that PNC submitted to the FFIEC under the Home Mortgage Disclosure Act to explore characteristics of applicants who are approved for the loan and characteristics of loans that the bank keeps on balance sheet. I find that borrower's income, loan-to-value ratio, whether the loan is conforming or jumbo, and borrower's race are significant determinants of approval, while loan term is not a significant factor after controlling for the others. However, even though white applicants are more likely to get loan approval than black applicants, the result does not prove the discriminatory lending behavior of the bank, as important credit risk variables such as credit score and employment history have not been controlled for.

Several findings are interesting. First, the bank uses third-party automated underwriting systems to originate over 90% of its conforming residential mortgage loans and then sell more than 70% of them. As a result, for conforming loan applicants, the bank seems to take the origination stage as given without the ability to set the loan rate, and only controls the securitization stage, in which the bank choose to retain safer loans. Moreover, since PNC keeps all jumbo loans it originates, the bank only grants loans to its low-risk applicants with much higher income and lower loan-to-value ratios, relative to conforming loans that are resalable. Lastly, compared to Quicken Loans Mortgage, the largest non-depository mortgage lender, PNC originates more jumbo loans, retains more loans, and actively keeps safer loans on balance sheet.

The rest of this case study is organized as follows. Section 2 provides a brief summary of PNC's mortgage loan approvals and analyzes its approval and pricing rule. Section 3 presents the differences in characteristics between sold and retained loans. Section 4 compares PNC and Quicken Loans to highlight the differences between a traditional depository institution and a shadow bank in their mortgage loan origination and securitization behaviors.

4.2 The loan approval decision

In this section, I analyze the loan approval and denial segmented by conforming status and borrower's races. At the first glance, the unconditional approval rate is similar regardless of whether the loan amount exceeds the agency threshold (Table 4.1). On the other hand, white applicants are more likely to be approved for the loans, compared to black and Asian applicants (Table 4.2). However, controlling for other factors such as borrower income, loan-to-value ratios, and loan term, both conforming status and race are significant determinants of the approval decision (Table 3.8), as are the risk premium pricing (Table 4.4).

First, to make all loans comparable, I include only conventional closed-end residential mortgage loan applications used for home purchases. In 2018, PNC received more than 17,000 applications for that type of loan and approved more than 14,500, or 85.5%. Table 4.1 reports the total number, approval and denial rates of conforming and jumbo loans that PNC processed in 2018. An application is classified as "Approved" if it has the action_taken value of 1, "Loan originated", or 2, "Application approved but not accepted", and is classified as "Denied" if it has the action_taken value of 3 in the HMDA data. Though jumbo loans take up a smaller portion in the overall application pool, they have quite similar approval rate (86.3%) as conforming loans (85.3%). A possible explanation for that high approval rate is that jumbo loan applicants are typically high-income households and loyal customers of the bank. More details about loan characteristics are shown in the next section.

Second, Table 4.2 reports loan approval rates across different races. White applicants have a much higher approval rate (86.9%), compared to other groups such as black (72.56%) and Asian (81.79%). However, since race may correlate with other

Table 4.1: Conforming vs Jumbo Application Approval

Status	Conforming	Jumbo	Total	Conforming_rate	Jumbo_rate
Approved	12,384	2,164	14,548	85.34%	86.35%
Denied	2,128	342	2,470	14.66%	13.65%
Total	14,512	2,506	17,018	*N/A*	*N/A*

credit risk factors used in the approval process, I estimate an approval rule with multiple factors.

Table 4.2: Approval Rates across Races

Race	Approved	Denied	Approval_rate
White	9,489	1,431	86.90%
Black	431	163	72.56%
Asian	1,410	314	81.79%
Others	3,218	562	85.13%

Table 3.8 reports results on two versions of the approval decision, the first of which uses additional dummy variables to represent the race of the applicant. The results are consistent with my expectations. Higher-income and lower-loan-to-value-ratio applicants are more likely to be granted a loan. Similarly, controlling for other factors, conforming loans are more likely to be approved due to its resalability. Interestingly, the length of loans (loan_term) is not a significant factor in the approval decision, reflecting PNC's strong liquidity position.

There is also a concern about whether the bank discriminates loan applicants based on race, as all three race dummies are statistically significant. However, before reaching an affirmative conclusion about the bank discriminatory lending behavior, we need information on applicant credit score and employment history, which are crucial credit risk factors in the loan approval process[1]. Moreover, though the races dummies are highly statistically significant (due to the large sample size), their

[1] Other banks in the HMDA data also share these patterns.

Table 4.3: A simple approval decision rule

	Dependent variable:	
	Approved = 1	
	(1)	(2)
Intercept	0.092	0.197
	(0.306)	(0.300)
Log_Income	0.463***	0.461***
	(0.039)	(0.038)
LTV	−0.014***	−0.014***
	(0.002)	(0.002)
Loan_term	0.001	0.001
	(0.0004)	(0.0004)
Conforming	0.499***	0.600***
	(0.083)	(0.082)
White	0.265***	
	(0.057)	
Black	−0.386***	
	(0.113)	
Asian	−0.250***	
	(0.082)	
Observations	15,767	15,767
Residual Deviance	12,412	12,492
Akaike Inf. Crit.	12,427.460	12,501.890
Note:	*p<0.1; **p<0.05; ***p<0.01	

marginal explanatory power is quite small. In particular, adding the dummies to the restricted model reduces its residual deviation by only 80, or 0.64%, from 12,492 to 12,412 (even though the Chi-squared test shows that the difference between the two models is statistically significant).

Table 4.4 reports results from the regression of approved loan rate spreads on a similar set of determinants as Table 3.8. The rate spread is the difference between the covered loan's annual percentage rate (APR) and the average prime offer rate (APOR), and is interpreted as the loan risk premium.

The estimates of the risk pricing regression have the expected signs. For example, high-income and low-loan-to-value-ratio applicants are granted a loan at a lower rate spread, reflecting their higher credit worthiness. Surprisingly, conforming loans, which are lower in loan amount and more resalable bear a higher risk premium. However, as shown later, conforming and jumbo loan applicants have very distinct characteristics and the bank seems to grant jumbo loans to a small number of its best clients.

4.3 The loan securitization decision

In this section, I analyze the differences in characteristics between the loans that PNC keeps on balance sheet and the loans it sells to a third party.

Overall, PNC securitizes 73.5% of its originated conforming loans but keeps 100% of its originated jumbo loans. During its origination process, PNC uses two automated underwriting systems from Fannie Mae (Desktop Underwriter) and Freddie Mac (Loan Prospector) for over 90% of conforming loan applications. The remaining 10% conforming loans and all jumbo loans originated use in-house or manual underwriting models. This observation highlights the importance of the resalability of conforming loans. For this type of loans, the bank has limited inputs in the approval decision and relies heavily on a third-party automatic system. On the other hand, since jumbo

Table 4.4: Risk premium pricing

	Dependent variable:	
	Rate_spread	
	(1)	(2)
Intercept	0.509***	0.539***
	(0.034)	(0.034)
Log_Income	−0.183***	−0.191***
	(0.005)	(0.005)
LTV	0.006***	0.006***
	(0.0002)	(0.0002)
Conforming	0.233***	0.260***
	(0.010)	(0.010)
White	0.062***	
	(0.007)	
Black	0.184***	
	(0.019)	
Asian	−0.086***	
	(0.011)	
Observations	13,561	13,561
R^2	0.325	0.310
Adjusted R^2	0.325	0.310
Residual Std. Error	0.345 (df = 13554)	0.349 (df = 13557)
F Statistic	1,086.702*** (df = 6; 13554)	2,028.271*** (df = 3; 13557)
Note:		*p<0.1; **p<0.05; ***p<0.01

loans are less resalable, the bank devotes more effort to screening and approves only the best applicants.

Compared to other depository financial institutions originating residential mortgage loans in the HMDA data, PNC has a higher than average securitization rate (73.5% versus 65% on average) and retains safer loans on balance sheet. There are several possible explanations for this strategy. First, the core business of PNC is corporate and institutional banking with the focus on commercial and industrial loans. The total loans held on the corporate and institution banking book is $137 billions, which is almost double of the total retail loans of $74 billions (2018 PNC 10-K form). Moreover, given its strong presence in the midwestern and southern states, PNC has superior advantages in building deep relationships with its industrial customers. As a result, at PNC, C&I loans not only outperform retail loans in average return on assets (1.63% versus 1.19%), but also have lower risk with the nonperforming rate of just 0.27% versus 1.52% in retail banking. Lastly, PNC has a relatively short history and little experience in the residential mortgage market. It just came back to this business after its acquisition of National City Corp during the 2008 financial crisis[2]. Therefore, it is no surprise that PNC has been taking a very conservative approach to gradually build up its residential mortgage portfolio.

Table 4.5 reports the detailed characteristics of residential mortgage loans that PNC originated. There are two interesting findings. First, jumbo loan borrowers have much higher income and lower loan-to-value ratio, compared to both conforming loans retained on balance sheet and those sold to a third party. More surprisingly, PNC is able to offer near prime rate to applicants qualified for jumbo loans. Second, PNC retains lower-risk-premium conforming loans on balance sheet. This reflects the bank preference for low-risk borrowers with higher income and lower loan-to-value

[2]PNC sold its residential mortgage business to Washington Mutual Inc. in 2000.

ratio, and points to the role of securitization as a mechanism for the bank to unload higher-risk loans.

Table 4.5: PNC's Securitization and loan characteristics

Loan Type	Conforming	Conforming	Jumbo
Securitization Decision	Retained	Sold	Retained
Count	3246	8999	2133
Vol ($B)	0.889	1.804	1.844
Loan_amount ($)	273,974.1	200,472.8	864,732.8
Interest_rate	4.69	4.56	4.01
Rate_spread	0.345	0.421	-0.093
Loan_term	337.7	336.9	353.1
Origination_charges ($)	1318.6	1285.4	1515.6
Income	125.1	102.4	382.9
Loan_to_value_ratio	77.38	81.43	75.68
Percent_within_type_count	26.51	73.49	100.00
Percent_within_type_vol	33.02	66.98	100.00

4.4 Shadow-Bank comparisons

In this section, I highlight the differences in origination and securitization behaviors between a shadow bank (Quicken Loans) and a traditional depository institution (PNC Bank).

Table 4.6: Quicken Loans approval rate breakdowns

Status	Conforming	Jumbo	Total	Conforming_rate	Jumbo_rate
Approved	92,805	1,597	94,402	83.766	70.383
Denied	17,986	672	18,658	16.234	29.617
Total	110,791	2,269	113,060		

There are three interesting differences: First, even though Quicken Loans is a much larger mortgage loan originator, its main business is in conforming loans, which is more than 98% of its originated loans, much higher than the 85% at PNC. Second, Quicken Loans charges much higher origination fees for both conforming and jumbo loans, which supports the view that shadow banks serve as a retail representative of securitizing agencies and earn commission fees. Lastly, it seems that Quicken Loans has no selectivity in its securitization choices, as it securitize more than 90% of its conforming loan portfolio, and the rate spreads, as well as other characteristics of retained and sold loans are quite similar. This observation highlights the role of securitization as the most important funding channel for the shadow banking industry.

Table 4.7: Quicken's Securitization and loan characteristics

Loan Type	Conforming	Conforming	Jumbo	Jumbo
Securitization Decision	Retained	Sold	Retained	Sold
Count	7194	85509	263	1333
Vol ($B)	1.751	21.106	0.190	0.968
Loan_amount ($)	243433.4	246829.3	723441.1	726717.9
Interest_rate	5.07	4.70	4.74	4.36
Rate_spread	0.534	0.523	0.092	0.027
Loan_term	349.5	346.3	347.6	353.3
Origination_charges ($)	2560.6	2536.5	4975.6	6394.3
Income	107.8	111.8	321.0	298.4
Loan_to_value_ratio	83.81	84.56	77.57	75.22
Percent_within_type_count	7.76	92.24	16.48	83.52
Percent_within_type_vol	7.66	92.34	16.42	83.58

4.5 Concluding Remarks

This chapter examines the mortgage loan approval process and securitization behaviors of PNC Bank as a supplement case study to Chapter 3. Given the extensive use of third-party automated underwriting systems for conforming loans, bank specific characteristics should have little impact on the pricing structure of originated mortgage loans. In other words, the loan rate spread is a good proxy of its riskiness. However, individual originators have different strategies and approaches in selecting which loans to retain on balance sheet. For example, given its superior performance in C&I banking, PNC is very conservative in the residential mortgage business. As a result, PNC sell 70% of its originated mortgage loans and retain safer loans with lower risk premium. In addition, this case study offers an interesting contrast in the securitization behavior between a traditional bank (PNC) and a non-depository financial institution (Quicken Loans). With its stable deposit funding source, PNC is able to approve and retain more jumbo loans, consistent with the bank's strategy to build relationships with wealthy clients. More importantly, PNC has the ability to selectively choose which loans to retain, instead of simply doing the "originate-to-distribute" and fee-earning business. This further highlights the importance of government-sponsored entities, like Fannie Mae and Freddie Mac, in setting the loan-purchase standards that determine the quality and systemic risk of the mortgage market.

Chapter 5

Conclusions

In this dissertation, I have discussed the composition of financial systemic risk and bank behaviors in securitization.

In chapter 1, the main finding is that connectedness risk is the main source of financial system risk. That result motivates me to study why financial institutions are highly interconnected and exposed to a common risk which only materializes in a systemic event. Since securitization is considered one of the predominant mechanisms that significantly raised the financial system leverage and spillover risk in the last crisis, in chapter 2, I develop a theoretical model to explain the motives and asset choices of banks engaging in securitization. The major prediction is that banks retain high-risk-high-return assets after adjusting for the regulatory cost in capital. Moreover, capital-constrained banks choose to keep relatively high risk assets and sell off safer ones, as arbitraging on different regulatory requirements of different asset classes to maximize return on capital is their main motive. On the other hand, risk-constrained banks choose to keep relatively low risk assets, as transferring risk is their main priority.

In chapter 3, I analyze the updated HMDA data to find empirical support for my theoretical predictions. The new HMDA data provides a unique opportunity to look at the mortgage loans that banks retain on balance sheet for the first time ever. Combining the HMDA and Call Reports, I am able to construct a rich dataset that has both bank and loan-level information on more than two million mortgage loans originated by all non-exempt banks in the US. That allows me to test several hypotheses about bank securitization behaviors. Most of the findings are consistent with my theoretical predictions, except that capital-constrained banks have a higher securitization rate. A possible explanation is there is no variations in capital ratio in the theoretical model, as banks fully utilize their capital allowed by regulators when securitization is permitted. In future work, I will extend the theoretical model to include multiple asset classes to accommodate different strategies and heterogeneity in bank uses of capital.

In chapter 4, I present a brief case study that highlights the approval process and securitization choices of a traditional bank (PNC) and compare to a non-bank institution (Quicken Loans). A traditional bank has advantages in funding sources that allow it to originate more jumbo loans, hold larger portion of originated loans on balance sheet, and selectively choose which loans to retain. This further emphasizes the importance of understanding bank behaviors in a complex financial operation such as securitization. Moreover, the striking differences between a traditional bank and a shadow bank in asset choices demand deeper analysis in my future work.

Two implications related to the upcoming changes in macroprudential policies are interesting. First, since the main driver of volatility in the financial system is interconnectedness risk, we need to strengthen regulations in the cross-sectional dimension to limit the spillover risk among financial institutions. There are proposals in this respect, such as the Volcker Rule that prohibits banks from certain trading activities. However, we still need more regulations on other sources that make financial industry more connected and prone to systemic risk, such as the repo and securitization markets. Second, when used properly, securitization can be a valuable mechanism for banks to mange idiosyncratic risk and liquidity, for borrowers to obtain cheaper loans, and for investors to have a high-yield and relatively safe financial instrument. However, since the regulatory risk weights are the same for different assets in the same class, regardless of their true credit risk, banks may find opportunities to arbitrage the differences. As a result, banks may appear to have more regulatory capital than the true buffer needed to cover losses when they materialize, which goes against the purpose of capital regulation in the first place. A new initiative in the upcoming Basel IV to have mortgage risk weights based on loan-to-value is an encouraging attempt to more closely align the regulatory measure of risk with the true risk of the asset. But the question is whether loan-to-value is a sufficient measure of risk and whether we should include other loan characteristics in assigning the regulatory risk weights to mortgage loans or other risky assets.

In conclusion, macroprudential policies and systemic risk is an immense and dynamic topic that demands more research in the future. My dissertation is a small endeavor to shed light on the importance of firm-level heterogeneity and to advance our understanding of systemic risk.

References

Daron Acemoglu, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608, 2015.

Viral V Acharya and Tanju Yorulmazer. Information contagion and bank herding. *Journal of money, credit and Banking*, 40(1):215–231, 2008.

Viral V Acharya, Philipp Schnabl, and Gustavo Suarez. Securitization without risk transfer. *Journal of Financial Economics*, 107(3):515–536, 2013.

Viral V Acharya, Deniz Anginer, and A Joseph Warburton. The end of market discipline? investor expectations of implicit government guarantees. 2016.

Viral V Acharya, Lasse H Pedersen, Thomas Philippon, and Matthew Richardson. Measuring systemic risk. *The Review of Financial Studies*, 30(1):2–47, 2017.

Tobias Adrian and Markus K. Brunnermeier. Covar. *American Economic Review*, 106(7):1705–41, July 2016.

Tobias Adrian and Hyun Song Shin. Financial intermediaries and monetary economics. In *Handbook of monetary economics*, volume 3, pages 601–650. Elsevier, 2010.

Tobias Adrian and Hyun Song Shin. Procyclical leverage and value-at-risk. *The Review of Financial Studies*, 27(2):373–403, 2013.

Massimiliano Affinito and Edoardo Tagliaferri. Why do (or did?) banks securitize their loans? evidence from italy. *Journal of Financial Stability*, 6(4):189–202, 2010.

Geokge A Akerlof. The market for ”lemons”: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500, 1970.

Meraj Allahrakha, Paul Glasserman, H Peyton Young, et al. *Systemic importance indicators for 33 US bank holding companies: an overview of recent data*. Office of Financial Research, 2015.

Franklin Allen and Douglas Gale. Financial contagion. *Journal of political economy*, 108(1):1–33, 2000.

Brent W Ambrose, Michael LaCour-Little, and Anthony B Sanders. Does regulatory capital arbitrage, reputation, or asymmetric information drive securitization? *Journal of Financial Services Research*, 28(1-3):113–133, 2005.

Xudong An, Yongheng Deng, and Stuart A Gabriel. Value creation through securitization: evidence from the cmbs market. *The Journal of Real Estate Finance and Economics*, 38(3):302–326, 2009.

Andrew Ang, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang. The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1):259–299, 2006.

Andrew Ang, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang. High idiosyncratic volatility and low returns: International and further us evidence. *Journal of Financial Economics*, 91(1):1–23, 2009.

Alessandro Barattieri, Laura Moretti, Vincenzo Quadrini, et al. Banks interconnectivity and leverage. Technical report, CEPR Discussion Papers, 2016.

Andreas Barth and Isabel Schnabel. Why banks are not too big to fail–evidence from the cds market. *Economic Policy*, 28(74):335–369, 2013.

James R Barth and Apanard Penny Prabha. An analysis of resolving too-big-to-fail banks throughout the united states. *Journal of Regional Analysis and Policy*, 44 (1100-2016-90137):1, 2014.

Miguel A Segoviano Basurto, Bradley Jones, Peter Lindner, and Johannes Blankenheim. *Securitization: lessons learned and the road ahead*. Number 13-255. International Monetary Fund, 2013.

Luc Bauwens, Sébastien Laurent, and Jeroen VK Rombouts. Multivariate garch models: a survey. *Journal of applied econometrics*, 21(1):79–109, 2006.

Anne Beatty and Scott Liao. Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, 58(2-3):339–383, 2014.

Sylvain Benoit, Jean-Edouard Colliard, Christophe Hurlin, and Christophe Pérignon. Where the risks lie: A survey on systemic risk. *Review of Finance*, 21(1):109–152, 2017.

Monica Billio, Mila Getmansky, Andrew W Lo, and Loriana Pelizzon. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics*, 104(3):535–559, 2012.

Tim Bollerslev. Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3):307–327, 1986.

Tim Bollerslev, Robert F Engle, and Jeffrey M Wooldridge. A capital asset pricing model with time-varying covariances. *Journal of political Economy*, 96(1):116–131, 1988.

Tim Bollerslev et al. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized arch model. *Review of Economics and statistics*, 72(3): 498–505, 1990.

Vitaly M Bord and Joao AC Santos. The rise of the originate-to-distribute model and the role of banks in financial intermediation. *Federal Reserve Bank of New York Economic Policy Review*, page 21, 2012.

Vitaly M Bord and Joao AC Santos. Does securitization of corporate loans lead to riskier lending? *Journal of Money, Credit and Banking*, 47(2-3):415–444, 2015.

Christian Brownlees and Robert F Engle. Srisk: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies*, 30(1):48–79, 2016.

Markus K Brunnermeier and Lasse Heje Pedersen. Market liquidity and funding liquidity. *The review of financial studies*, 22(6):2201–2238, 2008.

Greg Buchak, Gregor Matvos, Tomasz Piskorski, and Amit Seru. Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130(3): 453–483, 2018.

Charles W Calomiris and Joseph R Mason. Credit card securitization and regulatory arbitrage. *Journal of Financial Services Research*, 26(1):5–27, 2004.

M Angeles Carnero and M Hakan Eratalay. Estimating var-mgarch models in multiple steps. *Studies in Nonlinear Dynamics & Econometrics*, 18(3):339–365, 2014.

Barbara Casu, Andrew Clare, Anna Sarkisyan, and Stephen Thomas. Securitization and bank performance. *Journal of Money, Credit and Banking*, 45(8):1617–1658, 2013.

Nicola Cetorelli, Benjamin H Mandel, Lindsay Mollineaux, et al. The evolution of banks and financial intermediation: framing the analysis. *Federal Reserve Bank of New York Economic Policy Review*, 18(2):1–12, 2012.

Tri Vi Dang, Gary Gorton, and Bengt Holmström. Ignorance, debt and financial crises. *Yale University and Massachusetts Institute of technology, working paper*, 17, 2012.

Olivier De Bandt and Philipp Hartmann. Systemic risk: A survey. Technical report, European Central Bank, 2000.

Harry DeAngelo and Rene M Stulz. Liquid-claim production, risk management, and bank capital structure: Why high leverage is optimal for banks. *Journal of Financial Economics*, 116(2):219–236, 2015.

Peter DeMarzo and Darrell Duffie. A liquidity-based model of security design. *Econometrica*, 67(1):65–99, 1999.

Douglas W Diamond. Financial intermediation and delegated monitoring. *The review of economic studies*, 51(3):393–414, 1984.

Douglas W Diamond and Philip H Dybvig. Bank runs, deposit insurance, and liquidity. *Journal of political economy*, 91(3):401–419, 1983.

Francis X Diebold and Kamil Yılmaz. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134, 2014.

Fernando Duarte and Thomas M Eisenbach. Fire-sale spillovers and systemic risk. *FRB of New York Staff Report*, (645), 2018.

Darrell Duffie. Innovations in credit risk transfer: implications for financial stability. Technical report, Bank for International Settlements, 2008.

Peter J Elmer. Conduits: Their structure and risk. *FDIC Banking Rev.*, 12:27, 1999.

Robert F Engle. Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, pages 987–1007, 1982.

Robert F Engle and Kenneth F Kroner. Multivariate simultaneous generalized arch. *Econometric theory*, 11(1):122–150, 1995.

Isil Erel, Taylor Nadauld, and René M Stulz. Why did holdings of highly rated securitization tranches differ so much across banks? *The Review of Financial Studies*, 27(2):404–453, 2013.

Eugene F Fama. Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, 25(2):383–417, 1970.

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1):3–56, 1993.

Eugene F Fama and Kenneth R French. Multifactor explanations of asset pricing anomalies. *The journal of finance*, 51(1):55–84, 1996.

FDIC. *History of the Eighties: Lessons for the Future. Vol. 1, An Examination of the Banking Crises of the 1980s and Early 1990s.* Federal Deposit Insurance Corporation (FDIC), 1997.

Neil Fligstein, Adam Goldstein, et al. The transformation of mortgage finance and the industrial roots of the mortgage meltdown. Technical report, Institute of Industrial Relations, UC Berkeley, 2012.

Xavier Freixas, Luc Laeven, and José-Luis Peydró. *Systemic Risk, Crises, and Macroprudential Regulation.* Mit Press, 2015. ISBN 9780262028691. URL `http://www.jstor.org/stable/j.ctt17kk82g`.

Fangjian Fu. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of financial Economics*, 91(1):24–37, 2009.

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

Stefano Giglio, Bryan Kelly, and Seth Pruitt. Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, 119(3):457–471, 2016.

Gary Gorton and Andrew Metrick. *Securitization*, volume 2 of *Handbook of the Economics of Finance*, chapter 0, pages 1–70. Elsevier, 2013. doi: 10.1016/B978-0-44-453594-. URL `https://ideas.repec.org/h/eee/finchp/2-a-1-70.html`.

Gary B Gorton and Nicholas S Souleles. Special purpose vehicles and securitization. In *The risks of financial institutions*, pages 549–602. University of Chicago Press, 2007.

Peter R Hansen and Asger Lunde. A forecast comparison of volatility models: does anything beat a garch (1, 1)? *Journal of applied econometrics*, 20(7):873–889, 2005.

Samuel G Hanson and Adi Sunderam. Are there too many safe securities? securitization and the incentives for information production. *Journal of Financial Economics*, 108(3):565–584, 2013.

Nikolaus Hautsch, Julia Schaumburg, and Melanie Schienle. Financial network systemic risk contributions. *Review of Finance*, 19(2):685–738, 2014.

Bernard Herskovic, Bryan Kelly, Hanno Lustig, and Stijn Van Nieuwerburgh. The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics*, 119(2):249–283, 2016.

David Jones. Emerging problems with the basel capital accord: Regulatory capital arbitrage and related issues. *Journal of Banking & Finance*, 24(1-2):35–58, 2000.

Benjamin J Keys, Tanmoy Mukherjee, Amit Seru, and Vikrant Vig. Did securitization lead to lax screening? evidence from subprime loans. *The Quarterly journal of economics*, 125(1):307–362, 2010.

John Krainer and Elizabeth Laderman. Mortgage loan securitization and relative loan performance. *Journal of Financial Services Research*, 45(1):39–66, 2014.

Franco Modigliani and Leah Modigliani. Risk-adjusted performance. *The Journal of Portfolio Management*, 23(2):45–54, 1997.

Stewart C Myers and Nicholas S Majluf. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, 13(2):187–221, 1984.

Zoltan Pozsar, Tobias Adrian, Adam B Ashcraft, and Hayley Boesky. Shadow banking. *Economic Policy Review*, (Dec):1–16, 2013.

Andrei Shleifer and Robert W Vishny. Unstable banking. *Journal of financial economics*, 97(3):306–318, 2010.

Richard Stanton and Nancy Wallace. Cmbs subordination, ratings inflation, and regulatory capital arbitrage. *Financial Management (Wiley-Blackwell)*, 47(1):175 – 201, 2018. ISSN 00463892. URL `http://proxy.lib.ohio-state.edu/login?url=http://search.ebscohost.com/login.aspx`

Rene M Stulz. Risk management, governance, culture, and risk taking in banks. *Economic Policy Review*, (Aug):43–60, 2016.

Suresh Sundaresan. A review of merton's model of the firm's capital structure with its wide applications. *Annu. Rev. Financ. Econ.*, 5(1):21–41, 2013.

OFR Viewpoint. *Size Alone is Not Sufficient to Identify Systemically Important Banks*. Number 17-04 in Viewpoint Papers. Office of Financial Research, US Department of the Treasury, 2017.

Agustín Villar. Macroprudential frameworks: objectives, decisions and policy interactions. *BIS Paper*, (94a), 2017.

Richard A Werner. A lost century in economics: Three theories of banking and the conclusive evidence. *International Review of Financial Analysis*, 46:361–379, 2016.

Chapter A

Appendix to Chapter 2

A.1 Regulatory Measure of Risk

This section shows the derivation of the risk threshold that determines whether a bank with its own idiosyncratic risk σ_i is constrained by the capital regulation or by the risk governance constraint.

Recall: The capital constraint is

$$\omega p a_i^r \leq e_i \tag{A.1}$$

and the risk constraint is

$$VaR_i \leq e_i \tag{A.2}$$

where ω is the regulatory capital charge against the risky asset and $VaR_i = \left(r^f p + z\sigma_i - q\right) a_i^r$ is the bank $\alpha-$Value-at-Risk for holding a_i^r units of risky assets.

First, if the capital constraint A.1 is binding and the risk constraint A.2 is slack, then

$$\omega p a_i^r = e_i \geq VaR_i \tag{A.3}$$

from which we can rewrite as

$$\omega p \geq r^f p + z\sigma_i - q \tag{A.4}$$

which implies

$$\sigma_i \leq \frac{q - r^f p + \omega p}{z} \tag{A.5}$$

Second, if the capital constraint A.1 is slack and the risk constraint A.2 is binding, then

$$VaR_i = e_i \geq \omega p a_i^r \tag{A.6}$$

from which we can rewrite as

$$r^f p + z\sigma_i - q \geq \omega p \tag{A.7}$$

which implies

$$\sigma_i \geq \frac{q - r^f p + \omega p}{z} \tag{A.8}$$

Let denote $\bar{\sigma} = \dfrac{q - r^f p + \omega p}{z}$, which can be interpreted as a regulatory measure of risk.

Then, for a bank that has idiosyncratic risk σ_i less than $\bar{\sigma}$, it is constrained by the capital regulation. It means that even though the bank has enough equity to cover a larger value-at-risk, regulators do not allow it to do so.

On the other hand, for a bank that has idiosyncratic risk σ_i greater than $\bar{\sigma}$, it is constrained its internal risk governance. It means that even though regulators allow it to take more risk, the bank does not have enough risk-taking capacity to do so while maintaining its desirable level of risk.

A.2 Securitized Payoff Structure

The securitization market is assumed to be perfectly competitive, where banks can sell risky asset claims and purchase securitized bonds at the market price p_s. In a richer dynamic model, it can be shown that the price p_s is the market-clearing price that equates the supply of risky claims and demand for securitized bonds, i.e., $\sum_i \phi_i a_i^r = \sum_i a_i^s$. Then, the total payoff received from the underlying assets of the pool can be written as $W_s = \sum_i \phi_i a_i^r w_i$, where w_i is the payoff variable of the underlying assets. Then, the variance of the total pool payoff is positive, as

$$\begin{aligned} Var(W_s) &= Var(\sum_i \phi_i a_i^r w_i) && \text{(A.9)} \\ &= \sum_i (\phi_i a_i^r)^2 \, Var(w_i) \\ &= \sum_i (\phi_i a_i^r \sigma_i)^2 && \text{(A.10)} \end{aligned}$$

However, since the model does not have a tranching mechanism, assume that payoff paid to each securitized claim is on the pro rata basis. Then, the payoff of each individual securitized claim w_s can be written as total pool payoff divided by total securitized bonds issued,

$$w_s = \frac{\sum_i \phi_i a_i^r w_i}{\sum_i a_i^s} \tag{A.11}$$

Then, the expected value of securitized payoff is

$$\begin{aligned} E(w_s) &= E\left(\frac{\sum_i \phi_i a_i^r w_i}{\sum_i a_i^s}\right) \\ &= \frac{\sum_i \phi_i a_i^r E(w_i)}{\sum_i a_i^s} \\ &= \frac{\sum_i \phi_i a_i^r q}{\sum_i a_i^s} \\ &= q \end{aligned} \tag{A.12}$$

Assume risky payoff w_i is independent from each other, the variance of securitized payoff can be derived as

$$\begin{aligned} Var(w_s) &= Var\left(\frac{\sum_i \phi_i a_i^r w_i}{\sum_i a_i^s}\right) \\ &= Var\left(\sum_i \left(\frac{\phi_i a_i^r}{\sum_i a_i^s}\right) w_i\right) \\ &= \sum_i \left(\frac{\phi_i a_i^r}{\sum_i a_i^s}\right)^2 Var(w^i) \\ &= \sum_i \left(\frac{\phi_i a_i^r}{\sum_i \phi_i a_i^s}\right)^2 \sigma_i^2 \end{aligned} \tag{A.13}$$

Since each individual bank has an insignificant share of the securitization market, $\frac{\phi_i a_i^r}{\sum_i \phi_i a_i^s} \approx 0$, implying $Var(w_s)$ converges to 0. This captures the conventional wisdom that pooling is an effective risk-sharing method.

A.3 Proof of Proposition 1

Proposition 1. *When securitization is allowed, the regulatory capital constraint is always binding at the optimum.*

Proof: Recall the random portfolio payoff when securitization is allowed

$$W_i^p = (1-\phi_i)a_i^r w_i + a_i^s w_s - r^f((1-\phi_i)pa_i^r - e^i) - c(\phi_i a_r^i) \tag{A.14}$$

Using two assumptions about the securitization structure: (1) direct swap: $\phi_i a_i^r = a_i^s$ and (2) no arbitrage in funding source: $c(\phi_i a_r^i) = r^f p\phi_i a_r^i$, the portfolio payoff can be simplified as

$$\begin{aligned} W_i^p &= (1-\phi_i)a_i^r w_i + a_i^s w_s - r^f((1-\phi_i)pa_i^r - e^i) - c(\phi_i a_r^i) \\ &= (1-\phi_i)a_i^r w_i + \phi_i a_i^r w_s - r^f((1-\phi_i)pa_i^r - e^i) - r^f p\phi_i a_r^i \\ &= r^f e_i + a_i^r\left[(1-\phi_i)w_i + \phi_i w_s - r^f(1-\phi_i)p - r^f p\phi_i\right] \\ &= r^f e_i + a_i^r\left[(1-\phi_i)w_i + \phi_i w_s - r^f p\right] \end{aligned} \tag{A.15}$$

Given $E(w_i) = E(w_s) = q$, we have the expected portfolio payoff of bank i is

$$\begin{aligned} E(W_i^p) &= E(r^f e_i + a_i^r\left[(1-\phi_i)w_i + \phi_i w_s - r^f p\right]) \\ &= r^f e_i + a_i^r E((1-\phi_i)w_i + \phi_i w_s - r^f p) \\ &= \left(q - r^f p\right) a_r^i + r^f e_i \end{aligned} \tag{A.16}$$

Since risky assets yield positive excess return, $q - r^f p > 0$, the expected portfolio payoff increases in the risky asset holdings. In other words, banks would want to increase risky investment to infinity if there is no constraint. However, thanks to the regulatory and risk constraint, the bank can only increase its asset holdings to a certain level.

If there is any available room in the regulatory capital, i.e., $\omega p(1-\phi_i)a_i^r + \omega_s p_s a_i^s \leq e_i$, then the bank can increase a_s^i by originating new loans and converting them to securitized claims to achieve a higher expected return without breaking the VaR constraint since $VaR^i = a_i^r \left[r^f p + z\sigma_i - q\right] - a_i^s z\sigma_i$ decreasing in a_i^s.

As a result, the regulatory capital constraint is always binding, regardless of the initial conditions of the bank.

A.4 Proof of Proposition 2 (Capital-constrained Banks)

Proposition 2. *For capital-constrained banks, regulatory capital arbitrage is the main motive of securitization. They retain the risky asset if its expected regulatory-adjusted returns is equal or greater than that of securitized assets, i.e.*

$$\begin{cases} \phi = 1 & \text{if } \dfrac{\pi}{\omega} < \dfrac{\pi_s}{\omega_s} \\ \phi = 0 & \text{otherwise} \end{cases}$$

where ϕ is the securitization rate, $\pi = q/p, \pi_s = q/p_s$ are expected returns of risky and securitized assets, respectively, and ω, ω_s are the regulatory risk weight of the two assets.

Proof: Given the binding capital constraint, and under the assumption that securitization is a direct swap, the risky asset holding can be derived as

$$a_i^r = \frac{e_i}{\omega p - \phi_i(\omega p - \omega_s p_s)} \tag{A.17}$$

When $\dfrac{\pi}{\omega} < \dfrac{\pi_s}{\omega_s}$, or equivalently $\omega p > \omega_s p_s$, we get the risky asset holdings increasing in securitization rate (i.e. $\partial a_i^r/\partial \phi_i) > 0$. Since the portfolio expected return increases in a_i^r, banks can earn arbitrage profit by converting all of their originated loans into securitized claims without holding loan loss provision, as the securitized asset is considered riskless to individual banks. As a result, $\phi_i = 1$ if $\dfrac{\pi}{\omega} < \dfrac{\pi_s}{\omega_s}$.

On the other hand, when $\dfrac{\pi}{\omega} \geq \dfrac{\pi_s}{\omega_s}$, or equivalently $\omega p \leq \omega_s p_s$, it turns out that capital-constrained banks earn no benefit from securitization. The initial risky asset holding of capital-constrained bank is $a^r_{i0} = \frac{e_i}{\omega p} \geq \frac{e_i}{\omega p - \phi_i(\omega p - \omega_s p_s)} \forall \phi_i \in [0, 1]$, implying that the bank will get worse expected payoff if it has a positive securitization rate. Moreover, initially, capital-constrained banks still have available VaR, so they do not need securitized claims to reduce the risk, i.e. no benefit from the risk-transferring channel. As a result, the optimal choice for capital-constrained banks in this scenario is opting out of the securitization market, i.e. $\phi_i = 0$ if $\frac{\pi}{\omega} \geq \frac{\pi_s}{\omega_s}$.

A.5 Proof of Proposition 3 (Risk-constrained Banks)

Proposition 3. *For risk-constrained banks, risk transferring is the main motive of securitization. They always have a positive securitization rate and riskier banks securitize more*

$$\begin{cases} \phi = 1 & \text{if } \dfrac{\pi}{\omega} < \dfrac{\pi_s}{\omega_s} \\ \phi > 0 & \text{otherwise} \end{cases}$$

and

$$\frac{\partial \phi}{\partial \sigma_i} > 0$$

Proof: First, using the similar argument as in the proof of Proposition 2, we can show $\phi = 1$ if $\frac{\pi}{\omega} < \frac{\pi_s}{\omega_s}$.

However, it is more interesting in the scenario where $\frac{\pi}{\omega} \geq \frac{\pi_s}{\omega_s}$, as for the risk-constrained banks, they can still benefit from the risk-transferring channel by engaging in securitization. Moreover, the initial risky asset holding of risk-constrained banks is $a_{io}^r = \frac{e_i}{z\sigma_i + r^f p - q} < \frac{e_i}{\omega p}$, it is still possible for the risk-constrained banks to increase their investment in risky assets when $\frac{\pi}{\omega} \geq \frac{\pi_s}{\omega_s}$.

On the other hand, for risk-constrained banks, it is optimal to engage in securitization up to the point where both capital and risk constraints are binding. The reasoning is simple. Since the risk-constrained banks have available regulatory capital, but constrained by the risk governance, when securitization is allowed, these banks can use the available regulatory capital to originate new loans then swapping some of them into securitized claims until it fully utilized the total asset allowance. Since securitized claims earn less expected regulatory-adjusted return than risky assets, risk-constrained banks do not have convert all of their risk holdings into securitized claims to have higher expected return. At optimum, the binding VaR constraint indicates the optimal securitization rate as

$$\begin{aligned}
a_i^r \left[r^f p + z\sigma_i - q - \phi_i z\sigma_i\right] &= e_i \\
\frac{e_i}{\omega p - \phi_i(\omega p - \omega_s p_s)} \left[r^f p + z\sigma_i - q - \phi_i z\sigma_i\right] &= e_i \\
r^f p + z\sigma_i - q - \phi_i z\sigma_i &= \omega p - \phi_i(\omega p - \omega_s p_s) \\
\phi_i &= \frac{z\sigma_i - q + r^f p - \omega p}{z\sigma_i + (\omega_s p_s - \omega p)} \\
&= \frac{z\sigma_i - z\bar{\sigma}}{z\sigma_i + (\omega_s p_s - \omega p)} \\
&= \frac{z(\sigma_i - \bar{\sigma})}{z\sigma_i + (\omega_s p_s - \omega p)} > 0 \qquad \text{(A.18)}
\end{aligned}$$

as $\sigma_i > \bar{\sigma}$ for risk-constrained banks.

Moreover, the derivative of ϕ_i with respect to σ_i can be written as

$$\begin{aligned}
\frac{\partial \phi_i}{\partial \sigma_i} &= \frac{\left[z\sigma_i + (\omega_s p_s - \omega p)\right] z - z\left[z(\sigma_i - \bar{\sigma})\right]}{\left[z\sigma_i + (\omega_s p_s - \omega p)\right]^2} \\
&= \frac{z\left[z\sigma_i + (\omega_s p_s - \omega p) - z(\sigma_i - \bar{\sigma})\right]}{\left[z\sigma_i + (\omega_s p_s - \omega p)\right]^2} \\
&= \frac{z\left[(\omega_s p_s - \omega p) + z\bar{\sigma})\right]}{\left[z\sigma_i + (\omega_s p_s - \omega p)\right]^2} > 0 \qquad \text{(A.19)}
\end{aligned}$$

as $\omega_s p_s > \omega p$ and $z\bar{\sigma} > 0$.

This result implies that riskier banks benefit more from the risk-transferring channel, and hence have a higher securitization rate.