ESSAYS ON INTERMEDIARY ASSET PRICING

A Dissertation

by

SANG-OOK SHIN

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	Hwagyun Kim
Co-Chair of Committee,	Christa H.S. Bouwman
Committee Members,	Sorin M. Sorescu
	Yong Chen
	Tatevik Sekhposyan
Head of Department,	Sorin M. Sorescu

August 2019

Major Subject: Business Administration

ABSTRACT

The dissertation studies intermediary asset pricing, including two chapters. The first chapter examines how heterogeneity in intermediary capital – the equity capital ratio of the largest financial intermediaries in the U.S. – affects the cross-section of stock returns. I estimate the exposure (i.e., beta) of individual stocks to a shock in the dispersion of intermediary capital and find that stocks in the lowest beta decile generate an additional 6.8% - 8.2% annual return relative to stocks in the highest beta decile. Using data from Institutional (13F) Holdings, I also find evidence that low-capital intermediaries, who hold riskier assets than high-capital intermediaries, face leverage-induced fire sales during bad times. I propose a model of heterogeneous intermediary capital in which heterogeneous risk preference between high- and low-capital intermediaries leads to a countercyclical variation in aggregate risk aversion and a risk premium. The model states that the dispersion of intermediary capital is priced in the cross-section of asset prices, which supports the empirical findings.

The second chapter focuses on how bank capital affects bank stock performance. We show that capital does not affect returns unconditionally, but high-capital banks have higher risk-adjusted stock returns (alphas) than low-capital banks in bad times in and out of sample. Trading strategies earn 3.60% - 4.44% annually. The results are robust to: using different bad times and capital definitions, alternative asset pricing models, and ex-ante expected returns; controlling for performance-type delistings, short-sale constraints, and trading costs; and dropping the largest or smallest banks. Our results seem to be driven by a "Surprised Investor Channel" rather than by an "Informed Investor Channel."

DEDICATION

To my family.

ACKNOWLEDGMENTS

I am deeply indebted to my advisors, Hwagyun Kim and Christa Bouwman, for their extraordinary support and unwavering guidance during my Ph.D. years. I am extremely grateful to Hwagyun Kim for his insightful and inspiring advice as well as his patience throughout the process of wiring this dissertation. Without his advice, I would not have written a theory model in the dissertation. I would also like to extend my deepest gratitude to Christa Bouwman for her constructive advice and encouraging words. I have deeply admired her strong work ethic and enthusiasm for research.

I would like to thank my committee member, Sorin M. Sorescu, for his valuable comments and feedback. I would also like to extend my gratitude to Yong Chen and Tatevik Sekhposyan not only for being part of my dissertation committee, but for their intellectual contributions. I gratefully acknowledge helpful comments and suggestions from all other faculty members in our department. The dissertation would not have been possible without the incredible support from the Department of Finance at Mays Business School.

Finally, I would like to give my special thanks to my friends and colleagues in the Ph.D. program at Mays Business School.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supported by a dissertation committee consisting of Professors Hwagyun Kim, Christa H.S. Bouwman, Sorin M. Sorescu, and Yong Chen of the Department of Finance and Professor Tatevik Sekhposyan of the Department of Economics.

The work in Chapter 2 was collaborated with Professor Christa H.S. Bouwman and Hwagyun Kim of the Department of Finance.

All other work conducted for the dissertation was completed by the student independently.

Funding Sources

Graduate study was supported by a fellowship from Texas A&M University and Mays Business School.

TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

TABLE Page

1. INTRODUCTION

Traditionally, asset pricing models are based on household's consumption and assume that household consumers are marginal investors. These models are called consumption-based asset pricing models. The role of financial intermediation has not been emphasized in these models. Therefore, a pricing kernel specific to financial intermediaries' preference has not been carefully explored. In addition, the factors that determine stock prices of those intermediaries are ignored in asset pricing models since most asset pricing studies exclude financial firms from their samples. After the financial crisis in the late 2000's, as a new attempt to understand asset pricing through the lens of financial intermediaries, an "intermediary asset pricing" model has emerged.[1] Intermediary asset pricing argues that rather than household consumers, who are susceptible to behavioral biases, financial intermediaries are "true" marginal investors.

The purpose of the dissertation is to extend the intermediary asset pricing model by studying the cross-sectional difference in intermediary capital and its effect on stock returns in the U.S. The first chapter (Section 2) investigates how heterogeneous intermediary capital is priced in *industrial firm stocks*. The second chapter (Section 3) identifies how heterogeneous intermediary capital (particularly bank capital) is priced in *its own stocks*.

The first chapter constructs a stochastic discount factor that incorporates the dynamics of heterogeneous intermediary capital. In particular, intermediaries have different levels of capital in the cross-section while previous studies in intermediary asset pricing assume that intermediaries are identical. Thus, the time variations of capital held by high- and low-capital intermediaries may be different. This paper examines how the heterogeneity of intermediary capital plays a role in asset markets.

Using intermediary capital as a proxy for their risk aversion, I argue that risk aversion is *positively* related to intermediary capital: risk-averse intermediaries would build up precautionary capital whereas risk-tolerant intermediaries would invest more in risky assets, taking higher lever-

[1] See He and Krishnamurthy (2018) for the detail.

age. Combined with the different time variations of their capital, it is expected that aggregate risk aversion increases (decreases) when high- (low-) capital intermediaries hold more capital. Since investors want to hedge against this time-varying risk aversion, heterogeneous intermediary capital will be priced in the cross-section of asset returns. This paper provides theoretical and empirical evidence that supports the above-mentioned argument.

The second chapter examines how bank capital affects its own stock prices. Bank capital has been an important topic for researchers, regulators, and practitioners. Bank capital helps to improve bank stability, but it is costly to hold. Thus, previous studies find that the effect of bank capital on bank performance (e.g., survival, market share) can be either *positive* or *negative*. However, during bad times, the benefit of holding additional capital particularly outweighs the cost of it. This paper studies asset pricing implications of bank capital during bad times versus normal times.

If investors are able to correctly price such a beneficial effect of bank capital during bad times, we would not predict any abnormal returns on bank stocks during bad times. However, to the extent that investors fail to correctly value bank stocks in anticipation of future bad times, non-zero abnormal returns may appear. We find that high-capital banks outperform low-capital banks *conditionally* during bad times. The result is highly robust to numerous specifications of both *in-sample* tests and *out-of-sample* trading strategies.

The rest of the dissertation is organized as follows. Section 2 presents the first chapter, "Heterogeneous Intermediary Capital and the Cross-Section of Stock Returns." Section 3 explains the second chapter, "Bank Capital and Bank Stock Performance." Section 4 concludes. The Appendix offers proofs of Propositions and other supporting material.

2. HETEROGENEOUS INTERMEDIARY CAPITAL AND THE CROSS-SECTION OF STOCK RETURNS

2.1 Introduction

The role of financial intermediation has been emphasized in recent literatures to understand business cycles and financial markets. In particular, the financial crisis in the late 2000's has highlighted that frictions in financial intermediation help to explain the movement of asset prices, which in turn has led to the growing popularity of "intermediary asset pricing". Different from the traditional perspective of consumption-based asset pricing models,[1] intermediary asset pricing models argue that financial intermediaries are the marginal investors who can trade across various sophisticated asset classes and account for a major portion of trades. As intermediary capital affects their trading decisions, a stochastic discount factor should include the time variation in intermediary capital (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014).

Financial intermediaries have different levels of capital in the cross-section. Intuitively, low-capital intermediaries will have higher (lower) return on capital than high-capital intermediaries during good (bad) times due to leverage, implying that the time variation in capital of high- and low-capital intermediaries will be different. Heterogeneous agent models highlight that the cross-sectional difference of marginal investors in various aspects is important in asset pricing. For example, a risk premium can be driven by the cross-sectional distribution of agents' income and consumption (Constantinides and Duffie, 1996) or risk preference (Chan and Kogan, 2002; Gârleanu and Panageas, 2015). Existing studies in an intermediary asset pricing literature ignore heterogeneity in intermediary capital, though it seems important to examine heterogeneity of marginal investors under the framework of intermediary asset pricing models. This leads to the following research question: Can the dynamics of the heterogeneity in intermediary capital play an important

[1]The limitation of consumption-based asset pricing models has been reviewed extensively in prior studies. For example, household consumers are lazy in making consumption and investment decisions (Jagannathan and Wang, 2007), they rebalance portfolios very infrequently (Brunnermeier and Nagel, 2008), or information-averse households are inattentive to savings (Andries and Haddad, 2018).

role in determining a stochastic discount factor?

In this paper, I study the cross-sectional distribution of intermediary capital and its effect on asset pricing. My first empirical analysis focuses on how heterogeneity in intermediary capital affects the cross-section of stock returns. In detail, I measure the heterogeneity in intermediary capital as dispersion of capital ratios, that is, the difference between the 75^{th} and the 25^{th} percentile of the quasi-market capital ratio of the largest 30 intermediaries in the U.S.,[2] scaled by its 50^{th} percentile. It is important to note that the dispersion of capital ratios is defined so as to capture the fraction of capital controlled by high- versus low-capital intermediaries: the dispersion increases (decreases) when low-capital intermediaries lose (earn) more capital than high-capital intermediaries during bad (good) times. Consistently, I find that it is highly countercyclical. Next, using all stocks listed on NYSE, AMEX, or NASDAQ, I estimate each stock's exposure to a shock in the dispersion of capital ratios (i.e., dispersion beta, β^{DISP}). I find strong evidence that the dispersion of capital ratios is *negatively* priced in the cross-section of stock returns. Stocks in the lowest dispersion beta decile generate an additional 6.8% - 8.2% annual risk premium relative stocks in the highest dispersion beta decile, after controlling for various risk factors including the level of intermediary capital.

The results are consistent with Chan and Kogan (2002) and Gârleanu and Panageas (2015) who argue that when agents are heterogeneous in risk aversion, aggregate risk aversion exhibits a countercyclical variation due to compositional changes in aggregate wealth. Given that less risk-averse intermediaries who want to invest more into risky assets use higher leverage (equivalently, maintain lower capital), intermediary capital is positively associated with risk aversion of intermediaries.[3] Then, the aggregate risk aversion increases (decreases) in bad (good) times when low-capital intermediaries with *lower* risk aversion hold less (more) capital. This implies that risk captured by the dispersion beta is each stock's exposure to a shock in the aggregate risk aver-

[2]The financial intermediaries comprise mutual funds, hedge funds, broker-dealers, commercial banks, investment banks, or their holdings companies. Participation of these intermediaries in stock markets is sizable. Based on my sample, their stock holdings in the U.S. are over \$3.3 trillion, and the average ratio of stock holdings over book assets is 26.0% in 2012.

[3]Section 2.2 discusses the positive relation between intermediary capital and risk aversion in detail.

sion. Therefore, stocks with the high dispersion beta exhibit a lower risk premium, providing a hedge against the heightened risk aversion, and stocks with the low dispersion beta are riskier and therefore earn a higher premium.

To rationalize this conjecture, I propose a model of heterogeneous intermediary capital in an economy populated with two specialists and one household. A key feature of the model is that specialists have a power utility function with internal habits but exhibit heterogeneity in habit persistence, which leads to heterogeneous risk aversion of specialists. The constraint in raising capital allows a more risk-averse specialist to attract more equity capital from the household to form an intermediary, a feature consistent with the positive relation (documented in this paper) between capital of intermediaries and their risk aversion.

In addition, it is likely that low-capital intermediaries would face scarce funding liquidity in bad times, incurring a hike in margin requirements (liquidity spirals as in Brunnermeier and Pedersen, 2009). More importantly, if the shock is systematic, all low-capital intermediaries may be forced to deleverage by selling off assets, and this may lead leverage-induced fire sales (Bian, He, Shue, and Zhou, 2018). In contrast, high-capital intermediaries who have sufficient capital can potentially absorb these asset sales, as argued in Acharya and Viswanathan (2011). Given that high-capital intermediaries have higher risk aversion than low-capital intermediaries, they will not buy those assets unless the prices drop sufficiently. This further triggers fire sales during bad times. As a result, low- (high-) capital intermediaries may sell (buy) assets at prices lower than fundamental values, implying that the net worth of low-capital intermediaries would transfer to high-capital intermediaries during bad times.

To examine the aforementioned arguments, I perform tests to analyze the trading activity of financial intermediaries by using the Thomson Reuters Institutional (13F) Holdings database. At each quarter end, I manually match managers in the Institutional (13F) Holdings database with their holding companies in the Compustat Quarterly database. The matched data allow me to directly examine how different capital ratios of financial intermediaries affect their holdings of nonfinancial firm stocks and trades, especially during bad times (i.e., when the dispersion of capital ratios is high). I document the following results.

First, low-capital intermediaries sell substantial amounts of stocks during bad times while high-capital intermediaries do not. However, by tracking the types of stocks bought and sold by financial intermediaries, I show that high-capital intermediaries purchase significantly more stocks that low-capital intermediaries sell, and low-capital intermediaries sell significantly more stocks that high-capital intermediaries purchase during such times. This is consistent with the notion that there are asset transfers from low-capital intermediaries to high-capital intermediaries during bad times.

Second, to test whether the stocks sold by low-capital intermediaries are indeed fire-sold, I examine trading gains of financial intermediaries during bad times. Since the Thomson Reuters Institutional (13F) Holdings database provides neither the exact transaction date nor the parties involved in the transaction, I am only able to infer fire sales by observing trading gains (i.e., abnormal returns) of financial intermediaries in the following quarter. I find that high-capital intermediaries earn positive trading gains on stock purchases while low-capital intermediaries lose in terms of forgone returns on stock sales in the following quarter. That is, consistent with a fire sales interpretation, stocks are sold at prices lower than fundamental values.

Finally, when they trade stocks, there is a "trade mismatch" between high- and low-capital intermediaries. To see this, note the following. High-capital intermediaries may be so risk-averse that they are only willing to buy assets that have fallen in price (i.e., stocks with low dispersion betas). At the same time, low-capital intermediaries may hesitate to sell those assets if they believe prices have temporarily dropped below their fundamental values and will recover again. They may therefore choose to sell stocks that have experienced a modest price drop (i.e., stocks with moderate dispersion betas). In support of this argument, I show that during bad times, high-capital intermediaries tend to purchase more stocks with low dispersion betas whereas low-capital intermediaries are likely to sell more stocks with medium dispersion betas.

My paper adds to the literature on intermediary asset pricing. After the theoretical ground established (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014), Adrian, Etula, and

Muir (2014) and He, Kelly, and Manela (2017) test empirically that the level of intermediary capital (equivalently, the inverse of intermediary leverage) prices the cross-section of asset returns, including returns on equity portfolios. I provide the empirical evidence supporting the importance of the dispersion of intermediary capital in predicting stock returns, controlling for the level of intermediary capital. In the theoretical perspective, the level of intermediary capital captures wealth from a given utility function while the dispersion of intermediary capital captures the shape (i.e., curvature) of the utility function of a representative agent through compositional changes among heterogeneous agents.

There are also other studies that emphasize the important role of heterogeneous intermediaries in asset markets. While my paper addresses the heterogeneity in risk preference of intermediaries, financial intermediaries are modeled to be heterogeneous in terms of Value-at-Risk constraints in Coimbra and Rey (2018) or funding constraints in Ma (2018). These studies, including my work, feature the cross-sectional distribution of assets among intermediaries, which ultimately drives the risk premium. In the banking literature, the cross-sectional difference in bank capital has been shown to affect bank stock returns indirectly through the market beta (Baker and Wurgler, 2015) or conditionally during bad times (Bouwman, Kim, and Shin, 2018).

My work also complements the literature on heterogeneous agents and time-varying risk aversion. Chan and Kogan (2002) and Gârleanu and Panageas (2015) argue in their theoretical models that although agents' risk aversion is not time-varying, the aggregate risk aversion of the market can vary over time if agents are heterogeneous in risk aversion. Using intermediary capital as a proxy for risk aversion, I find empirical evidence that is consistent with their predictions; the aggregate risk aversion and the risk premium are countercyclical. Related, Brunnermeier and Nagel (2008) use micro-level data (i.e., Panel Study of Income Dynamics) to test how changes in risk aversion through a habit preference affect individuals' asset allocation. Gârleanu and Pedersen (2011) document that risk-tolerant agents operate with high leverage and that in bad times, a premium may rise once margin requirement starts to bind, reflecting scarce funding liquidity.

This paper is, to my best knowledge, the first attempt to directly investigate stock holdings of financial intermediaries in the U.S. By manually matching 13F managers with their holding companies, I am able to observe how financial intermediaries (and their subsidiaries) trade stocks, which enables me to analyze fire sales during bad times. While adverse selection prevents unconstrained investors from buying assets unless prices of those assets drop sufficiently in Dow and Han (2018), I argue that it is high risk-aversion that induces high-capital intermediaries buy assets only at discounted prices. This work is also consistent with Santos and Veronesi (2018), who argue in their model that levered agents fire-sell their risky assets to reduce leverage as asset prices decline during bad times. In addition, Bian, He, Shue, and Zhou (2018) empirically test leverage-induced fire sales in the Chinese stock market using proprietary account-level trading data for margin accounts in the middle of 2015 and find that investors whose leverage is close to the maximum level strongly sell their assets during the stock market crash.

2.2 Heterogeneous Intermediary Capital

In this section, I discuss the role of the heterogeneous intermediary capital in explaining the cross-section of stock returns. Prior studies on intermediary asset pricing have focused on the level of intermediary capital. He and Krishnamurthy (2013) argue that intermediary capital represents the health of the intermediary sector: When an intermediary's constraint to raise capital is binding, intermediary capital becomes scarce, which leads to a higher risk premium. Based on this theoretical motivation, He, Kelly, and Manela (2017) find that intermediary capital, measured using market values, is positively priced in the cross-section of asset returns. In contrast, Adrian, Etula, and Muir (2014) use book leverage as a proxy for intermediary leverage to capture funding liquidity and find the positive price of risk for the leverage of financial intermediaries. Because intermediaries lower their leverage when funding constraints tighten (Brunnermeier and Pedersen, 2009), intermediary leverage, measured using book values, is procyclical as documented in Adrian and Shin (2010, 2014).

Since leverage is simply the inverse of the capital ratio, the two strands of studies seem to contradict each other.[4] However, as argued in Santos and Veronesi (2018), while deleveraging

[4]Note that Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) use different definitions for financial

of low capital intermediaries in bad times causes book leverage to decrease, market leverage can increase if a high discount rate would push down the market value of capital faster than the decrease in debt. Therefore, the book capital ratio is expected to be procyclical, while the market capital ratio is to be countercyclical.

I argue that it is important to look beyond the level of intermediary capital: Intermediary capital appears to vary in the cross-section as well. From a principal component analysis of the quasi-market capital ratio based on the largest 30 intermediaries in the U.S., I find that the first two factors have eigenvalues greater than one. The first factor appears to represent the level of intermediary capital as standardized scores of the 25^{th} percentile and the 75^{th} percentile for the first factor are similar (i.e., 0.058 and 0.053, respectively). In contrast, the second seems to be the dispersion of intermediary capital as standardized scores of the 25^{th} percentile and the 75^{th} percentile for the second factor are in the opposite signs (i.e., -0.097 and 0.151, respectively). If the key features that drive this cross-sectional difference are associated with intermediaries' trading behaviors, it is potentially important to incorporate the heterogeneity in intermediary capital to examine the role of financial intermediaries in asset markets.

How does heterogeneous intermediary capital affect the trading behavior of intermediaries? As mentioned in the Introduction, I postulate that intermediary capital is closely related to the risk preference of intermediaries and that the intermediary capital appears to be positively associated with risk aversion of intermediaries. Specifically, risk aversion may induce intermediaries to have high capital in that risk-averse intermediaries want to build up precautionary capital against an adverse shock in economic downturns. In terms of a portfolio choice, risk-tolerant intermediaries want to invest more into risky assets than risk-averse intermediaries do, thereby leading them to borrow more and take higher leverage. On the other hand, capital can also reduce risk-taking behavior of intermediaries. For example, low-capital intermediaries with a limited liability have risk-shifting incentives and are likely to take an excessive risk at the expense of debt holders. According to the banking literature, as capital increases, banks' incentives to pursue high risk decline

intermediaries; the former defines intermediaries as security broker-dealers from the Federal Reserve *Flow of Funds*, and the latter defines intermediaries as *Primary Dealers* - Federal Reserve Bank of New York

(Furlong and Keeley, 1989), and their incentives to monitor borrowers strengthen (Holmstrom and Tirole, 1997; Allen, Carletti, and Marquez, 2011).[5] Whether intermediary capital is indeed positively related to risk aversion could ultimately be an empirical question. Thus, as suggestive evidence, it is worthwhile investigating stock holdings of high- and low-capital intermediaries to empirically link their capital and risk preferences.

Figure 2.1 shows the relation between intermediary capital ratios and the risk characteristics of stocks owned by the largest 9 intermediaries in the U.S. that span at lease 30 quarters in the sample. It supports the channel in which intermediary capital is negatively associated with risk-taking behaviors (i.e., high risk aversion). It appears that high-capital intermediaries tend to hold stocks with lower market betas (in Panel A), lower return volatility (in Panel B), and larger market capitalization (in Panel C). Such differences are potentially more pronounced during bad times. For instance, in 2007, Lehman Brothers has a market capital ratio of 4.9% and holds stocks with a market beta of 2.70 on average whereas Bank of New York Mellon has a market capital ratio of 24.8% and holds stocks with a market beta of 0.79 on average. More generally, intermediaries holding stocks with distinctive risk characteristics played a critical role in the pricing of these stocks during the crisis as we have experienced after the Lehman failure in 2008.

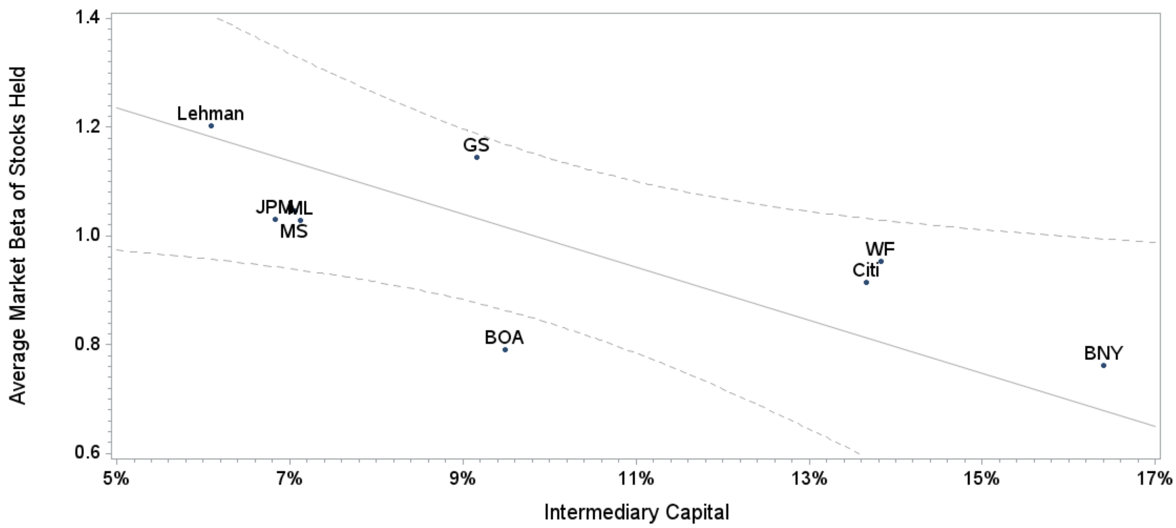
Given that low-capital intermediaries are more highly leveraged and hold riskier stocks than high-capital intermediaries, it is expected that low-capital intermediaries will be more adversely affected by a negative shock in the stock market than high-capital intermediaries. Thus, the relative difference in capital ratios (measured in market values) should be higher during bad times. Figure 2.2 supports this notion. It presents the level and the dispersion of intermediary capital ratios, based on the largest 30 intermediaries in the U.S., from 1973/Q1 to 2016/Q4. In Panel A, the 25^{th} percentile of intermediary capital increases (decreases) faster during good (bad) times than the 75^{th} percentile of intermediary capital. Likewise, dispersion of capital ratios, defined as the difference

[5] There is an opposite view that intermediary capital is negatively associated with risk aversion, arguing that intermediaries have more capital in equilibrium if they hold riskier assets in their balance sheets. To mitigate this concern, I measure intermediary capital based on marker values. A higher discount rate due to having riskier assets will discount their market capital. Thus, the effect of having extra book capital would be largely canceled out when intermediary capital is measured based on market values.

Figure 2.1
Intermediary Capital and Risk Preference

This figure depicts the relation between intermediary capital of the largest 9 intermediaries in the U.S. and three risk characteristics of the nonfinancial firm stocks they hold. The 9 intermediaries include *Bank of America*, *Bank of New York Mellon*, *Citigroup*, *Goldman Sachs*, *JP Morgan Chase*, *Lehman Brothers*, *Merrill Lynch*, *Morgan Stanley*, and *Wells Fargo & Company*. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. The risk characteristics are: market beta, estimated from monthly regressions using 5-year rolling windows (Panel A); stock return volatility, defined as the quarterly standard deviation of daily stock returns (Panel B); and the log of market capitalization, the number of shares outstanding times the share price (Panel C). At the end of each quarter, risk characteristics are averaged within each intermediary and then averaged over the sample period. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The solid line represents the fitted regression line, and two dashed lines represent the 95% confidence limits. The sample period covers 1980/Q1 to 2012/Q4.

Panel A: Average Market Beta of Stock Held



Panel B: Average Volatility of Stock Held

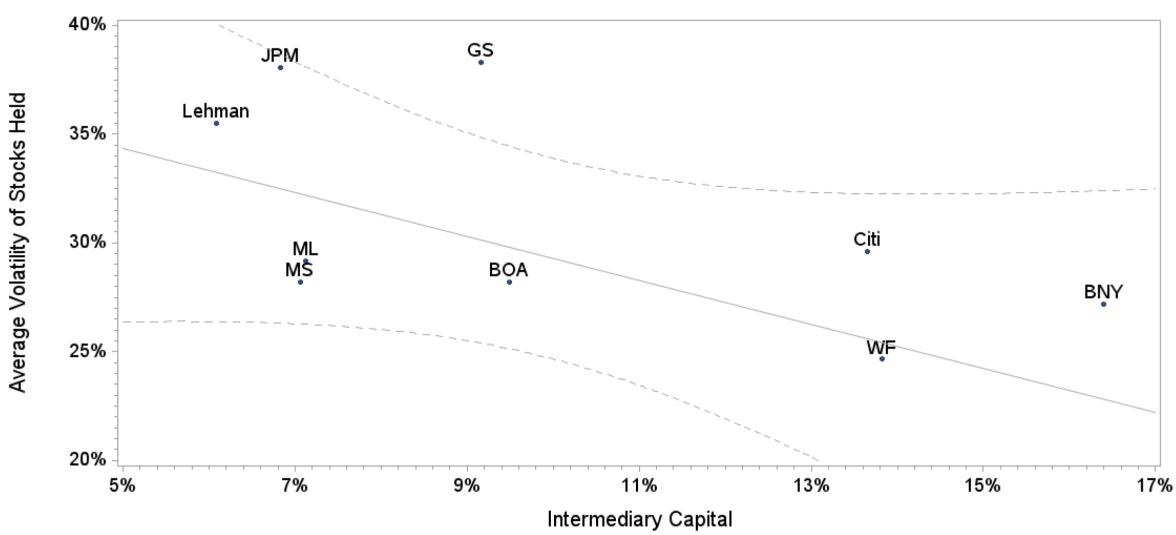
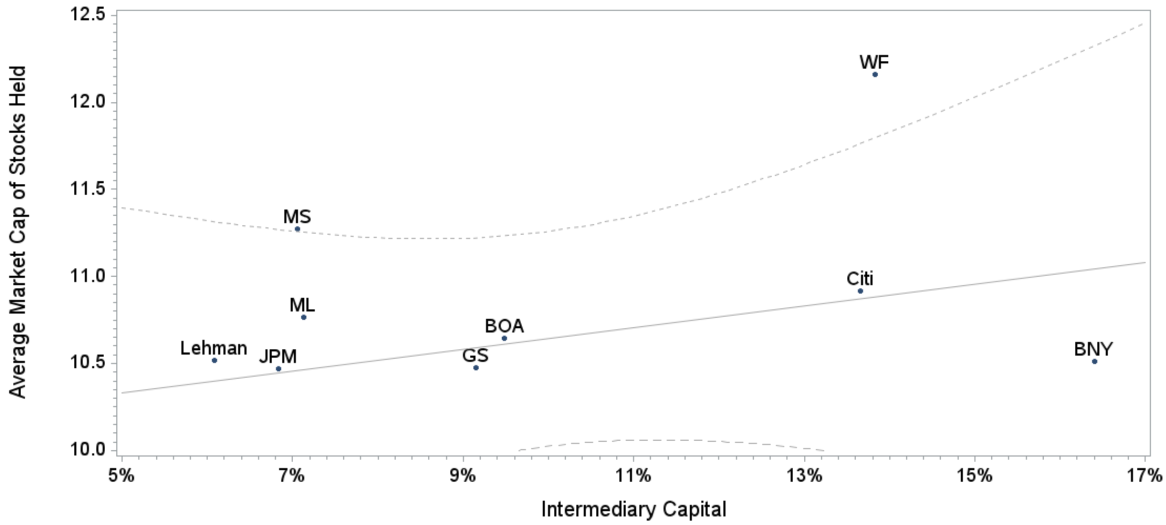


Figure 2.1 Continued

Panel C: Average Market Cap of Stock Held



between the 75^{th} and the 25^{th} percentile of intermediary capital, scaled by its 50^{th} percentile, shows a countercyclical variation in Panel B. Hence, the negative shock in the stock market induces the dispersion of capital ratios (as well as a portion of stocks held by high-capital intermediaries) to rise, which then drives up the aggregate risk aversion.[6] In the end, the shock in the dispersion of capital ratios generates a risk premium and is priced in the cross-section of stock returns.[7]

Furthermore, if a negative shock is sufficiently large and systematic, low-capital intermediaries may be faced with binding margin constraints (Brunnermeier and Pedersen, 2009)[8] and are forced to deleverage by selling off assets. In contrast, high-capital intermediaries do not face such constraints and may be able to buy those assets (Acharya and Viswanathan, 2011). As shown in Panel A of Figure 2.2, high-capital intermediaries experienced a rise in market capital while low-capital intermediaries lost their capital during the financial crisis. This is consistent with the

[6]Note that if intermediaries are homogeneous in risk preference, the negative shock would alter the dispersion of capital ratios but not affect the aggregate risk aversion.

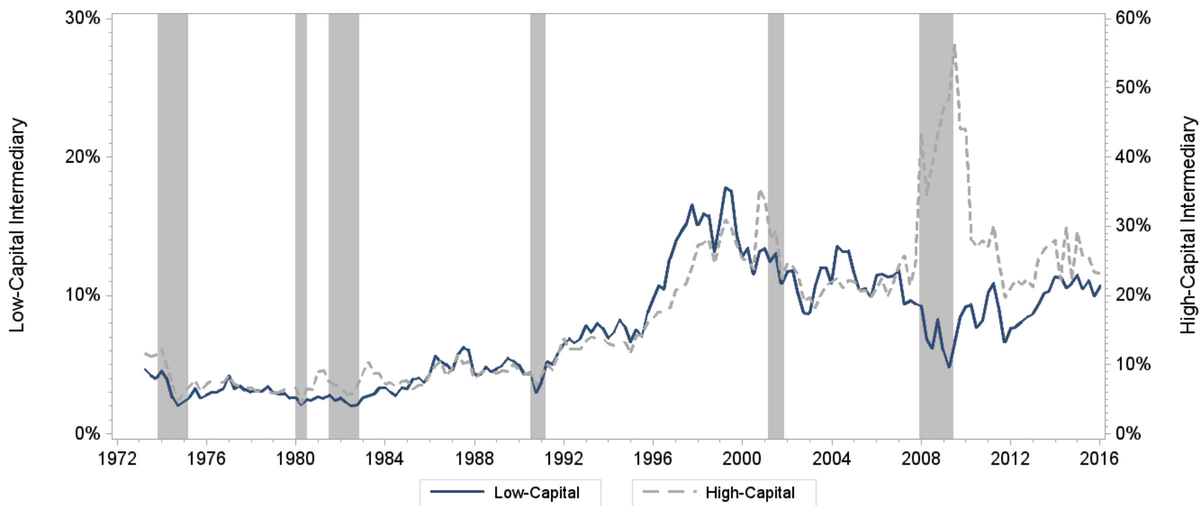
[7]In Section 2.6, I provide a model of heterogeneous intermediary capital where a more risk-averse specialist form an intermediary with higher capital and show that how the dispersion in an intermediary capital is priced in the cross-section of stock returns.

[8]The shock incurs losses in positions of low-capital intermediaries. If a cushion against the shock is not enough, low-capital intermediaries are likely to hit the margin constraints.

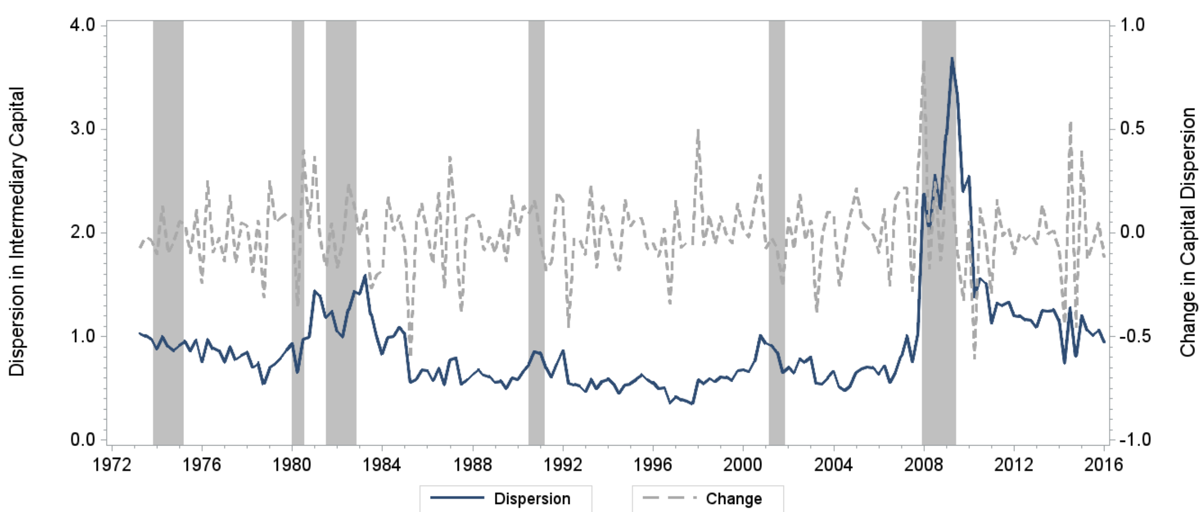
Figure 2.2
Level and Dispersion of Intermediary Capital Ratio

This figure depicts intermediary capital of the largest 30 intermediaries in the U.S. Panel A plots the level of intermediary capital. The dashed line represents the 75^{th} percentile of intermediary capital while the solid line represents the 25^{th} percentile of intermediary capital. Panel B plots the dispersion of intermediary capital, measured as the difference between the 75^{th} and the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile, in the solid line. The change in the dispersion of intermediary capital is shown by the dashed line. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The shaded areas represent NBER recessions. The sample period covers 1973/Q1 to 2016/Q4.

Panel A: Capital Ratios of High- and Low-Capital Intermediaries



Panel B: Dispersion of Intermediary Capital Ratios



argument that low-capital intermediaries sell their assets to high-capital intermediaries at prices lower than fundamental values during bad times.

2.3 Data

I use the Center for Research in Security Prices (CRSP) database to obtain stock-level data for nonfinancial firms and intermediaries, the Compustat database to obtain nonfinancial firm- and intermediary-level data. I also use the Thomson Reuters Institutional (13F) Holdings database to retrieve holdings of intermediaries and their subsidiaries. To obtain the stock holdings of intermediaries, I manually match managers (*mgrno*) in the Institutional (13F) Holdings database and financial intermediaries (*gvkey*) in the Compustat database. In particular, I use a name matching algorithm of the Levenshtein distance to match names of the 13F managers with names of their holding companies up to ten and then review the initial matched-sets manually to finalize the matching.

The sample period covers January 1973 to December 2016. I choose January 1973 as the start because there was a large influx of intermediaries in the CRSP database in 1972. The empirical tests with the Institutional (13F) Holdings database cover 1980/Q1 to 2012/Q4. I exclude the period of 2013/Q1 - 2016/Q4 from the sample due to data quality problems in the Institutional (13F) Holdings database.[9]

2.3.1 Financial Intermediaries

The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code are 6000-6200 or 6712. The main empirical analyses focus on the largest 30 intermediaries based on market capitalization at the end of each quarter. This yields a list of 118 unique intermediaries over the sample period (See Table C.1 for the list). Since the largest 30 intermediaries hold the majority of assets in financial markets, their capital would be more relevant to determine the pricing kernel for financial assets. It seems defensible to focus on the largest 30 given that the number of U.S. primary dealers used in He, Kelly, and

[9] In 2013 onward, institutional 13F reports are often stale and omitted, certain securities may be excluded, and the number of shares are often reported inconsistently with splits.

Manela (2017), ranges from 17 to 46, and there are 29 U.S. banks among the Global Systemically Important Banks (G-SIB) and the Systemically Important Financial Institution (SIFI) in 2017.[10]

Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity:

$$Capr = \frac{\textit{market value of equity}}{\textit{market value of equity} + \textit{book value of debt}}. \tag{2.3.1}$$

Using intermediary capital defined in (2.3.1), I measure the dispersion of capital ratios in quater t as the difference between the 75^{th} and the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile:

$$DISP_t^{Capr} = \frac{Capr_t^{75^{th}} - Capr_t^{25^{th}}}{Capr_t^{50^{th}}}. \tag{2.3.2}$$

Table 2.1 Panel A presents summary statistics for intermediaries. The statistics are averaged over quartiles based on intermediary capital. Several things are noteworthy. First, there are substantial variations in intermediary capital. High-capital intermediaries have six times higher capital ratio than low-capital intermediaries: 36.02% versus 5.68%. Second, high-capital intermediaries are far smaller than low-capital intermediaries, both in market value and in book value terms. Moreover, high-capital intermediaries tend to have lower book-to-market ratio and higher profitability and prior returns (i.e., momentum) than low-capital intermediaries. Market beta and asset growth are relatively stable across quartiles.

Note that book assets reported in Panel A do not comprise assets under management (AUM), which is an off-balance sheet item. In particular, AUM are the total market value of assets held by financial intermediaries on behalf of their clients while book assets are assets which they actually own in their balance sheet. The amount of AUM is not trivial relative to their book assets. In 2017, for instance, *JP Morgan Chase* had total AUM of $2.03 trillion and book assets of $2.53 trillion,

[10]In Section 2.5.6, I also test using the largest 40 or 50 intermediaries.

and *BlackRock* had total AUM of \$6.29 trillion and book assets of \$0.22 trillion.[11] Importantly, stock holdings of financial intermediaries out of total AUM have grown significantly. Based on my sample of the largest 30 intermediaries in the U.S., the value-weighted average of the ratios of total stock holdings reported in the Institutional (13F) Holdings database over book assets was 6.5% in 1980 but increased to 26.0% in 2012.[12] Thus, it appears that trading behaviors of financial intermediaries for stocks (primarily by their asset management arms) are sizable to their overall business operations.

Figure 2.2 shows intermediary capital over time. The shaded areas represent NBER recessions. Panel A shows that intermediary capital is closely related to the economic cycle. However, capital of high-capital intermediaries is countercyclical whereas that of low-capital intermediaries is procyclical. This becomes more stark when plotting the dispersion of capital ratios between high- and low-capital intermediaries and changes in the dispersion. Panel B illustrates that the dispersion of capital ratios is highly countercyclical, as discussed in Section 2.2. The dispersion of capital ratios is mostly less than one in good times whereas it peaks at 3.7 in the financial crisis. Consistently, changes in the dispersion become volatile in bad times.

2.3.2 Nonfinancial Firm Stocks

Test assets are common stocks of nonfinancial firms, identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). I also exclude tiny stocks (price less than \$5). For each stock, I estimate its exposure to the shock or change in the dispersion of capital ratios: the dispersion beta, defined as

$$\beta_t^{DISP} = \frac{Cov\left(\Delta DISP_t^{Capr}, r_t^i\right)}{Var\left(r_t^i\right)}. \tag{2.3.3}$$

I obtain β_t^{DISP} using 5-year rolling window regressions, $r_t^i - r_t^f = \alpha + \beta^{DISP,i}\Delta DISP_t^{Capr} + \beta^{MKT,i}MKT_t + \varepsilon_t^i$, where r_t^i is the quarterly return on nonfinancial firm stock, r_t^f is the one-month

[11] See annual reports of *JP Morgan Chase* and *BlackRock*.

[12] The ratio is 14.4% on average over the entire sample period of 1980 - 2012.

Table 2.1
Summary Statistics

This table reports the summary statistics. Panel A shows the statistics for intermediaries. At the end of each quarter, the largest 30 intermediaries in the U.S. are sorted into quartiles based on intermediary capital. Panel B shows the statistics for nonfinancial firm stocks. At the beginning of each month, nonfinancial firm stocks are sorted into deciles based on the dispersion beta. The statistics presented in each column indicate the value-weighted averages within each group, which are then averaged over time. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. The dispersion beta is estimated from quarterly regressions using 5-year rolling windows. r_t^i is a monthly returns on nonfinancial firm stock. $DISP_t^{Capr}$ is the dispersion of intermediary capital measured as the difference between the 75^{th} percentile and the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile. Capital Ratio (Market) is the quasi-market capital ratio. Capital Ratio (Book) is defined as book equity over total assets. β^{MKT} is the market beta, estimated from monthly regressions using 5-year rolling windows. Market capitalization and book assets (i.e., total assets) are represented in billion dollars. B/M is the book-to-market ratio, book equity over market capitalization. Profitability is measured as ROE, income before extraordinary items over lagged book equity. Asset growth is measured as the percentage change in total assets. Momentum is a cumulative return over the previous one year, skipping the last month. Stock Returns are valued-weighted at the monthly frequency. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1973 to December 2016.

Panel A: Summary Statistics for the Largest 30 Intermediaries by Capital Ratio Quartile

	Low	2	3	High
Capital Ratio (Market)	5.68%	9.24%	13.57%	36.02%
Capital Ratio (Book)	5.43%	6.99%	8.18%	23.57%
β^{MKT}	1.30	1.12	1.10	1.25
Market Cap ($B)	27.83	21.49	20.27	13.27
Book Assets ($B)	380.29	170.38	108.78	33.66
B/M	1.22	0.90	0.69	0.52
Profitability (ROE)	2.82%	3.44%	3.98%	5.99%
Asset Growth (I/A)	3.98%	3.26%	3.97%	4.59%
Momentum	11.40%	14.39%	16.25%	24.00%

Panel B: Summary Statistics for Nonfinancial Firm Stocks by Dispersion Beta Decile

	Low	2	3	4	5	6	7	8	9	High
β^{DISP}	−0.45	−0.21	−0.13	−0.08	−0.03	0.02	0.07	0.12	0.19	0.39
β^{MKT}	1.30	1.14	1.07	1.03	1.00	0.99	0.99	1.00	1.04	1.23
Market Cap ($B)	1.24	2.46	3.06	3.45	3.81	3.91	3.86	3.82	3.12	1.91
Book Assets ($B)	1.23	2.36	2.86	3.10	3.38	3.48	3.43	3.58	3.34	1.95
B/M	0.70	0.74	0.74	0.74	0.73	0.74	0.75	0.75	0.75	0.67
Profitability (ROE)	1.77%	2.19%	2.41%	2.64%	2.68%	2.63%	2.62%	2.63%	2.48%	1.90%
Asset Growth (I/A)	3.39%	2.69%	2.46%	2.52%	2.43%	2.49%	2.56%	2.73%	2.80%	3.62%
Momentum	33.12%	21.55%	19.29%	17.96%	17.58%	17.34%	17.40%	18.08%	18.67%	25.65%
Stock Return	2.67%	2.10%	1.88%	1.69%	1.85%	1.68%	1.78%	1.68%	1.76%	2.08%

Treasury bill rate compounded over a quarter, MKT_t is the quarterly return on the market (i.e., the CRSP value-weighted index) less r_t^f.

Table 2.1 Panel B shows summary statistics for nonfinancial firm stocks based on the dispersion beta decile. First, there are substantial variations in the dispersion beta. While stocks in the lowest decile have dispersion beta of -0.45, stocks in the highest decile have the dispersion beta of +0.39. Second, stocks in the lowest decile tend to have higher market beta, book-to-market ratio, and prior returns, and smaller size than those in the highest decile. However, the differences in these characteristics are not so remarkable that one would argue that variations in the dispersion beta are simply spanned by other risk characteristics. Finally, stocks in the lowest decile earn annually 7.08%[13] higher (t-statistics = 5.04) than those in the highest decile.

2.4 Main Results

2.4.1 Intermediary Capital Ratios and Risk Preferences

Section 2.2 showed how intermediary capital is related to risk aversion of intermediaries, and Figure 2.1 provided preliminary evidence that intermediary capital seems to be negatively associated with risk-taking behavior of intermediaries. To formally test this, I estimate the risk preference of intermediaries from risk characteristics of stocks that intermediaries hold.

Table 2.2 presents how intermediary capital affects the risk characteristics of their holdings. I regress the risk characteristics of stocks held by intermediaries on their capital ratios. I use three risk measures: market beta, return volatility, and size (i.e., log of market capitalization) of stocks that the largest 30 intermediaries in the U.S. hold, reported in the Institutional (13F) Holdings database. Since stocks may be held by multiple intermediaries, intermediary capital and size are averaged within each stock using the number of shares held as a weight. I find the evidence that high-capital intermediaries tend to hold stocks with significantly lower betas and return volatility and higher market capitalization. This suggests that high-capital intermediaries seem to have higher risk aversion than low-capital intermediaries. In terms of economic significance, high-capital intermediaries hold stocks which exhibit 0.04 lower beta and 1.15% lower annual

[13] $7.08\% = (2.67\% - 2.08\%) \times 12$

volatility[14] than low-capital intermediaries.[15]

If low-capital intermediaries (who are more highly leveraged) hold riskier stocks on their balance sheets, they would be more sensitive to an adverse shock than high-capital intermediaries, and then the price of their assets would drop further than that of high-capital intermediaries in bad times. Moreover, such an adverse shock would cause low-capital intermediaries facing margin constraints to sell their assets to deleverage (Brunnermeier and Pedersen, 2009). If the shock is large and systematic enough to induce all low-capital intermediaries to sell assets together, they have to sell at fire-sales prices. On the other hand, high-capital intermediaries, who do not face such margin constraints, may have sufficient capacity to absorb these assets and can buy these assets (Acharya and Viswanathan, 2011) at prices lower than fundamental values. As a result, net worth will be transferred from low- to high-capital intermediaries in bad times.

Figure 2.2 suggested that the dispersion of capital ratios is countercyclical. I now test this formally by regressing the dispersion of capital ratios on bad time dummy. I use two time measures: the financial crisis (from July 2007 to December 2009) and NBER recessions.

Table 2.3 shows that the dispersion of capital ratios increases to 2.51 (= 1.76 + 0.75) during the financial crisis in Column (1) and 1.85 (= 1.06 + 0.79) during NBER recessions in Column (4). Both findings are consistent with the dispersion of capital ratios being countercyclical. Importantly, it seems that this countercyclicality can be attributed to both high- and low-capital intermediaries. In Columns (2) and (3), low- (high-) capital intermediaries tend to have significantly lower (higher) capital during the financial crisis. Similarly, in Columns (5) and (6), low- (high-) capital intermediaries tend to have significantly lower (higher) capital during NBER recessions. As a result, high-capital intermediaries end up with even higher capital ratios whereas low-capital intermediaries have even lower capital ratios in bad times.

[14] $0.04 = (36.02\% - 5.68\%) \times (-0.129); 1.15\% = (36.02\% - 5.68\%) \times (-0.019) \times \sqrt{4}$

[15] The economic significance presented in Table 2.2 appears to be smaller than in Figure 2.1. It is possible that these risk characteristics are rather persistent within a firm-level and then the firm fixed effect may lower the magnitude of the effect.

Table 2.2
Risk Preferences of Intermediaries

This table reports the results of OLS regressions in which the risk characteristics of nonfinancial firm stocks held in the largest 30 intermediaries in the U.S. are regressed on the capital ratios of these intermediaries plus controls. Three risk characteristics include: market beta, estimated from monthly regressions using 5-year rolling windows; stock return volatility, defined as the quarterly standard deviation of daily stock returns; and the log of market capitalization, the number of shares outstanding times the share price. Since stocks can be held by multiple intermediaries, intermediary capital and size are averaged within each stock using the number of shares held as a weight. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. Intermediary size is measured as the log of the intermediary's market capitalization. Other controls measured in the stock level include B/M (book-to-market ratio, book equity over market capitalization), MOM (momentum, a cumulative return over the previous one year, skipping the last month), ROE (profitability, income before extraordinary items over lagged book equity), and I/A (asset growth, the percentage change in total assets). The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers 1980/Q1 to 2012/Q4. Standard errors are clustered by stock. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) β^{MKT}	(2) Return Volatility	(3) Market Cap
Intermediary Capital	-0.129***	-0.019***	0.167***
	[-3.73]	[-3.28]	[3.51]
Intermediary Size	0.020***	-0.001	0.184***
	[3.02]	[-0.95]	[19.42]
B/M	-0.009	-0.143**	0.197
	[-0.33]	[-2.56]	[1.30]
MOM	0.009**	-0.009***	0.232***
	[2.25]	[-10.27]	[24.38]
ROE	0.005	0.004**	0.001
	[0.57]	[2.39]	[0.08]
I/A	-0.020	0.001	0.044
	[-1.15]	[0.22]	[0.78]
Firm FE	Yes	Yes	Yes
Year × Quarter FE	Yes	Yes	Yes
N	458,183	458,183	458,183
adj. R^2	0.608	0.532	0.889

Table 2.3
Countercyclicality in Dispersion of Intermediary Capital Ratios

This table reports the results of OLS regressions showing how the dispersion of intermediary capital changes during bad times. I use two bad time measures: the financial crisis (from July 2007 to December 2009) and NBER recessions. $\mathbb{1}(t$ = Bad Time) is one if month *t* is in a bad time and zero otherwise. The dispersion of intermediary capital ($DISP^{Capr}$) is measured as the difference between the 75^{th} percentile ($Capr^{75^{th}}$) and the 25^{th} percentile ($Capr^{75^{th}}$) of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile. Intermediary capital is measured using the quasi-market capital ratio, that is, the market value of equity over the sum of the book value of debt and the market value of equity. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The sample period covers 1973/Q1 to 2016/Q4. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Bad Time Def.	*Financial Crisis*			*NBER Recessions*		
	(1)	(2)	(3)	(4)	(5)	(6)
	$DISP^{Capr}$	$Capr^{25^{th}}$	$Capr^{75^{th}}$	$DISP^{Capr}$	$Capr^{25^{th}}$	$Capr^{75^{th}}$
$\mathbb{1}(t$ = Bad Time)	1.76***	−0.02*	0.23***	1.06***	−0.02**	0.12***
	[16.09]	[−1.86]	[9.67]	[7.37]	[−2.28]	[4.64]
Intercept	0.75***	0.10***	0.19***	0.79***	0.10***	0.20***
	[24.01]	[30.66]	[28.38]	[16.71]	[30.67]	[23.46]
N	121	121	121	121	121	121
adj. R^2	0.682	0.020	0.436	0.308	0.034	0.146

2.4.2 Asset Pricing Tests

In this section, I investigate how the dispersion of capital ratios is priced in the cross-section of stock returns. As discussed earlier, asymmetric responses to an adverse shock between high- and low-capital intermediaries lead to compositional changes in stock ownership, which in turn produce (countercyclical) time-varying risk aversion of a representative agent given that high-capital intermediaries are more risk-averse than low-capital intermediaries. Thus, a rise in the dispersion of capital ratios in bad times causes asset prices to decline and a risk premium to increase. This further implies that stocks that covary negatively with the shock in the dispersion of capital ratios would earn a higher risk premium and that stocks that covary positively with the shock in the dispersion of capital ratios would be hedging and should exhibit a lower risk premium. To test this hypothesis, I estimate the following Fama-MacBeth regressions:

$$r_{t+1}^{i} - r_{t+1}^{f} = \alpha + \lambda^{DISP}\beta_{t}^{DISP,i} + \sum_{k=1}^{K}\lambda^{k}\beta_{t}^{k,i} + \varepsilon_{t+1}^{i} \tag{2.4.1}$$

where the dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. Also, λ^{DISP} is the price of risk in the dispersion of capital ratios, and $\beta^{DISP,i}$ is the dispersion beta defined in Section 2.3.

Table 2.4 presents the results. After controlling for various risk characteristics, including the betas for the level of intermediary capital from Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017), I find that stocks with low dispersion betas earn significantly higher returns than stocks with high dispersion betas. In other words, dispersion of capital ratios is negatively priced in the cross-section of stock returns. In terms of economic significance, difference between the dispersion betas from the highest and the lowest deciles is 0.84 ($= 0.39 - (-0.45)$), and estimated price of risk in the dispersion of capital ratios ranges from -0.81 to -0.33. This implies that relative to stocks in the highest dispersion betas, stocks in the lowest dispersion betas earn an additional premium of 3.3% - 8.2% per annum.

Table 2.5 uses portfolio approaches to see if portfolios based on the dispersion beta earn abnormal returns. At the beginning of each month, stocks are sorted in deciles based on their dispersion betas (using NYSE breaks). Next, the portfolios are value-weighted in Panel A and equal-weighted in Panel B. I use five different factor models: FF5 is the Fama-French five factor model (Fama and French, 2015); FF5+PS adds the liquidity factor (Pástor and Stambaugh, 2003) to FF5; FF5+MOM adds the momentum factor (Jegadeesh and Titman, 1993) to FF5; FF5+AEM adds the intermediary leverage factor (Adrian, Etula, and Muir, 2014) to FF5; and FF5+HKM adds the intermediary capital factor (He, Kelly, and Manela, 2017) to FF5. Regardless of the model, I find that stocks with low dispersion betas earn significantly higher abnormal returns than stocks with high dispersion betas. Again, investors are likely to pay lower prices for stocks that have negative covariance with the shock in the dispersion of capital ratios, implying a higher risk

Table 2.4
Fama-MacBeth Regressions

This table reports the estimation results for the Fama-MacBeth regressions. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 2.1, is estimated from quarterly regressions using 5-year rolling windows. β^{MKT} is the market beta, estimated from monthly regressions using 5-year rolling windows. β^{AEM} represents the beta for the intermediary leverage factor in Adrian, Etula, and Muir (2014), and β^{HKM} represents the intermediary capital factor in He, Kelly, and Manela (2017), both estimated from quarterly regressions using 5-year rolling windows. Following Carhart (1997) and Fama and French (2015), I also control for Size (the log of market capitalization), B/M (book-to-market ratio, book equity over market capitalization), MOM (momentum, a cumulative return over the previous one year, skipping the last month), OP (operating profitability, annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by lagged book equity), and I/A (asset growth, the percentage change in total assets). The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.81***	−0.78***	−0.49***	−0.46***	−0.33***	−0.33***	−0.35**
	[−4.25]	[−4.57]	[−3.25]	[−3.49]	[−2.69]	[−2.72]	[−2.55]
β^{MKT}		0.29	0.30*	0.27*	0.30**	0.13	0.20
		[1.61]	[1.71]	[1.83]	[2.00]	[0.98]	[1.28]
β^{AEM}			0.32***		0.15***	0.13***	0.15***
			[4.71]		[3.38]	[3.01]	[3.32]
β^{HKM}			0.17***		0.11**	0.11**	0.10*
			[3.19]		[2.33]	[2.33]	[1.85]
Size				−0.47***	−0.47***	−0.36***	−0.33***
				[−12.22]	[−12.20]	[−11.49]	[−9.64]
B/M				0.10	0.09	0.13	0.14
				[0.96]	[0.85]	[1.43]	[1.24]
MOM				0.04	0.04	0.03	−0.16
				[0.19]	[0.24]	[0.17]	[−0.80]
OP				−0.04	−0.04	0.04	−0.06
				[−0.32]	[−0.35]	[0.34]	[−0.57]
I/A				−0.77***	−0.76***	−0.81***	−0.83***
				[−7.40]	[−7.40]	[−7.96]	[−7.68]
IVOL						34.64***	46.65***
						[6.59]	[8.02]
$\beta^{\Delta VXO}$							−8.21
							[−1.59]

Table 2.5
Abnormal Returns based on Dispersion Beta: Portfolio Approach

This table reports abnormal returns of decile portfolios based on the dispersion beta. Portfolios are value-weighted in Panel A and equal-weighted in Panel B. FF5 is the Fama-French five factor model (Fama and French, 2015), FF5+PS adds the liquidity factor (Pástor and Stambaugh, 2003) to FF5, FF5+MOM adds the momentum factor (Jegadeesh and Titman, 1993) to FF5, FF5+AEM adds the intermediary leverage factor (Adrian, Etula, and Muir, 2014) to FF5, and FF5+HKM adds the intermediary capital factor (He, Kelly, and Manela, 2017) to FF5. The dispersion beta, defined in Table 2.1, is estimated from quarterly regressions using 5-year rolling windows. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Abnormal Returns of Value-Weighted Portfolios based on Dispersion Beta

	(1) FF5	(2) FF5 + PS	(3) FF5 + MOM	(4) FF5 + IVOL	(5) FF5 + AEM	(6) FF5 + HKM
H−L	−0.58%***	−0.62%***	−0.62%***	−0.57%***	−0.58%***	−0.57%***
	[−3.20]	[−3.48]	[−3.37]	[−3.15]	[−3.17]	[−3.13]
Low	0.51%***	0.52%***	0.56%***	0.49%***	0.52%***	0.52%***
	[4.09]	[4.31]	[4.39]	[4.03]	[4.17]	[4.10]
2	0.18%	0.17%	0.26%**	0.17%	0.17%	0.16%
	[1.35]	[1.32]	[2.00]	[1.25]	[1.23]	[1.21]
3	0.06%	0.05%	0.10%	0.06%	0.05%	0.06%
	[0.60]	[0.44]	[0.86]	[0.56]	[0.43]	[0.52]
4	0.07%	0.07%	0.09%	0.07%	0.07%	0.06%
	[0.77]	[0.86]	[1.00]	[0.82]	[0.83]	[0.69]
5	0.17%**	0.17%**	0.16%**	0.17%**	0.18%**	0.18%**
	[2.07]	[2.07]	[2.02]	[2.00]	[2.12]	[2.19]
6	0.11%	0.10%	0.10%	0.11%	0.10%	0.11%
	[1.45]	[1.33]	[1.31]	[1.48]	[1.29]	[1.43]
7	0.00%	−0.01%	−0.02%	0.00%	0.00%	0.01%
	[0.07]	[−0.11]	[−0.22]	[0.04]	[0.02]	[0.16]
8	−0.10%	−0.10%	−0.11%	−0.09%	−0.10%	−0.10%
	[−1.19]	[−1.14]	[−1.36]	[−1.11]	[−1.13]	[−1.15]
9	−0.08%	−0.09%	−0.11%	−0.08%	−0.08%	−0.08%
	[−0.79]	[−0.90]	[−1.09]	[−0.75]	[−0.82]	[−0.83]
High	−0.07%	−0.10%	−0.06%	−0.08%	−0.06%	−0.05%
	[−0.52]	[−0.74]	[−0.45]	[−0.60]	[−0.44]	[−0.41]

Table 2.5 Continued

Panel B: Abnormal Returns of Equal-Weighted Portfolios based on Dispersion Beta

	(1) FF5	(2) FF5 + PS	(3) FF5 + MOM	(4) FF5 + IVOL	(5) FF5 + AEM	(6) FF5 + HKM
H−L	−0.62%***	−0.63%***	−0.68%***	−0.61%***	−0.60%***	−0.61%***
	[−4.62]	[−4.71]	[−5.03]	[−4.56]	[−4.42]	[−4.60]
Low	1.46%***	1.46%***	1.56%***	1.44%***	1.44%***	1.46%***
	[11.36]	[11.83]	[11.98]	[11.56]	[11.06]	[11.23]
2	0.85%***	0.84%***	0.94%***	0.84%***	0.84%***	0.84%***
	[9.71]	[9.73]	[10.88]	[9.75]	[9.59]	[9.61]
3	0.64%***	0.62%***	0.71%***	0.63%***	0.63%***	0.64%***
	[8.92]	[9.06]	[10.59]	[9.01]	[8.81]	[8.80]
4	0.46%***	0.44%***	0.53%***	0.46%***	0.45%***	0.46%***
	[6.90]	[6.83]	[8.88]	[7.01]	[6.82]	[6.70]
5	0.65%***	0.62%***	0.70%***	0.65%***	0.64%***	0.64%***
	[8.24]	[8.22]	[9.38]	[8.32]	[8.32]	[8.15]
6	0.43%***	0.41%***	0.47%***	0.44%***	0.42%***	0.43%***
	[7.25]	[7.03]	[7.86]	[7.25]	[7.26]	[7.17]
7	0.53%***	0.52%***	0.57%***	0.53%***	0.52%***	0.52%***
	[10.26]	[9.80]	[11.14]	[10.39]	[10.22]	[10.11]
8	0.44%***	0.43%***	0.46%***	0.44%***	0.43%***	0.44%***
	[6.52]	[6.12]	[6.65]	[6.55]	[6.39]	[6.56]
9	0.45%***	0.44%***	0.50%***	0.45%***	0.45%***	0.46%***
	[5.87]	[5.65]	[6.54]	[5.90]	[5.91]	[5.93]
High	0.84%***	0.83%***	0.89%***	0.83%***	0.84%***	0.85%***
	[9.68]	[9.79]	[10.96]	[9.79]	[9.70]	[10.24]

premium. H - L portfolio earns monthly abnormal returns of -0.57% to -0.68%, which implies that estimated risk premium is 6.8% - 8.2% per annum.[16] Overall, the results show that dispersion of capital ratios indeed is priced in the cross-section of stock returns.

[16] A trading strategy that buys stocks in the lowest decile and sells short stocks in the highest decile can earn positive abnormal returns. To test whether the 'L - H' portfolio is actually profitable, two issues need to be addressed. First, short-sale constraints may limit the ability of making profits from short-selling stocks. As shown in Table 2.5, most of the trading profits are attributed to the long-leg rather than the short-leg. Thus, short-sale constraints have little impact on the trading profits. Second, trading stocks entails costs. Therefore, it is important to check if the portfolio is still profitable after controlling for trading costs. Frazzini, Israel, and Moskowitz (2015) document that each trade costs up to 10 bps for large cap stocks and 20 bps for small cap stocks. Assuming 20 bps as an average trading cost, I find that trading-cost-adjusted profits (i.e., α of the L-H portfolio) are significant at the 1% level with an annual risk premium of 6.0% - 7.2%.

2.4.3 Trading Activity of Intermediaries

As shown in Panel B of Figure 2.2, the dispersion of intermediary capital is countercyclical, which in turn leads to a countercyclical variation in aggregate risk aversion. As long as low-capital intermediaries experience more severe declines in their capital than high-capital intermediaries during bad times, asymmetric responses to the shock and compositional changes in the stock ownership can induce countercyclical variation in the aggregate risk aversion.[17] Interestingly, Table 2.3 shows that capital *increases* in high-capital intermediaries in spite of the fact that the high cost of capital would discount their market value and make it difficult for them to raise new capital during bad times. I argue that this pattern is consistent with low-capital intermediaries being forced to deleverage and selling off their assets to high-capital intermediaries at fire-sales prices during such times.

I now explore whether the trading activity of both sets of intermediaries is consistent with this. Ideally, I would like to identify the exact transaction date and the parties involved in the transaction to establish whether or not assets are fire-sold. Since the Thomson Reuters Institutional (13F) Holdings database provides neither the exact transaction date nor the parties involved in the transaction, I can only indirectly infer whether they are fire-sold from the trading volumes during the quarter and the trading gains, or abnormal returns, in the following quarter.[18] Note that the list of the largest 30 intermediaries can change every quarter and therefore an entry to (an exit from) the list may result in a spurious increase (decrease) in stock holdings, which potentially biases trading activities of the intermediaries. To avoid this issue, I include all intermediaries that have been listed as the largest 30 intermediaries at least once.

[17] That means increase in capital of high-capital intermediaries is not a necessary condition for the countercyclical variation in the aggregate risk aversion.

[18] That is, the agents who bought (sold) an asset at a price lower than the fundamental value would earn positive (negative) abnormal returns in the subsequent period.

I perform the following regressions:

$$\textit{Stock Purchases}^{I}_{m,t} = \gamma_0 + \gamma_1 DISP^{Capr}_{t} + \textit{Controls}_{m,t} + \textit{FE} + \varepsilon^{I}_{m,t} \tag{2.4.2}$$

$$\textit{Stock Sales}^{I}_{m,t} = \gamma_0 + \gamma_1 DISP^{Capr}_{t} + \textit{Controls}_{m,t} + \textit{FE} + \varepsilon^{I}_{m,t} \tag{2.4.3}$$

where m represents 13F managers, and $\textit{Stock Purchases}^{I}_{t}$ and $\textit{Stock Sales}^{I}_{t}$, $I \in \{H, L\}$, are defined as the total amount of stocks bought and sold, respectively, in quarter t, measured in billion dollars. High- and low-capital intermediaries are the ones above and below the 50^{th} percentile of intermediary capital. The dispersion of capital ratios ($DISP^{Capr}_{t}$), defined in (2.3.2), is a proxy for bad times, as aggregate risk aversion increases with the dispersion of capital ratios. Control variables include intermediary size (measured as the log of market capitalization) and portfolio size (measured as the log of portfolio size of 13F manager). For trading gains, I run the following regression:

$$\begin{aligned}\textit{Trading Gains}^{I}_{m,t+1} &= \theta_0 + \theta_1 \mathbb{1}(\textit{Intermediary Capital}_t = Low) \times DISP^{Capr}_{t} \\ &+ \theta_2 \mathbb{1}(\textit{Intermediary Capital}_t = Low) + \theta_3 DISP^{Capr}_{t} + \textit{Controls}_{m,t} + \textit{FE} + \varepsilon^{I}_{m,t+1}. \end{aligned} \tag{2.4.4}$$

where $\textit{Trading Gains}^{I}_{m,t+1} \equiv \dfrac{\sum |n_t| p_t \times \alpha_{t+1}}{\sum |n_t| p_t}$, n_t is the signed number of shares traded, p_t is the price at the end of quarter t, and α_{t+1} is the abnormal return in the quarter $t+1$, estimated using the Fama-French five factor model (Fama and French, 2015).[19] $\mathbb{1}(\textit{Intermediary Capital}_t = Low)$ is an indicator function which takes the value of one if the intermediary capital ratio of a 13F manager is lower than the median in quarter t and zero otherwise.

Table 2.6 shows the regressions results for trading volume from Equations (2.4.2) and (2.4.3) for high-capital intermediaries (Panel A) and low-capital intermediaries (Panel B). First, as the dispersion of capital ratios increases, high-capital intermediaries do not significantly reduce stock

[19] Note that $n_t > 0$ represents stock purchases and $n_t < 0$ represents stock sales. Thus, $\textit{Trading Gains}^{I}_{m,t+1}$ from stock purchases are defined as $\frac{\sum \mathbb{1}(n_t>0)|n_t|p_t \times \alpha_{t+1}}{\sum |n_t| p_t}$, and $\textit{Trading Gains}^{I}_{m,t+1}$ from stock sales are defined as $\frac{\sum \mathbb{1}(n_t<0)|n_t|p_t \times \alpha_{t+1}}{\sum |n_t| p_t}$.

Table 2.6
Trading Volume

This table reports the results of OLS regressions for trading volume of 13F institutional investment managers who belong to the largest 30 intermediaries in the U.S. based on market capitalization. Panels A and B show the results using subsamples of managers who belong to high- and low-capital intermediaries, ones above and below the 50^{th} percentile of intermediary capital. Dependent variables are trading volume of managers from stock trades (i.e., purchases and sales) in quarter t, measured in billion dollars. For each stock, trading volume is computed as the number of shares traded during the quarter t times the price at the end of quarter t. The trading volume for All Stocks is defined as the sum of trading volumes of all stocks traded during the quarter. The trading volume for Stocks ($\Delta IO^L < 0$) is the sum of trading volumes of stocks traded in which low-capital intermediaries reduce their holdings during the quarter. Similarly, the trading volume for Stocks ($\Delta IO^H > 0$) is the sum of trading volumes of stocks traded in which high-capital intermediaries raise their holdings during the quarter. $DISP^{Capr}$ is the dispersion of intermediary capital, defined in Table 2.1. Intermediary size is measured as the log of the intermediary's market capitalization. Portfolio size is the log of the total portfolio size of the manager. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers 1980/Q1 to 2012/Q4. Standard errors are clustered by 13F manager. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Trading Volume for Managers of High-Capital Intermediary

	Stock Purchases		*Stock Sales*
	(1)	(2)	(3)
	All Stocks	Stocks ($\Delta IO^L < 0$)	All Stocks
$DISP^{Capr}$	-0.255	1.666**	2.715
	[-0.37]	[2.53]	[0.89]
Intermediary Size	0.044	-0.376	1.088
	[0.08]	[-0.67]	[1.27]
Portfolio Size	1.251***	0.659***	0.373
	[2.82]	[2.73]	[0.90]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	2,072	2,057	2,072
adj. R^2	0.298	0.230	0.239

Panel B: Trading Volume for Managers of Low-Capital Intermediary

	Stock Purchases	*Stock Sales*	
	(1)	(2)	(3)
	All Stocks	All Stocks	Stocks ($\Delta IO^H > 0$)
$DISP^{Capr}$	-6.470**	9.645*	8.310**
	[-2.58]	[1.95]	[2.16]
Intermediary Size	-0.280	2.114**	1.399***
	[-0.19]	[2.59]	[2.75]
Portfolio Size	3.755***	0.271	0.048
	[2.71]	[0.30]	[0.09]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	1,575	1,575	1,574
adj. R^2	0.440	0.338	0.207

purchases and raise stock sales (Columns (1) and (3) in Panel A). However, as the dispersion of capital ratios increases, low-capital intermediaries do significantly reduce their stock purchases and raise their stock sales (Columns (1) and (2) in Panel B). These results provide evidence that low-capital intermediaries deleverage by selling off assets while high-capital intermediaries do not exhibit similar behavior.

More importantly, I am interested in whether high-capital intermediaries purchase stocks that low-capital intermediaries sell during bad times and, similarly, whether low-capital intermediaries sell stocks that high-capital intermediaries buy during such times. Since the identity of the parties involved in the transaction is not observable from the data, I use the change in ownership by high- and low-capital intermediaries to classify the stocks that high-capital intermediaries purchase and low-capital intermediaries sell. Specifically, I identify the stocks that high-capital intermediaries purchase as ones in which they raise their holdings during quarter t ($\Delta IO^H > 0$); and the stocks that low-capital intermediaries sell as ones in which they reduce their holdings during quarter t ($\Delta IO^L < 0$).

Column (2) of Panel A shows that as the dispersion of capital ratios increases, high-capital intermediaries purchase significantly more stocks that low-capital intermediaries sell. Also, Column (3) of Panel B indicates that as the dispersion of capital ratios increases, low-capital intermediaries sell significantly more stocks that high-capital intermediaries purchase. It is apparent that there are asset transfers from low-capital intermediaries to high-capital intermediaries during bad times.

Table 2.7 summarizes the trading gains of high- and low-capital intermediaries to show at what price they trade stocks during bad times, estimating Equation (2.4.4). There are two sources of trading gains that intermediaries can earn: stocks bought can appreciate in value, and stocks sold can depreciate in value. The latter is not a realized return, but more related to forgone returns on sales. If low-capital intermediaries sell stocks to high-capital intermediaries at fire-sale prices (i.e., at prices lower than fundamental values), one would expect that high-capital intermediaries earn positive returns on stock purchases, and low-capital intermediaries lose in terms of forgone returns on sales in the following period when stock prices return to their fundamental values.

In Pane A, I find the evidence that is consistent with the argument above. As the dispersion of capital ratios increases, low-capital intermediaries earn lower abnormal trading gains than high-capital intermediaries in the following quarter. Also, the difference is mainly attributed to the price depreciation of stocks sold in Column (3), implying that low-capital intermediaries suffer losses from stock sales.

Panels B and C present the trading gains separately for high- and low-capital intermediaries. In both panels, buying (selling) stocks would result in positive (negative) returns during bad times, implying that stock prices, in general, deflate during bad times. However, the trading gains, reported in Panel A, are mainly attributed to positive returns from purchases on stocks by high-capital intermediaries (Column (2) of Panel B) and negative returns from forgone losses on stock sales by low-capital intermediaries (Column (3) of Panel C). As the dispersion of capital ratios rose to 2.51 in the financial crisis as in Table 2.3, high- (low-) capital intermediaries earn (lose) abnormal returns of 1.51% (1.81%)[20] from purchases (sales) of stocks over the following quarter $t + 1$ in the financial crisis.[21]

Altogether, the findings in Tables 2.6 and 2.7 are consistent with the hypothesis that low-capital intermediaries sell their stocks to high-capital intermediaries at fire-sale prices during bad times.

2.5 Additional Tests and Robustness Checks

This section presents the results of additional tests to establish the robustness of the empirical findings in Section 2.4.

2.5.1 Comparison with Other Risk Aversion Measures

Since the dispersion of capital ratios in Equation (2.3.2) captures time-varying weights of capital held by intermediaries who are different in risk aversion, it is (positively) related to aggregate risk aversion. Therefore, it is important to compare the dispersion of capital ratios with other risk

[20] 1.51% = 2.51 × 0.60% and 1.81% = 2.51 × 0.72%

[21] As an extreme case, for 2008/Q3-Q4, high-capital intermediaries earned abnormal trading gains of 4.8% while low-capital intermediaries suffered abnormal trading losses of 5.3%.

Table 2.7
Trading Gains

This table reports the results of OLS regressions for trading gains of 13F institutional investment managers who belong to the largest 30 intermediaries in the U.S. Panel A shows the results using the whole sample. Panels B and C show the results using subsamples of managers who belong to high- and low-capital intermediaries. Dependent variables are abnormal trading gains for stock purchases (sales) by managers in quarter $t+1$ from stocks purchased (sold) in quarter t, estimated using the Fama-French five factor model (Fama and French, 2015). The sum of trading gains from stock purchases and sales is total grading gains. $\mathbb{1}$(Intermediary Capital = Low) is one if the manager belongs to a low-capital intermediary and zero otherwise. High- and low-capital intermediaries are the ones above and below the 50^{th} percentile of intermediary capital. $DISP^{Capr}$ is the dispersion of intermediary capital, defined in Table 2.1. Intermediary size is measured as the log of the intermediary's market capitalization. Portfolio size is the log of the total portfolio size of the manager. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers 1980/Q1 to 2012/Q4. Standard errors are clustered by 13F manager. t-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Trading Gains by Intermediary Capital

	(1) Total (%)	(2) Buy (%)	(3) Sell (%)
$\mathbb{1}$(Intermediary Capital = Low) $\times$ $DISP^{Capr}$	-0.401**	-0.025	-0.375***
	[-2.14]	[-0.21]	[-2.92]
$\mathbb{1}$(Intermediary Capital = Low)	0.408	-0.002	0.411**
	[1.28]	[-0.01]	[2.27]
$DISP^{Capr}$	0.177	0.503**	-0.326*
	[0.68]	[2.43]	[-1.92]
Intermediary Size	0.197	0.063	0.135
	[0.85]	[0.45]	[0.93]
Portfolio Size	0.278*	-0.020	0.299
	[1.88]	[-0.24]	[1.40]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	3,660	3,660	3,660
adj. R^2	0.009	0.005	0.029

Panel B: Trading Gains for Managers of High-Capital Intermediary

	(1) Total (%)	(2) Buy (%)	(3) Sell (%)
$DISP^{Capr}$	0.245	0.600**	-0.355
	[0.77]	[2.14]	[-1.64]
Intermediary Size	0.732	0.266	0.467
	[1.04]	[0.64]	[1.26]
Portfolio Size	0.289	-0.049	0.338
	[1.37]	[-0.33]	[1.02]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	2,072	2,072	2,072
adj. R^2	0.006	-0.009	0.014

Table 2.7 Continued

Panel C: Trading Gains for Managers of Low-Capital Intermediary

	(1) Total (%)	(2) Buy (%)	(3) Sell (%)
$DISP^{Capr}$	-0.367	0.357*	-0.724***
	[-1.39]	[1.90]	[-4.05]
Intermediary Size	-0.180	-0.105	-0.074
	[-0.78]	[-0.58]	[-0.52]
Portfolio Size	0.283**	0.055	0.228**
	[2.38]	[0.49]	[2.38]
Manager FE	Yes	Yes	Yes
Year and Quarter FE	Yes	Yes	Yes
N	1,575	1,575	1,575
adj. R^2	0.046	0.073	0.052

aversion measures in existing studies.

The first set of measures is sentiment indices, including the Investor Sentiment Index of Baker and Wurgler (2006) and the Michigan Consumer Sentiment Index (MCSI) from the Surveys of Consumers, conducted by the University of Michigan. Although risk aversion measures an investors' attitude towards risk, the sentiment index is based on psychological and behavioral biases because it captures how much investors/consumers are optimistic or pessimistic about future market and economic conditions. However, at least empirically, we may expect that sentiment is likely to be high in the state of the world in which aggregate risk aversion is low. The second measure is the variance risk premium, a well-known indicator of risk aversion (Rosenberg and Engle, 2002; Bollerslev, Gibson, and Zhou, 2011; Bekaert and Hoerova, 2016). The premium is defined as the difference between the risk-neutral variance and the realized variance, where the risk-neutral variance is the square of the Chicago Board Options Exchange (CBOE)'s VIX and the realized variance is the sum of squared 5-minute returns of the S&P 500 Index. Finally, I use the Risk Aversion Index developed by Bekaert, Engstrom, and Xu (2019).[22]

Table 2.8 shows a correlation matrix among various risk aversion measures. Consistent with

[22]The authors extract the implied risk aversion from a no-arbitrage asset pricing model for equities and corporate bonds.

Table 2.8
Correlation with Other Risk Aversion Measures

This table reports a correlation matrix among risk aversion measures. $DISP^{Capr}$ is the dispersion of intermediary capital, defined in Equation (2.3.2); Investor Sentiment is defined in Baker and Wurgler (2006); the Michigan Consumer Sentiment Index (MCSI) is from the Surveys of Consumers, conducted by the University of Michigan; Variance Risk Premium is defined as the difference between the risk-neutral variance and the realized variance of S&P 500 Index; and BEX Risk Aversion is obtained from Bekaert, Engstrom, and Xu (2019). The sample period covers from 1972/Q4 to 2016/Q4. Due to limited data availability, Variance Risk Premium and BEX Risk Aversion start from 1990/Q1 and 1986/Q2, respectively. p-values are in square brackets.

(1) $DISP^{Capr}$	(2) Investor Sentiment	(3) Consumer Sentiment	(4) Variance Risk Premium	(5) BEX Risk Aversion
1.000	-0.149	-0.534	0.117	0.306
	[0.048]	[0.000]	[0.226]	[0.001]
	1.000	0.375	0.033	-0.149
		[0.000]	[0.736]	[0.101]
		1.000	-0.057	-0.227
			[0.558]	[0.011]
			1.000	0.701
				[0.000]
				1.000

the arguments mentioned above, the dispersion of capital ratios is negatively correlated with the sentiment indices and positively correlated with the variance risk premium and the BEX risk aversion index.

2.5.2 Trading Activity of Intermediaries and Risk Characteristics of Stocks

Section 2.4.3 investigated trading activity by intermediaries with different capital ratios during bad times. This leads to a question of which stocks these intermediaries trade. In particular, when low-capital intermediaries are forced to sell assets after being hit by an adverse shock, they may be reluctant to sell stocks that have experienced severe price collapses (i.e., stocks with low dispersion betas) to avoid huge losses from selling those stocks. However, risk-averse high-capital intermediaries may not be interested in buying assets from low-capital intermediaries unless prices have dropped sufficiently. I now address this by directly investigating changes in holdings of intermediaries at the stock-level.

Table 2.9 presents the trading volume of stocks by high- and low-capital intermediaries in

Panel A and B, respectively. Trading volume is defined as the dollar amount of net purchases in a stock for a quarter t scaled by the manager's portfolio size. As in Tables 2.6 and 2.7, high- and low-capital intermediaries have capital ratios above and below the 50^{th} percentile, respectively, of the largest 30 intermediaries in the U.S. High- (Low-) β^{DISP} stocks belong to the highest (lowest) three deciles in the dispersion beta. Stocks in the middle four deciles are denoted as Med-β^{DISP}.

Panel A shows that high-capital intermediaries purchase significantly larger amounts of stocks with Low-β^{DISP} than those with Med- or High-β^{DISP} when the dispersion of capital ratios is high (i.e., during bad times). In contrast, Panel B provides evidence that low-capital intermediaries sell significantly larger amounts of stocks with Med-β^{DISP} than those with Low- or High-β^{DISP} when the dispersion of capital ratios is high. Interestingly, the findings in Table 2.9 document that there is a *trade mismatch* between high- and low-capital intermediaries during bad times. High-capital intermediaries are so risk averse that they are willing to buy only stocks that have sufficiently fallen in price. At the same time, low-capital intermediaries do not want to sell those assets if they believe that prices have temporarily dropped below fundamental values and will recover again. Rather, they choose to sell stocks that have experienced modest price drop.

2.5.3 Long-Term Predictability of Abnormal Returns

In this section, I investigate how the abnormal returns based on the dispersion beta are persistent by analyzing the long-term predictability. If the abnormal returns found in Table 2.5 are due to market mispricing, they will be arbitraged away in a short period of time given that markets are sufficiently complete. To rule out this possibility, it is necessary to test whether the abnormal returns are persistent in the long-term.

Table 2.10 shows the long-term predictability of the abnormal returns based on the dispersion beta. In particular, portfolios are formed at the beginning of month $t + i$, for $i = 1, 3, \cdots, 24$, using the dispersion beta available at the end of month t. The portfolios are either value-weighted (Panel A) or equal-weighted (Panel B). The spreads between high-dispersion beta stocks and low-dispersion beta stocks are statistically significant almost up to 24 months. The magnitude of the abnormal returns of H-L portfolios is stable over 12 months (with an annual risk premium in the

Table 2.9
Trading Activity of Intermediaries and Risk Characteristics of Stocks

This table reports the results of OLS regressions for the trading activity of intermediaries. Panel A presents the trading activities of high-capital intermediaries, and Panel B presents those of low-capital intermediaries. High- and low-capital intermediaries have capital ratios above and below the 50^{th} percentile. Dependent variables are trading volume, defined as the dollar-value of net purchases in a stock during a quarter scaled by the manager's portfolio size. $\mathbb{1}(\beta^{DISP}$ = High) is one if stocks belong to the highest three deciles in the dispersion beta and zero otherwise. $\mathbb{1}(\beta^{DISP}$ = Med) is one if stocks belong to the middle four deciles in the dispersion beta and zero otherwise. $\mathbb{1}(\beta^{DISP}$ = Low) is one if stocks belong to the lowest three deciles in the dispersion beta and zero otherwise. $DISP^{Capr}$ is the dispersion of intermediary capital, defined in Table 2.1. Intermediary size is the log of the intermediary's market capitalization. β^{MKT} is the market beta, estimated from monthly regressions using 5-year rolling windows. Market Cap is the log of the stock's market capitalization. B/M is the book-to-market ratio, book equity over market capitalization. MOM is momentum, the cumulative return over the previous one year, skipping the most recent month. ROE is income before extraordinary items over lagged book equity. I/A is asset growth, the percentage change in total assets. Return Volatility is the quarterly standard deviation of daily stock returns. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers 1980/Q1 to 2012/Q4. Standard errors are clustered by 13F manager and stock. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Trading Volume of High-Capital Intermediary

	(1) Volume	(2) Volume	(3) Volume	(4) Volume
$\mathbb{1}(\beta^{DISP}$ = Low) $\times$ $DISP^{Capr}$	6.787***			6.986***
	[2.72]			[2.74]
$\mathbb{1}(\beta^{DISP}$ = Med) $\times$ $DISP^{Capr}$		0.498		0.491
		[0.32]		[0.52]
$\mathbb{1}(\beta^{DISP}$ = High) $\times$ $DISP^{Capr}$			-1.310	0.707
			[-1.00]	[0.47]
$\mathbb{1}(\beta^{DISP}$ = Low)	-8.491***			-8.393*
	[-4.46]			[-1.80]
$\mathbb{1}(\beta^{DISP}$ = Med)		-3.547***		-3.106
		[-4.28]		[-1.08]
$\mathbb{1}(\beta^{DISP}$ = High)			4.315***	0.444
			[6.44]	[0.16]
Controls	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year $\times$ Quarter FE	Yes	Yes	Yes	Yes
N	1,687,770	1,687,770	1,687,770	1,687,770
adj. R^2	0.058	0.058	0.058	0.058

Table 2.9 Continued

Panel B: Trading Volume of Low-Capital Intermediary

	(1) Volume	(2) Volume	(3) Volume	(4) Volume
$\mathbb{1}(\beta^{DISP}$ = Low) $\times$ $DISP^{Capr}$	1.646			1.912
	[0.73]			[1.09]
$\mathbb{1}(\beta^{DISP}$ = Med) $\times$ $DISP^{Capr}$		-4.813**		-4.907***
		[-2.32]		[-5.07]
$\mathbb{1}(\beta^{DISP}$ = High) $\times$ $DISP^{Capr}$			1.597	0.145
			[0.58]	[0.06]
$\mathbb{1}(\beta^{DISP}$ = Low)	0.831			-1.071
	[0.60]			[-0.66]
$\mathbb{1}(\beta^{DISP}$ = Med)		6.566**		4.582*
		[2.49]		[1.72]
$\mathbb{1}(\beta^{DISP}$ = High)			-6.601	-5.099
			[-1.33]	[-0.90]
Controls	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year $\times$ Quarter FE	Yes	Yes	Yes	Yes
N	1,927,980	1,927,980	1,927,980	1,927,980
adj. R^2	0.114	0.114	0.114	0.114

range of 6.8% to 8.6%) and then gradually attenuates afterwards.

The persistent abnormal returns reported in Table 2.10 are also related to the persistence of the dispersion beta. The (untabulated) results indicate that the probability that stocks in the lowest decile stay in the same decile after one quarter, one year, and two years is 84.2%, 63.8%, and 46.3%, respectively and that the probability that stocks in the highest decile stay in the same decile after one quarter, one year, and two years is 83.1%, 60.2%, and 43.0%, respectively. Such a slow-moving beta is consistent with the persistent abnormal returns of the portfolios based on the dispersion beta.

2.5.4 Controlling Industry Effect

Equation (2.4.1) can be misspecified if the dispersion beta is clustered by industry. As discussed in Lyon, Barber, and Tsai (1999) and Johnson, Moorman, and Sorescu (2009), this industry clustering may lead to a spurious relation between risk characteristics being tested and stock re-

Table 2.10
Long-Term Abnormal Returns based on Dispersion Beta

This table reports abnormal returns of long-short portfolios that buy high-dispertion beta stocks and sell short low -dispersion beta stocks (H-L) up to 24 months. Portfolios are value-weighted in Panel A and equal-weighted in Panel B. FF5 is the Fama-French five factor model (Fama and French, 2015), FF5+PS adds the liquidity factor (Pástor and Stambaugh, 2003) to FF5, FF5+MOM adds the momentum factor (Jegadeesh and Titman, 1993) to FF5, FF5+AEM adds the intermediary leverage factor (Adrian, Etula, and Muir, 2014) to FF5, and FF5+HKM adds the intermediary capital factor (He, Kelly, and Manela, 2017) to FF5. The dispersion beta, defined in Table 2.1, is estimated from quarterly regressions using 5-year rolling windows. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Long-Term Abnormal Returns of H-L Portfolios (VW) based on Dispersion Beta

	(1)	(2)	(3)	(4)	(5)	(6)
	FF5	FF5 + PS	FF5 + MOM	FF5 + IVOL	FF5 + AEM	FF5 + HKM
$t+1$	-0.58%***	-0.62%***	-0.62%***	-0.57%***	-0.58%***	-0.57%***
	[-3.20]	[-3.48]	[-3.37]	[-3.15]	[-3.17]	[-3.13]
$t+3$	-0.62%***	-0.65%***	-0.61%***	-0.61%***	-0.61%***	-0.61%***
	[-3.31]	[-3.44]	[-3.29]	[-3.25]	[-3.28]	[-3.27]
$t+6$	-0.67%***	-0.69%***	-0.66%***	-0.66%***	-0.66%***	-0.68%***
	[-3.64]	[-3.73]	[-3.59]	[-3.55]	[-3.59]	[-3.62]
$t+9$	-0.58%***	-0.60%***	-0.56%***	-0.57%***	-0.57%***	-0.58%***
	[-3.35]	[-3.45]	[-3.26]	[-3.25]	[-3.32]	[-3.32]
$t+12$	-0.59%***	-0.62%***	-0.58%***	-0.58%***	-0.59%***	-0.60%***
	[-3.54]	[-3.71]	[-3.44]	[-3.43]	[-3.52]	[-3.53]
$t+15$	-0.53%***	-0.56%***	-0.51%***	-0.53%***	-0.53%***	-0.52%***
	[-2.76]	[-2.89]	[-2.67]	[-2.72]	[-2.80]	[-2.76]
$t+18$	-0.41%**	-0.43%**	-0.39%**	-0.40%**	-0.41%**	-0.40%**
	[-2.14]	[-2.22]	[-2.08]	[-2.07]	[-2.19]	[-2.13]
$t+21$	-0.40%**	-0.40%**	-0.32%*	-0.40%**	-0.42%**	-0.39%**
	[-2.24]	[-2.21]	[-1.85]	[-2.25]	[-2.37]	[-2.24]
$t+24$	-0.27%	-0.31%	-0.26%	-0.27%	-0.30%	-0.27%
	[-1.22]	[-1.34]	[-1.17]	[-1.21]	[-1.38]	[-1.25]

Table 2.10 Continued

Panel B: Long-Term Abnormal Returns of H-L Portfolios (EW) based on Dispersion Beta

	(1) FF5	(2) FF5 + PS	(3) FF5 + MOM	(4) FF5 + IVOL	(5) FF5 + AEM	(6) FF5 + HKM
$t+1$	-0.62%***	-0.63%***	-0.68%***	-0.61%***	-0.60%***	-0.61%***
	[-4.62]	[-4.71]	[-5.03]	[-4.56]	[-4.42]	[-4.60]
$t+3$	-0.58%***	-0.58%***	-0.61%***	-0.58%***	-0.57%***	-0.57%***
	[-4.46]	[-4.44]	[-4.77]	[-4.40]	[-4.36]	[-4.50]
$t+6$	-0.70%***	-0.69%***	-0.72%***	-0.69%***	-0.68%***	-0.68%***
	[-5.75]	[-5.74]	[-5.93]	[-5.66]	[-5.63]	[-5.85]
$t+9$	-0.69%***	-0.69%***	-0.70%***	-0.68%***	-0.66%***	-0.68%***
	[-5.75]	[-5.80]	[-5.72]	[-5.67]	[-5.61]	[-5.82]
$t+12$	-0.67%***	-0.67%***	-0.67%***	-0.66%***	-0.65%***	-0.66%***
	[-5.99]	[-6.12]	[-6.10]	[-5.91]	[-5.87]	[-5.98]
$t+15$	-0.59%***	-0.60%***	-0.57%***	-0.59%***	-0.59%***	-0.59%***
	[-4.93]	[-5.12]	[-4.85]	[-4.91]	[-5.06]	[-4.98]
$t+18$	-0.47%***	-0.47%***	-0.44%***	-0.47%***	-0.47%***	-0.47%***
	[-4.14]	[-4.26]	[-3.95]	[-4.11]	[-4.22]	[-4.19]
$t+21$	-0.43%***	-0.42%***	-0.39%***	-0.43%***	-0.44%***	-0.43%***
	[-3.87]	[-3.89]	[-3.41]	[-3.90]	[-4.04]	[-3.93]
$t+24$	-0.24%**	-0.25%**	-0.22%*	-0.24%**	-0.25%**	-0.24%**
	[-2.07]	[-2.15]	[-1.89]	[-2.07]	[-2.23]	[-2.12]

turns. To rule out the possibility of the industry clustering in the dispersion beta, I include industry fixed effect in the Fama-MacBeth regressions as follows:

$$r^i_{t+1} - r^f_{t+1} = \alpha + \lambda^{DISP}\beta^{DISP,i}_t + \sum_{k=1}^{K}\lambda^k\beta^{k,i}_t + Z^j + \varepsilon^i_{t+1} \qquad (2.5.1)$$

where Z^j is the industry fixed effect. For each month, stocks are assigned to each industry based on SIC codes and the Fama-French 10-industry classification.

Table 2.11 shows the estimation results of Equation (2.5.1). The dispersion beta (β^{DISP}) appears to be negatively priced in the cross-section of stock returns. The estimated price of risk for the dispersion beta is similar to the one without the industry effect in Table 2.4, implying that the relation between the dispersion beta and stock returns is hardly influenced by any unobserved heterogeneity across industry (e.g., the industry clustering).

Table 2.11
Fama-MacBeth Regressions: Controlling for Industry Effect

This table reports the estimation results for the Fama-MacBeth regressions controlling for the industry effect. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 2.1, is estimated from quarterly regressions using 5-year rolling windows. I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 2.4. To control unobserved heterogeneity across industry, I also include industry fixed effect based on the Fama-French 10-industry classification. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.75***	−0.73***	−0.49***	−0.44***	−0.35***	−0.34***	−0.38***
	[−5.13]	[−5.21]	[−3.92]	[−3.87]	[−3.12]	[−3.16]	[−3.01]
β^{MKT}		0.19	0.19	0.26**	0.28**	0.13	0.18
		[1.25]	[1.28]	[2.05]	[2.10]	[1.13]	[1.36]
β^{AEM}			0.32***		0.15***	0.13***	0.14***
			[5.19]		[3.67]	[3.29]	[3.31]
β^{HKM}			0.13***		0.08**	0.08*	0.08*
			[3.03]		[2.05]	[1.94]	[1.74]
Size				−0.46***	−0.45***	−0.36***	−0.33***
				[−12.49]	[−12.47]	[−11.67]	[−9.90]
B/M				0.22**	0.22**	0.24***	0.24**
				[2.58]	[2.50]	[3.03]	[2.48]
MOM				−0.10	−0.10	−0.10	−0.26
				[−0.57]	[−0.56]	[−0.60]	[−1.35]
OP				0.08	0.07	0.14	0.03
				[0.64]	[0.63]	[1.23]	[0.30]
I/A				−0.85***	−0.85***	−0.88***	−0.87***
				[−8.57]	[−8.60]	[−9.07]	[−8.39]
IVOL						32.25***	44.03***
						[6.52]	[8.16]
$\beta^{\Delta VXO}$							−7.58
							[−1.55]

Table 2.12

Alternative Dispersion of Capital Ratios: Balancing Size of High- and Low-Capital Intermediaries

This table reports the estimation results for the Fama-MacBeth regressions. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 2.1, is estimated from quarterly regressions using 5-year rolling windows. To account for the difference in size (i.e., market capitalization) of high- and low-capital intermediaries, the dispersion of intermediary capital is defined differently so that the total market capitalizations of high- and low-capital intermediaries are similar: the difference between the 75^{th} percentile and the 10^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile. I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 2.4. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.51***	−0.49***	−0.28**	−0.30***	−0.19**	−0.20**	−0.21**
	[−3.54]	[−3.71]	[−2.38]	[−3.06]	[−2.14]	[−2.30]	[−2.20]
β^{MKT}		0.32*	0.33*	0.28*	0.31**	0.14	0.20
		[1.74]	[1.82]	[1.86]	[2.04]	[1.03]	[1.32]
β^{AEM}			0.35***		0.16***	0.13***	0.16***
			[4.90]		[3.42]	[3.09]	[3.58]
β^{HKM}			0.14***		0.10**	0.11**	0.10*
			[2.67]		[2.18]	[2.26]	[1.79]
Size				−0.47***	−0.47***	−0.36***	−0.33***
				[−12.19]	[−12.19]	[−11.48]	[−9.64]
B/M				0.11	0.10	0.14	0.15
				[1.06]	[0.94]	[1.51]	[1.32]
MOM				0.04	0.05	0.03	−0.16
				[0.21]	[0.25]	[0.17]	[−0.78]
OP				−0.05	−0.04	0.04	−0.06
				[−0.35]	[−0.34]	[0.35]	[−0.56]
I/A				−0.77***	−0.76***	−0.82***	−0.84***
				[−7.42]	[−7.42]	[−7.96]	[−7.66]
IVOL						34.63***	46.63***
						[6.58]	[8.01]
$\beta^{\Delta VXO}$							−8.08
							[−1.57]

2.5.5 Balancing Size of High- and Low-Capital Intermediaries

When the dispersion of capital ratios is defined in Equation (2.3.2), the X^{th} percentile of the intermediary capital of the largest 30 intermediaries in the U.S. is simply based on the number of the intermediaries and does not account for the size of the intermediaries. Summary statistics in Panel A of Table 2.1 report that high-capital intermediaries tend to be smaller than low-capital intermediaries. Therefore, total size of intermediaries above the 75^{th} percentile of intermediary capital is lower than that below its 25^{th} percentile.[23]

To measure the X^{th} percentile of the intermediary capital by incorporating the size of intermediaries, I redefine the dispersion of capital ratios so that the total market capitalization of high- and low-capitalization are similar: the difference between the 75^{th} percentile and the 10^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile.[24]

$$DISP_t^{Capr} = \frac{Capr_t^{75^{th}} - Capr_t^{10^{th}}}{Capr_t^{50^{th}}} \tag{2.5.2}$$

Table 2.12 reports the results based on Equation (2.5.2). Similar to Table 2.4, I continue to find that the dispersion beta (β^{DISP}) is significantly and negatively priced in the cross-section of stock returns.

2.5.6 Using Largest 40 or 50 Intermediaries

The main results in Section 2.4 define financial intermediaries to be the largest 30 intermediaries. Ideally, I would like to include all intermediaries that are large enough to make their capital important in characterizing the pricing kernel. However, there is no clear-cut way to determine how many intermediaries are marginal investors. To test if my choice of the number of intermediaries affects the results, I now alternatively measure the dispersion of capital ratios using the largest 40 or 50 intermediaries.

[23] Total market capitalizations above the 75^{th} percentile and below the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S. are \$93 billion and \$223 billion on average.

[24] Total market capitalizations below the 10^{th} and 11^{th} percentile are \$71 billion and \$103 billion, respectively, on average. For simplicity, I report the results based on the 10^{th} percentile, but the results based on the 11^{th} percentile are also significant at the 1% or 5% level.

Table 2.13
Alternative Dispersion of Capital Ratios: Using Largest 40 or 50 Intermediaries

This table reports the estimation results for the Fama-MacBeth regressions. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 2.1, is estimated from quarterly regressions using 5-year rolling windows. However, the dispersion of intermediary capital is defined using the largest 40 or 50 intermediaries. I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 2.4. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 40 or 50 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Top 40 Intermediaries			*Top 50 Intermediaries*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.47***	−0.67***	−0.26*	−0.41***	−0.26*	−0.17
	[−2.72]	[−4.07]	[−1.91]	[−2.89]	[−1.96]	[−1.40]
β^{MKT}	0.30*	0.32*	0.15	0.34*	0.32*	0.13
	[1.68]	[1.82]	[1.17]	[1.85]	[1.79]	[1.02]
β^{AEM}		0.29***	0.11**		0.35***	0.15***
		[3.93]	[2.15]		[5.15]	[3.60]
β^{HKM}		0.17***	0.12**		0.20***	0.13***
		[3.19]	[2.52]		[3.73]	[2.77]
Size			−0.36***			−0.36***
			[−11.74]			[−11.61]
B/M			0.14			0.14
			[1.46]			[1.52]
MOM			0.04			0.02
			[0.25]			[0.13]
OP			0.03			0.04
			[0.28]			[0.36]
I/A			−0.83***			−0.82***
			[−8.08]			[−7.93]
IVOL			34.26***			34.75***
			[6.50]			[6.61]

Table 2.13 summarizes the results. In Columns (1) - (3), I find that the dispersion beta (β^{DISP}) based on the largest 40 intermediaries is still significantly priced in the cross-section of stock returns, but the price of risk is rather smaller than in Table 2.4. In Columns (4) - (6), the results based on the largest 50 intermediaries are marginally significant or insignificant. It appears that at least some intermediaries outside the largest 40 intermediaries can be inappropriate to be viewed as marginal investors.

2.5.7 Using Book Capital Ratio

In Section 2.4, I measure intermediary capital based on market values. It is interesting to examine if consistent results are obtained when the book capital ratio is used to estimate the dispersion beta. As discussed in He, Kelly, and Manela (2017), if intermediaries perfectly implement mark-to-market for their holdings of financial assets, intermediary capital measured based on market values and book values should be aligned. When the intermediaries are selling off assets to reduce debt, the book capital ratio continues to rise. However, if a high discount rate during bad times pushes down the market value of capital faster than the debt decreases, the market capital ratio declines (Santos and Veronesi, 2018). Therefore, the book capital ratio could move in the opposite direction as the market capital ratio. Furthermore, it may seem hard to argue that the change in intermediaries' book capital ratio matters in the pricing kernel, because the book capital ratio is largely determined endogenously by intermediaries. Nevertheless, I now rerun my analyses using book capital ratios.

Figure 2.3 shows the level and the dispersion of capital ratios measured using book values. Different from Figure 2.2, which uses market values, low-capital intermediaries raise their capital ratios in the financial crisis (i.e., they deleverage) (See Panel A). Nevertheless, the dispersion of capital ratios in Panel B indicates countercyclical variation, although it seems less volatile than the dispersion of capital ratios in market values shown in Panel B of Figure 2.2.[25]

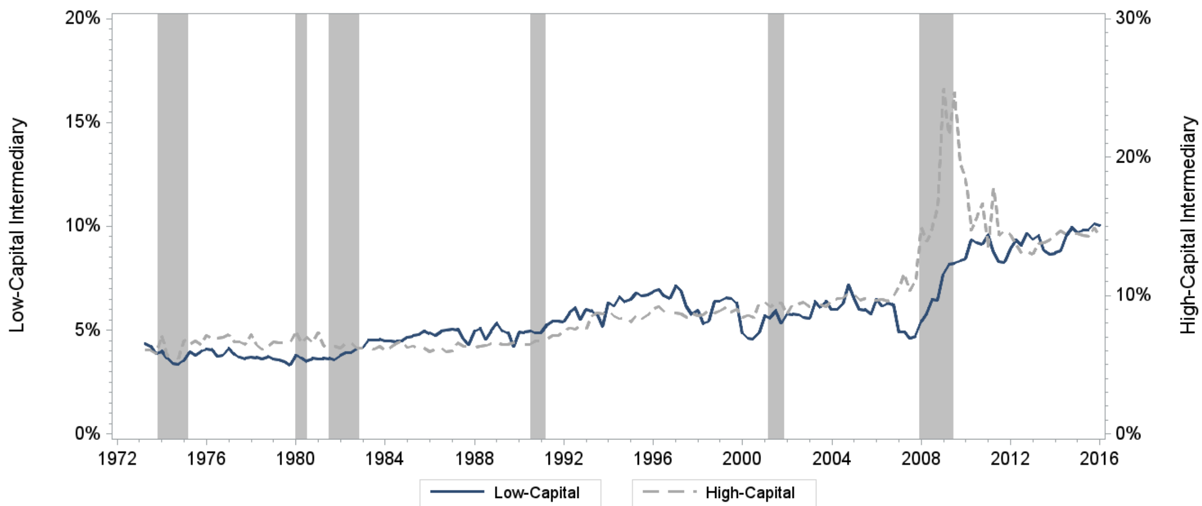
Table 2.14 repeats Table 2.4 but uses the book capital ratio to define intermediary capital. Not

[25]The 75^{th} (25^{th}) percentile of the *quasi-market* capital ratio of the largest 30 intermediaries in the U.S. and the 75^{th} (25^{th}) percentile of the *book* capital ratio of the largest 30 intermediaries in the U.S. are positively correlated at 0.86 (0.56). Also, the correlation between the dispersion of capital ratios in market value and book value terms is 0.78.

Figure 2.3
Level and Dispersion of Intermediary Capital Ratios: Book Capital Ratio

This figure depicts intermediary capital of the largest 30 intermediaries in the U.S. Panel A plots the level of intermediary capital. The dashed line represents the 75^{th} percentile of intermediary capital while the solid line represents the 25^{th} percentile of intermediary capital. Panel B plots the dispersion of intermediary capital, measured as the difference between the 75^{th} and the 25^{th} percentile of intermediary capital of the largest 30 intermediaries in the U.S., scaled by its 50^{th} percentile, in the solid line. The change in the dispersion of intermediary capital is shown by the dashed line. Intermediary capital is measured using the book capital ratio, that is, the book value of equity over the sum of the book value of debt and the book value of equity. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The shaded areas represent NBER recessions. The sample period covers 1973/Q1 to 2016/Q4.

Panel A: Capital Ratios of High- and Low-Capital Intermediaries



Panel B: Dispersion of Intermediary Capital Ratios

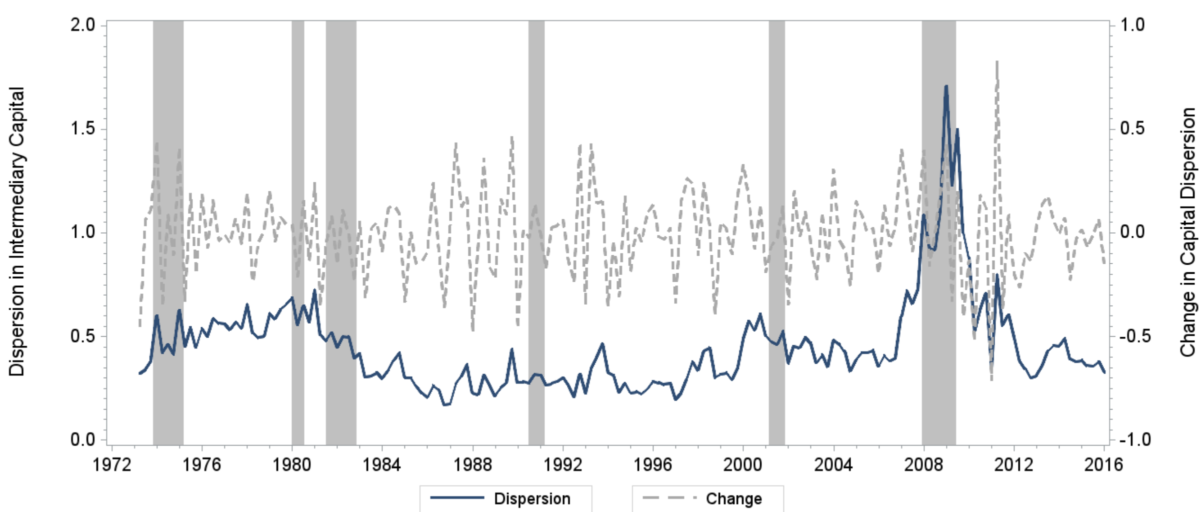


Table 2.14

Alternative Dispersion of Capital Ratios: Using Book Capital Ratio

This table reports the estimation results for the Fama-MacBeth regressions. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 2.1, is estimated from quarterly regressions using 5-year rolling windows. However, the dispersion of intermediary capital is defined using the book capital ratio (instead of the quasi-market capital ratio). I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 2.4. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 40 or 50 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). The sample period covers January 1978 to December 2016. Standard errors are adjusted using the Newey-West method. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.40**	−0.36**	−0.40**	−0.08	−0.15	−0.14	0.01
	[−2.34]	[−2.25]	[−2.45]	[−0.67]	[−1.07]	[−1.06]	[0.04]
β^{MKT}		0.31*	0.32*	0.30**	0.32**	0.14	0.21
		[1.72]	[1.76]	[1.99]	[2.06]	[1.08]	[1.37]
β^{AEM}			0.27***		0.10**	0.08*	0.14***
			[3.56]		[2.09]	[1.74]	[2.73]
β^{HKM}			0.21***		0.13***	0.13***	0.12**
			[4.17]		[2.78]	[2.79]	[2.31]
Size				−0.47***	−0.47***	−0.36***	−0.33***
				[−12.33]	[−12.19]	[−11.46]	[−9.71]
B/M				0.11	0.09	0.14	0.14
				[1.02]	[0.89]	[1.45]	[1.24]
MOM				0.03	0.03	0.01	−0.16
				[0.17]	[0.14]	[0.05]	[−0.81]
OP				−0.04	−0.05	0.04	−0.06
				[−0.34]	[−0.37]	[0.30]	[−0.53]
I/A				−0.77***	−0.76***	−0.82***	−0.83***
				[−7.38]	[−7.43]	[−7.99]	[−7.63]
IVOL						34.71***	46.91***
						[6.58]	[8.05]
$\beta^{\Delta VXO}$							−7.97
							[−1.54]

Table 2.15
Subsample Tests

This table reports the estimation results for the Fama-MacBeth regressions in subsample periods. In columns (1) - (3) of Panel A, the sample period covers January 1978 to December 1999. In columns (4) - (6) of Panel A, the sample period covers January 2000 to December 2016. In Panel B, the financial crisis (July 2007 to December 2009) and NBER recessions are excluded from the sample period in columns (1) - (3) and columns (4) - (6), respectively. Dependent variables are monthly returns on nonfinancial firm stocks in excess of the one-month Treasury bill rate. The dispersion beta, defined in Table 2.1, is estimated from quarterly regressions using 5-year rolling windows. I control for β^{MKT}, β^{AEM} (Adrian, Etula, and Muir, 2014), β^{HKM} (He, Kelly, and Manela, 2017), Size (the log of market capitalization), B/M (book-to-market ratio), MOM (momentum), OP (operating profitability, and I/A (asset growth), defined in Table 2.4. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6). Standard errors are adjusted using the Newey-West method. *t*-statistics are in square brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Subsample Periods Before and After 2000

Sample Period	*1978 - 1999*			*2000 - 2016*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.60***	−0.53**	−0.33**	−1.01***	−0.45**	−0.33*
	[−2.74]	[−2.36]	[−2.00]	[−3.97]	[−2.36]	[−1.87]
β^{MKT}	0.19	0.15	0.13	0.42	0.51*	0.12
	[0.85]	[0.66]	[0.77]	[1.48]	[1.84]	[0.63]
β^{AEM}		0.23***	0.06		0.44***	0.21***
		[2.95]	[1.09]		[3.76]	[3.38]
β^{HKM}		0.08	−0.00		0.28***	0.25***
		[1.36]	[−0.03]		[3.10]	[3.28]
Size			−0.33***			−0.40***
			[−7.81]			[−8.82]
B/M			0.17			0.09
			[1.62]			[0.54]
MOM			0.65***			−0.76**
			[4.25]			[−2.38]
OP			0.11			−0.06
			[0.62]			[−0.47]
I/A			−0.89***			−0.71***
			[−6.43]			[−4.85]
IVOL			23.69***			48.65***
			[3.94]			[5.97]

Table 2.15 Continued

Panel B: Subsample Periods Excluding Bad Times

Sample Period	*Excluding Financial Crisis*			*Excluding NBER Recessions*		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$	$r^i - r^f$
β^{DISP}	−0.75***	−0.53***	−0.38***	−0.75***	−0.52***	−0.36***
	[−4.50]	[−3.42]	[−3.09]	[−4.47]	[−3.33]	[−2.83]
β^{MKT}	0.19	0.21	0.10	0.23	0.25	0.10
	[1.09]	[1.23]	[0.78]	[1.41]	[1.51]	[0.82]
β^{AEM}		0.27***	0.12***		0.29***	0.13***
		[4.67]	[2.74]		[4.52]	[2.77]
β^{HKM}		0.16***	0.09*		0.16***	0.10*
		[2.99]	[1.88]		[2.77]	[1.86]
Size			−0.37***			−0.35***
			[−11.11]			[−10.24]
B/M			0.16*			0.17*
			[1.82]			[1.76]
MOM			0.22*			0.13
			[1.71]			[0.91]
OP			0.07			−0.00
			[0.59]			[−0.01]
I/A			−0.83***			−0.85***
			[−7.79]			[−7.67]
IVOL			34.19***			36.42***
			[6.38]			[6.54]

surprisingly, the dispersion beta (β^{DISP}) is not significantly priced in the cross-section of stock returns even though the signs on the price of the risk remain negative as in Table 2.4. These results suggest that it is more appropriate to measure intermediary capital in market values than in book values to obtain the pricing kernel of marginal investors.

2.5.8 Subsample Tests

Table 2.15 repeats Table 2.4 for subsample periods to test the effect of the dispersion beta (β^{DISP}) on the cross-section of stock returns changes over time. In Panel A, the subsample periods are before 2000 and after 2000. I find that the dispersion beta is priced in the cross-section of stock returns over the subsample periods. The effect remains statistically and economically significant.

As shown in Figure 2.2, dispersion of intermediary capital is unusually high during the financial crisis (or similarly during NBER recessions). It may be possible that the dispersion beta is priced in the cross-section of stock returns only in economic bad times, not normal times. In Panel B of Table 2.15, I test this possibility by excluding the financial crisis in Columns (1) - (3) or NBER recessions in Columns (4) - (6) from the sample period. I continue to find the significant price of risk for the dispersion beta in these subsample periods and confirm that my main results are not driven by the bad times.

2.6 Model of Heterogeneous Intermediary Capital

Based on the empirical findings in the previous sections, I develop a model of heterogeneous intermediary capital in which the dispersion of intermediary capital is priced in the cross-section of stock returns. The model provides a mechanism that a risk-averse (risk-tolerant) manager forms a high- (low-) capital intermediary and that asymmetric responses to a shock between the two intermediaries change the proportion of capital held by a high- versus a low-capital intermediary, thereby leading to a countercyclical variation in aggregate risk aversion. The model also shows that the dispersion of intermediary capital generates a sizable risk premium in addition to that attributable to the level of intermediary capital.

2.6.1 Setup

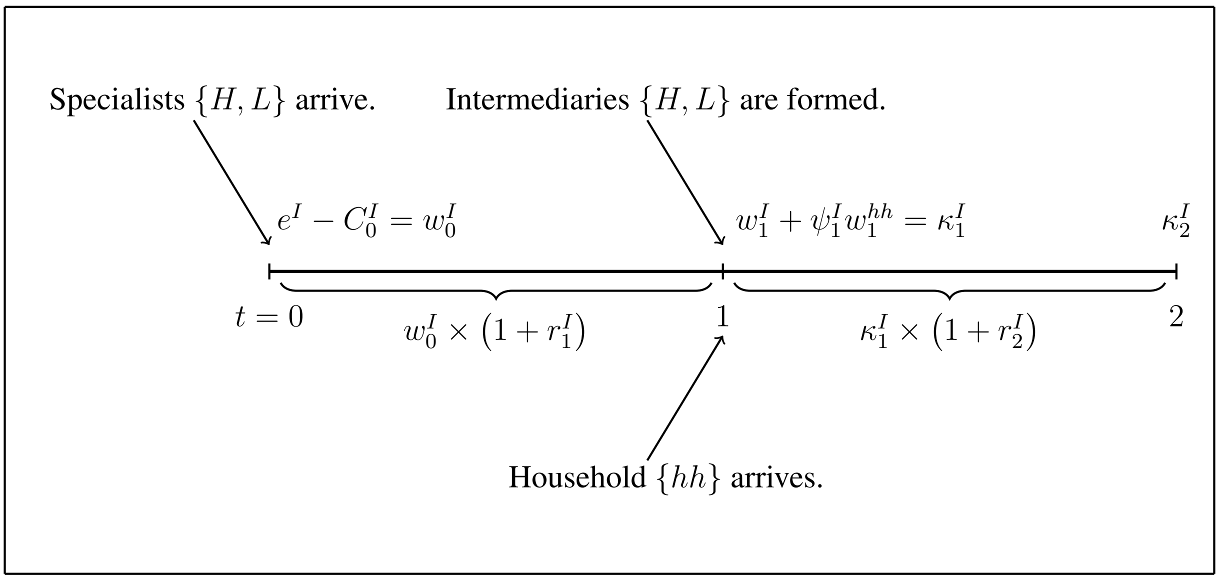
The timeline of the economy is described in Figure 2.4. The economy is populated with two specialists $\{H, L\}$ and one household $\{hh\}$. There are three periods, $t = \{0, 1, 2\}$. At $t = 0$, the two specialists receive an endowment of $e^H = e^L$. As shown in Section 2.6.2, specialist H has a more persistent habit than specialist L in their utility functions, which then gives rise to heterogeneous risk aversion between the specialists. The household arrives at $t = 1$ with an endowment of e^{hh}. There are two types of assets, a risky asset, a, and a risk-free asset, f, available to invest at $t = \{0, 1\}$.

Following He and Krishnamurthy (2013), the household cannot directly invest in the risky asset,[26] but can directly invest in the risk-free asset or indirectly invest in the risky asset through

[26] Households' participation in financial markets can be limited due to lack of skills (van Rooij, Lusardi, and Alessie, 2011) or fixed participation costs (Vissing-Jorgensen, 2003) among others. Although the households' partic-

Figure 2.4
Timeline of Economy

This figure depicts the timeline of the economy described in the model. There are three agents: two specialists $I \in \{H, L\}$ and a household hh. The amount of wealth (w_0^I) and capital (κ_1^I) available to invest by specialists and intermediaries, respectively, is indicated above the timeline. The growth of wealth (w_0^I) and capital (κ_1^I) is displayed below the timeline. At $t = 0$, the specialists arrive in the market with an endowment of e^I and consume C_0^I. At $t = 1$, the household arrives in the market with an endowment of e^{hh} and consumes C_1^{hh}. After consuming C_1^I at $t = 1$, the specialists form intermediaries using their post-consumption wealth of $w_1^I = w_0^I \times (1 + r_1^I) - C_1^I$ plus the household's contribution of $\psi_1^I w_1^{hh}$, where $w_1^{hh} = e^{hh} - C_1^{hh}$. Intermediary capital at $t = 1$, $\kappa_1^I = w_1^I + \psi_1^I w_1^{hh}$, grows to $\kappa_2^I = \kappa_1^I \times (1 + r_2^I)$, where r_2^I is a return on investment at $t = 2$. κ_2^I is distributed and consumed by all agents at their respective ratios.



intermediaries.[27] Specialists are able to invest both in the risky asset and the risk-free asset without a short-sale constraint. Each specialist forms an intermediary using her own wealth and funds provided by the household. Specifically, at $t = 1$, the household allocates ψ_1^H of her (post-consumption) wealth, w_1^{hh}, to specialist H and ψ_1^L of her wealth to specialist L to purchase equity capital of intermediaries. Thus, intermediary capital would be $\kappa_1^H \equiv w_1^H + \psi_1^H w_1^{hh}$ for intermediary H and $\kappa_1^L \equiv w_1^L + \psi_1^L w_1^{hh}$ for intermediary L.

ipation is not completely limited in reality, I make this restriction to make sure that that households are not marginal investors.

[27] One can think of a case where households entrust their investment to asset management companies, e.g. *Black-Rock*, *Schwab Charles*, etc.

The return on the risky asset, a, follows a stochastic process:

$$r_t^a = \mu_t + \sigma_t \varepsilon_t, \quad \varepsilon_t \sim i.i.d.\mathcal{N}(0,1). \tag{2.6.1}$$

Denote α_t^I to be the portion of the risky asset in specialists' portfolios. $1 - \alpha_t^I$ is the portion of the risk-free asset in their portfolios. The return on intermediary capital is then

$$r_{t+1}^I = \alpha_t^I \left(r_{t+1}^a - r_{t+1}^f \right) + r_{t+1}^f \tag{2.6.2}$$

where $I \in \{H, L\}$ and r_t^f is the return on the risk-free asset. The total supply of the risky asset is normalized to one: $\alpha_t^H \left(w_t^H + \psi_t^H w_t^{hh} \right) + \alpha_t^L \left(w_t^L + \psi_t^L w_t^{hh} \right) = 1$. The risk-free asset, issued by specialists/intermediaries, is in zero net supply: $\left(1 - \alpha_t^H\right) \left(w_t^H + \psi_t^H w_t^{hh} \right) + \left(1 - \alpha_t^L\right) \left(w_t^L + \psi_t^L w_t^{hh} \right) + \left(1 - \psi_t^H - \psi_t^L\right) w^{hh} = 0$.

2.6.2 Specialist Problem

Specialists maximize their expected utility over lifetime, $t \in \{0, 1, 2\}$ under budget constraints. To incorporate time-varying risk aversion of the specialists, I consider the utility function accounting for a habit.

$$\max_{\{C_t^I, \alpha_t^I\}} E\left[\sum_{t=0}^{2} e^{-\rho t} u\left(C_t^I, X_t^I\right) \right] \quad \text{subject to} \quad w_{t+1}^I = w_t^I \left(1 + r_{t+1}^I\right) - C_{t+1}^I \tag{2.6.3}$$

where $u\left(C_t^I, X_t^I\right) = \frac{\left(C_t^I - X_t^I\right)^{1-\gamma}}{1-\gamma}$. C_t^I is the specialists' consumption, X_t^I is their habits, and γ is a curvature parameter. The habits, X_t^I, are determined by the specialists' history of consumption. To account for the heterogeneous risk aversion of the two specialists, I suppose that specialist H has a more persistent habit than specialist L.

$$X_t^I = \begin{cases} \eta \sum_{j=1}^{t} \left(\phi^I\right)^j C_{t-j}^I & \text{if } t > 0 \\ 0 & \text{if } t = 0 \end{cases} \tag{2.6.4}$$

where $0 < \phi^L < \phi^H \leq 1$ and $\eta < 1$.[28]

Next, I obtain the first-order condition for (2.6.3) to solve specialists' consumption:

$$E\Big[\left(C_0^I\right)^{-\gamma} - \left\{\eta\phi^I - \left(1+r_1^I\right)\right\} e^{-\rho}\left(C_1^I - \eta\phi^I C_0^I\right)^{-\gamma} \\ - \left\{\phi^I + \left(1+r_1^I\right)\right\}\eta\phi^I e^{-2\rho}\left(C_2^I - \eta\phi^I C_1^I - \eta\left(\phi^I\right)^2 C_0^I\right)\Big] = 0. \quad (2.6.5)$$

Assuming the consumption growth of the two specialists to be a random walk (Campbell and Cochrane, 1999), $\Delta c_1 = g + \sigma_c \varepsilon_1$, where $\Delta c_1 = log\frac{C_1}{C_0}$, specialists' consumption at $t = 0$ is given by:

$$C_0^I = E\left[C_2^I\left(\left\{\frac{Z_1^I\left(G - \eta\phi^I\right)^{-\gamma} + 1}{Z_2^I}\right\}^{-\frac{1}{\gamma}} + \eta\phi^I G + \eta\left(\phi^I\right)^2\right)^{-1}\right] \quad (2.6.6)$$

where $G \equiv exp\left(g + \sigma_c\varepsilon_1\right)$, $Z_1^I \equiv \left[\left(1+r_1^I\right) - \eta\phi^I\right]e^{-\rho} > 0$, and $Z_2^I \equiv \left[\phi^I + \left(1+r_1^I\right)\right]\eta\phi^I e^{-2\rho} > 0$. Since $\partial C_0^I/\partial\phi^I < 0$, $C_0^H < C_0^L$ and $C_1^H < C_1^L$. This is intuitive, as argued in Campbell and Cochrane (1999): existence of the habit term, X_t^I, would lower the lifetime marginal utility of consumption today because consumption today reduces future utilities. Therefore, specialist H who exhibits a more persistent habit consumes less than specialist L.

Further, the Arrow-Pratt measure of relative risk aversion for specialists is:

$$\Gamma_t^I = -\frac{C_t^I u''\left(C_t^I - X_t^I\right)}{u'\left(C_t^I - X_t^I\right)} = \frac{\gamma}{S_t^I}. \quad (2.6.7)$$

where $S \equiv \frac{C-X}{C}$ is the surplus consumption ratio. Since $X_0^H = X_0^L = 0$, the surplus consumption ratio at $t = 0$ is equal to one, and then risk aversion of the two specialists is $\Gamma_0^H = \Gamma_0^L = \gamma$. Importantly enough, a more persistent habit for specialist H leads to the lower surplus consumption ratio and therefore higher risk aversion for specialist H at $t = 1$. Based on their risk aversion, the specialists will choose optimal portfolios using the risky asset and the risk-free asset at $t = 1$. This is presented in Proposition 1.

[28]Note that if $\phi = 0$, an agent does not develop a habit. The utility function in (2.6.3) reduces to a simple CRRA utility function.

Proposition 1 (Risk Aversion and Portfolio Choices)**.**

(i) Specialist H has higher risk aversion than specialist L at $t = 1$.

$$\Gamma_1^H > \Gamma_1^L \tag{2.6.8}$$

(ii) Specialist L demands a higher portion of her wealth into the risky asset than specialist H at $t = 1$.

$$\alpha_1^H < \alpha_1^L \tag{2.6.9}$$

Proof: See Appendix A.1

As in He and Krishnamurthy (2013), α_t^I is typically greater than one, implying that specialists take leveraged positions to invest more into the risky asset by issuing the risk-free asset to the household. Proposition 1 shows that the risk-tolerant specialist (type = L) takes higher leverage than the risk-averse specialist (type = H) at $t = 1$.

2.6.3 Household Problem

The household maximizes expected lifetime utility over $t \in \{1, 2\}$ under the following constraints. First, a budge constraint asserts that the household's (post-consumption) wealth will be allocated into equity capital of intermediaries and the risk-free asset. Second, there is a minimum capital requirement to have a viable intermediary sector. Thus, the household is required to purchase at least a certain amount of equity capital from the intermediaries. Finally, the household limits the amount of equity capital purchased from each intermediary.[29] In particular, the household purchases equity capital of each intermediary up to a multiple (m) of w_t^I. w_t^I refers to "skin in the game" for specialists (He and Krishnamurthy, 2013). The utility function of the household

[29]Equivalently, this implies that an intermediary faces a capital constraint.

is given as follows:

$$\max_{\{C_t^{hh},\psi_t^H,\psi_t^L\}} E\left[\sum_{t=1}^{2} e^{-\rho t}\left(-\frac{e^{-AC_t^{hh}}}{A}\right)\right] \quad \text{subject to} \tag{2.6.10}$$

$$w_{t+1}^{hh} = \psi_t^H w_t^{hh} r_{t+1}^H + \psi_t^L w_t^{hh} r_{t+1}^L + \left(1 - \psi_t^H - \psi_t^L\right) w_t^{hh} r_{t+1}^f - C_{t+1}^{hh} \tag{2.6.11}$$

$$\kappa_t^H + \kappa_t^L = w_t^H + w_t^L + w_t^{hh}\left(\psi_t^H + \psi_t^L\right) \geq \tilde{\kappa} \tag{2.6.12}$$

$$\psi_t^I w_t^{hh} \leq m w_t^I, \quad I \in \{H, L\} \tag{2.6.13}$$

where C_t^{hh} is the household's consumption, and $A > 0$ is an absolute risk aversion of the household. (2.6.11) - (2.6.13) represent the budget constraint, the minimum capital requirement, and the capital constraint, respectively.

Given that the household's consumption is normally distributed, the household's objective function is then equivalent to:

$$\max_{\{\psi_t^H,\psi_t^L\}} \psi_t^H E_t\left[r_{t+1}^H - r_{t+1}^f\right] + \psi_t^L E_t\left[r_{t+1}^L - r_{t+1}^f\right] - \frac{A}{2} Var_t\left[\psi_{t+1}^H r_{t+1}^H + \psi_{t+1}^L r_{t+1}^L\right] \tag{2.6.14}$$

subject to (2.6.12) and (2.6.13).

Using Equation (2.6.2), the first-order conditions with respect to ψ_t^H and ψ_t^L as well as inequality constraints follow that

$$\alpha_t^H E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\alpha_t^H\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right) Var_t\left[r_{t+1}^a\right] - \left(\theta_t^H + \theta_t^C\right) w_t^{hh} = 0 \tag{2.6.15}$$

$$\alpha_t^L E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\alpha_t^L\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right) Var_t\left[r_{t+1}^a\right] - \left(\theta_t^L + \theta_t^C\right) w_t^{hh} = 0 \tag{2.6.16}$$

$$\theta_t^C\left[\tilde{\kappa} - w_t^H - w_t^L - w_t^{hh}\left(\psi_t^H + \psi_t^L\right)\right] = 0 \tag{2.6.17}$$

$$\theta_t^H\left(\psi_t^H w_t^{hh} - m w_t^H\right) = 0 \tag{2.6.18}$$

$$\theta_t^L\left(\psi_t^L w_t^{hh} - m w_t^L\right) = 0 \tag{2.6.19}$$

where θ_t^C, θ_t^H, and θ_t^L are the Lagrange multipliers associated with constraints. Here, I focus on the most realistic case where the minimum capital requirement in (2.6.12) and the capital constraints in (2.6.13) are slack (i.e., $\theta_t^C = \theta_t^H = \theta_t^L = 0$).[30]

As discussed in Section 2.6.2, the specialist who has a more persistent habit together with higher risk aversion consumes less at $t \in \{0, 1\}$. This further implies that specialist H has larger wealth available to invest in intermediary than specialist L at $t = 1$, which leads to the tighter capital constraint for specialist L than specialist H from (2.6.13). Therefore, the household is more willing to purchase equity capital of intermediary H than that of intermediary L. I summarize the household's allocation in Proposition 2.

Proposition 2 (Household's Allocation)**.** *There is a minimum capital* $\tilde{\kappa}^* \equiv w_t^{hh} \dfrac{2Y_t}{\alpha_t^H + \alpha_t^L} + \left(w_t^H + w_t^L\right)$ *that satisfies* $\psi_t^H > \psi_t^L$ *where* $Y_t \equiv \frac{1}{A} \frac{\mu_t - r_t^f}{\sigma_t^2}$,

$$\psi_t^H \geq \frac{\alpha_t^L \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - Y_t}{\alpha_t^L - \alpha_t^H}, \quad \textit{and} \quad \psi_t^L \leq \frac{Y_t - \alpha_t^H \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}}}{\alpha_t^L - \alpha_t^H}. \tag{2.6.20}$$

In other words, if the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^*$*, the household purchases more equity capital from intermediary* H *than from intermediary* L *(i.e.,* $\psi_t^H > \psi_t^L$*).*[31]

Proof: See Appendix A.1

Proposition 2 argues that the household allocates a larger portion of her wealth to intermediary H than to intermediary L. Hence, the intermediary capital, defined as the sum of the wealth of a specialist and the amount that the household allocates to purchase equity capital of an intermediary, is higher in intermediary H than in intermediary L.

Proposition 3 (Intermediary Capital)**.** *If the minimum capital requirement is sufficiently high, say* $\tilde{\kappa} > \tilde{\kappa}^*$*, the specialist who has higher (lower) risk aversion forms an intermediary with higher*

[30] Other cases will be considered in Appendix A.2.

[31] To guarantee that $\psi_t^H > 0$ and $\psi_t^L > 0$, I impose additional assumptions on the risk aversion of household, such that $A > \frac{1}{\alpha_t^L}\left(\frac{\mu_t - r_t^f}{\sigma_t^2} \Big/ \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}}\right)$ and $A < \frac{1}{\alpha_t^H}\left(\frac{\mu_t - r_t^f}{\sigma_t^2} \Big/ \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}}\right)$, respectively. These assumptions imply that the household's risk aversion should be sufficiently high (low), so that the household allocates a nonzero amount of her wealth into intermediary H (intermediary L).

(lower) capital.

$$\kappa_1^H = w_1^H + \psi_1^H w_1^{hh} > \kappa_1^L = w_1^L + \psi_t^L w_1^{hh} \tag{2.6.21}$$

Proof: See Appendix A.1

Proposition 3 (combined with Proposition 1) suggests the positive relation between intermediary capital and risk aversion, which is consistent with the discussion in Section 2.2 and empirical evidence in Figure 2.1 and Table 2.2

2.6.4 Asset Prices

Having established that a more risk-averse specialist attracts more equity capital from the household to form an intermediary than a less risk-averse specialist, I derive a pricing equation for the risky asset, a. In this economy, low-capital intermediary L is more highly leveraged than high-capital intermediary H, (i.e., $\alpha_t^L > \alpha_t^H$), so the risky asset is held more in the intermediary L than the intermediary H. When a negative shock arrives in this asset, the intermediary L loses more capital than the intermediary H. Thus, the fraction of capital controlled by the intermediary H (intermediary L) increases (decreases), which induces the relative difference in capital between the two intermediaries and consequently the aggregate risk aversion to rise in bad times. In order for the intermediary H, who are more risk-averse, to take a larger portion of the risky asset in bad times, the risk premium should rise as well.

Suppose an agent's risk-bearing capacity is a function of her consumption and risk aversion. Following Bhamra and Uppal (2009), Gârleanu and Pedersen (2011), and Gârleanu and Panageas (2015) among others, the sum of each agent's risk-bearing capacity is the risk-bearing capacity of the economy as a whole. That is:

$$\frac{C^H}{\Gamma^H} + \frac{C^L}{\Gamma^L} \equiv \frac{C^H + C^L}{\Gamma}, \quad \text{or} \quad \Gamma \equiv \frac{1}{\dfrac{C^H}{C^H + C^L}\dfrac{1}{\Gamma^H} + \dfrac{C^L}{C^H + C^L}\dfrac{1}{\Gamma^L}} \tag{2.6.22}$$

where Γ is the aggregate risk aversion of the economy.

From Equation (2.6.1), a shock, ε_t, arrives in the risky asset at $t = 2$. Because of the different leverage positions of the two intermediaries, the shock is negatively related to the dispersion in intermediary capital, defined as $DISP_t^{Capr} \equiv \frac{\kappa_t^H - \kappa_t^L}{\kappa_t}$.[32] Note that a consumption function is a monotonic transformation of wealth. This results in the negative relationship between the shock in the risky asset and the dispersion in specialists' consumption. In other words, upon arrival of a positive (negative) shock, the portion of capital held by intermediary L increases (decreases), and consequently, the portion of consumption of specialist L rises (falls) as well. These arguments are summarized in Proposition 4.

Proposition 4 (Dispersion of Intermediary Capital and of Specialists' Consumption)**.**

(1) The positive (negative) shock in the risky asset at $t = 2$ *leads to a decline (rise) in the dispersion in intermediary capital.*

$$\varepsilon_2 \left(\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} \right) < 0 \tag{2.6.23}$$

(2) The positive (negative) shock in the risky asset at $t = 2$ *leads to a decline (rise) in the dispersion in specialists' consumption.*

$$\varepsilon_2 \left(\frac{C_2^H - E\left[C_2^H\right]}{E\left[C_2^H\right]} - \frac{C_2^L - E\left[C_2^L\right]}{E\left[C_2^L\right]} \right) < 0 \tag{2.6.24}$$

Proof: See Appendix A.1

Since a negative shock lowers the surplus consumption ratio (i.e., $S = \frac{C-X}{C}$) of the agents who exhibit habits in their utility function, risk aversion of each agent is countercyclical. More importantly, the compositional change in specialists' consumption induced by the shock also has an impact on the aggregate risk aversion of the economy. That is, the aggregate risk aversion gets closer toward that of a risk-averse (risk-tolerant) agent upon arrival of the negative (positive) shock. Overall, if a negative shock arrives in the risky asset, $\varepsilon_2 < 0$, then aggregate risk aversion rises, and if a positive shock arrives in the risky asset, $\varepsilon_2 > 0$, then aggregate risk aversion falls.

[32] Again, the dispersion is to capture the relative proportion of capital held by the high- versus low-capital intermediary (i.e., $\frac{\kappa_t^H}{\kappa_t} - \frac{\kappa_t^L}{\kappa_t}$). Its empirical counterpart is shown in (2.3.2).

Proposition 5 (Countercyclical Aggregate Risk Aversion)**.** *At $t = 2$, the shock in the risky asset and aggregate risk aversion are inversely related.*

$$\varepsilon_2 \Gamma_2 < 0 \tag{2.6.25}$$

Proof: See Appendix A.1

How does the dispersion of intermediary capital affect aggregate risk aversion? It is evident from Proposition 4 that the change in the dispersion of intermediary capital gives rise to the change in the dispersion of specialists' consumption. Thus, during bad times when the dispersion of intermediary capital rises, specialist H will enjoy a larger stake in consumption than good times. This compositional change subsequently affects the aggregate risk aversion if specialists are heterogeneous in their risk aversion.

Proposition 6 (Dispersion of Intermediary Capital and Aggregate Risk Aversion)**.** *At $t = 2$, the dispersion of intermediary capital is positively associated with the aggregate risk aversion of the market.*

$$\left(\frac{\kappa_2^H - \kappa_2^L}{\kappa_2} \right) \Gamma_2 > 0 \tag{2.6.26}$$

Proof: See Appendix A.1

To emphasize the important role of heterogeneous preference between the two specialists in the aggregate risk aversion, suppose that if specialists are homogeneous in risk preference and the leverage position accordingly, intermediaries will be symmetrically affected from the shock. This further implies that the shock would not change the dispersion of intermediary capital. If so, the positive relation between the dispersion of intermediary capital and the aggregate risk aversion of the market in Proposition 6 no longer holds, and then the dispersion of intermediary capital does not affect the aggregate risk aversion of the market.

Next, I derive the Euler equation for the risky asset, a, that incorporates Proposition 6. In a complete market, specialists' discount factor, M_t, follows that

$$M_t = \xi^H e^{-\rho t}\left(C_t^H - X_t^H\right) = \xi^L e^{-\rho t}\left(C_t^L - X_t^L\right) \tag{2.6.27}$$

where ξ^H and ξ^L are Pareto weights for the specialists. Equation (2.6.27) implies that $C_t^H - X_t^H = \left(M_t/\xi^H e^{-\rho t}\right)^{-\frac{1}{\gamma}}$ and $C_t^L - X_t^L = \left(M_t/\xi^L e^{-\rho t}\right)^{-\frac{1}{\gamma}}$.[33] Therefore, the Euler equation for the representative investor is

$$E_t\left[\frac{M_{t+1}}{M_t}R^a_{t+1}\right] = E_t\left[e^{-\rho}\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left(\frac{S_{t+1}}{S_t}\right)^{-\gamma}R^a_{t+1}\right] = 1. \tag{2.6.28}$$

A log-linear approximation leads to the following equation.[34]

$$E_t\left[r^a_{t+1} - r^f_{t+1}\right] + \frac{1}{2}Var_t\left[r^a_{t+1}\right] = \gamma Cov_t\left[\Delta c_{t+1}, r^a_{t+1}\right] + \gamma Cov_t\left[\Delta s_{t+1}, r^a_{t+1}\right] \tag{2.6.29}$$

[33] Equation (2.6.22) can be rewritten using these relations,

$$\begin{aligned}
\frac{1}{\Gamma_t} = \frac{C_t - X_t}{\gamma C_t} &= \frac{C_t^H}{C_t}\frac{C_t^H - X_t^H}{\gamma C_t^H} + \frac{C_t^L}{C_t}\frac{C_t^L - X_t^L}{\gamma C_t^L} = \frac{\left(M_t/\xi^H e^{-\rho t}\right)^{-\frac{1}{\gamma}}}{\gamma C_t} + \frac{\left(M_t/\xi^L e^{-\rho t}\right)^{-\frac{1}{\gamma}}}{\gamma C_t} \\
\Leftrightarrow C_t - X_t &= \left(M_t/\xi^H e^{-\rho t}\right)^{-\frac{1}{\gamma}} + \left(M_t/\xi^L e^{-\rho t}\right)^{-\frac{1}{\gamma}} = \left[\left(\xi^H\right)^{\gamma} + \left(\xi^H\right)^{\gamma}\right]\left(M_t/e^{-\rho t}\right)^{-\frac{1}{\gamma}} \\
\Leftrightarrow M_t &= \left[\left(\xi^H\right)^{\frac{1}{\gamma}} + \left(\xi^H\right)^{\frac{1}{\gamma}}\right]^{\gamma} e^{-\rho t}\left(C_t - X_t\right)^{-\gamma}.
\end{aligned}$$

[34] Taking logarithms of each side,

$$\begin{aligned}
&E_t\left[-\rho - \gamma log\left(\frac{C_{t+1}}{C_t}\right) - \gamma log\left(\frac{S_{t+1}}{S_t}\right) + logR^a_{t+1}\right] \\
&+ \frac{\gamma^2}{2}Var_t\left[log\left(\frac{C_{t+1}}{C_t}\right)\right] + \frac{\gamma^2}{2}Var_t\left[log\left(\frac{S_{t+1}}{S_t}\right)\right] + \gamma^2 Cov_t\left[log\left(\frac{C_{t+1}}{C_t}\right), log\left(\frac{S_{t+1}}{S_t}\right)\right] \\
&+ \frac{1}{2}Var_t\left[logR^a_{t+1}\right] - \gamma Cov_t\left[log\left(\frac{C_{t+1}}{C_t}\right), logR^a_{t+1}\right] - \gamma Cov_t\left[log\left(\frac{S_{t+1}}{S_t}\right), logR^a_{t+1}\right] = 0
\end{aligned}$$

For the risk-free asset,

$$\begin{aligned}
&E_t\left[-\rho - \gamma log\left(\frac{C_{t+1}}{C_t}\right) - \gamma log\left(\frac{S_{t+1}}{S_t}\right) + logR^f_{t+1}\right] \\
&+ \frac{\gamma^2}{2}Var_t\left[log\left(\frac{C_{t+1}}{C_t}\right)\right] + \frac{\gamma^2}{2}Var_t\left[log\left(\frac{S_{t+1}}{S_t}\right)\right] + \gamma^2 Cov_t\left[log\left(\frac{C_{t+1}}{C_t}\right), log\left(\frac{S_{t+1}}{S_t}\right)\right] = 0.
\end{aligned}$$

The difference between two equations results in Equation (2.6.29).

where $r^a_{t+1} = logR^a_{t+1}$, $r^f_{t+1} = logR^f_{t+1}$, $\Delta c_{t+1} = log\frac{C_{t+1}}{C_t}$, and $\Delta s_{t+1} = log\frac{S_{t+1}}{S_t}$. Since $\frac{dC^I}{C^I} \propto \frac{d\kappa^I}{\kappa^I}$ and $\Delta s_{t+1} = -log\left(\frac{\gamma/S_{t+1}}{\gamma/S_t}\right) = -log\left(\frac{\Gamma_{t+1}}{\Gamma_t}\right) \propto -\Delta\left(\frac{\kappa^H_{t+1}-\kappa^L_{t+1}}{\kappa_{t+1}}\right)$, Equation (2.6.29) is further approximated to

$$E_t\left[r^a_{t+1} - r^f_{t+1}\right] \approx \lambda^{LEVEL} \underbrace{Cov_t\left[\Delta\kappa_{t+1}, r^a_{t+1}\right]}_{\text{Shock in Level of Capital}} - \lambda^{DISP} \underbrace{Cov_t\left[\Delta\left(\frac{\kappa^H_{t+1} - \kappa^L_{t+1}}{\kappa_{t+1}}\right), r^a_{t+1}\right]}_{\text{Shock in Dispersion of Capital}} \tag{2.6.30}$$

where $\lambda^{LEVEL} > 0$ and $\lambda^{DISP} > 0$ capture the prices of the risks from the shock in level of capital and the shock in dispersion of capital. Thus, the risk premium is determined by the compensation for the exposure to the shock in the dispersion of capital (λ^{DISP}) in addition to the shock in the level of capital (λ^{LEVEL}). Empirically, the negative sign for λ^{DISP} in (2.6.30) corresponds to the negative price of risk for λ^{DISP} in the asset pricing tests of (2.4.1).

2.6.5 Calibration

Now, I present a numerical example to provide quantitative implications of the model presented in previous subsections. In this calibration, I focus on the most realistic situation in Section 2.6.3, where inequality constraints in (2.6.12) and (2.6.13) are slack.

Parameters used to calibrate are described in Table 2.16 Panel A. First, the unconditional mean and volatility of the risky asset and the risk-free rate are chosen to match the data in the post-war period. In detail, annualized value-weighted returns and volatilities on S&P 500 from January 1950 to December 2016 were roughly 10% and 14% on average. The annualized one-monthly Treasury Bill rate during the same period approaches 4%. Thus, I set $\mu = 10\%$, $\sigma = 16\%$, and $r^f = 4\%$. Second, the initial endowment of all agents, including the two specialists (e^H and e^L) and the household (e^{hh}), is assumed to be 100, and their time preference (ρ) is supposed to be 0.05. Third, in the specialists' utility function, I use a curvature parameter $\gamma = 2$ following Campbell and Cochrane (1999). Specialists' risk aversion is driven by a habit process, X^I_t in (2.6.4), which is a function of common habit persistence (η), and heterogeneous habit persistence (ϕ^H and ϕ^L). I choose $\eta = 0.95$, $\phi^H = 0.9$, and $\phi^L = 0.1$ so that specialist H has higher risk

Table 2.16
Calibration

This table reports the numerical example of the model. Panel A presents parameters used in the calibration. Panel B shows outcomes of the calibration: risk premium, $E[r^a_{t+1} - r^f_{t+1}]$, risk aversion of specialists, Γ^I_1, intermediary leverage, α^I_1, and intermediary capital, κ^I_1 for $I \in \{H, L\}$. The first column indicates the baseline outcome based on the parameters in Panel A. In the remaining columns in Panel B, I also present how the baseline outcome varies by changing a parameter indicated in the first row while keeping other parameters constant.

Panel A: Parameter Choices

Parameter	Description	Value
μ	Unconditional Mean of Return on Risky Asset	10%
σ	Unconditional Volatility of Return on Risky Asset	14%
r^f	Return on Risk-Free Asset	4%
e^I	Initial Endowment of Specialists	100
e^{hh}	Initial Endowment of Household	100
ρ	Time Preference	0.05
γ	Curvature Parameter of Specialists' Utility Function	2
η	Habit Persistence (Common)	0.95
ϕ^H	Habit Persistence (type = H)	0.9
ϕ_L	Habit Persistence (type = L)	0.1
A	Risk Aversion of Household	3
g	Consumption Growth	0.02
σ_c	Consumption Volatility	0.02

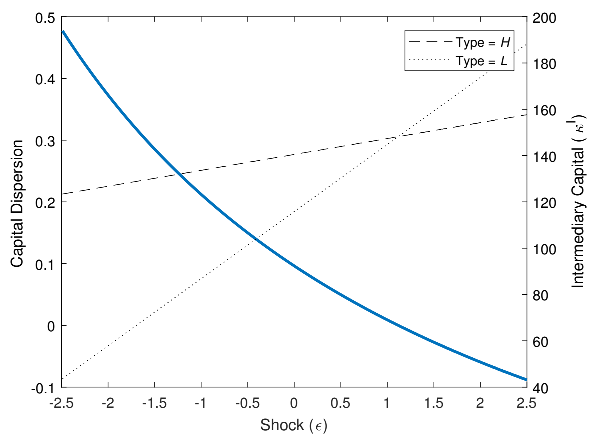
Panel B: Simulation Outcomes

Outcome	Baseline	(ϕ_H, ϕ_L) $= (0.6, 0.3)$	$\gamma = 1$	$A = 5$	$\eta = 0.65$
Risk Premium	8.44%	11.79%	4.17%	8.82%	11.79%
Risk Premium due to *Capital Level*	2.47%	4.36%	1.49%	2.58%	4.26%
Risk Premium due to *Capital Dispersion*	5.97%	7.44%	2.68%	6.24%	7.53%
Risk Aversion (type = H)	12.50	4.54	6.25	12.5	4.69
Risk Aversion (type = L)	2.21	2.78	1.10	2.21	2.14
Leverage (type = H)	0.37	1.01	0.74	0.37	0.98
Leverage (type = L)	2.08	1.65	4.16	2.08	2.15
Intermediary Capital (type = H)	105.0	105.0	88.7	88.3	95.9
Intermediary Capital (type = L)	52.6	48.7	25.7	36.0	34.9

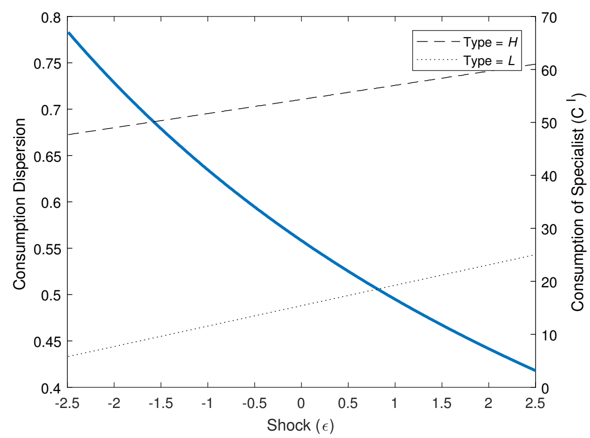
Figure 2.5
Calibration

This figure depicts the intermediary capital (κ_2^I), specialists' consumption (C_2^I), and the their risk aversion (Γ_2^I) for $I \in \{H, L\}$ as well as the aggregate risk aversion, implied by the model. Panel (a) indicates the relation in (5.33); Panel (b) indicates the relation in (5.34); Panel (c) indicates the relation in (5.37); and Panel (d) indicates the relation in (5.38). In Panels (a) and (b), the solid line represents the dispersion of intermediary capital and specialists' consumption. In Panel (c), the solid line represents the aggregate risk aversion of the economy. In Panels (a) - (c), the dashed line represents quantities of the specialist/intermediary H while the dotted line represents quantities of the specialist/intermediary L. To simulate the economy, I generate a random draw from the $i.i.d.$ normal distribution for each outcome in a shock at $t = 2$. I repeat this exercise 10,000 times to compute average quantities represented in vertical axises.

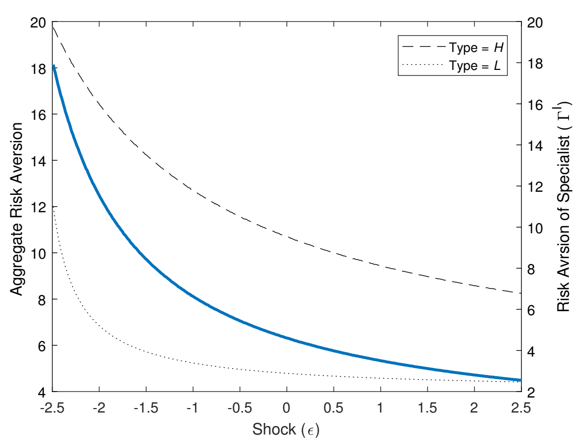
(a)



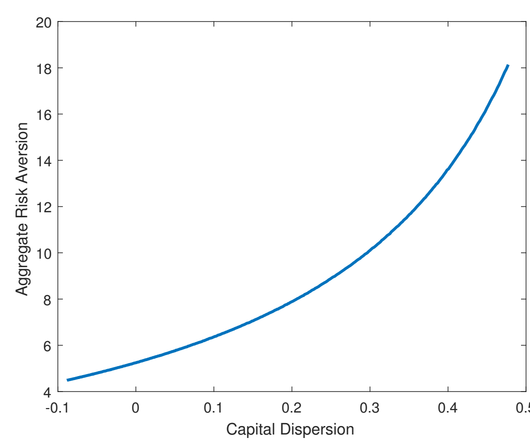
(b)



(c)



(d)



aversion than specialist L. Fourth, the risk aversion of the household (A) is set to be 3, so as to make the household have higher risk aversion than specialist L but lower risk aversion than specialist H. This choice is not sensitive to key outcomes of the model since the household is restricted to directly invest in the risky asset. Finally, unconditional mean (g) and volatility (σ_c) of consumption are chosen to be 2%.

Based on these parameters, I run a random sampling of a shock (ε_t) in the economy at $t \in \{1, 2\}$, which drives both the return on the risky asset and the consumption growth, from the $i.i.d.$ normal distribution. I repeat this exercise 10,000 times to obtain conditional moments.

Table 2.16 Panel B documents the outcomes of the calibration. All moments are measured at $t = 1$. The baseline outcomes in the first column are based on the parameters described in Panel A. The model produces a risk premium of 8.44%. More importantly, if I decompose the risk premium as in Equation (2.6.30), the risk premium due to the capital level is only 2.47%, but the dispersion of intermediary capital generates an additional risk premium of 5.97%. Furthermore, the risk aversion of specialist H ($\Gamma^H = 12.50$) is more than 5 times greater than the risk aversion of specialist L ($\Gamma^L = 2.21$). Consistent with the risk aversion, specialist L ($\alpha^L = 2.08$) has a higher leverage than specialist H ($\alpha^H = 0.37$). The capital of intermediary H ($\kappa^H = 105.0$) is almost twice the capital of intermediary L ($\kappa^L = 52.6$). The moments reported in this column are consistent with the argument of the model as well as the empirical findings in Figure 2.1 and Table 2.2: a risk-averse (risk-tolerant) specialist develops a high- (low-) capital intermediary and holds less risky (riskier) portfolio.

In the remaining columns in Panel B, I change the value of ϕ^H and ϕ^L, γ, A, or η one at a time while keeping the other parameters constant to examine how the baseline outcome varies accordingly. First, relative to the baseline model, I lower the habit persistence of specialist H and raise that of specialist L to reduce the degree of heterogeneity in habit persistence (i.e., $(\phi^H, \phi^L) = (0.6, 0.3)$). As shown in the second column, the changes in ϕ^H and ϕ^L lead to a decline in the degree of heterogeneity in risk aversion between two specialists; the risk aversion of specialist H is only 1.5 times greater than that of specialist L (4.54 versus 2.78). Interestingly, this is not accompanied with a lower risk premium; the risk premium increases to 11.79%. Specialist H now requires a lower premium on the risky asset but raises its leverage instead, thereby increasing the specialist H's proportion in the risky asset market from 26.2% to 56.9%.[35] The resulting increase in aggregate risk aversion may explain the higher risk premium than that in the baseline model.

Second, since γ influences decisions of both specialists, lowering γ to 1 reduces the risk aversion of both specialists by half and doubles the leverage of both specialists, which in turn curtails the risk premium by half. With regard to the household's allocation, as specialists become more risk-tolerant, the household is less willing to purchase equity capital of intermediaries. Thus, the capital of both intermediaries is lower than in the baseline model.

Third, as noted earlier, the risk aversion of the household, who is restricted to directly invest in the risky asset, should not matter to the risk premium. Not surprisingly, setting $A = 5$ does not affect the conditional moments, except for intermediary capital, in the fourth column. The more risk-averse household now invests less in equity capital of intermediaries but more in the risk-free asset, and this causes total intermediary capital to decline by 27%.

Finally, as η decreases to 0.65, internal habits (X^H and X^L) decreases as well. This leads to a rise in the surplus consumption ratio and a reduction in risk aversion. Similar to the case with $(\phi^H, \phi^L) = (0.6, 0.3)$ in the second column, however, the effect of their lower risk aversion is dampened by the increase in the portion of the specialist H (i.e., α^H), who is more risk-averse, in the risky asset market. Hence, the risk premium rises to 11.79%.

Figure 2.5 shows the variation in key quantities (e.g., the intermediary capital (κ_2^I), the specialists' consumption (C_2^I), the risk aversion (Γ_2^I) for $I \in \{H, L\}$, and the aggregate risk aversion) in each outcome for a shock at $t = 2$. In Panel (a), as a positive shock hits the economy, capital of both intermediaries grows, but the higher leverage of intermediary L makes the capital of the intermediary L grow faster than that of intermediary H, which generates the negative relation between the shock and dispersion of intermediary capital in (2.6.23). If the shock is greater than about one standard deviation above the mean of zero, the capital of the intermediary L exceeds that of the

[35] $\frac{0.37\times105.0}{0.37\times105.0+2.08\times52.6} \rightarrow \frac{1.01\times105.0}{1.01\times105.0+1.65\times48.7}$

intermediary H, and then the dispersion of intermediary capital turns negative. As expected, the shock has a similar effect on the specialists' consumption as shown in Panel (b), and this confirms the inverse relation between the shock and dispersion of specialists' consumption in (2.6.24).

Panel (c) confirms the notion that the habit makes agents more (less) risk-averse during bad (good) times. More importantly, aggregate risk aversion approaches the risk aversion of specialist H during bad times ($\varepsilon < 0$) and the risk aversion of specialist L during good times ($\varepsilon > 0$) since the aggregate risk aversion is determined by the consumption weights of the specialists (and their risk aversion). Finally, combining Panels (b) and (c) leads to the key implication of the model: dispersion of intermediary capital is positively associated with the aggregate risk aversion of the market, as shown in (2.6.26).

2.7 Conclusion

This paper studies how heterogeneity in intermediary capital, measured as the dispersion of the market capital ratio of the largest 30 intermediaries in the U.S., affects the cross-section of stock returns. I posit that the heterogeneity in intermediary capital would capture the countercyclical variation in aggregate risk aversion, which elicits the countercyclical risk premium accordingly. The exposure (i.e., beta) of nonfinancial stocks to shock in the dispersion of capital ratios generates an annual premium of 6.8% - 8.2%. Using the Thomson Reuters Institutional (13F) Holdings database, I also find evidence that low-capital intermediaries, who hold riskier assets than high-capital intermediaries, would face leverage-induced fire-sales once a sufficiently large and systematic adverse shock arrives in stock markets. I develop a model of heterogeneous intermediary capital in which the dispersion of intermediary capital is priced in the cross-section of asset prices, which supports the empirical findings.

3. BANK CAPITAL AND BANK STOCK PERFORMANCE

3.1 Introduction

Bank capital is a central part of prudential regulation. Despite its importance, we do not know much about how bank capital affects bank stock returns. Bankers often argue that the effect is negative and that higher capital leads to diminished shareholder value in banking.[1] Some theories agree that it is costly for banks to operate with higher capital (Diamond and Rajan, 2001; Gorton and Winton, 2017). In contrast, numerous other banking theories predict that bank capital positively affects various aspects of performance: it enhances the bank's survival probability (Holmstrom and Tirole, 1997; Allen, Carletti, and Marquez, 2011; Acharya, Mehran, and Thakor, 2016); improves its market share and profitability (Allen, Carletti, and Marquez, 2011; Mehran and Thakor, 2011);[2] and increases the bank's market value (Mehran and Thakor, 2011).[3]

Theories on the relation between bank capital and bank performance generally do not distinguish between different economic times. The empirical literature on financial crises, however, documents that capital is especially beneficial during crises. For example, Berger and Bouwman (2013) study the relation between capital and performance (survival probability, market share, and profitability) to find that capital benefits large banks (assets over $3 billion) during banking crises, not during other times.[4] Calomiris and Nissim (2014) find that the value attached by the market to bank capital increased during the 2007-2009 financial crisis. Pérignon, Thesmar, and Vuillemey (2016) document that capital also benefited banks in Europe during this crisis: high-capital banks were still able to access uninsured wholesale funding during the crisis, thereby avoiding diminished access to funding that plagued their low-capital banks. While these papers do not address

[1]Thakor (2014) discusses six potential reasons for why bankers object to higher capital ratios: (i) resistance is part of a negotiating game with regulators and politicians; (ii) desire to maximize the tax benefits of debt; (iii) desire to maximize the deposit insurance put option; (iv) CEO pay is tied to ROE; (v) government protection; and (vi) debt overhang.

[2]Mechanically, higher capital leads to a lower return on equity (Modigliani and Miller, 1963).

[3]Miles, Yang, and Marcheggiano (2013) support the view that more capital is beneficial to banks. Admati, Demarzo, Hellwig, and Pfleiderer (2013) argue that while socially beneficial, more capital may hurt bank shareholders.

[4]They document that, in contrast, capital benefits small banks at all times.

the asset pricing implications of bank capital, they suggest that an examination thereof may benefit from distinguishing between times of stress and normal times. Of the small number of papers on bank stock performance (discussed below), only one distinguishes between different economic times, but does so with only a few years of data.

This leads to our first (and main) research question: Do high-capital banks show better *risk-adjusted* stock performance than low-capital banks and does the effect of capital differ across normal times and bad economic times? Adequately controlling for risk is critical. Since bank capital not only directly affects the bank's risk but also influences its risk-taking propensity, banks with higher capital may earn higher returns simply because investors view them as riskier. However, if abnormal stock return performance persists even after including various pricing factors, then this would mean that bank capital plays a "special" role in determining bank stock prices. In this light, we examine alphas, adjusting for numerous sources of risk.

We find that bank capital does not predict bank stock performance unconditionally, but it does so conditionally: high-capital banks outperform low-capital banks during bad times. During other times, the performance differences across high-capital and low-capital banks are statistically insignificant (alphas and t-statistics close to zero).[5] This result is highly robust and is obtained using both *in-sample* tests and *out-of-sample* trading strategies which buy high-capital banks and sell low-capital banks during times predicted to be bad. Our main trading strategy yields risk-adjusted returns of 0.30% - 0.37% per month (3.60% - 4.44% per year). To our knowledge, conditional trading strategies have not been explored in the literature -our novel approach can be useful in future studies.

Before presenting our empirical approach and results in more detail, we address two important issues about the relationship of our paper to previous research on this topic. First, our result is novel. Baker and Wurgler (2015), the paper most closely related to ours, examines the cost-of-capital implication of bank capital. It finds that high-capital banks have lower (forward) betas

[5]It is possible to observe significant outperformance during bad times and insignificant underperformance during other times because, based on all the bad times measures used, there are far fewer bad times than other times. However, we find similar results even when using the union set of bad times, which roughly classifies half the periods as bad times.

and that bank stocks with low (realized) betas have higher realized stock returns (the "low beta anomaly" found in other contexts). It does not directly test whether high-capital banks outperform low-capital banks, controlling for risk. Our tests of this hypothesis reveal that this relation does not hold. That paper also does not distinguish between normal times and bad times like we do. This is an important distinction because we show that capital is only associated with outperformance during bad times. Further, our result does *not* inadvertently pick up the "large-bank effect" documented by Gandhi and Lustig (2015). They show that implicit government guarantees (i.e., Too Big to Fail) cause the largest commercial banks to be less risky and thus have lower risk-adjusted returns. Since the largest banks tend to have the lowest capital ratios, we have performed every analysis in this paper while controlling for their large-bank effect in different ways, and find that our result is robust.

Second, our result of positive risk-adjusted stock returns of high-capital banks in bad times is surprising for several reasons. (i) One may believe that high-capital banks are *riskier* than low-capital banks (Koehn and Santomero, 1980; Besanko and Kanatas, 1996). Hence, the returns of high-capital banks are expected to be higher than those of low-capital banks, and the return differences get larger during bad times due to higher risk. However, we show that high-capital banks are *less risky* (as measured by their return volatility, market beta, and loadings on conventional risk factors such as the value premium factor), and importantly, adding numerous risk factors in our tests does not change the result. (ii) Taking as given that high-capital banks are *safer*, their ex ante expected returns should be lower, but their ex-post realized returns during bad times can be higher because their stock prices will drop less during such times as unexpected adverse shocks hit the banking sector. In this case, one may argue that our econometric implementation of our *in-sample* analysis is misled since we should focus on ex-ante expected returns (which are lower) rather than on ex-post realized returns (which are higher). If true, our *out-of-sample* trading strategies, in which we use predicted bad times, should yield no significant risk-adjusted returns because high-capital bank stocks would be more expensive in anticipation of bad times. However, we find that our result holds using *out-of-sample* trading strategies. Further and more directly, our result holds even when using ex-ante measures of expected returns (instead of ex-post realized returns). Thus, our econometric specification is valid and our findings are robust.

Let us now present our empirical methodology. The main *in-sample* analyses compare the stock performance of high- and low-capital banks during bad times and other times using five asset pricing models that control for risk in alternative ways. We focus on commercial banks and use book equity over total assets as our main capital ratio measure. We sort banks independently into quintiles based on their capital ratios and size to form 25 portfolios, calculate value-weighted average capital ratios and stock returns in each portfolio, and then compute the simple average of the five size-quintile capital ratios and stock returns for each capital quintile. We view high-capital (low-capital) banks to be banks in the top (bottom) quintile and document that they have 16.31% (6.48%) capital, on average. Our main *in-sample* bad-times proxy is a dummy = 1 if month t has bank stock return volatility (modeled using an exponential generalized autoregressive heteroscedasticity of order 1, EGARCH(1,1), model) exceeding the 80^{th} percentile (in sample), and zero otherwise.[6] We use five linear factor models: (i) the Fama and French (1993) 3-factor model; (ii) the Carhart (1997) 4-factor model; (iii) the Fama and French (2015) 5-factor model; (iv) the Fama-French 5-factor model plus Pástor and Stambaugh (2003)'s liquidity factor; and (v) the Fung and Hsieh (2001) 9-factor model.

We perform numerous checks to establish the robustness of our *in-sample* result that high-capital banks show higher (risk-adjusted) abnormal returns than low-capital banks during bad times, but not during other times. First, falsification tests show that our results do not hold for industrial firms or non-bank financial firms, implying that bank stocks are different. Second, the results are not driven by the largest banks: we obtain similar results when excluding these banks or when controlling for Gandhi and Lustig (2015)'s size factor. Third, the results are robust to: controlling for nonsynchronous trading, e.g., by dropping the smallest stocks; using time-varying betas; controlling for differences in (market) betas; controlling for up to ten bank-specific risk factors; using panel regressions that control for bank-specific risk in alternative ways; and using

[6]Since volatility is persistent with a GARCH parameter of 0.93, we show that our results are robust to using alternative bad times stock return volatility cutoffs.

Fama-MacBeth regressions. The Internet Appendix in addition shows that our results: (a) are not driven by the recent crisis; (b) are robust to using seven alternative bad times proxies and even their union and intersection sets; (c) are not caused by banks that delisted for performance-related reasons; (d) are robust to the use of benchmark-adjusted returns; (e) are comparable using data from the Bank Regulatory Database; (f) are robust to using regulatory and market capital ratios; and (g) also hold when using value-added performance measures. Results void of look-ahead bias are similar.

The *out-of-sample* tests are based on several alternative trading strategies. Each strategy buys high-capital banks and sells low-capital banks during times *out-of-sample* predicted to be bad. Our main trading strategy does nothing during other times, while the other trading strategies may do the same or the opposite. Performance is assessed using the asset pricing models discussed above.

To establish the robustness of our *out-of-sample* result that our trading strategies yield positive risk-adjusted returns, we perform several analyses, which all yield consistent results. First, we show that the results are not driven by the largest banks. Second, to account for the possibility that the commonly-used asset pricing models employed by us may not adequately capture bank-specific risks, we add up to ten bank-specific risk factors to each factor model. Third, we relax the assumption that investors can buy and sell portfolios of high- and low-capital banks without any restrictions: we control for short sale constraints using three different approaches. The Internet Appendix in addition shows that our results also hold: (a) using alternative bad-times proxies and their union and intersection sets; (b) using regulatory and market capital ratios; (c) when taking into account the costs of trading bank stocks; (d) when relaxing a standard assumption in asset pricing ("realized future returns are a good proxy for expected returns") by estimating and using ex-ante measures of expected returns.

Having established that high-capital banks outperform low-capital banks during bad times, we ask our second research question: What drives such outperformance? We explore two possible channels: the "Informed Investor Channel" and the "Surprised Investor Channel."

The "Informed Investor Channel" expects that informed investors better understand the benefits of higher capital during bad times than uninformed investors, and are also better at judging when bad times have arrived. If so, informed investors may continue to sell low-capital stocks to (and/or buy high-capital stocks from) uninformed investors during bad times. The relative advantage of informed investors, which affects the downward (upward) price pressure on low-capital (high-capital) stocks, may explain the outperformance of high-capital banks during bad times. To examine this channel, we focus on institutional investors, who are generally considered to be informed and as such, they may drive stock returns (Badrinath, Kale, and Noe, 1995; Bennett, Sias, and Starks, 2003; Boehmer and Kelley, 2009; Campbell, Ramadorai, and Schwartz, 2009). We obtain quarterly institutional ownership of banks data from Thomson Reuters' 13F database. Our investigations show that institutional ownership of both high- and low-capital banks is rather stable across normal times and bad times. This holds regardless of whether we focus on total institutional ownership or split institutions into different groups using investor classification data from Brian Bushee's website. Thus, our results do not seem to be driven by an "Informed Investor Channel."

The "Surprised Investor Channel" asserts that during bad times investors are surprised by the better-than-expected performance of high-capital banks (relative to that of low-capital banks). This could happen if investors are unaware of the value of high capital during bad times or underestimate the likelihood and severity of bad times and revise their beliefs too sluggishly (relative to a Bayesian rational person) as bad times evolve. If so, the spread between the prices of high- and low-capital banks during good times is not sufficiently high, and there will be a continuing increase in the price spread between these banks (and thus higher returns for high-capital banks) during bad times. This behavioral explanation is consistent with recent theories of banking crises (Gennaioli, Shleifer, and Vishny, 2015; Thakor, 2015, 2016) and nascent evidence (Baron and Xiong, 2017). To examine this channel, we perform various analyses. We first examine if the outperformance of high-capital banks during bad times evolves in a way consistent with the theories, and find that it does: the outperformance is greatest initially and smallest toward the end of the bad times. Next, we focus on earnings surprises, the normalized difference between actual and expected earnings (proxied by analyst forecasts), and on three-day CARs around the earnings announcement date.

We find that both are significantly higher for high-capital banks during bad times, not during other times. Thus, the evidence seems consistent with the "Surprised Investor Channel."

We acknowledge that significant alphas can be caused by missing risk factors or by mispricing. We argue that our results are not likely to be caused by the former. First, all our tests include numerous standard risk factors, and robustness tests add up to ten bank-related risk factors. Second, and more importantly, if alpha is associated with missing risk factors, then higher-risk stocks should have higher returns. However, we find that high-capital banks, which - as discussed above - are less risky, have higher returns.[7] Thus, we argue that our results seem to be caused by mispricing: the stock price of high (low) capital banks is not sufficiently high (low) in anticipation of bad times. The "Surprised Investor Channel" results also seem to confirm this interpretation.

Our paper is related to a literature on the relation between leverage and stock returns for industrial firms (Bhandari, 1988; Fama and French, 1992; Vuolteenaho, 2002). This literature tends to focus on default risk instead of leverage per se, and finds a negative relation (Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008), no relation (Garlappi, Shu, and Yan, 2008), or a positive relation (Vassalou and Xing, 2004; Chava and Purnanandam, 2010).[8] Unlike our paper, this literature does not explicitly investigate the links between leverage and stock returns.

Our paper is also related to a small literature on bank stock performance.[9] Fahlenbrach,

[7]George and Hwang (2010) show that, in the presence of market frictions, firms with higher financial distress costs optimally choose lower leverage (i.e., higher capital) to avoid distress, but they retain exposure to the systematic risk of bearing distress costs in low states. Expected returns to high-capital firms are therefore greater than those to low-capital firms. According to our falsification test results for industrial firms, however, high-capital industrial firms do not show greater risk-adjusted stock returns than low-capital industrial firms, suggesting that this effect is controlled by the risk factors used in our empirical models. That is, our results show a sharp contrast between banks and industrial firms even after considering risk factors related to market frictions and the resultant capital structure choices.

[8]We use three approaches to address distress risk beyond the effect covered by the Fama-French book-to-market factor. First, one of the factor models used throughout is Fung and Hsieh's, which includes a credit spread factor that captures distress risk to some extent. Second, we drop banks that delist for performance-type reasons in Section IA.1.2. Third, we add bank-specific risk factors, some of which capture differences in distress risk to some extent, to the standard factor models in Sections 3.3.1.6 and 3.3.2.3. If these analyses still do not sufficiently address distress risk, this can bias our results. To see the direction of the potential bias, suppose we controlled for default risk by adding a CDS spread factor. Since high- (low-) capital banks are less (more) risky in bad times, they will have low (high) loadings on the CDS risk factor. Including this would increase our estimated alphas. Thus, our alphas are rather conservatively estimated.

[9]Some papers examine theoretically how intermediary balance sheets (in particular leverage) affect asset prices (Adrian and Boyarchenko, 2012; Brunnermeier and Sannikov, 2014). Related, He and Krishnamurthy (2013) propose a segmented asset market model in which the representative intermediary is a marginal investor with a financial capital

Prilmeier, and Stulz (2012) find that bank stock performance during the 1998 crisis predicts stock performance during the subprime lending crisis. Using data from 12 countries from 2006Q1 - 2009Q1, Demirguc-Kunt, Detragiache, and Merrouche (2013) show that high-capital banks earned higher returns during the crisis and their evidence suggests that this is driven by the largest banks. As highlighted above, Baker and Wurgler (2015) find that high-capital banks have lower (forward) betas and that bank stocks with low (realized) betas have higher realized stock returns, and Gandhi and Lustig (2015) document a size effect on returns - the largest commercial banks have the lowest risk-adjusted returns.[10] Only one of these papers distinguishes between good and bad times like our paper does (but it does so with only a few years of data), which is critical to highlight the special role of capital in the banking sector, compared to other industries.

3.2 Data, Sample, and Factor Models

We obtain stock-related data from the monthly Center for Research in Security Prices (CRSP) database. Most accounting data are retrieved from the quarterly Compustat database. Some analyses use accounting data from the quarterly Bank Regulatory database. The sample period runs from Jan. 1994 through Dec. 2015. January 1994 is the starting point because Compustat coverage of banks was relatively poor and subject to sample-selection bias before this month.[11,12]

---

constraint. In their model, changes in intermediary wealth become the main risk factor, and the authors focus on the market level risk premium. Adrian, Etula, and Muir (2014) find that the measures suggested by He and Krishnamurthy (2013) based on intermediaries' wealth changes do not span the cross-section of average returns. In addition, Adrian, Etula, and Muir (2014) show empirically that book leverage of broker-dealers has predictive power for asset prices. We use their measure as one of the bank-specific risk factors in Sections 3.3.1.6 and 3.3.2.3.

[10] Baker and Wurgler argue that its findings are consistent with the low-beta / betting-against-beta anomaly documented for non-financial firms. We perform a robustness check to address the betting-against-beta anomaly in Section 3.3.1.7.

[11] Compustat coverage of banks picks up in 1989, improves dramatically in 1993Q4 (the number of banks with total assets available more than doubles), and is "complete" soon thereafter. Standard and Poor's Client Support explained the reasons for this. Edgar's electronic filing, phased in during 1994-1995, facilitated the collection of financial statement data of all listed institutions from the mid-1990s onward. In prior years, predominantly the largest institutions were included in the database because Compustat relied on companies mailing them financial statement information. (Likely) due to client demand, they instigated a major data collection effort in 1993, attempting to improve coverage of financials. They added up to five years of data when available. In particular many smaller financials were added at this time.

[12] We also perform our main in-sample and out-of-sample analyses using a slightly longer sample period (1987 - 2015) and obtain qualitatively similar results to the ones reported in the paper. In those analyses, we use financial statement data from Compustat data to the extent possible and augment these with data on listed banks and listed bank holding companies (BHCs) from the Bank Regulatory database. Internet Appendix IA.1.4 explains how we perform the matching. Since BHC data only starts in 1986 and we use lagged data in our analyses, we start these analyses in

The sample includes commercial banks, identified as firms with header (i.e., current) SIC code 60 or historical (i.e., in each observation year) SIC code 6712 as in Gandhi and Lustig (2015).[13] We exclude foreign banks and closed-end funds;[14] and bank-months with negative capital ratios to avoid survivorship bias.[15] The number of unique institutions is 1,350 (on average 555 per month).

Our analyses focus on bank capital, defined as (common) book equity over total assets at the beginning of month t using the most recent Compustat quarterly financials. Internet Appendices IA.1.4 and IA.2.3 instead use two regulatory capital ratios and a market capital ratio.

Table 3.1 presents summary statistics on key variables.[16] Panel A shows summary statistics on the portfolios used in our main in-sample analyses (see Section 3.3.1). It shows characteristics of portfolios of banks independently sorted into quintiles by Market Cap (calculated as the stock price times the number of shares outstanding) and Capital Ratio (measured as book equity over total assets). For each variable shown, we end up with 25 portfolios: we calculate the value-weighted (VW) average value in each portfolio and report the simple average of the five size-quintile values for each capital quintile. Four things are noteworthy. First, on average, high-capital banks operate with substantially more capital than low-capital banks: 16.31% versus 6.48%. Second, there is a negative correlation between capital and size. It is therefore important to note that our results are robust to including the Gandhi and Lustig (2015) size factor (see Sections 3.3.1.3 and 3.3.2.2). Third, high- minus low-capital ("H-L") portfolios earn returns that are small and not significant: 11 basis points (t-stat = 0.72). Fourth, there is a negative relation between capital and risk measures

1987.

[13]As highlighted in that paper, there is no unique way to find all commercial banks in CRSP. The literature often identifies them manually. The chosen identification approach ensures that BHCs are consistently included in our analyses. For example, if one were to identify commercial banks using *header* SIC code 60, several of the largest banks would drop out of the sample. Adding *historical* SIC code 6712 to the screen, correctly adds these institutions back to the sample. Nonetheless, if we identify commercial banks with Compustat *historical* SIC code 60, if available, and otherwise Compustat *header* SIC code 60, and rerun our main tests, we obtain results that are similar in terms of alphas and t-statistics (available upon request).

[14]A small number of closed-end funds have *header* SIC code 60 or *historical* SIC code 6712, such as "American Government Income Fd In" and "York Financial Corp."

[15]Only 21 banks ever had negative capital ratios, affecting a mere 0.08% of bank-month observations.

[16]As indicated in the table, all variables, except Stock Return, are winsorized at the 1% and 99% levels. It is important to winsorize variables used in some analyses such as panel regressions (including Fama-MacBeth) to reduce the impact of outliers. It is not critical to winsorize variables in the portfolio approaches used in the rest of the paper: for example, without winsorization, we obtain identical coefficients and t-statistics in our main in-sample and out-of-sample analyses.

Table 3.1
Summary Statistics on Bank Fundamentals and Bank Stock Characteristics

This table reports summary statistics. Panel A shows the characteristics of portfolios of banks independently sorted into quintiles by Market Cap and Capital Ratio, where Market Cap is market capitalization in billions of dollars calculated as the number of shares outstanding times the stock price, and Capital Ratio is (common) book equity over total assets. Panel A also shows: Market Capital Ratio, defined as Market Cap divided by the sum of Market Cap and the book value of debt; Tier 1 Risk-Based Capital Ratio, defined as tier 1 capital over total risk-weighted assets; Total Risk-Based Capital Ratio, defined as total capital (i.e., the sum of tier 1 and tier 2 capital) over total risk-weighted assets; Total Assets, the book value of assets in billions of dollars; BETA, market beta estimated using monthly returns over a 60-month (minimum: 24-month) rolling window; Return Volatility, the realized monthly volatility; and Stock Return, monthly stock returns. For each variable shown, we end up with 25 portfolios: we calculate the value-weighted (VW) average value in each portfolio and report the simple average of the five size-quintile values for each capital quintile. Panel B shows the same characteristics of portfolios of banks as Panel A, but stocks are now independently sorted into quintiles by Total Assets (instead of Market Cap) and Capital Ratio. Panel C contains capital ratio transition matrices, showing the probability of moving from one capital ratio quintile to another after one quarter or after one year. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The number of unique institutions is 1,350. All variables, except Stock Return, are winsorized at the 1% and 99% levels. The sample period is from Jan. 1994 - Dec. 2015.

Panel A: Characteristics of Portfolios of Banks Independently Sorted by Market Cap and Capital Ratio

	Low Capital	2	3	4	High Capital
Capital Ratio	6.48%	8.11%	9.32%	10.79%	16.31%
Market Capital Ratio	9.38%	11.12%	12.54%	14.19%	19.80%
Tier 1 Risk-Based Capital Ratio	9.65%	10.55%	11.13%	12.35%	14.73%
Total Risk-Based Capital Ratio	12.95%	13.38%	14.10%	15.56%	21.53%
Market Cap ($B)	5.31	6.83	7.52	3.91	2.89
Total Assets ($B)	46.03	57.57	57.28	26.39	13.21
BETA	0.71	0.64	0.62	0.57	0.58
Return Volatility	2.54%	2.35%	2.30%	2.25%	2.21%
Stock Return	0.82%	1.15%	0.99%	1.03%	0.93%

Panel B: Characteristics of Portfolios of Banks Independently Sorted by Total Assets and Capital Ratio

	Low Capital	2	3	4	High Capital
Capital Ratio	6.57%	8.11%	9.33%	10.82%	18.32%
Market Capital Ratio	10.11%	11.94%	13.61%	15.45%	24.87%
Tier 1 Risk-Based Capital Ratio	9.81%	10.69%	11.32%	12.52%	15.29%
Total Risk-Based Capital Ratio	12.84%	13.34%	14.06%	15.55%	22.05%
Market Cap ($B)	5.25	6.80	7.55	4.01	3.46
Total Assets ($B)	45.28	57.37	57.30	26.81	14.32
BETA	0.63	0.61	0.60	0.57	0.71
Return Volatility	2.56%	2.32%	2.23%	2.17%	2.11%
Stock Return	0.68%	1.04%	0.92%	0.94%	0.93%

Table 3.1 Continued

Panel C: Capital Ratio Transition Matrices

		Quarter t				
		Low	2	3	4	High
Quarter $t+1$	Low	89.6%	11.2%	0.6%	0.2%	0.0%
	2	8.9%	77.5%	13.3%	0.8%	0.2%
	3	0.9%	10.1%	76.3%	12.3%	0.6%
	4	0.4%	0.9%	9.1%	80.7%	8.8%
	High	0.3%	0.2%	0.6%	6.1%	90.4%
Quarter $t+4$	Low	77.2%	23.3%	3.8%	1.1%	0.5%
	2	16.6%	55.9%	25.3%	5.4%	1.0%
	3	4.0%	16.8%	53.0%	25.2%	3.0%
	4	1.4%	3.3%	15.9%	58.0%	20.0%
	High	0.8%	0.7%	1.9%	10.2%	75.5%

such as return volatility and beta (market beta estimated using monthly returns over a 60-month rolling window, with a minimum of 24 months): banks in the lowest capital quintile have a beta of 0.71 while those in the highest capital quintile have a beta of 0.58. Similarly, the monthly return volatility of the highest capital quintile banks is lower by 33 basis points.

Table 3.1 Panel B shows summary statistics on portfolios used in a robustness check in which we independently sort portfolios of banks into quintiles by Total Assets (instead of Market Cap) and Capital Ratio. The insights from this panel are similar to those obtained from Panel A, except that the relation between capital and beta is slightly positive in this case. However, in our time-series regression with portfolio returns, we show that high-capital banks have significantly lower market betas. Moreover, as an important preview: *all* our results hold regardless of whether we measure size as Market Cap or Total Assets.

Table 3.1 Panel C presents capital ratio transition matrices, showing the probability of moving from one capital quintile to another after one quarter (Subpanel C1) or after one year (Subpanel C2). They highlight that bank capital ratios are persistent. For low-capital banks, the probability of still being a low-capital bank after one quarter and one year is 89.6% and 77.2%, respectively. For high-capital banks, the probability of still being a high-capital bank after one quarter and one year is 90.4% and 75.5%, respectively. The probability that a low-capital bank becomes a high-capital bank (or vice versa) is negligible: 0.3% (0.0%) after one quarter and 0.8% (0.5%) after one year.

The shaded areas in Figure 3.1 Panel A represent our main *in-sample* bad times definition, which is based on stock return volatility (Black, 1976; Schwert, 1989; Veronesi, 1999) in the banking sector: a bad time is a month in which VW bank stock return volatility is greater than the 80^{th} percentile of bank stock return volatility measured over the full sample period.[17] Stock return volatility is modeled using an exponential generalized autoregressive heteroscedasticity of order 1, EGARCH(1,1), model. Panel B shows an alternative bad times definition, used in some robustness checks, based on equal-weighted (EW) bank stock return volatility. Many alternative in-sample (out-of-sample) definitions are discussed and used in Internet Appendix IA.1.1 (IA.2.2).

The five linear factor models used in most analyses in Section 3.3 include: FF3, the Fama-French 3-factor model, which includes MKT (return on the market in excess of the one-month Treasury bill rate), SMB (the difference between the average portfolio returns of small and big stocks), and HML (the difference between the average portfolio returns of value and growth stocks) factors (Fama and French, 1993); FFC4, the Carhart 4-factor model, which adds a momentum factor (UMD: the difference between the average portfolio returns of high and low prior return stocks) to FF3 (Carhart, 1997); FF5, the Fama-French 5-factor model, which adds a profitability factor (RMW: the difference between the average portfolio returns of stocks with robust and weak operating profitability) and an investment factor (CMA: the difference between the average portfolio returns of conservative and aggressive investment stocks) to FF3 (Fama and French, 2015); FF5+LQ, which adds a liquidity factor to FF5 (Pástor and Stambaugh, 2003); and FH9, the Fung-Hsieh 9-factor model, which includes nine hedge fund risk factors (Fung and Hsieh, 2001).[18]

[17]To avoid look-ahead bias, we also perform analyses which predict bad times using an EGARCH(1,1) or a random walk model, and obtain comparable results (see Section 3.3.1.1). Our out-of-sample analyses also use this alternative approach (see Section 3.3.2).

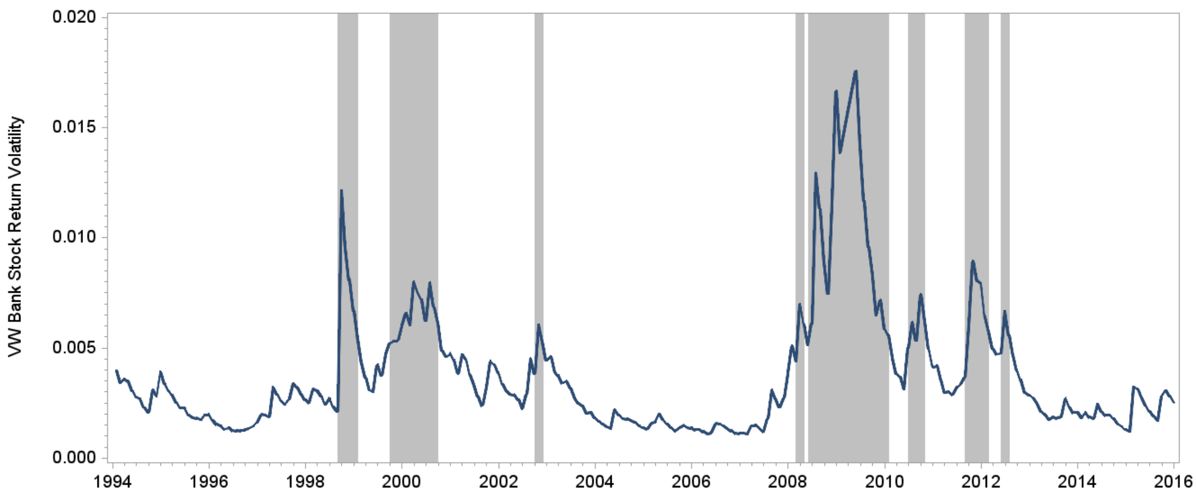
[18]Fung and Hsieh (2001)'s factors include two equity-oriented factors (the return on the S&P 500 and the return spread between Russell 2000 and the S&P 500), two bond-oriented factors (the change in the 10-year Treasury yield and the change in spread between the Baa bond yield and the 10-year Treasury yield), and five trend-following factors (returns on bond, currency, commodity, short-term interest, and stock index lookback straddles).

Figure 3.1

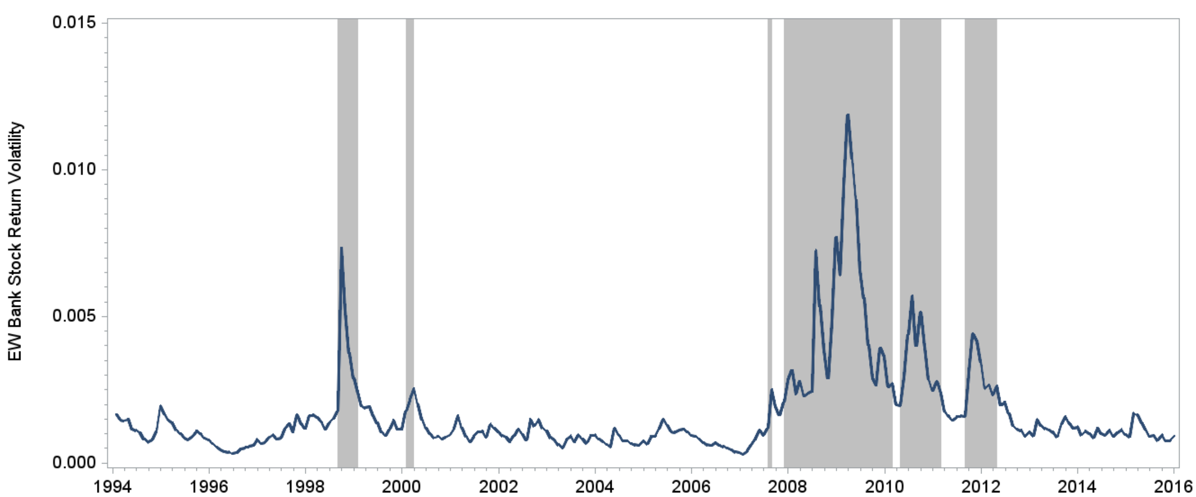
Main In-Sample Bad Times Definition: High Stock Return Volatility in the Banking Sector

The shaded areas in Panel A represent our main in-sample bad times definition. A bad time is a month in which VW bank stock return volatility is greater than the 80^{th} percentile of bank stock return volatility measured over the full sample period (Jan. 1994 - Dec. 2015). Stock return volatility is modeled using an EGARCH(1,1) model. Panel B shows an alternative bad times definition based on EW bank stock return volatility. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712.

Panel A: Main In-Sample Bad Times Definition based on VW Bank Stock Return Volatility



Panel B: Alternative In-Sample Bad Times Definition based on EW Bank Stock Return Volatility



3.3 High-Capital Banks Outperform Low-Capital Banks during Bad Times

This section addresses the first question: Do high-capital banks show better risk-adjusted stock performance than low-capital banks and does the effect of capital differ across normal times and bad economic times? It presents many *in-sample* and *out-of-sample* analyses which strongly suggest that high-capital banks outperform low-capital banks during bad times only. It also includes falsification tests using industrial and non-bank financial firms which suggest that banks are special.

3.3.1 *In-sample* methodology and results

3.3.1.1 Main in-sample methodology and results

To examine whether high-capital banks outperform low-capital banks during different economic times, we use the following linear factor model:

$$R_{pt} = \alpha_0 + \alpha_{BT} BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}, \tag{3.3.1}$$

where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles. BT_t is a dummy = 1 if month t is a bad time, and zero otherwise. As explained in Section 3.2: our main in-sample proxy defines a month to be a bad time if VW bank stock return volatility (modeled using an EGARCH(1,1), model) exceeds its 80^{th} percentile. f_{it} are factor returns in month t obtained using the five linear factor models mentioned in Section 3.2: FF3, FFC4, FF5, FF5+LQ, and FH9.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios to account for the negative correlation between capital and size shown in Table 3.1. Capital and size (market capitalization) are both defined in Section 3.2. Next, we compute monthly VW or EW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size-quintile portfolio returns.

We do the following to ensure that capital ratios are available when investors form portfolios. If a bank files a 10-K or 10-Q within three months of a fiscal-period end, we match the capital ratio from that 10-K or 10-Q to stock returns starting the month after the filing date. If it files more than three months after a fiscal-period end (2.3% of all filings) or if Compustat does not report a filing date (7.6% of all filings), we match the capital ratio from the 10-K or 10-Q to stock returns starting four months after the fiscal-period end to balance concerns about look-ahead bias and the possible use of stale information.[19] So if it files its Q1 10-Q on May 15, we match its Q1 capital ratio to its stock returns in June, July, and August; but if it files its Q1 10-Q on July 17, we match its Q1 capital ratio to its stock returns in July, August, and September.

Table 3.2 Panel A presents - as a starting point - *unconditional* differences in risk-adjusted returns between high- and low-capital portfolios, α of H-L, using five factor models. In the first column, these unconditional differences are small and largely statistically insignificant, indicating that high-capital banks do not outperform low-capital banks in general.[20] The last two columns split the sample by economic regimes into bad times and other times. The unconditional differences are big and highly significant in bad times, yet not in other times.

Table 3.2 Panel B shows *conditional* risk-adjusted returns during bad times, α_{BT}, obtained using the Fama and French (2015) 5-factor model for bank stocks sorted into capital ratio quintiles. The results show that high-capital banks outperform low-capital banks during bad times by 1.49% per month.[21] Since 20% of all months are classified as bad times, this translates into an

[19] Using a four-month period in such cases seems defendable given that the Securities and Exchange Commission (SEC) requires that firms file 10-Ks (10-Qs) within 90 (45) days or less over our sample period. Roughly, they have to file 10-Ks within 90 days of fiscal-year end (through 2002) / 75 days (in 2003) / 60 days (from 2004 onward) and 10-Qs within 45 days of fiscal-quarter end (through 2003) / 40 days (in 2004) / 35 days (from 2005 onward). For exact details, see: *http://www.sec.gov/rules/final/33-8128.htm*. Thomas and Zhang (2011) use a four-month delay for all firms.

[20] Cooper, Jackson, and Patterson (2003) find that changes in leverage and other bank fundamentals help predict bank stock returns in the cross-section for the period of 1986 to 1999. To check if our result is sensitive to the time period, we re-estimate our models using this sample period. We find that our results do not change: the estimated α of H-L is insignificant using all five models. Specifically, FF3 α is -0.12% (t-statistic: -0.53); FFC4 α is -0.03% (t-statistic: -0.12); FF5 α is 0.02% (t-statistic: 0.06); FF5+LQ α is 0.02% (t-statistic: 0.06); and FH9 α is -0.14% (t-statistic: -0.55).

[21] The α estimates across quintiles are not completely monotonic. This is common in empirical asset pricing. Chang, Choi, Kim, and Park (2016) show that some of the nonlinearity is associated with the time-varying and stochastic nature of error volatilities. Even the most common anomalies such as the size effect and book-to-market effect (observed using quintile or decile portfolios) show highly nonlinear patterns. In comparison, our estimates feature

Table 3.2

Risk-Adjusted Returns of High- and Low-Capital Banks during Bad Times

This table reports risk-adjusted returns of capital ratio-sorted portfolios of bank stocks. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements. The goal is to establish the difference in risk-adjusted returns of high- and low-capital banks during bad times, α_{BT}. Return estimates are obtained using the following model (except in Panel E): $R_{pt} = \alpha_0 + \alpha_{BT} BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below); BT_t is a dummy = 1 if month t is a bad time, defined as bank stock return volatility (modeled using an EGARCH(1,1) model) exceeding the 80^{th} percentile (in sample), and zero otherwise; f_{it} are factor returns in month t obtained using five linear factor models.

Panel A presents *unconditional* risk-adjusted returns for high- minus low-capital portfolios, α of H-L, using the five factor models, restricting α_{BT} to zero. It presents this for the full sample and for the full sample split into economic regimes (bad times and other times). Panel B shows *conditional* risk-adjusted returns, α_{BT}, obtained using the Fama and French (2015) 5-factor model for bank stocks sorted into capital ratio quintiles. It shows results based on VW average portfolio returns and defines bad times based on VW bank stock return volatility. Panel C shows conditional risk-adjusted returns, α_{BT}, for high- minus low-capital bank portfolios using the five factor models. It shows results based on both VW and EW average portfolio returns and defines bad times alternatively based on VW and EW bank stock return volatility. When forming portfolios, bank size is measured as Market Cap (the number of shares outstanding times the share price measured at the beginning of month t). Panel D is comparable to Panel C but uses Total Assets (the book value of assets) instead to measure bank size. Panel E avoids look-ahead bias: it replaces BT_t with $BT_{predicted,t}$, a dummy = 1 if month t is *predicted* to be a bad time, defined as bank stock return volatility calculated using VW average bank stock returns from Jan. 1984 to month $t-1$ exceeding the 80^{th} percentile, and zero otherwise. Volatility is modeled using an EGARCH(1,1) model and using a random walk model, i.e., $E_{t-1}(vol_t) = vol_{t-1}$.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization in Panels A-C and E, and as Total Assets in Panel D. Next, we compute monthly VW or EW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

Panel A: Unconditional Risk-Adjusted Returns of High- minus Low-Capital (H-L) Portfolios

	Full Sample	Split Into Economic Regimes	
Economic Regimes	All Times	Bad Times	Other Times
	α of H-L	α of H-L	α of H-L
FF3	0.28%*	1.55%***	-0.07%
	(1.84)	(3.32)	(-0.44)
FFC4	0.25%	1.66%***	-0.06%
	(1.59)	(3.67)	(-0.38)
FF5	0.22%	1.34%***	-0.03%
	(1.38)	(2.69)	(-0.17)
FF5+LQ	0.23%	1.35%***	-0.04%
	(1.40)	(2.73)	(-0.25)
FH9	0.19%	1.99%***	-0.18%
	(1.10)	(3.38)	(-1.11)

Table 3.2 Continued

Panel B: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Banks during Bad Times based on FF5

	α_0	$\boldsymbol{\alpha_{BT}}$	MKT	SMB	HML	RMW	CMA
Low Capital	0.39%*	**-2.18%*** **	0.83***	0.29***	0.66***	0.03	-0.07
	(1.73)	**(-4.42)**	(15.77)	(4.20)	(7.05)	(0.29)	(-0.53)
2	0.57%***	**-1.13%*** **	0.71***	0.28***	0.65***	0.07	-0.08
	(3.02)	**(-2.73)**	(16.06)	(4.76)	(8.25)	(0.77)	(-0.72)
3	0.50%***	**-1.64%*** **	0.72***	0.32***	0.66***	0.10	-0.09
	(2.63)	**(-3.97)**	(16.16)	(5.39)	(8.29)	(1.13)	(-0.78)
4	0.46%***	**-1.15%*** **	0.66***	0.28***	0.53***	0.11	0.05
	(2.69)	**(-3.08)**	(16.57)	(5.24)	(7.45)	(1.38)	(0.49)
High Capital	0.33%**	**-0.68%* **	0.62***	0.27***	0.41***	0.07	0.05
	(2.05)	**(-1.96)**	(16.75)	(5.55)	(6.20)	(0.96)	(0.51)
H - L	-0.07%	**1.49%*** **	-0.21***	-0.02	-0.25***	0.04	0.12
	(-0.38)	**(3.97)**	(-5.18)	(-0.38)	(-3.50)	(0.50)	(1.17)

Panel C: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Banks during Bad Times

Average Portfolio Returns:	VW	EW	VW	EW
Bank Stock Return Volatility:	VW	VW	EW	EW
	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L
FF3	1.54%***	1.34%***	2.06%***	1.94%***
	(4.14)	(3.46)	(5.72)	(5.21)
FFC4	1.62%***	1.39%***	2.15%***	2.01%***
	(4.34)	(3.58)	(5.97)	(5.36)
FF5	**1.49%*** **	1.27%***	2.05%***	1.94%***
	(3.97)	(3.27)	(5.69)	(5.19)
FF5+LQ	1.50%***	1.27%***	2.05%***	1.94%***
	(3.97)	(3.26)	(5.67)	(5.18)
FH9	1.72%***	1.55%***	2.13%***	2.06%***
	(4.57)	(3.90)	(5.75)	(5.28)

Panel D: Risk-Adjusted Returns of High- Minus Low-Capital (H-L) Banks during Bad Times: Use Total Assets instead of Market Cap to Measure Bank Size when Forming Portfolios

Average Portfolio Returns:	VW	EW	VW	EW
Bank Stock Return Volatility:	VW	VW	EW	EW
	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L
FF3	1.92%***	1.94%***	1.97%***	2.16%***
	(4.53)	(3.82)	(4.68)	(4.31)
FFC4	2.03%***	2.05%***	2.08%***	2.28%***
	(4.78)	(4.04)	(4.95)	(4.56)
FF5	1.93%***	1.87%***	1.95%***	2.13%***
	(4.51)	(3.66)	(4.63)	(4.26)
FF5+LQ	1.94%***	1.87%***	1.95%***	2.13%***
	(4.52)	(3.65)	(4.61)	(4.26)
FH9	1.95%***	2.01%***	1.85%***	2.09%***
	(4.86)	(4.01)	(4.56)	(4.16)

Table 3.2 Continued

Panel E: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Portfolios during Times *Predicted* to be Bad

Stock Return Volatility Forecasted using:	EGARCH(1,1) Model	Random Walk Model
	α_{BT} of H-L	α_{BT} of H-L
FF3	1.39%***	1.31%***
	(3.86)	(3.60)
FFC4	1.45%***	1.38%***
	(4.02)	(3.79)
FF5	1.39%***	1.29%***
	(3.87)	(3.55)
FF5+LQ	1.40%***	1.29%***
	(3.88)	(3.54)
FH9	1.58%***	1.43%***
	(4.25)	(3.87)

annual outperformance by high-capital banks of $1.49\% \times 0.2 \times 12 = 3.57\%$. While both types of banks underperform during such times, the underperformance by high-capital banks is significantly smaller (-0.68% versus -2.18% per month). Note that $\alpha_0 + \alpha_{BT}$ (-0.07 + 1.49%) captures the total effect in bad times: it is comparable to the estimated α in the second column of Panel A (1.34% based on FF5) instead of the first column of Panel A (0.22%), which captures the average effect in both good and bad times. Figure 3.2 shows that the outperformance of high-capital banks during bad times is greater when the bad times cutoff is higher, but they start to outperform at the 5% level using cut-offs above the 40^{th} percentile.

Table 3.2 Panel C shows the difference in risk-adjusted returns between high- and low-capital banks during bad times, α_{BT} of H-L, using five linear factor models. The four columns use alternative weighting schemes (VW or EW) for portfolio returns and stock return volatility. The first column shows our main specification, which uses VW average portfolio returns and defines bad times based on VW bank stock return volatility.[22] The emboldened result based on the Fama-French 5-factor model is identical to that shown in Panel B. The results in the four columns are

mild nonlinearities.

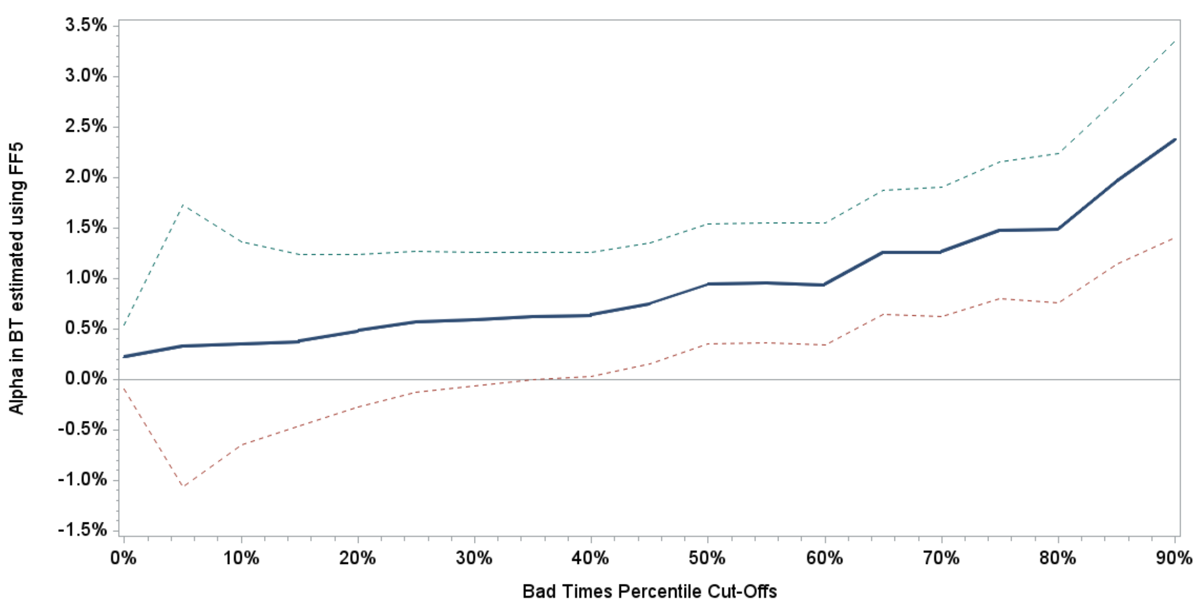
[22]We obtain comparable results when portfolios are rebalanced annually at the end of June. As in Fama and French (1993), the accounting variables for these sorts are for the fiscal year ending in the previous calendar year, while market capitalization is as of June. (Results are available upon request.)

Figure 3.2

Returns of High- and Low-Capital Banks during Bad Times: Alternative Bad Times Cut-Offs

This figure shows the difference in risk-adjusted returns of high- and low-capital banks during bad times, α_{BT}, based on alternative bad times percentile cut-offs using data from Jan. 1994 - Dec. 2015. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712.The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements. The estimates are obtained using a five-factor model (Fama and French, 2015): $R_{pt} = \alpha_0 + \alpha_{BT} BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for high- and low-capital banks; BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility exceeding a cut-off that varies here from zero to the 90^{th} percentile (in sample), and zero otherwise; f_{it} are the five Fama-French factors ($i = 1, \cdots, K$, with $K = 5$) in month t.

At the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization, the number of shares outstanding times the share price measured at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. VW bank stock return volatility is modeled using an EGARCH(1,1) model. The solid line indicates mean estimates, and the two dotted lines represent 5% confidence bounds.



consistent and show that high-capital banks show higher risk-adjusted returns than low-capital banks during bad times at the 1% level. The outperformance during bad times by high-capital banks is 1.27% to 2.15% per month, or 3.05% to 5.16% per year.[23]

The results in Panel C are based on portfolio sorts by bank capital and size, measured as market capitalization. While standard in the asset pricing literature, there are two potential concerns. First, bank regulators measure bank size as (the book value of) total assets. Second, our results may be driven by the well-known one-month reversal found in stock returns since monthly sorts on market capitalization may sort past-month winners (losers) disproportionally into quintile five (one). To address these concerns, we now measure size as total assets. Table 3.2 Panel D shows that we obtain results that are comparable or stronger: the coefficients tend to be bigger and the t-statistics tend to be higher than those shown in Panel C. In fact, *all* the results in our paper are comparable or stronger when we use total assets (not shown for brevity but available upon request from the authors).[24] Possibly, the stronger results are driven by the fact that the difference in the capital ratio of high- and low-capital banks is more pronounced when using total assets (18.32% - 6.57% = 11.75% in Table 3.1 Panel B versus 16.31% - 6.48% = 9.83% in Table 3.1 Panel A).

Another potential concern with the results in Panel C is that they are subject to a look-ahead bias since bad times are defined using information from the full sample period. Table 3.2 Panel E avoids look-ahead bias: it replaces BT_t with $BT_{predicted,t}$, a dummy = 1 if month t is *predicted* to be a bad time, defined as bank stock return volatility calculated using VW average bank stock returns from Jan. 1984 to month $t-1$ exceeding the 80^{th} percentile, and zero otherwise. Volatility is alternatively modeled using an EGARCH(1,1) model and a random walk model, i.e., $E_{t-1}(vol_t) = vol_{t-1}$.[25] The outperformance of high-capital banks during bad times is somewhat smaller than that presented in the first column of Table 3.2 Panel C, but remains highly significant.

[23]Since bad times obtained using EW return volatility put more emphasis on the recent financial crisis and less on the dot.com bubble period (see Figure 3.1) and since the outperformance of high-capital banks is greater during the recent financial crisis (to be shown in Internet Appendix IA.1.1), the results based on EW return volatility are stronger.

[24]The only exceptions are two robustness checks in which we use the VIX to measure bad times, but we still find significance (at the 10% level) in those cases.

[25]Using the EGARCH(1,1) and random walk models, we have Type I errors (a good time is predicted to be a bad time) in 8.5% and 8.5% of the cases, respectively; and we have Type II errors (a bad time is not predicted to be one) in 22.6% and 26.4% of the cases, respectively. Thus, our out-of-sample volatility forecasts are rather reliable.

These results have potentially important policy implications. While regulators emphasize the role of capital in lowering default risk and related systemic risk, bankers typically view large capital holdings as leading to lower liquidity creation and reduced shareholder value. Our results suggest that high-capital banks' shareholders benefit in bad times (Panel A second column and Panels B-E) and do not suffer during other times (Panel A third column). Thus, holding more capital is beneficial, because it helps banks outperform in bad times without hurting their stock performance during other times.

3.3.1.2 Falsification tests: Are banks special?

It is useful to examine if our results are bank-specific. To address this, we rerun our analyses while focusing first on industrial firms and then on non-bank financial firms. Industrial firms are all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database excluding financial firms, identified as firms with *header* SIC code 6 or *historical* SIC code 6. Non-bank financial firms are all financial firms excluding commercial banks.[26] Figure 3.3 depicts stock return volatility, modeled using an EGARCH(1,1) model, at industrial firms (Panels A-B) and non-bank financial firms (Panels C-D). Panels A and C (B and D) show VW (EW) stock return volatility. The shaded regions in each panel represent bad times, defined as months in which volatility is greater than its 80^{th} percentile (in sample). Our main bad times proxies in this section are based on VW stock return volatility being high (above the 80^{th} percentile) in sample.

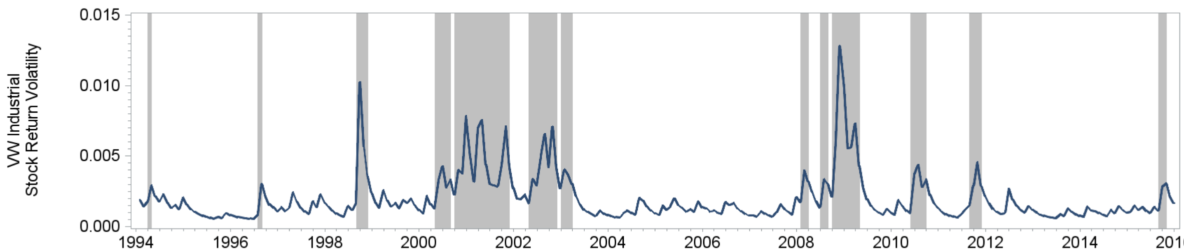
Table 3.3 presents results. Panel A shows the difference in *unconditional* risk-adjusted returns of high- and low-capital firms using five alternative factor models. For industrial firms, the difference is positive and significant in three cases, providing some evidence that unconditionally, high-capital industrial firms outperform low-capital ones. The unconditional return differences are small and not significant for non-bank financial firms. Panel B contains *conditional* risk-adjusted returns based on the Fama-French 5-factor model. It shows that during bad times, the difference

[26] As before, commercial banks are identified as firms with *header* SIC code 60 or *historical* SIC code 6712. We exclude firm-month observations of firms with negative capital ratios to avoid survivorship bias: 17.23% of all industrial firms have negative capital ratios at least once during the sample period, affecting 3.20% of all firm-month observations (for non-bank financials: 7.26% and 1.26%, respectively).

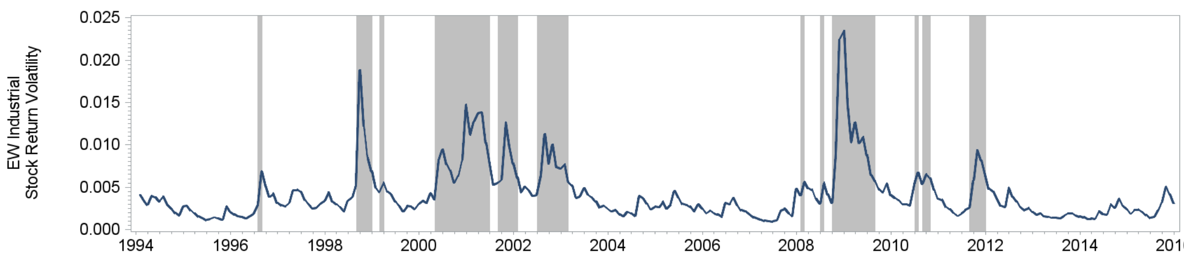
Figure 3.3
Bad Times Definition for Falsification Tests: High Stock Return Volatility at Industrial and Non-Bank Financial Firms

This figure depicts stock return volatility at industrial and non-bank financial firms modeled using an EGARCH(1,1) model. Panels A and B (C and D) depict VW and EW industrial firm (non-bank financial firm) stock return volatility, respectively. The shaded regions represent bad times, defined as months in which such volatility is greater than its 80^{th} percentile (in sample). Industrial firm stocks are identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database excluding financial firms, identified as firms with *header* SIC code (CRSP item HSICCD) 6 or *historical* SIC code (CRSP item SICCD) 6. Non-bank financial firms are viewed to be all financial firms (identified as indicated above) excluding commercial banks, identified as all firms with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The sample period is from Jan. 1994 - Dec. 2015.

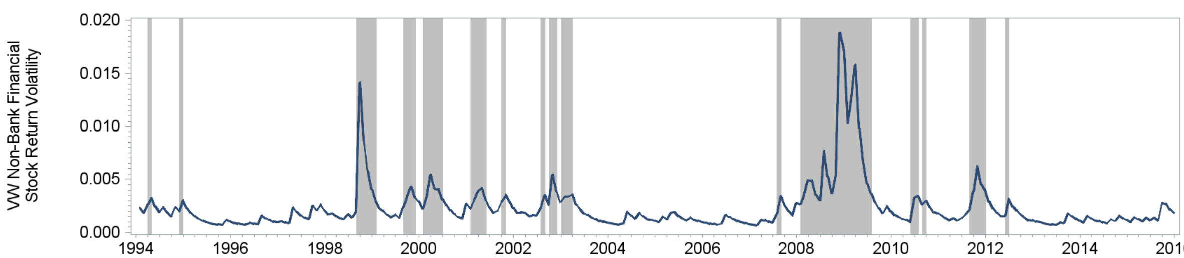
Panel A: VW Industrial Firm Stock Return Volatility



Panel B: EW Industrial Firm Stock Return Volatility



Panel C: VW Non-Bank Financial Firm Stock Return Volatility



Panel D: EW Non-Bank Financial Firm Stock Return Volatility

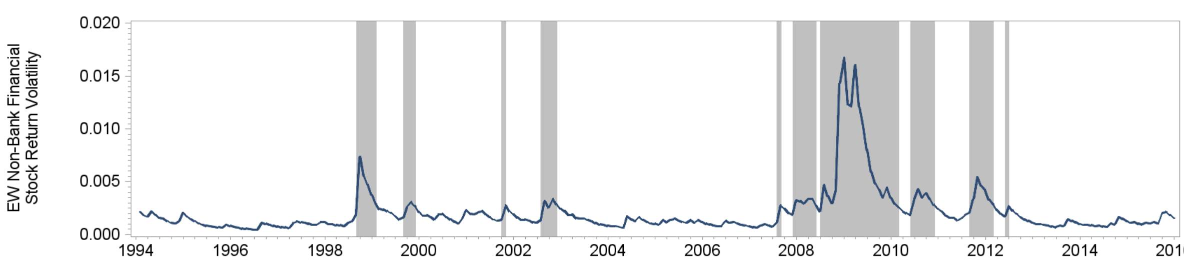


Table 3.3

Falsification Tests: Risk-Adjusted Returns of High- and Low-Capital *Industrial Firms* and *Non-Bank Financial Firms* during Bad Times

This table addresses if banks are special by using data on industrial and non-bank financial firms rather than banks. The goal is to establish the difference in risk-adjusted returns of high- and low-capital firms during bad times, α_{BT} of H-L. Industrial firms are identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database excluding financial firms, identified as firms with *header* SIC code (CRSP item HSICCD) 6 or *historical* SIC code (CRSP item SICCD) 6. Non-bank financial firms are viewed to be all financial firms (identified as indicated above) excluding commercial banks, identified as all firms with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The return estimates are obtained using the following model: $R_{pt} = \alpha_0 + \alpha_{BT} BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for industrial firm or non-bank financial firm stocks sorted into capital ratio quintiles (explained below). In most specifications shown, BT_t is a dummy = 1 if month t is a bad time, defined as VW stock return volatility of industrial firms or non-bank financial firms exceeding the 80^{th} percentile, and zero otherwise (in sample). Stock return volatility is modeled using an EGARCH(1,1) model. f_{it} are factor returns in month t obtained using five linear factor models.

Panels A-C present results separately for industrial and non-bank financial firms: Panel A shows unconditional risk-adjusted returns, restricting α_{BT} to zero. Panel B contains conditional risk-adjusted returns based on FF5, the Fama-French 5-factor model, during bad times. Panel C shows the difference in risk-adjusted returns of high-and low-capital firms during bad times, α_{BT} of H-L, using five alternative factor models. Results are shown for the main specification (bad times identified using VW stock return volatility over the entire sample period), but also using EW stock return volatility, and for specifications that avoid look-ahead bias by using times predicted to be bad.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort industrial firm or non-bank financial firm stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization, the number of shares outstanding times the share price measured at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

Panel A: Unconditional Risk-Adjusted Returns of High- minus Low-Capital (H-L) Industrial and Non-Bank Financial Firms using Alternative Factor Models

Sample:	Industrial firms	Non-bank financial firms
	α of H-L	α of H-L
FF3	0.26%*	0.23%
	(1.90)	(1.36)
FFC4	0.18%	0.12%
	(1.34)	(0.74)
FF5	0.47%***	0.21%
	(3.42)	(1.15)
FF5+LQ	0.47%***	0.12%
	(3.40)	(0.66)
FH9	-0.13%	-0.02%
	(-0.54)	(-0.08)

Table 3.3 Continued

Panel B1: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Industrial Firms during Bad Times based on FF5

Sample:	Industrial firms						
	α_0	α_{BT}	MKT	SMB	HML	RMW	CMA
Low Capital	-0.11%	0.10%	1.09***	0.67***	0.47***	-0.22**	-0.22**
	(-0.56)	(0.24)	(24.53)	(11.23)	(5.88)	(-2.50)	(-2.03)
2	0.03%	0.21%	0.99***	0.63***	0.36***	-0.06	-0.18**
	(0.19)	(0.63)	(28.11)	(13.22)	(5.68)	(-0.88)	(-2.07)
3	0.10%	0.47%	0.98***	0.66***	0.25***	-0.23***	-0.26***
	(0.68)	(1.44)	(28.84)	(14.46)	(4.00)	(-3.29)	(-3.08)
4	0.25%*	0.10%	0.99***	0.70***	-0.11*	-0.34***	-0.26***
	(1.84)	(0.31)	(30.68)	(16.12)	(-1.89)	(-5.17)	(-3.21)
High Capital	0.29%*	0.49%	0.97***	0.69***	-0.30***	-0.61***	-0.36***
	(1.74)	(1.32)	(24.74)	(13.12)	(-4.25)	(-7.77)	(-3.73)
H - L	0.40%***	0.39%	-0.12***	0.02	-0.77***	-0.39***	-0.14
	(2.67)	(1.18)	(-3.52)	(0.39)	(-12.25)	(-5.52)	(-1.60)

Panel B2: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Non-Bank Financial Firms during Bad Times based on FF5

Sample:	Non-bank financial firms						
	α_0	α_{BT}	MKT	SMB	HML	RMW	CMA
Low Capital	0.00%	-0.19%	1.09***	0.33***	0.91***	-0.07	-0.20*
	(-0.01)	(-0.44)	(23.85)	(5.43)	(11.00)	(-0.77)	(-1.80)
2	0.19%	-0.21%	0.90***	0.49***	0.70***	0.15**	-0.24***
	(1.25)	(-0.66)	(26.15)	(10.72)	(11.35)	(2.24)	(-2.78)
3	0.25%	-0.15%	0.89***	0.56***	0.63***	0.09	-0.23**
	(1.37)	(-0.38)	(20.86)	(9.82)	(8.32)	(1.06)	(-2.21)
4	0.28%*	0.03%	0.78***	0.47***	0.54***	0.13*	-0.14
	(1.81)	(0.08)	(21.36)	(9.64)	(8.20)	(1.86)	(-1.59)
High Capital	0.27%**	-0.55%**	0.71***	0.47***	0.27***	-0.06	-0.10
	(2.17)	(-2.00)	(24.39)	(11.92)	(5.06)	(-1.12)	(-1.31)
H - L	0.28%	-0.36%	-0.38***	0.13**	-0.64***	0.01	0.11
	(1.39)	(-0.84)	(-8.25)	(2.18)	(-7.74)	(0.06)	(0.96)

Table 3.3 Continued

Panel C1: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Industrial Firms during Bad Times using Alternative Factor Models

Sample:	Industrial Firms			
	Industrial Firm Return Volatility			
Bad Times Definition:	VW Avg. Obtained in-sample	EW Avg. Obtained in-sample	VW Avg. Predicted using EGARCH(1,1) model	VW Avg. Predicted using random walk model
	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L
FF3	0.01%	0.00%	0.08%	0.16%
	(0.04)	(-0.01)	(0.23)	(0.47)
FFC4	0.20%	0.18%	0.12%	0.44%
	(0.60)	(0.53)	(0.37)	(1.32)
FF5	0.39%	0.24%	0.13%	0.37%
	(1.18)	(0.75)	(0.39)	(1.17)
FF5+LQ	0.39%	0.24%	0.13%	0.37%
	(1.18)	(0.74)	(0.39)	(1.18)
FH9	0.17%	0.04%	1.04%*	0.50%
	(0.30)	(0.07)	(1.88)	(0.91)

Panel C2: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Non-Bank Financial Firms during Bad Times using Alternative Factor Models

Sample:	Non-Bank Financial Firms			
	Non-Bank Financial Firm Return Volatility			
Bad Times Definition:	VW Avg. Obtained in-sample	EW Avg. Obtained in-sample	VW Avg. Predicted using EGARCH(1,1) model	VW Avg. Predicted using random walk model
	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L
FF3	-0.33%	-0.60%	-0.07%	-0.56%
	(-0.77)	(-1.40)	(-0.18)	(-1.35)
FFC4	-0.18%	-0.30%	-0.17%	-0.25%
	(-0.42)	(-0.70)	(-0.43)	(-0.61)
FF5	-0.36%	-0.61%	-0.09%	-0.55%
	(-0.84)	(-1.42)	(-0.22)	(-1.33)
FF5+LQ	-0.34%	-0.62%	0.01%	-0.65%
	(-0.81)	(-1.48)	(0.03)	(-1.60)
FH9	0.28%	0.02%	0.05%	-0.13%
	(0.56)	(0.04)	(0.10)	(-0.26)

in risk-adjusted returns between high- and low-capital firms, α_{BT} of H-L, is insignificant for industrial firms (0.39% per month; t-stat 1.18) and for non-bank financial firms (-0.36% per month; t-stat -0.84). Panel C shows similar evidence using five alternative factor models.[27] Results are shown using VW and EW stock return volatility, and for specifications that avoid look-ahead bias by using times predicted to be bad (based on EGARCH and random walk models).

Combined, these results suggest that banks are special: the role of capital in banks is very different from its role in industrial and non-bank financial firms.

3.3.1.3 Control for Gandhi and Lustig (2015)'s size effect

Table 3.1 Panels A and B document that there is a negative relation between bank capital and bank size. This raises a concern that our results are driven by bank size rather than bank capital. To elaborate, Gandhi and Lustig (2015) document that - controlling for all known risk factors - the largest banks have significantly lower returns than smaller banks, and this differential is particularly pronounced during financial crisis, or bad economic, times. They argue that this is caused by larger banks having higher recovery rates during a crisis since these banks are deemed too-big-to-fail and hence the government absorbs some of their tail risk. While we try to ensure that our results are driven by bank capital rather than by bank size (by first constructing VW returns for 25 size and bank capital portfolios and then taking the simple average across five size quintiles to generate portfolio returns for each capital quintile), it is possible that we have not done enough.

We address this concern two ways. First, we exclude banks in the largest size quintile. Second, we rerun our main regressions while controlling for Gandhi and Lustig (2015)'s size factor, which is replicated as follows. At the beginning of January in each year of our sample period (1994 - 2015),[28] we sort bank stocks into deciles based on their market capitalization and compute VW average returns in each decile over the year. Using these ten portfolios, we estimate residuals from a five factor model (Fama-French's three factors and two bond factors)[29] and extract the loadings

[27]For industrial firms, the difference is positive and significant at the 10% level in one case (based on FH9).

[28]We obtain similar results when we construct the factor using data from 1980 - 2013 as in Gandhi and Lustig (2015) and when using data from 1980 - 2015.

[29]The two bond factors are: *ltg*, the monthly change in the 10-year Treasury constant maturity yield less the one-month Treasury bill rate, and *crd*, the monthly change in Moody's Baa yield less the one-month Treasury bill rate.

for the principal components. Because the second principal component loads positively on small banks and negatively on large banks, as reported by Gandhi and Lustig (2015), it is used to create a size factor. Specifically, the size factor is defined as the product of the normalized weights for the second principal component and the residuals of the ten portfolios.

Table 3.4 shows that both approaches yield results comparable to those in the first column of Table 3.2 Panel C, suggesting that our results are not driven by Gandhi and Lustig (2015)'s size effect.

3.3.1.4 Control for nonsynchronous trading

It is well-known that small firm stocks may be subject to nonsynchronous trading. We address this possibility two ways: by including lagged factor returns as in Scholes and Williams (1977), and by excluding the smallest size quintile when computing returns for each capital ratio quintile.

Table 3.5 uses both approaches and shows results similar to those in the first column of Table 3.2 Panel C, suggesting that our results are not significantly affected by nonsynchronous trading.

3.3.1.5 Control for time-varying betas

It is possible that the effects of some risk factors are amplified or reduced during bad times, and that this is priced in the stock market. If so, the state-dependent nature of abnormal performance we have documented could merely result from ignoring this conditionality of risk. To verify that this does not drive our results, we re-estimate our models by allowing the intercept and risk exposures to interact with bad times:[30]

$$R_{pt} = \alpha_0 + \alpha_{BT} BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \sum_{i=1}^{K} \beta_{BT_i} f_{it} BT_t + \varepsilon_{it}, \qquad (3.3.2)$$

where β_{BT} measures the sensitivity of bank stock returns to the degree of co-movement of risk (f_{it}) and the economic state of the world (BT_t).

Table 3.6 Panel A shows the estimates of α_0 and β_i, and Panel B shows the conditional coeffi-

[30]This is similar to a regime-switching model, used by Acharya, Amihud, and Bharath (2013) and others, in that all regression coefficients can change depending on the regime.

Table 3.4

Risk-Adjusted Returns of High- and Low-Capital Banks during Bad Times: Results Controlling for Gandhi and Lustig (2015)'s Size Effect

This table reports the difference in risk-adjusted returns of high- and low-capital banks during bad times, α_{BT} of H-L, while controlling for Gandhi and Lustig (2015)'s size effect. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements. The return estimates are obtained using the following model: $R_{pt} = \alpha_0 + \alpha_{BT}BT_t + \sum_{i=1}^{K}\beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below); BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility (modeled using an EGARCH(1,1) model) exceeding the 80^{th} percentile (in sample), and zero otherwise; f_{it} are factor returns in month t obtained using five linear factor models.

Gandhi and Lustig (2015)'s size effect is controlled for in two ways. First, we exclude banks in the largest size quintile when computing returns for each capital ratio quintile. Second, we control for Gandhi and Lustig (2015)'s size factor, GL, which is replicated as follows. At the beginning of January in each year of our sample period (1994 - 2015), we sort bank stocks into deciles based on their market capitalization and compute VW average returns across deciles over the year. Using these ten portfolios, we estimate residuals from a five factor model, which includes Fama-French's three factors and two bond factors: *ltg*, the monthly change in the 10-year Treasury constant maturity yield less the one-month Treasury bill rate, and *crd*, the monthly change in Moody's Baa yield less the one-month Treasury bill rate.) We then run a principal component analysis for the residuals. Finally, the size factor is defined as the product of the normalized weights for the second principal component and the residuals of the ten portfolios.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the four smallest size quintile portfolio returns in the first column, and as the simple average of all five size quintiles in the second column. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

Control for a Size Effect by Excluding Banks in the Largest Size Quintile		Control for a Size Effect by Controlling for Gandhi and Lustig (2015)'s Size Factor	
	α_{BT} of H-L		α_{BT} of H-L
FF3	1.72%***	FF3 + GL	1.40%***
	(4.38)		(3.75)
FFC4	1.73%***	FFC4 + GL	1.48%***
	(4.40)		(3.95)
FF5	1.66%***	FF5 + GL	1.35%***
	(4.21)		(3.57)
FF5+LQ	1.66%***	FF5+LQ + GL	1.35%***
	(4.20)		(3.57)
FH9	1.93%***	FH9 + GL	1.60%***
	(4.76)		(4.24)

Table 3.5
Risk-Adjusted Returns of High- and Low-Capital Banks during Bad Times: Results Controlling for Nonsynchronous Trading

This table reports the difference in risk-adjusted returns of high- and low-capital banks during bad times, α_{BT} of H-L, while controlling for nonsynchronous trading. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements. The return estimates are obtained using the following model: $R_{pt} = \alpha_0 + \alpha_{BT} BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below); BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility (modeled using an EGARCH(1,1) model) exceeding the 80^{th} percentile (in sample), and zero otherwise; f_{it} are factor returns in month t obtained using five linear factor models.

To account for the possibility that small bank stocks are subject to nonsynchronous trading bias, we estimate the risk-adjusted bank stock returns after controlling for nonsynchronous trading using two approaches. Following Scholes and Williams (1977), we add lagged factor returns on the right-hand-side of the equation. Alternatively, portfolio returns of the smallest size quintile are excluded when computing returns for each capital ratio quintile.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of all five size quintile portfolio returns in the first column, and as the simple average of the four largest size quintiles in the second column. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

Control for Non-Synchronous Trading:	As in Scholes and Williams (1977)	By Excluding Banks in the Smallest Size Quintile
	α_{BT} of H-L	α_{BT} of H-L
FF3	1.44%***	1.41%***
	(3.96)	(3.99)
FFC4	1.45%***	1.53%***
	(3.99)	(4.36)
FF5	1.39%***	1.36%***
	(3.78)	(3.80)
FF5+LQ	1.42%***	1.36%***
	(3.86)	(3.81)
FH9	1.61%***	1.61%***
	(4.37)	(4.57)

cients α_{BT} and β_{BT_i} from equation (3.3.2). We continue to find that the alpha of the H-L portfolio in bad times (1.36%) is positive and highly significant even after controlling for time-varying risk. The alpha here is (1.49% - 1.36% =) 13 basis points lower than α_{BT} of H-L in Table 3.2 Panel B, which does not take conditionality of risk into account. To assess what drives this drop in alpha, we look at the loadings on the five factors. As can be seen, the loading on the profitability factor, RMW, changes substantially and becomes positive in bad times, implying that high-capital banks have unexpectedly high profitability in such times. The other factor loadings change little in bad times. Combined, this suggests that the conditional profitability factor accounts for most of the 13 basis point outperformance of high-capital banks against low-capital banks during bad times.

Table 3.6 Panel C shows that similar results obtain using the other factor models: we find significant alpha in bad times after controlling for the conditionality of risk. Thus, high-capital banks show greater risk-adjusted returns than low-capital banks during bad times. Panel and Fama-Macbeth regressions (Internet Appendices IA.1.6 and IA.1.7) lend further support to this conclusion.

3.3.1.6 Control for bank-specific risk factors

The linear factor models used so far intend to capture risks faced by firms in general. While one could argue that these asset pricing models should also work for banks, they were not constructed to capture bank-specific risks. One potential concern is that we do not adequately control for such risks, implying that we might be merely capturing that high-capital banks are riskier than low-capital banks. Initial evidence suggests the opposite: the difference in the estimated market beta for the highest- and lowest-capital bank quintiles is (0.62 - 0.83 =) -0.21 (Table 3.2 Panel B); and high-capital banks have lower return volatility (Table 3.1 Panel A). Recognizing that this may not be sufficient and given the endogeneity of bank capital (riskier banks may optimally choose to hold more capital, implying that high-capital banks are aligned with higher bank-specific risks), we now rerun our regressions while adding ten bank-specific risk factors to the five linear factor models. We first add (most of) these factors one by one and then present results while adding all ten factors to each model.

Table 3.6
Risk-Adjusted Returns of High- and Low-Capital Banks during Bad Times: Results Controlling for Time-Varying Betas

This table reports the difference in risk-adjusted returns of high- and low-capital banks during bad times, α_{BT} of H-L, while allowing risk factors to co-vary with bad times. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements. The return estimates are obtained using the following model: $R_{pt} = \alpha_0 + \alpha_{BT} BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \sum_{i=1}^{K} \beta_{BT_i} f_{it} BT_t + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below); BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility (modeled using an EGARCH(1,1) model) exceeding the 80^{th} percentile (in sample), and zero otherwise; f_{it} are factor returns in month t obtained using up to five linear factor models.

Panel A shows the α_0 and β_i regression coefficients, obtained using FF5 for bank stocks sorted into capital ratio quintiles (see below). Panel B shows conditional (α_{BT} and β_{BT_i}) regression coefficients using FF5. Panel C shows returns of high- minus low-capital (H-L) banks during bad times, obtained while allowing betas to differ between good and bad times using five factor models.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

Panel A: Unconditional Risk-Adjusted Returns of High- minus Low-Capital (H-L) Banks based on FF5

	α_0	MKT	SMB	HML	RMW	CMA
Unconditional Coefficients	-0.03%	-0.20***	-0.02	-0.19*	-0.10	0.13
	(-0.15)	(-3.90)	(-0.29)	(-1.93)	(-1.00)	(1.04)

Panel B: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Banks during Bad Times based on FF5: Controlling for Conditional Beta

	$\boldsymbol{\alpha_{BT}}$	MKT_{BT}	SMB_{BT}	HML_{BT}	RMW_{BT}	CMA_{BT}
Conditional Coefficients	**1.36%*** **	0.00	0.10	-0.20	0.44**	0.00
	(3.36)	(-0.01)	(0.83)	(-1.33)	(2.42)	(0.01)

Panel C: Risk-Adjusted Returns of High- Minus Low-Capital (H-L) Banks during Bad Times using Alternative Factor Models: Controlling for Conditional Beta

	α_{BT} of H-L
FF3	1.62%***
	(4.23)
FFC4	1.72%***
	(4.51)
FF5	**1.36%*** **
	(3.36)
FF5+LQ	1.39%***
	(3.43)
FH9	2.17%***
	(4.64)

The bank-specific risk factors that we add in Table 3.7 Panel A include: a funding liquidity risk factor alternatively constructed using broker-dealer leverage from the Federal Reserve's Flow of Funds Accounts (Adrian, Etula, and Muir, 2014)[31] or using bond liquidity premiums (Fontaine and Garcia, 2012);[32] a systemic risk factor (Brownlees and Engle, 2017);[33] a yield curve factor defined as the change in the 10-year treasury constant maturity yield minus the one-year treasury constant maturity yield; two financials' ROE and (financials minus non-financials) return spread factors (Adrian, Friedman, and Muir, 2016);[34] a bank asset risk factor, defined as the VW return on the highest quintile minus the VW return on the lowest quintile, constructed using non-performing assets ratios, loan loss reserve ratios, interest income ratios,[35] or loan concentration ratios.[36] The last column adds all ten bank-specific risk factors to the factor models. Panel B adds them to FF5 and displays only the coefficients on the bank-specific risk factors since the coefficients of the FF5 factors are largely unchanged.

Table 3.7 Panel A shows the results, which are similar to those in the first column of Table 3.2 Panel C. The fact that they are obtained while controlling for bank-specific risks diminishes concerns that high-capital banks are riskier and that this somehow drives our main results. Panel B states that higher bank capital is related to higher financials' ROE, a lower (financials minus non-financials) return spread, lower non-performing assets, and higher interest income, consistent

[31] Broker-dealer leverage is defined as total financial assets of broker-dealers divided by (their total financial assets minus their total liabilities). See Table L.130 Security Brokers and Dealers of the Flow of Funds: *http://www.federalreserve.gov/apps/fof/FOFTables.aspx*. We first obtain broker-dealer leverage shocks by seasonally adjusting log changes in the level of broker-dealer leverage. We then compute the exposures (i.e., broker-dealer leverage betas) of bank excess returns on broker-dealer leverage shocks using 5-year rolling window time-series regressions. Finally, we define the broker-dealer leverage factor as the VW return difference between the highest and lowest broker dealer leverage beta quintile.

[32] Data on bond liquidity premiums are downloaded from Fontaine's website: *http://jean-sebastienfontaine.com*.

[33] Their systemic risk variable measures the capital shortfall the financial system is expected to experience conditional on a market decline. The systemic risk factor is created in a similar fashion as the broker-dealer leverage factor.

[34] Financials' ROE is defined as VW returns for financials in the highest ROE quintile minus VW returns for financials in the lowest ROE quintile. The spread is defined as VW returns for financials in excess of the market return for non-financials. Financials are all institutions with SIC codes 6000-6799 based on Compustat's *historical* SIC code, Compustat's *header* SIC code, CRSP's *historical* SIC code, and CRSP's *header* SIC code (use the first non-missing SIC code in this order).

[35] This is based on the rationale that a bank would charge higher interest rates on riskier loans.

[36] The loan concentration ratio is defined using the Herfindahl-Hirschman index (HHI): $HHI = \left(\frac{RealEstateLoans}{TotalAssets}\right)^2 + \left(\frac{CommercialandIndustrialLoans}{TotalAssets}\right)^2 + \left(\frac{ConsumerLoans}{TotalAssets}\right)^2$. Since details on loan portfolios are not available in Compustat, we use the Bank Regulatory Database to compute loan concentration ratios.

with lower bank-specific risks. Despite that, the results show that these bank-risk factors cannot fully account for the special role played by bank capital in bad times.

Table 3.7
Risk-Adjusted Returns of High- and Low-Capital Banks during Bad Times: Results Controlling for Bank-Specific Risk Factors

This table reports the difference in risk-adjusted returns of high- and low-capital banks during bad times, α_{BT} of H-L, while controlling explicitly for various bank-specific risk factors. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements. The return estimates are obtained using the following model: $R_{pt} = \alpha_0 + \alpha_{BT}BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \sum_{i=1}^{K} \beta_{BT_i} f_{it} BT_t + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below); BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility (modeled using an EGARCH(1,1) model) exceeding the 80^{th} percentile (in sample), and zero otherwise; f_{it} are factor returns in month t obtained using five linear factor models.

The bank-specific risk factors that are alternatively added to the five linear factor models used so far (and described in the next paragraph) are as follows: 1) a funding liquidity risk factor constructed using broker-dealer leverage (Adrian, Etula, and Muir, 2014); 2) a funding liquidity risk factor constructed using bond liquidity premiums Fontaine and Garcia (2012); 3) a systemic risk factor (Brownlees and Engle, 2017); 4) a term spread risk factor; 5&6) two financial institutions' ROE and (financials minus non-financials) return spread factors (Adrian, Friedman, and Muir, 2016); 7) a bank asset risk factor constructed using non-performing assets ratios; 8) a bank asset risk factor constructed using loan loss reserve ratio; 9) a bank asset risk factor constructed using interest income ratios; and 10) a bank asset risk factor constructed using loan concentration ratios. The last column adds all ten bank-specific risk factors to the factor models. Panel B adds all ten risk factors to FF5 and shows the factor loadings on the bank-specific risk factors only.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period runs from Jan. 1994 through Dec. 2015.

Panel A: Risk-Adjusted Returns of High- Minus Low-Capital (H-L) Banks during Bad Times Controlling for Additional Risk Factors

	1)	2)	3)	4)	5) and 6)	7)	8)	9)	10)	
Risk Factor(s) Added:	Broker-Dealer Leverage	Bond Liquidity Premiums	Systemic Risk	Term Spread	FROE and SPREAD	Non-performing Assets Ratios	Loan Loss Reserve Ratios	Interest Income Ratios	Loan Concentration Ratios	All 10 Risk Factors
	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L	α_{BT} of H-L
FF3	1.55%***	1.36%***	1.54%***	1.57%***	1.51%***	1.41%***	1.55%***	1.62%***	1.70%***	1.38%***
	(4.15)	(3.49)	(4.18)	(4.23)	(4.23)	(3.84)	(4.23)	(4.37)	(4.55)	(3.68)
FFC4	1.62%***	1.44%***	1.60%***	1.62%***	1.54%***	1.48%***	1.59%***	1.67%***	1.72%***	1.37%***
	(4.35)	(3.68)	(4.33)	(4.36)	(4.27)	(4.03)	(4.33)	(4.51)	(4.62)	(3.63)
FF5	1.50%***	1.30%***	1.49%***	1.51%***	1.47%***	1.38%***	1.51%***	1.57%***	1.67%***	1.37%***
	(3.98)	(3.30)	(4.02)	(4.05)	(4.08)	(3.72)	(4.08)	(4.20)	(4.42)	(3.59)
FF5+LQ	1.50%***	1.30%***	1.49%***	1.51%***	1.48%***	1.38%***	1.51%***	1.58%***	1.67%***	1.39%***
	(3.99)	(3.29)	(4.02)	(4.05)	(4.09)	(3.72)	(4.09)	(4.21)	(4.42)	(3.67)
FH9	1.70%***	1.50%***	1.68%***	1.74%***	1.48%***	1.51%***	1.60%***	1.78%***	1.87%***	1.39%***
	(4.54)	(3.82)	(4.58)	(4.65)	(4.18)	(4.14)	(4.44)	(4.76)	(4.99)	(3.72)

Panel B: Loadings on the Bank-Specific Risk Factors Only (Estimations based on FF5 plus Ten Bank-Specific Risk Factors)

	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)
Risk Factor:	Broker-Dealer Leverage	Bond Liquidity Premiums	Systemic Risk	Term Spread	FROE	SPREAD	Non-performing Assets Ratios	Loan Loss Reserve Ratios	Interest Income Ratios	Loan Concentration Ratios
Low Capital	-0.01	0.00	0.03	1.36*	-0.05	0.57***	0.14***	0.06	-0.02	0.02
	(-0.41)	(-1.17)	(0.89)	(1.89)	(-1.21)	(8.77)	(3.81)	(1.43)	(-0.32)	(0.40)
2	0.01	0.00	0.02	1.61***	0.01	0.57***	0.08***	0.07**	-0.04	0.04
	(0.48)	(-0.30)	(0.76)	(2.91)	(0.46)	(11.35)	(2.98)	(2.31)	(-0.90)	(1.11)
3	0.02	0.00	0.03	1.07**	-0.03	0.54***	0.06**	0.15***	0.00	0.04
	(0.67)	(-1.10)	(1.06)	(1.99)	(-0.88)	(11.09)	(2.13)	(4.73)	(-0.10)	(1.17)
4	-0.01	0.00	0.03	0.42	-0.03	0.53***	0.05*	0.07**	0.04	0.06
	(-0.39)	(-0.26)	(1.18)	(0.80)	(-0.99)	(11.09)	(1.77)	(2.20)	(0.95)	(1.56)
High Capital	0.01	0.00	0.08***	0.92*	0.02	0.45***	0.07***	0.01	0.06*	0.05
	(0.27)	(-0.07)	(2.73)	(1.74)	(0.65)	(9.46)	(2.71)	(0.40)	(1.69)	(1.31)
H - L	0.02	0.00	0.04	-0.44	0.07*	-0.12**	-0.07**	-0.05	0.08*	0.03
	(0.66)	(1.22)	(1.22)	(-0.67)	(1.85)	(-1.99)	(-1.98)	(-1.25)	(1.70)	(0.61)

Table 3.8
Risk-Adjusted Returns of High- and Low-Capital Banks during Bad Times: Results Controlling for Differences in (Market) Betas

This table reports the difference in risk-adjusted returns of high- and low-capital banks during bad times, α_{BT} of H-L, while controlling for differences in (market) betas. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements. The return estimates are obtained using the following model: $R_{pt} = \alpha_0 + \alpha_{BT}BT_t + \sum_{i=1}^{K} \beta_i f_{it} + \sum_{i=1}^{K} \beta_{BT_i} f_{it} BT_t + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below); BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility (modeled using an EGARCH(1,1) model) exceeding the 80^{th} percentile (in sample), and zero otherwise; f_{it} are factor returns in month t obtained using five linear factor models.

We control for differences in (market) betas as follows. Portfolios are rebalanced monthly: at the beginning of month t, we first sort bank stocks into terciles based on their betas (estimated using monthly returns over a 60-month (minimum: 24-month) rolling window). We then independently sort bank stocks into terciles within each beta tercile based on their capital ratio and size to form 27 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. In this setup, banks in each capital ratio tercile have roughly comparable betas. Next, we compute monthly VW average returns for the 27 portfolios. We calculate returns for each capital ratio tercile as the simple average of the 9 beta-size tercile portfolio returns. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

	α_{BT} of H-L
FF3	0.82%***
	(3.02)
FFC4	0.83%***
	(3.05)
FF5	0.79%***
	(2.89)
FF5+LQ	0.80%***
	(2.94)
FH9	0.86%***
	(3.27)

3.3.1.7 Control for (market) betas

While the previous section ameliorates the concern that high-capital banks may be riskier, it brings up a new issue. Frazzini and Pedersen (2014) and Baker and Wurgler (2015) report that high (low) beta assets are associated with low (high) alphas. They argue that a factor based upon differences in betas, a "betting-against-beta" factor, may be needed in addition to the typical market factor to better explain the cross-section of stock returns.

To formally address this concern, we perform an analysis that aims to explicitly control for the effects of beta. Specifically, at the beginning of month t, we first sort bank stocks into terciles based on their market betas, which are estimated using monthly returns over a 60-month (minimum: 24) rolling window. We then independently sort bank stocks within each beta tercile based on their capital ratio and size (market capitalization) to form 27 portfolios. In this setup, banks in each capital ratio tercile have roughly comparable betas. Next, we compute monthly VW average returns for the 27 portfolios. We calculate returns for each capital ratio tercile as the simple average of the 9 beta-size tercile portfolio returns. If the "betting-against-beta" factor produced our result, the conditional alpha estimates from these tests should be insignificant.

Table 3.8 shows that our main conclusion remains: high-capital banks earn higher risk-adjusted returns than low-capital banks in bad times, even after taking into account the anomaly of "betting against beta."[37] Internet Appendices IA.1.6 and IA.1.7 (with panel and Fama-Macbeth regressions) further confirm this.

3.3.1.8 Additional robustness check shown in the Internet Appendix

The Internet Appendix additionally shows that our in-sample results: are not driven by the recent financial crisis, and are robust to using seven alternative bad times proxies and to using their union or intersection sets (Section IA.1.1); are not caused by banks that delisted for performance-related reasons (Section IA.1.2); are robust to the use of benchmark-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997) (Section IA.1.3); are comparable using data from the Bank Regulatory Database (Section IA.1.4); are robust to using regulatory and market-based capital ratios (Section IA.1.5), panel regressions (Section IA.1.6), and Fama-MacBeth regressions (Section IA.1.7); and hold using value-added performance measures (Berk and van Binsbergen, 2015) (Section IA.1.8).

[37] The coefficients are smaller than those shown in the first column of Table 3.2 Panel C, but this is not surprising since we triple sort by beta, capital ratio and size ($3 \times 3 \times 3 = 27$ portfolios). Sorting stocks into quintiles would have yielded 125 ($5 \times 5 \times 5$) portfolios and would have raised concerns about the effects of each portfolio containing relatively few stocks.

3.3.2 High-capital banks outperform low-capital banks *out of sample*

3.3.2.1 Main out-of-sample methodology and results

To assess out-of-sample performance, it is necessary to use trading strategies conditional upon predicted bad times. To our knowledge, conditional trading strategies have not been explored in the literature - our approach is novel and can be useful in future studies. We create five alternative trading strategies, summarized in Table 3.9 Panel A. Our main strategy, Strategy #1, is the simplest: it buys high-capital banks and sells low-capital banks during times *predicted* to be bad (H-L), and does nothing during other times ($\varnothing$). Our main out-of-sample bad times proxy defines month t to be bad if VW bank stock return volatility is *forecasted* to be greater than the 80^{th} percentile of bank stock return volatility from Jan. 1984 to month $t-1$.

The remaining four strategies also buy high-capital banks and sell low-capital banks during times predicted to be bad, but differ in what to do during other times. We split such times into two regions: predicted OK times versus predicted good times (stock return volatility is forecasted to be in between the 80^{th} and 20^{th} percentiles versus lower than the 20^{th} percentile of bank stock return volatility from Jan. 1984 to month $t-1$, respectively). During times predicted to be OK, the other strategies alternatively buy high-capital banks and sell low-capital banks (H-L), do the exact opposite (L-H), or do nothing ($\varnothing$). During times predicted to be good, the other strategies do not buy high-capital banks and sell low-capital banks: they do the exact opposite (L-H) or do nothing ($\varnothing$).

Risk-adjusted returns per trading strategy are obtained using the following factor model:

$$R_{pt} = \alpha + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}, \tag{3.3.3}$$

where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles. f_{it} are factor returns in month t obtained using the five linear factor models discussed in Section 3.2. Our analyses examine which trading strategies yield significantly positive risk-adjusted returns.

Table 3.9
Trading Performance of High- and Low-Capital Portfolios

This table formulates five alternative trading strategies buying and selling portfolios of high- and low-capital banks during times predicted to be bad / OK / good, and reports their performance. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements.

Panel A presents five trading strategies which buy and sell high- and low-capital banks (or do nothing) during times predicted to be bad / OK / good, defined as month t in which VW bank stock return volatility is forecasted to be greater than the 80^{th} percentile / in between the 20th and 80^{th} percentiles / lower than the 20^{th} percentile of VW bank stock return volatility from Jan. 1984 to month $t-1$. Stock return volatility is modeled using an EGARCH(1,1) model. 'H-L' denotes buying high-capital banks and selling low-capital banks, 'L-H' denotes the opposite, '$\varnothing$' implies no trading. Panel B summarizes the trading performance by showing raw, risk-unadjusted returns and Sharpe ratios. Panel C estimates risk-adjusted returns per trading strategy using a linear factor model: $R_{pt} = \alpha + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles and f_{it} are factor returns in month t obtained using five linear factor models.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. When forming portfolios, bank size is measured as Market Cap (the number of shares outstanding times the share price measured at the beginning of month t). Panel D uses the book value of assets instead to measure bank size. Panel E estimates risk-adjusted returns using FF5, the Fama-French 5-factor model, for trading strategies that use alternative cut-offs to determine bad / OK / good times. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

Panel A: Five Alternative Trading Strategies

Volatility Regime:	Strategy #1	Strategy #2	Strategy #3	Strategy #4	Strategy #5
High 20% (*Predicted* Bad Times)	H-L	H-L	H-L	H-L	H-L
Medium 60% (*Predicted* OK Times)	$\varnothing$	H-L	L-H	H-L	$\varnothing$
Low 20% (*Predicted* Good Times)	$\varnothing$	$\varnothing$	L-H	L-H	L-H

Panel B: Summary of Trading Performance

	Strategy #1	Strategy #2	Strategy #3	Strategy #4	Strategy #5
Annualized Mean Raw Returns	3.32%**	2.29%	5.33%***	3.28%*	4.30%***
	(2.59)	(1.19)	(2.74)	(1.67)	(3.22)
Annualized Sharpe Ratio	0.55	0.25	0.58	0.36	0.69

Table 3.9 Continued

Panel C: Risk-Adjusted Returns of Trading Strategies

	Strategy #1	Strategy #2	Strategy #3	Strategy #4	Strategy #5
	α	α	α	α	α
FF3	0.37%***	0.36%**	0.46%***	0.43%***	0.45%***
	(3.66)	(2.37)	(2.82)	(2.79)	(4.19)
FFC4	0.33%***	0.32%**	0.42%**	0.39%**	0.40%***
	(3.27)	(2.09)	(2.55)	(2.48)	(3.78)
FF5	0.31%***	0.29%*	0.40%**	0.35%**	0.38%***
	(2.90)	(1.82)	(2.30)	(2.18)	(3.36)
FF5+LQ	0.30%***	0.29%*	0.38%**	0.35%**	0.36%***
	(2.82)	(1.80)	(2.17)	(2.13)	(3.22)
FH9	0.31%***	0.26%	0.43%**	0.33%*	0.38%***
	(2.72)	(1.57)	(2.39)	(1.97)	(3.23)

Panel D: Risk-Adjusted Returns of Trading Strategies Using Total Assets instead of Market Cap to Measure Size when Forming Portfolios

	Strategy #1	Strategy #2	Strategy #3	Strategy #4	Strategy #5
	α	α	α	α	α
FF3	0.45%***	0.36%**	0.63%***	0.44%**	0.53%***
	(4.31)	(2.11)	(3.63)	(2.50)	(4.68)
FFC4	0.42%***	0.30%*	0.61%***	0.38%**	0.49%***
	(3.97)	(1.77)	(3.48)	(2.14)	(4.31)
FF5	0.41%***	0.30%*	0.62%***	0.39%**	0.51%***
	(3.74)	(1.66)	(3.42)	(2.13)	(4.24)
FF5+LQ	0.42%***	0.30%*	0.62%***	0.39%**	0.50%***
	(3.76)	(1.68)	(3.36)	(2.09)	(4.17)
FH9	0.36%***	0.23%	0.57%***	0.30%*	0.44%***
	(3.36)	(1.30)	(3.07)	(1.69)	(3.71)

Panel E: FF5 Risk-Adjusted Returns of Trading Strategies using Different Cut-Offs for Times Predicted to be Bad / OK / Good

	Strategy #1	Strategy #2	Strategy #3	Strategy #4	Strategy #5
	α	α	α	α	α
High 20% / Medium 60% / Low 20%	0.31%***	0.29%*	0.40%**	0.35%**	0.38%***
	(2.90)	(1.82)	(2.30)	(2.18)	(3.36)
High 30% / Medium 40% / Low 30%	0.37%***	0.36%**	0.52%***	0.50%***	0.51%***
	(3.00)	(2.36)	(3.05)	(3.13)	(3.89)
High 40% / Medium 20% / Low 40%	0.40%***	0.39%**	0.58%***	0.56%***	0.57%***
	(3.14)	(2.58)	(3.44)	(3.44)	(4.06)
High 50% / Low 50%	0.38%***	0.38%***	0.54%***	0.54%***	0.54%***
	(2.71)	(2.71)	(3.24)	(3.24)	(3.24)

Table 3.9 examines the performance of the trading strategies summarized in Panel A. For brevity, the discussion focuses on Strategy #1, our main strategy, which buys high-capital banks and sells low-capital banks during times predicted to be bad and does nothing in other times.

As a first step, Table 3.9 Panel B summarizes banks' trading performance by presenting their annualized mean raw returns and their annualized Sharpe ratios. Strategy #1 yields annualized mean *raw* returns of 3.32% and has an annualized Sharpe ratio of 0.55.

Table 3.9 Panel C estimates each trading strategy's *risk-adjusted* returns.[38] Strategy #1 yields positive and significant *risk-adjusted* returns ranging from 0.30% to 0.37% per month depending on the factor model used. This translates into annual returns ranging from 3.60% to 4.44%. The results in this panel are based on portfolio sorts by bank capital and size, measured as market capitalization. Table 3.9 Panel D shows that when we instead use (the book value of) total assets to measure bank size, the results are comparable or stronger. Table 3.9 Panel E changes the stock return volatility cut-offs to determine bad / OK / good times. We now view months in which stock return volatility is forecasted to be in the top 20%, 30%, 40%, or 50% to be bad times and, similarly, times in which it is forecasted to be in the bottom 20%, 30%, 40%, or 50% to be good times. The results shown all use the Fama-French 5-factor model. The results seem highly robust: Strategy #1 yields significantly positive risk-adjusted abnormal returns regardless of the cut-offs used.[39]

In every panel, the other strategies convey a similar message: results tend to be stronger based on Strategies #3 and #5, and somewhat weaker for Strategies #2 and #4. This also tends to hold in the robustness tests presented below. For brevity, the discussion therefore focuses on Strategy #1, but the results based on the other strategies are in Internet Appendix IA.2.1.

[38]We obtain comparable results when portfolios are rebalanced annually at the end of June as in Fama and French (1993). See footnote 23 for further details. (Results available from the authors.)

[39]In the bottom row, the performance of strategies #1 and #2 is identical, as is the performance of strategies #3 - #5. The reason is that these strategies differ only in the actions taken during times predicted to be OK. Since the bottom row only distinguishes between bad and good times (stock return volatility forecasted to be in the top and bottom 50%, respectively), OK times are non-existent.

Table 3.10

Trading Performance of High- and Low-Capital Portfolios during Bad Times: Results Controlling for Gandhi and Lustig (2015)'s Size Effect

This table controls for Gandhi and Lustig (2015)'s size effect. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements.

The table shows the risk-adjusted returns of trading strategy #1, which buys high-capital banks and sells low-capital banks during times predicted to be bad, and does nothing during other times. A month is predicted to be a bad time if that month's VW bank stock return volatility is forecasted to be greater than the 80^{th} percentile of bank stock return volatility from Jan. 1984 to month $t-1$. Stock return volatility is modeled using an EGARCH(1,1) model. Risk-adjusted returns are estimated using a linear factor model: $R_{pt} = \alpha + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below). f_{it} are factor returns in month t obtained using five linear factor models.

Gandhi and Lustig (2015)'s size effect is controlled for by alternatively: 1) excluding banks in the largest size quintile when computing returns for each capital ratio quintile; and 2) controlling for Gandhi and Lustig (2015)'s size factor, which is replicated as follows. At the beginning of January in each year of our sample period (1994 - 2015), we sort bank stocks into deciles based on their market capitalization and compute VW average returns across deciles over the year. Using these ten portfolios, we estimate residuals from a five factor model, which includes Fama-French's three factors and two bond factors: *ltg*, the monthly change in the 10-year Treasury constant maturity yield less the one-month Treasury bill rate, and *crd*, the monthly change in Moody's Baa yield less the one-month Treasury bill rate.) We then run a principal component analysis for the residuals. Finally, the size factor is defined as the product of the normalized weights for the second principal component and the residuals of the ten portfolios.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the four smallest size quintile portfolio returns in the first column, and as the simple average of all five size quintiles in the second column. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Risk-Adjusted Returns of Trading Strategy #1 while:			
Excluding Banks in the Largest Size Quintile		Controlling for Gandhi and Lustig (2015)'s Size Factor	
	α		α
FF3	0.41%***	FF3 + GL	0.37%***
	(4.15)		(3.66)
FFC4	0.39%***	FFC4 + GL	0.33%***
	(3.91)		(3.27)
FF5	0.34%***	FF5 + GL	0.31%***
	(3.30)		(2.92)
FF5+LQ	0.33%***	FF5+LQ + GL	0.31%***
	(3.14)		(2.83)
FH9	0.33%***	FH9 + GL	0.30%***
	(2.98)		(2.71)

3.3.2.2 Trading performance while controlling for Gandhi and Lustig (2015)'s size effect

Section 3.3.1.3 showed that our in-sample results are not driven by Gandhi and Lustig (2015)'s size effect. We now examine whether the out-of-sample results are also robust to alternatively excluding banks in the largest size quintile and controlling for Gandhi and Lustig (2015)'s size factor.

Table 3.10 shows that we obtain results that are similar to those in the first column of Table 3.9 Panel C, suggesting that our results are not driven by Gandhi and Lustig (2015)'s size effect.

3.3.2.3 Trading performance controlling for bank-specific risk factors

As indicated in Section 3.3.1.6, our use of commonly-used asset pricing models may be inappropriate because they may not adequately capture bank-specific risks. We rerun the main out-of-sample regressions while adding the bank-specific risk factors introduced in that section to the five factor models. As before, we first add (most of) them one by one and then add all ten factors to each model.

Table 3.11 shows that Strategy #1 yields positive and significant risk-adjusted returns in every panel, which is similar to the findings presented in the first column of Table 3.9 Panel C. These results are obtained while controlling for bank-specific risks, diminishing concerns that our main results are driven by high-capital banks being riskier than low-capital banks.

3.3.2.4 Trading performance controlling for short sale constraints

Our trading strategies buy high-capital banks and short low-capital banks in times predicted to be bad. A critical assumption that we have made so far is that bank stocks can be bought and sold without restrictions. In practice, there may be short-selling constraints which prevent investors from shorting bank stocks. If it is harder to short low-capital banks, which show far worse risk-adjusted stock performance than high-capital banks during bad times (-2.18% versus -0.68%: Table 3.2 Panel B), it is possible that our trading strategies do not yield positive abnormal returns after taking into account short sale constraints. To address this, we use three approaches.

Table 3.11

Trading Performance of High- and Low-Capital Portfolios during Bad Times: Results Controlling for Bank-Specific Risk Factors

This table controls for various bank-specific risk factors. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements.

The table shows the risk-adjusted returns of trading strategy #1, which buys high-capital banks and sells low-capital banks during times predicted to be bad, and does nothing during other times. A month is predicted to be a bad time if that month's VW bank stock return volatility is forecasted to be greater than the 80^{th} percentile of bank stock return volatility from Jan. 1984 to month $t-1$. Stock return volatility is modeled using an EGARCH(1,1) model. Risk-adjusted returns are estimated using a linear factor model: $R_{pt} = \alpha + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below). f_{it} are factor returns in month t obtained using five linear factor models. To these models, we add bank-specific risk factors: 1) a funding liquidity risk factor constructed using broker and dealer leverage (Adrian, Etula, and Muir, 2014); 2) a funding liquidity risk factor constructed using bond liquidity premiums (Fontaine and Garcia, 2012); 3) a systemic risk factor (Brownlees and Engle, 2017); 4) a term spread risk factor; 5&6) two financial institutions' ROE and (financials minus non-financials) return spread factors (Adrian, Friedman, and Muir, 2016); 7) a bank asset risk factor constructed using non-performing assets ratios; 8) a bank asset risk factor constructed using loan loss reserve ratio; 9) a bank asset risk factor constructed using interest income ratios; and 10) a bank asset risk factor constructed using loan concentration ratios. The last column adds all ten bank-specific risk factors to the factor models.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

	1)	2)	3)	4)	5) and 6)	7)	8)	9)	10)	
Risk Factor(s) Added:	Broker-Dealer Leverage	Bond Liquidity Premiums	Systemic Risk	Term Spread	FROE and SPREAD	Non-performing Assets Ratios	Loan Loss Reserve Ratios	Interest Income Ratios	Loan Concentration Ratios	All 10 Risk Factors
	α	α	α	α	α	α	α	α	α	α
FF3	0.35%***	0.38%***	0.36%***	0.37%***	0.32%***	0.33%***	0.37%***	0.38%***	0.36%***	0.30%***
	(3.47)	(3.77)	(3.56)	(3.63)	(3.16)	(3.23)	(3.64)	(3.70)	(3.53)	(2.94)
FFC4	0.31%***	0.34%***	0.33%***	0.34%***	0.30%***	0.30%***	0.34%***	0.34%***	0.33%***	0.29%***
	(3.12)	(3.38)	(3.24)	(3.28)	(3.00)	(2.90)	(3.32)	(3.30)	(3.24)	(2.83)
FF5	0.28%***	0.31%***	0.31%***	0.31%***	0.27%**	0.29%***	0.31%***	0.32%***	0.31%***	0.25%**
	(2.72)	(2.96)	(2.95)	(2.87)	(2.54)	(2.66)	(2.89)	(2.96)	(2.90)	(2.44)
FF5+LQ	0.29%***	0.30%***	0.31%***	0.30%***	0.27%**	0.28%***	0.31%***	0.31%***	0.30%***	0.26%**
	(2.73)	(2.84)	(2.90)	(2.77)	(2.52)	(2.60)	(2.85)	(2.87)	(2.81)	(2.49)
FH9	0.32%***	0.32%***	0.28%**	0.31%***	0.30%***	0.26%**	0.31%***	0.31%***	0.29%***	0.31%***
	(2.97)	(2.89)	(2.55)	(2.78)	(2.86)	(2.30)	(2.87)	(2.75)	(2.60)	(2.91)

Our first approach excludes stocks with substantial short sale constraints. In those cases, there is strong demand to sell such stocks short, while the supply of shares to borrow is limited. To classify a stock as short sale constrained, we first calculate its short demand, defined as short interest (i.e., the number of common shares shorted) over the total number of shares outstanding. Short interest data on a sufficiently large number of stocks are available in Compustat from August 2003 onward, so the sample period for this analysis is restricted to August 2003 through December 2015. In line with the literature on firms in general (Dechow, Hutton, Meulbroek, and Sloan, 2001), the short demand distribution is highly skewed: no short positions are observed for 1% of the observations; 86% have small short positions; and 13% have over 5% of their outstanding shares shorted. We view bank stocks as short sale constrained if their short demand is over 5%.[40]

The second approach excludes a period during which the SEC placed a temporary ban on short sales in 797 financial stocks (Kolasinski, Reed, and Thornock, 2013; Boehmer, Jones, and Zhang, 2013). While the ban only lasted a few weeks (Sept. 18 - Oct. 8, 2008), it spanned two quarters. To be conservative, we therefore exclude 2008:Q3 and 2008:Q4 from our sample period.

The third approach focuses on lending fees. A recent literature argues that borrowing stock and selling it short is risky since stock loans can be recalled at any time. As a result, future stock lending fees are uncertain and this hinders short-selling. Muravyev, Pearson, and Pollet (2016), however, show that investors can avoid this uncertainty because they can use the option market to establish a synthetic short position at a fixed lending fee. We identify the periods when stocks are shorted and the NYSE size decile each bank stock belongs to. We adjust stock returns by the option-implied lending fees obtained from Table 1 in Muravyev, Pearson, and Pollet (2016): 0.250% for size deciles 1 - 4, 0.375% for size deciles 5 - 9, and 1.000% for size decile 10.

Table 3.12 shows that our main findings are intact even after addressing short-sale constraints using these three approaches.[41] This highlights the economic significance of our results.

[40]Dechow, Hutton, Meulbroek, and Sloan (2001) classify firms with over 0.5% (5%) of outstanding shares shorted as firms with "high" ("very large") short positions. If we use the 0.5% cutoff, we lose more than half of the sample. In that case, the results are weaker but generally remain significant.

[41]It may be surprising that the effects in first column tend to be stronger (higher alphas and greater significance) than those in Table 3.9 Panel C. This is driven by the shorter sample period: the results are slightly weaker compared to results based on a sample from Aug. 2003 - Dec. 2015 that does not drop these stocks (untabulated for brevity).

Table 3.12
Trading Performance of High- and Low-Capital Portfolios: Results Controlling for Short Sale Constraints

This table recognizes that short-selling constraints may exist which prevent investors from shorting bank stocks and uses three alternative approaches to address this. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements.

The table shows the risk-adjusted returns of trading strategy #1, which buys high-capital banks and sells low-capital banks during times predicted to be bad, and does nothing during other times. A month is predicted to be a bad time if that month's VW bank stock return volatility is forecasted to be greater than the 80^{th} percentile of bank stock return volatility from Jan. 1984 to month $t-1$. Stock return volatility is modeled using an EGARCH(1,1) model. Risk-adjusted returns are estimated using a linear factor model: $R_{pt} = \alpha + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where R_{pt} are monthly portfolio returns in excess of the one-month Treasury bill rate for bank stocks sorted into capital ratio quintiles (explained below). f_{it} are factor returns in month t obtained using five linear factor models.

Results are shown for three short-sale-constraints approaches. (1) Exclude stocks with substantial short sale constraints. To classify a stock as short sale constrained, we first calculate its short demand, defined as short interest (i.e., the number of common shares shorted) over the total number of shares outstanding. Short interest data are available from Compustat from Aug. 2003 onward, so the sample period for this analysis is restricted to Aug. 2003 through Dec. 2015. We view bank stocks as short sale constrained if their short demand is over 5%. (2) Remove 2008:Q3 and 2008:Q4, which includes several weeks (Sept. 18, 2008, through Oct. 8, 2008) during which the SEC imposed a temporary ban on short sales in 797 financial stocks. (3) Control for option-implied stock lending fees.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

	Risk-Adjusted Returns of Trading Strategy #1 while:		
	(1)	(2)	(3)
	Excluding Bank Stocks with Short Interest greater than 5%	Excluding SEC's Temporary Ban on Short Sales Period	Controlling for Option-Implied Stock Lending Fees
	α	α	α
FF3	0.53%***	0.27%***	0.37%***
	(3.23)	(2.92)	(3.60)
FFC4	0.48%***	0.23%**	0.33%***
	(3.02)	(2.50)	(3.21)
FF5	0.43%***	0.26%***	0.30%***
	(2.66)	(2.63)	(2.85)
FF5+LQ	0.42%**	0.23%**	0.30%***
	(2.55)	(2.33)	(2.76)
FH9	0.50%***	0.24%**	0.30%***
	(2.76)	(2.34)	(2.67)

3.3.2.5 Additional robustness checks shown in the Internet Appendix

The Internet Appendix shows that our out-of-sample results: are robust to using alternative trading strategies (Section IA.2.1), different bad times proxies and their union or intersection (Section IA.2.2), and to using regulatory and market-based capital ratios (Section IA.2.3); and continue to hold even after taking trading costs into account (Frazzini, Israel, and Moskowitz, 2015) (Section IA.2.4) and when using ex ante expected returns (Section IA.2.5).

3.4 Why Do High-Capital Banks Outperform Low-Capital Banks during Bad Times?

This section addresses the second question: Why do high-capital banks outperform low-capital banks during bad times? It explores two possible channels: an "Informed Investor Channel" and a "Surprised Investor Channel."

3.4.1 "Informed Investor Channel"

It is possible that trading between informed and uninformed investors causes our results. Informed investors may be more cognizant than uninformed investors of the benefits of owning high-capital banks in bad times and may be better able to predict when bad times occur. It is then conceivable that informed investors continue to sell low-capital stocks to (and/or buy high-capital stocks from) uninformed investors during bad times, influencing the prices of these banks. The relative advantage of informed investors can affect the degrees of downward price pressure on low-capital stocks and upward price pressure on high-capital stocks, and this may explain the outperformance of high-capital banks during bad times.

To investigate this "Informed Investor Channel," we focus on institutional investors, who are generally considered to be informed investors and as such may drive stock returns (Badrinath, Kale, and Noe, 1995; Bennett, Sias, and Starks, 2003; Irvine, Lipson, and Puckett, 2007; Boehmer and Kelley, 2009; Campbell, Ramadorai, and Schwartz, 2009; Boulatov, Hendershott, and Livdan, 2013; Hendershott, Livdan, and Schürhoff, 2015). Specifically, we examine whether institutional investors reduce their holdings of low-capital bank stocks and/or increase their holdings of high-capital bank stocks during bad times. We obtain quarterly institutional ownership of banks data from Thomson Reuters' 13F (formerly known as CDA/Spectrum) database. Institutional ownership is defined as the number of shares held by institutional investors over the number of shares outstanding. At each quarter end, we independently sort bank stocks into quintiles based on their capital ratio (book equity over total assets from Compustat's quarterly database) and size (market capitalization) to form 25 portfolio. We compute VW average institutional ownership for each of these portfolios. Institutional ownership for each capital ratio quintile is then calculated as the simple average of institutional ownership in the five size quintile portfolios. Since institutional investor data are only available quarterly, bad times are now quarters during which all three months are bad (i.e., have high stock return volatility). Internet Appendix Table IA.16 shows similar results using EW average institutional ownership and when bad times are quarters during which at least two months are bad.

Table 3.13 Panel A shows that unconditionally, low-capital banks have slightly greater institutional ownership than high-capital banks (see first column: 29.99% vs 28.64%).[42] Importantly, the last two columns show that institutional ownership of low-capital banks is rather stable across normal times and bad times, as is their ownership of high-capital banks. Thus, the relative outperformance of high-capital banks during bad times does not seem to be driven by institutional investors dumping shares of low-capital banks and/or buying sizeable stakes in high-capital banks during such times. Figure 3.4, which shows institutional ownership of high- and low-capital banks over time, seems to corroborate these findings.[43] Ownership of low-capital banks tends to be higher through the middle of 2010, when ownership of high-capital banks increased substantially.[44] But again, for our purposes, it is the difference in ownership across bad and other times that matters rather than the level of ownership per se. The figure does suggest that during the recent financial

[42]A recent working paper by Garel, Petit-Romec, and Vander Vennet (2018) shows panel regressions which suggest the exact opposite. The discrepancy is driven by our definition of bank size: consistent with our main analysis, Table 3.13 defines size to be market capitalization. Internet Appendix Table IA.16 shows that when we instead define bank size to be total assets, we obtain their result: high-capital banks have higher institutional ownership. Importantly, however, using either definition we obtain the result (detailed in the rest of this section) that institutional investor behavior is rather similar across normal times and bad times and hence does not seem to drive our results.

[43]Figure 3.1 Panel A shows an extra bad time in 2012 because it uses monthly instead of quarterly data.

[44]It is outside the scope of this paper to examine what drives the big increase in institutional ownership in high-capital banks after the crisis. It is not driven by outliers: the increase occurs among both small banks (lowest two size quintiles) and large banks (highest two size quintiles), although the increase is greatest among small banks.

Table 3.13
Informed Investor Channel: Institutional Ownership of Banks

This table explores the "Informed Investor Channel." It contains institutional ownership of banks by capital ratio quintile for the full sample period (1994Q1 - 2015Q4) and separately during bad times and normal times. Institutional ownership is measured quarterly as the number of shares held by institutional investors in Thomson Reuters' 13F database over the total number of shares. At each quarter end, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. The capital ratio is defined as book equity over total assets using Compustat's quarterly financial statements, while size is defined as market capitalization, the number of shares outstanding times the share price. Next, we compute VW average institutional ownership for the 25 portfolios. Institutional ownership for each capital ratio quintile is then calculated as the simple average of institutional ownership in the five size quintile portfolios. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. Bad times are the (calendar) quarters during which all three months of the quarter have $BT_t = 1$. BT_t is a dummy = 1 if month t is bad, defined as bank stock return volatility (modeled using an EGARCH(1,1) model) exceeding the 80^{th} percentile (in sample), and zero otherwise. Normal times represent the (calendar) quarters excluding bad times.

Panel A shows total institutional ownership of banks by capital ratio quintile. Panels B-D categorize institutional investors by their investment type, style, or horizon (based on Brian Bushee's classifications).

Panel A: Institutional Ownership of Banks

	Full Sample	Normal Times	Bad Times
Low capital	29.99%	30.05%	29.64%
2	27.50%	27.71%	26.33%
3	27.13%	27.26%	26.44%
4	26.59%	26.47%	27.28%
High capital	28.64%	28.88%	27.25%

Panel B: Institutional Ownership of Banks by Investor Type

Type	Bank	Insurance Co.	Inv. Co.	Inv. Advisor	Corporate Pension Fund	Public Pension Fund	University and Foundation	Others
				Full Sample				
Low capital	5.54%	1.83%	4.91%	16.67%	0.56%	1.16%	0.15%	2.52%
2	5.75%	1.71%	4.53%	14.65%	0.49%	1.12%	0.25%	2.40%
3	5.76%	1.79%	4.59%	14.16%	0.42%	1.11%	0.25%	2.61%
4	5.50%	1.54%	4.57%	14.69%	0.67%	1.10%	0.18%	2.16%
High capital	4.47%	1.72%	4.94%	17.30%	0.48%	1.09%	0.39%	2.33%
				Normal Times				
Low capital	5.43%	1.81%	4.93%	16.84%	0.57%	1.16%	0.15%	2.55%
2	5.77%	1.71%	4.56%	14.79%	0.49%	1.14%	0.27%	2.34%
3	5.81%	1.83%	4.63%	14.18%	0.41%	1.10%	0.27%	2.53%
4	5.48%	1.53%	4.52%	14.64%	0.62%	1.11%	0.18%	2.10%
High capital	4.43%	1.67%	5.06%	17.46%	0.48%	1.10%	0.39%	2.40%
				Bad Times				
Low capital	6.16%	1.89%	4.80%	15.68%	0.49%	1.17%	0.17%	2.36%
2	5.60%	1.65%	4.31%	13.79%	0.46%	1.04%	0.14%	2.73%
3	5.45%	1.60%	4.42%	14.07%	0.46%	1.14%	0.12%	3.01%
4	5.59%	1.58%	4.81%	14.99%	0.96%	1.09%	0.13%	2.45%
High capital	4.72%	2.01%	4.25%	16.40%	0.49%	1.03%	0.34%	1.95%

Table 3.13 Continued

Panel C: Institutional Ownership of Banks by Investment Style

Type	Large/Value Style	Large/Growth Style	Small/Value Style	Small/Growth Style
Full Sample				
Low capital	11.61%	5.82%	10.41%	3.77%
2	11.29%	5.59%	8.93%	3.18%
3	10.78%	5.70%	9.40%	3.03%
4	10.29%	5.16%	9.83%	3.20%
High capital	9.96%	5.19%	10.95%	4.65%
Normal Times				
Low capital	11.47%	5.93%	10.41%	3.90%
2	11.29%	5.70%	8.97%	3.19%
3	10.77%	5.78%	9.39%	2.94%
4	10.11%	5.18%	9.75%	3.33%
High capital	9.89%	5.33%	10.97%	4.74%
Bad Times				
Low capital	12.42%	5.23%	10.45%	3.01%
2	11.34%	4.93%	8.69%	3.12%
3	10.82%	5.23%	9.44%	3.55%
4	11.35%	5.06%	10.31%	2.50%
High capital	10.32%	4.37%	10.80%	4.16%

Panel D: Institutional Ownership of Banks by Investment Horizon

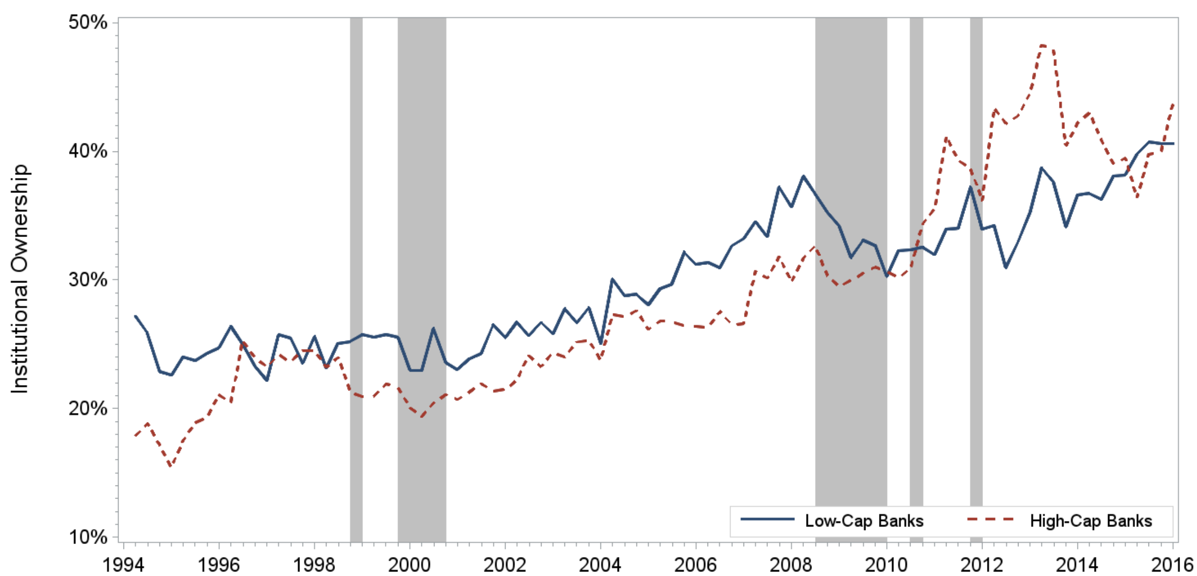
Type	Dedicated	Quasi-Indexer	Transient
Full Sample			
Low capital	5.59%	20.36%	6.17%
2	4.82%	19.45%	5.04%
3	4.97%	19.10%	5.12%
4	4.93%	18.42%	5.28%
High capital	6.12%	18.68%	6.31%
Normal Times			
Low capital	5.91%	20.28%	5.96%
2	5.22%	19.52%	4.90%
3	5.21%	19.11%	4.96%
4	5.18%	18.27%	5.08%
High capital	6.12%	18.78%	6.18%
Bad Times			
Low capital	3.75%	20.84%	7.34%
2	2.52%	19.02%	5.85%
3	3.59%	19.02%	6.07%
4	3.45%	19.34%	6.40%
High capital	6.08%	18.11%	7.08%

crisis, institutional investors dropped low-capital banks more so than they did high-capital banks. However, as indicated before, all our results continue to hold when we exclude that crisis.

Figure 3.4
Exploring the Informed Investor Channel: Institutional Ownership of Banks over Time

This figure depicts institutional ownership of high- and low-capital banks over our sample period (Jan. 1994 - Dec. 2015). Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements.

Institutional ownership of high- and low-capital banks is calculated as follows. Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization, the number of shares outstanding times the share price. Next, we compute monthly VW average institutional ownership for the 25 portfolios. We calculate ownership for each capital ratio quintile as the simple average of ownership in the five size quintile portfolios.



It is possible that our focus on total institutional ownership masks dissimilar behaviors by different groups of institutional investors. If one group is better able to anticipate future performance of banks, only that group trades in a way that drives the return pattern we find. To address this, we perform three alternative splits using investor classification data from Brian Bushee's website.[45]

[45] See: *http://acct.wharton.upenn.edu/faculty/bushee*.

First, we split institutions by investor type. It is well-known that Spectrum's investor type code variable is not reliable after 1998, when Thomson-Reuters integrated data from Technimetrics: many institutions were improperly classified as "others" (code 5). Bushee corrected these data and distinguishes between eight investor types, which we use here: banks (Spectrum type code 1), insurance companies (code 2), investment companies (code 3), independent investment advisors (type 4), corporate (private) pension funds (code 5), public pension funds (code 5), university and foundation endowments (code 5), and others (code 5). Second, we classify institutions based on their investment styles or preferences for firm size and growth into four groups as in Abarbanell, Bushee, and Smith Raedy (2003): large/value, large/growth, small/value, and small/growth. Third, we split investors based on their expected investment horizon into three groups as in Bushee (2001): dedicated investors (long-term investors with large stakes and low turnover), quasi-indexers (long-term investors with a passive buy-and-hold investment strategy), and transient investors (short-term investors with high portfolio turnover and highly diversified holdings).

Panels B-D show that, regardless of how we split institutional investors into different groups, each group's ownership of low-capital banks is rather similar across normal times and bad times. The same holds for their ownership of high-capital banks. Thus, it does not seem that differential institutional investor behavior drives our results.

3.4.2 "Surprised Investor Channel"

Another potential reason for why high-capital bank stocks outperform low-capital bank stocks during bad times is that investors may be unaware of the value of high capital during bad times or underestimate the likelihood and severity of bad times ex ante. If so, investors may be surprised by the better-than-expected performance of high-capital banks (relative to that of low-capital banks) during such times. As argued in the Introduction, the spread between the prices of high- and low-capital banks may not be sufficiently high during good times, and there will be a continuing increase in the price spread between high- and low-capital banks (and thus higher returns for high-capital banks) during bad times, consistent with recent theories on banking crises.[46] We now examine this "Surprised Investor Channel."

We first check if the outperformance of high-capital banks during bad times evolves in a way suggested by the theories. If the mispricing is resolved slowly over time, we should see that α_{BT} is the biggest early on during bad times and the smallest toward the end. To test this, we dissect each bad time into three parts (first month, middle months, and last month) and estimate:[47]

$$R_{pt} = \alpha_0 + \alpha_{BT^{First}} BT_t^{First} + \alpha_{BT^{Middle}} BT_t^{Middle} + \alpha_{BT^{Last}} BT_t^{Last} + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}, \quad (3.4.1)$$

where BT_t^{First} = 1 if month $t-1$ is not a bad time but month t is; BT_t^{Middle} = 1 if month t is a bad time but BT_t^{First} = 0 and BT_t^{Last} = 0; BT_t^{Last} = 1 if month $t+1$ is not a bad time but month t is.

Table 3.14 Panel A shows that the outperformance of high-capital banks during bad times is the greatest during the first month, continues during the middle months, and is insignificant and small in the last month. This is consistent with expectations and supports the "Surprised Investor Channel." A possible concern is that the observed return pattern is driven by bad times being most (least) severe during the first (last) month. To address this, Panel B shows the level of monthly stock return volatility. While bad times are clearly more volatile than other times, the first and last months during bad times tend to be similar in severity, suggesting that this concern is not valid.

Another way of testing this channel is to focus on earnings surprises, commonly captured using standardized unanticipated earnings (SUEs) (Livnat and Mendenhall, 2006):

$$SUE = \frac{EPS^{Act} - EPS^{For}}{P} \times 100. \quad (3.4.2)$$

[46] In Gennaioli, Shleifer, and Vishny (2015), investors do not instantaneously and correctly revise their beliefs about the magnitude of a crisis: they underweight bad news during long-lasting good times, and then they underweight good news during a long-lasting crisis. Such non-Bayesian learning can lead to slow belief revision. Thakor (2016) shows that even with rational learning, one can get slow belief revision about the magnitude of the crisis and then a sharp revision in beliefs if there is "model uncertainty" in addition to uncertainty about the state of the world within a given model.

[47] Every bad time contains at least two months. If it contains two months, the middle period contains zero observations.

Table 3.14

Surprised Investor Channel: Risk-Adjusted Returns of High- minus Low-Capital Banks during the Beginning / Middle / End of Bad Times

This table explores the "Surprised Investor Channel" by examining whether investors learn about the hypothesized mispricing of high- and low-capital banks as bad times evolve. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. The capital ratio is defined as book equity over total assets at the beginning of month t using the most recent Compustat quarterly financial statements. We use the fact that bad times tend to cluster. To test whether α_{BT} is bigger (smaller) in the first (last) months of consecutive bad times than during the middle months, we estimate: $R_{pt} = \alpha_0 + \alpha_{BT^{First}} BT_t^{First} + \alpha_{BT^{Middle}} BT_t^{Middle} + \alpha_{BT^{Last}} BT_t^{Last} + \sum_{i=1}^{K} \beta_i f_{it} + \varepsilon_{it}$, where$BT_t^{First}$ = 1 if month $t-1$ is not a bad time but month t is a bad time, defined as bank stock return volatility (modeled using an EGARCH(1,1) model) exceeding the 80^{th} percentile (in sample), and zero otherwise.BT_t^{Middle} = 1 if month t is a bad time but BT_t^{First} = 0 and BT_t^{Last} = 0. BT_t^{Last} = 1 if month $t+1$ is not a bad time but month t is. f_{it} are factor returns in month t obtained using five linear factor models. Panel A shows the results of these regressions. Panel B shows the level of volatility as a proxy for the severity of bad times during the first, middle, and last months of consecutive bad times.

Portfolios are rebalanced monthly: at the beginning of each month t, we independently sort bank stocks into quintiles based on their capital ratio and size to form 25 portfolios. Capital is defined as above, while size is defined as market capitalization at the beginning of month t. Next, we compute monthly VW average returns for the 25 portfolios. We calculate returns for each capital ratio quintile as the simple average of the five size quintile portfolio returns. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

Panel A: Risk-Adjusted Returns of High- minus Low-Capital (H-L) Banks during the First, Middle, and Last Months of Consecutive Bad Times

	α_{First} of H-L	α_{Middle} of H-L	α_{Last} of H-L
FF3	2.25%**	1.79%***	-0.27%
	(2.59)	(4.19)	(-0.32)
FFC4	2.20%**	1.88%***	-0.16%
	(2.54)	(4.39)	(-0.19)
FF5	2.16%**	1.75%***	-0.30%
	(2.47)	(4.06)	(-0.34)
FF5+LQ	2.15%**	1.75%***	-0.30%
	(2.44)	(4.05)	(-0.35)
FH9	2.45%***	1.91%***	0.10%
	(2.77)	(4.40)	(0.11)

Panel B: Level of Volatility during the First, Middle, and Last Months of Consecutive Bad Times

	No. of Obs.	Mean	Median	Max	Min
BT^{First}	8	8.26%	7.84%	11.03%	7.30%
BT^{Middle}	37	9.76%	8.94%	16.04%	7.32%
BT^{Last}	8	7.59%	7.53%	7.88%	7.28%
$OtherTimes$	211	5.02%	4.98%	7.22%	3.31%

Table 3.15
Surprised Investor Channel: Earnings Surprises

This table explores the "Surprised Investor Channel" by examining the relation between bank capital and standardized unexpected earnings (SUEs) during bad times and other times. The SUE is defined as: $SUE = \frac{EPS^{Act} - EPS^{For}}{P} \times 100$, where EPS^{Act} is actual EPS in quarter t reported in I/B/E/S Detail History, EPS^{For} is the median forecasts for quarter t reported in I/B/E/S Detail History, and P is the stock price at the end of the previous fiscal quarter. BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility exceeding the 80^{th} percentile in sample (Panel A) or VW bank stock return volatility being forecasted to be greater than the 80^{th} percentile of bank stock return volatility from Jan. 1984 to month $t-1$ (Panel B). Stock return volatility is modeled using an EGARCH(1,1) model. The capital ratio is the log of book equity over total assets. Size is the log of market capitalization. BTM is the log of the book-to-market ratio defined as book equity over market capitalization. All independent variables are winsorized at the 1% and 99% levels. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is from Jan. 1994 - Dec. 2015.

Panel A: In-Sample Bad Times

Dependent Variable:	SUE					
	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio_BT	16.61**	16.70**	17.17**	16.69***	16.60**	17.31**
	(2.58)	(2.57)	(2.45)	(2.62)	(2.57)	(2.47)
Capital ratio	9.81***	9.79***	9.21***	10.26***	9.94***	9.28***
	(3.38)	(3.34)	(3.06)	(3.59)	(3.39)	(3.08)
Size	2.00***	1.97***	1.81***	2.17***	2.02***	1.84***
	(3.53)	(3.48)	(3.30)	(3.65)	(3.49)	(3.30)
BTM	-4.28***	-4.30***	-4.50***	-4.98***	-4.33***	-4.58***
	(-2.72)	(-2.73)	(-2.77)	(-3.01)	(-2.80)	(-2.84)
Forecast within	90 days	60 days	30 days	90 days	60 days	30 days
Forecast after Fiscal Quarter End	Yes	Yes	Yes	No	No	No
Bank and Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8,852	8,810	8,651	8,852	8,810	8,651
adj. R-sq	0.217	0.219	0.221	0.216	0.220	0.223

Panel B: Out-of-Sample Bad Times

Dependent Variable:	SUE					
	(1)	(2)	(3)	(4)	(5)	(6)
Capital ratio_BT	13.44**	13.48**	14.54**	13.65**	13.44**	14.66**
	(2.43)	(2.43)	(2.35)	(2.50)	(2.42)	(2.37)
Capital ratio	10.78***	10.80***	10.35***	11.17***	10.93***	10.43***
	(3.40)	(3.38)	(3.09)	(3.58)	(3.41)	(3.11)
Size	2.11***	2.07***	1.85***	2.27***	2.13***	1.87***
	(3.55)	(3.51)	(3.30)	(3.67)	(3.52)	(3.30)
BTM	-4.20***	-4.22***	-4.50***	-4.90***	-4.26***	-4.59***
	(-2.65)	(-2.65)	(-2.77)	(-2.93)	(-2.71)	(-2.84)
Forecast within	90 days	60 days	30 days	90 days	60 days	30 days
Forecast after Fiscal Quarter End	Yes	Yes	Yes	No	No	No
Bank and Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8,852	8,810	8,651	8,852	8,810	8,651
adj. R-sq	0.212	0.214	0.217	0.211	0.215	0.219

The numerator measures the analyst forecast error, or the difference between actual earnings per share, EPS^{Act}, and investors' earnings expectations proxied by the median analyst forecast, EPS^{For}. In line with the literature, we use the median (instead of the mean) forecast because it is less sensitive to outliers. The denominator is the stock price at the end of the fiscal quarter, P. Results are similar if it is measured 3 days before the earnings announcement date (see Internet Appendix Table IA.17). The EPS numbers are from the I/B/E/S Detail History - Unadjusted File, and the share price is from CRSP. We use EPS^{Act} and P "as is," but adjust EPS^{For} using CRSP adjustment factors for any stock splits and dividends that took place between the forecast and earnings release dates.

We regress the SUE on: the log of the capital ratio interacted with a bad times dummy (BT, our main in-sample and out-of-sample proxies based on stock return volatility in the banking sector), the log of the capital ratio (book equity over total assets), the log of bank size (market capitalization), the log of the book-to-market ratio (BTM, book equity over market capitalization), and bank and year-month fixed effects.[48] Size and BTM are measured at the end of the fiscal quarter.

There are two important timing issues regarding the measurement of the SUE and bank capital. The first one is: which capital ratio do investors know on the earnings announcement date? Financial statements (which contain capital ratios) are released well after earnings are announced: banks in our sample on average announce their Q1 - Q3 (Q4) earnings 24 (32) days after fiscal-quarter end and their financial statements 19 (52) days later.[49] If we use contemporaneous capital ratios, meaning that we relate, say, the Q1 SUE to Q1 capital, we may therefore be assuming that investors have perfect foresight of what Q1 capital will be.[50] To address this, we checked the earnings releases of various banks at different points in time, and found that they all included information about bank capital. Based on this (small-sample) evidence, it seems appropriate to use contemporaneous capital in our analysis because investors learn jointly about earnings and capital

[48]The uninteracted bad times dummy drops out of the regressions due to the inclusion of year-month fixed effects. This regression setup is inspired by Core, Guay, and Rusticus (2006), who explore earnings surprises as one channel through which weak governance may cause weak stock returns.

[49]The respective medians are 22 (26) and 19 (50) days.

[50]In this case, the relation between capital and the SUE can potentially also be affected by the mechanical positive relation between capital and earnings, although it is not clear why this would necessarily affect the SUE.

ratios at the time of the earnings release. Nonetheless, we obtain consistent results using lagged capital (see Internet Appendix Table IA.17). The second timing issue concerns the choice of the forecast horizon. We are trying to link SUEs to bank capital during different economic times to find out whether surprised investors may drive the relative outperformance of high-capital banks during bad times. It therefore seems proper to use forecasts made relatively close to the earnings announcement date. Since it is not clear empirically what "close" means and to show robustness of our results, we use six alternative specifications: forecasts made within 90 / 60 / 30 days of the earnings announcement date, while alternatively requiring or not requiring that these forecasts are made after the prior fiscal quarter end.[51]

Table 3.15 shows the in-sample (Panel A) and out-of-sample (Panel B) results based on contemporaneous capital. In both panels, the coefficients on the capital ratio and the capital ratio interacted with the bad times dummy are positive and significant. To address their economic significance, focus on Column (1) in Panel A. The coefficients on the capital ratio of 9.81 and on the interacted capital ratio of 16.61 suggest that if the capital ratio were 10 percent higher,[52] the SUE would be 0.981 higher during normal times and (1.661 + 0.981 =) 2.642 higher during bad times. Both effects are sizeable given that the mean SUEs of low- and high-capital banks are -1.01 and 0.05 during normal times, respectively, and -9.18 and -0.35 during bad times, respectively. The other columns show similar magnitudes of the effects. Thus, high-capital banks have higher SUEs than low-capital banks during bad times, consistent with the "Surprised Investor Channel."

As a final way to address this channel, we examine whether the earnings announcement CARs of high-capital banks are higher than those of low-capital banks during bad times. We focus on 3-day CARs measured from one day before to one day after the announcement date, (-1,+1). We first calculate daily abnormal returns for the event window using four models: (i) a market model;

[51] Livnat and Mendenhall (2006) use forecasts made in the 90 days prior to the earnings announcement. Hutton, Lee, and SHU (2012) and Keskek, Tse, and Tucker (2014) focus on a 30-day window. The mean (median) number of analyst forecasts during the time periods shown in Table 3.15 are: 2.4, 2.4, 2.4, 7.3, 4.4, and 3.3 (1, 1, 1, 5, 3, and 2), respectively.

[52] Recall from Table 3.1 that, on average, the capital ratios of high-capital banks are more than 100 percent higher than those of low-capital banks: 16.31% versus 6.48%.

Table 3.16

Surprised Investor Channel: Cumulative Abnormal Returns around Earnings Announcements

This table reports 3-day cumulative abnormal returns (CARs) over (-1,+1) around the earnings announcement date (Compustat item RDQ): $CAR_t = \gamma_0 + \gamma_B BT_t + \varepsilon_t$. Abnormal returns are computed using: a market model; FF3, the Fama-French 3-factor model; FFC4, the Carhart 4-factor model; and FF5, the Fama-French 5-factor model. For FF3, FFC4, and FF5, the pre-estimation period for betas is from $t-250$ to $t-21$. We compute VW average CARs for 25 portfolios (independently sorted into quintiles by capital ratio and size) and then calculate CARs for each capital ratio quintile as the EW average of the five size quintiles. In Panel A, BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility exceeding the 80^{th} percentile (in sample). In Panel B, BT_t is a dummy = 1 if month t is a bad time, defined as VW bank stock return volatility being forecasted to be greater than the 80^{th} percentile of bank stock return volatility from Jan. 1984 to month $t-1$ (out-of-sample). Stock return volatility is modeled using an EGARCH(1,1) model. The capital ratio is the log of book equity over total assets. Size is the log of market capitalization. BTM is the log of the book-to-market ratio defined as book equity over market capitalization. CARs and capital ratios are measured contemporaneously. Banks are commercial banks, identified as all firms listed on NYSE, AMEX, and NASDAQ in the CRSP database with *header* SIC code (CRSP item HSICCD) 60 or *historical* SIC code (CRSP item SICCD) 6712. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period runs from Jan. 1994 through Dec. 2015.

Panel A: In-Sample Bad Times

Dependent variable:	CAR (-1, +1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MktModel	FF3	FFC4	FF5	MktModel	FF3	FFC4	FF5
Capital ratio_BT	0.73**	0.69**	0.82**	0.77**	1.29*	1.30*	1.28*	1.25*
	(2.09)	(1.97)	(2.50)	(2.34)	(1.78)	(1.80)	(1.77)	(1.74)
Capital ratio	0.77**	0.68*	0.45	0.46	0.82	0.77	0.72	0.71
	(2.31)	(1.88)	(1.49)	(1.51)	(1.53)	(1.55)	(1.46)	(1.42)
Size	-0.59***	-0.52***	-0.48***	-0.47***	-1.17***	-0.99***	-0.96***	-0.98***
	(-4.81)	(-3.99)	(-3.82)	(-3.85)	(-4.75)	(-4.15)	(-3.94)	(-4.25)
BTM	0.49*	0.49*	0.44*	0.54**	-0.29	-0.20	-0.30	-0.16
	(1.92)	(1.84)	(1.69)	(2.07)	(-0.66)	(-0.50)	(-0.73)	(-0.40)
SUE					0.05***	0.04***	0.04***	0.04***
					(4.15)	(3.65)	(3.64)	(3.72)
Bank & Yr-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	46,002	44,842	44,829	44,818	8,448	8,400	8,398	8,397
adj. R-sq	0.040	0.036	0.036	0.038	0.092	0.071	0.064	0.069

Panel B: Out-of-Sample Bad Times

Dependent variable:	CAR (-1, +1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MktModel	FF3	FFC4	FF5	MktModel	FF3	FFC4	FF5
Capital ratio_BT	0.76**	0.72**	0.83**	0.82**	2.07***	2.19***	2.17***	2.10***
	(2.30)	(2.03)	(2.43)	(2.40)	(3.42)	(3.59)	(3.47)	(3.44)
Capital ratio	0.76**	0.66*	0.44	0.44	0.49	0.38	0.33	0.34
	(2.17)	(1.72)	(1.32)	(1.30)	(0.97)	(0.80)	(0.70)	(0.70)
Size	-0.59***	-0.52***	-0.48***	-0.47***	-1.18***	-1.00***	-0.97***	-0.98***
	(-4.83)	(-3.99)	(-3.83)	(-3.86)	(-4.83)	(-4.21)	(-4.00)	(-4.31)
BTM	0.49*	0.49*	0.44*	0.54**	-0.26	-0.17	-0.26	-0.13
	(1.90)	(1.83)	(1.67)	(2.05)	(-0.61)	(-0.42)	(-0.65)	(-0.32)
SUE					0.04***	0.04***	0.04***	0.04***
					(4.11)	(3.61)	(3.60)	(3.68)
Bank & Yr-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	46,002	44,842	44,829	44,818	8,448	8,400	8,398	8,397
adj. R-sq	0.040	0.036	0.036	0.038	0.093	0.073	0.066	0.070

(ii) FF3; (iii) FFC4; and (iv) FF5.[53] For FF3, FFC4, and FF5, we use a pre-estimation period from $t - 250$ to $t - 21$. Each CAR is calculated by summing the abnormal returns over the 3-day window. We compute VW average CARs for the 25 portfolios (obtained by independently sorting bank stocks into quintiles based on their capital ratio and size as in our main analysis) and then calculate CARs for each capital ratio quintile as the simple average of the five size quintile portfolio CARs.

Table 3.16 Panels A and B show the in-sample and out-of-sample results, respectively. The first four columns in each panel show the results using the four asset pricing models and include the same independent variables as Table 3.15. The coefficient on the capital ratio is positive but not always significant, while the coefficient on the capital ratio interacted with the bad times dummy is positive and significant in all cases. This suggests that the CAR is not significantly greater for banks with higher capital ratios during normal times, but it is during bad times. The last four columns add the SUE as an additional regressor. The sample sizes drop because only observations for which the SUE could be calculated are included. Not surprisingly, the coefficient on the SUE is positive and significant: bigger earnings surprises are associated with higher CARs. Interestingly, the coefficient on capital interacted with the bad times dummy remains positive and significant, implying that higher capital is associated with higher CARs over and above the earnings surprise effect.

The results here collectively suggest that investors slowly update their beliefs during bad times, and are surprised about the better-than-expected performance of high-capital banks (relative to low-capital banks) during bad times as evidenced by higher SUEs and CARs, consistent with the "Surprised Investor Channel."

3.5 Conclusion

This paper addressed two related questions. The first question is: Do high-capital banks show better *risk-adjusted* stock performance than low-capital banks and does the effect differ dur-

[53]We cannot use two models used in our main analyses, FF5+LQ and FH9, because daily data are not available for all of the factors included in those models.

ing normal times and bad times? We find strong evidence that high-capital banks exhibit better risk-adjusted stock performance than low-capital banks in bad times, but not during other times. This holds in sample and using out-of-sample trading strategies. The results are robust to: using different bad times and capital definitions, alternative asset pricing models, and ex-ante expected returns; controlling for performance-type delistings, short-sale constraints, and trading costs; and dropping the largest or smallest banks. The second question is: What drives the outperformance of high-capital banks during bad times? We investigate two channels and conclude that, consistent with recent behavioral theories of financial crises, our results seem to be driven by a "Surprised Investor Channel" rather than an "Informed Investor Channel."

While our paper does not examine bank stock performance after regulators impose higher capital requirements, our results suggest that additional capital held by banks can be beneficial to shareholders in bad times, without significantly affecting stock performance in normal times.

4. SUMMARY AND CONCLUSIONS

This dissertation studies intermediary asset pricing. In particular, I am interested in theoretical and empirical analyses of the role of financial intermediaries in asset markets, which has been emphasized since the financial crisis.

The first paper, titled "Heterogeneous Intermediary Capital and the Cross-Section of Stock Returns", investigates how heterogeneity in intermediary capital affects trading activity of intermediaries and the cross-section of stock returns. Prior studies have attempted to empirically find that intermediary capital affects asset returns. However, depending on how they measure intermediary capital, it could be either procyclical or countercyclical. Existing models based on a single representative intermediary can not fully explain these empirical patterns. Therefore, I develop a model of heterogeneous intermediary capital in which heterogeneous risk preferences between high- and low-capital intermediaries leads to time-varying risk aversion as well as a risk premium. My model can explain that (1) an intermediary with a risk-averse manager builds higher capital than one with a risk-tolerant manager, (2) dispersion of intermediary capital between high- and low-capital intermediaries is positively associated with the aggregate risk aversion of the market, and (3) the dispersion of intermediary capital is negatively priced in the cross-section of asset returns. Consistent with these predictions, I empirically find that the dispersion of intermediary capital is indeed priced in the cross-section of stock returns and generates a risk premium of 7.0% - 8.4% per year.

The second paper, titled "Bank Capital and Bank Stock Performance", examines how bank capital affects its stock returns. We find that investors fail to correctly price bank capital in anticipation of bad times so that high-capital banks have higher abnormal returns than low-capital banks in bad times. This could happen if investors are unaware of the value of high capital during bad times or underestimate the likelihood and severity of bad times and revise their beliefs too sluggishly as bad times evolve. If so, the spread between the prices of high- and low-capital banks during good times is not sufficiently high, and there will be a continuing increase in the price spread between these banks during bad times. Consistent with the argument, we find that earnings surprises are significantly higher for high-capital banks than low-capital banks during bad times, supporting "Surprised Investor Channel."

Overall, the theoretical and empirical evidence from my dissertation emphasizes that intermediary capital is important to explain asset prices and helps to identify mechanisms that are missing from existing asset pricing models.

REFERENCES

Abarbanell, Jeffery S., Brian J. Bushee, and Jana Smith Raedy, 2003, Institutional Investor Preferences and Price Pressure: The Case of Corporate Spin-Offs, *Journal of Business* 76, 233–261.

Acharya, Viral V., Yakov Amihud, and Sreedhar T. Bharath, 2013, Liquidity Risk of Corporate Bond Returns: Conditional Approach, *Journal of Financial Economics* 110, 358–386.

Acharya, Viral V., Hamid Mehran, and Anjan V. Thakor, 2016, Caught between Scylla and Charybdis? Regulating Bank Leverage When There Is Rent Seeking and Risk Shifting, *Review of Corporate Finance Studies* 5, 36–75.

Acharya, Viral V, and S Viswanathan, 2011, Leverage, Moral Hazard, and Liquidity, *Journal of Finance* 66, 99–138.

Admati, Anat R., Peter M Demarzo, Martin F Hellwig, and Paul Pfleiderer, 2013, Fallacies, Irrelevant Facts, and Myths in the Discussion of Capital Regulation : Why Bank Equity is Not Expensive, *Working Paper* .

Adrian, Tobias, and Nina Boyarchenko, 2012, Intermediary Leverage Cycles and Financial Stability, *Federal Reserve Bank of New York Staff Reports* No. 567.

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial Intermediaries and the Cross-Section of Asset Returns, *Journal of Finance* 69, 2557–2596.

Adrian, Tobias, Evan Friedman, and Tyler Muir, 2016, The Cost of Capital of the Financial Sector, *Federal Reserve Bank of New York Staff Reports* No. 755.

Adrian, Tobias, and Hyun Song Shin, 2010, Liquidity and Leverage, *Journal of Financial Intermediation* 19, 418–437.

Adrian, Tobias, and Hyun Song Shin, 2014, Procyclical Leverage and Value-at-Risk, *Review of Financial Studies* 27, 373–403.

Allen, Franklin, Elena Carletti, and Robert Marquez, 2011, Credit Market Competition and Capital Regulation, *Review of Financial Studies* 24, 983–1018.

Andries, Marianne, and Valentin Haddad, 2018, Information Aversion, *Working Paper* .

Badrinath, S.G., Jayant R. Kale, and Thomas H. Noe, 1995, Of Shepherds, Sheep, and the Cross-autocorrelations in Equity Returns, *Review of Financial Studies* 8, 401–430.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, *Journal of Finance* 61, 1645–1680.

Baker, Malcolm, and Jeffrey Wurgler, 2015, Do Strict Capital Requirements Raise the Cost of Capital? Bank Regulation, Capital Structure, and the Low-Risk Anomaly, *American Economic Review* 105, 315–320.

Baron, Matthew, and Wei Xiong, 2017, Credit Expansion and Neglected Crash Risk, *Quarterly Journal of Economics* 132, 713–764.

Bekaert, Geert, Eric Engstrom, and Nancy R. Xu, 2019, The Time Variation in Risk Appetite and Uncertainty, *Working Paper* .

Bekaert, Geert, and Marie Hoerova, 2016, What Do Asset Prices Have to Say About Risk Appetite and Uncertainty?, *Journal of Banking & Finance* 67, 103–118.

Bennett, James A., Richard W. Sias, and Laura T. Starks, 2003, Greener Pastures and the Impact of Dynamic Institutional Preferences, *Review of Financial Studies* 16, 1203–1238.

Berger, Allen N., and Christa H.S. Bouwman, 2013, How Does Capital Affect Bank Performance during Financial Crises?, *Journal of Financial Economics* 109, 146–176.

Berk, Jonathan B., and Jules H. van Binsbergen, 2015, Measuring Skill in the Mutual Fund Industry, *Journal of Financial Economics* 118, 1–20.

Besanko, David, and George Kanatas, 1996, The Regulation of Bank Capital: Do Capital Standards Promote Bank Safety?, *Journal of Financial Intermediation* 5, 160–183.

Bhamra, Harjoat S., and Raman Uppal, 2009, The Effect of Introducing a Non-Redundant Derivative on the Volatility of Stock-Market Returns When Agents Differ in Risk Aversion, *Review of Financial Studies* 22, 2303–2330.

Bhandari, Laxmi Chand, 1988, Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence, *Journal of Finance* 43, 507–528.

Bian, Jiangze, Zhiguo He, Kelly Shue, and Hao Zhou, 2018, Leverage-Induced Fire Sales and

Stock Market Crashes, *Working Paper* .

Black, Fischer, 1976, Studies of Stock Price Volatility Changes, in *Proceedings of the 1976 Meetings of the Business and Economics Statistics Section*, 177–181.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2013, Shackling Short Sellers: The 2008 Shorting Ban, *Review of Financial Studies* 26, 1363–1400.

Boehmer, Ekkehart, and Eric K. Kelley, 2009, Institutional Investors and the Informational Efficiency of Prices, *Review of Financial Studies* 22, 3563–3594.

Bollerslev, Tim, Michael Gibson, and Hao Zhou, 2011, Dynamic Estimation of Volatility Risk Premia and Investor Risk Aversion from Option-Implied and Realized Volatilities, *Journal of Econometrics* 160, 235–245.

Boulatov, A., T. Hendershott, and D. Livdan, 2013, Informed Trading and Portfolio Returns, *Review of Economic Studies* 80, 35–72.

Bouwman, Christa H. S., Hwagyun Kim, and Sang-Ook Shin, 2018, Bank Capital and Bank Stock Performance, *Working Paper* .

Brownlees, Christian, and Robert F. Engle, 2017, SRISK: A Conditional Capital Shortfall Measure of Systemic Risk, *Review of Financial Studies* 30, 48–79.

Brunnermeier, Markus K, and Stefan Nagel, 2008, Do Wealth Fluctuations Generate Time-Varying Risk Aversion? Micro-Evidence on Individuals' Asset Allocation, *American Economic Review* 98, 713–736.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market Liquidity and Funding Liquidity, *Review of Financial Studies* 22, 2201–2238.

Brunnermeier, Markus K., and Yuliy Sannikov, 2014, A Macroeconomic Model with a Financial Sector, *American Economic Review* 104, 379–421.

Bushee, Brian J., 2001, Do Institutional Investors Prefer Near-Term Earnings over Long-Run Value?, *Contemporary Accounting Research* 18, 207–246.

Calomiris, Charles W., and Doron Nissim, 2014, Crisis-Related Shifts in the Market Valuation of Banking Activities, *Journal of Financial Intermediation* 23, 400–435.

Campbell, John Y., and John H. Cochrane, 1999, By Force of Habit: A ConsumptionâĂŘBased Explanation of Aggregate Stock Market Behavior, *Journal of Political Economy* 107, 205–251.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In Search of Distress Risk, *Journal of Finance* 63, 2899–2939.

Campbell, John Y., Tarun Ramadorai, and Allie Schwartz, 2009, Caught on Tape: Institutional Trading, Stock Returns, and Earnings Announcements, *Journal of Financial Economics* 92, 66–91.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57–82.

Chan, Yeung Lewis, and Leonid Kogan, 2002, Catching Up with the Joneses: Heterogeneous Preferences and the Dynamics of Asset Prices, *Journal of Political Economy* 110, 1255–1285.

Chang, Yoosoon, Yongok Choi, Hwagyun Kim, and Joon Y. Park, 2016, Evaluating Factor Pricing Models using High-Frequency Panels, *Quantitative Economics* 7, 889–933.

Chava, Sudheer, and Amiyatosh Purnanandam, 2010, Is Default Risk Negatively Related to Stock Returns?, *Review of Financial Studies* 23, 2523–2559.

Coimbra, Nuno, and Hélène Rey, 2018, Financial Cycles with Heterogeneous Intermediaries, *Working Paper* .

Constantinides, George M., and Darrell Duffie, 1996, Asset Pricing with Heterogeneous Consumers, *Journal of Political Economy* 104, 219–240.

Cooper, Michael J., William E. Jackson, and Gary A. Patterson, 2003, Evidence of Predictability in the Cross-Section of Bank Stock Returns, *Journal of Banking & Finance* 27, 817–850.

Core, John E., Wayne R. Guay, and Tjomme O. Rusticus, 2006, Does Weak Governance Cause Weak Stock Returns? An Examination of Firm Operating Performance and Investors' Expectations, *Journal of Finance* 61, 655–687.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035.

Dechow, Patricia M, Amy P Hutton, Lisa Meulbroek, and Richard G Sloan, 2001, Short-Sellers, Fundamental Analysis, and Stock Returns, *Journal of Financial Economics* 61, 77–106.

Demirguc-Kunt, Asli, Enrica Detragiache, and Ouarda Merrouche, 2013, Bank Capital: Lessons from the Financial Crisis, *Journal of Money, Credit and Banking* 45, 1147–1164.

Diamond, Douglas W., and Raghuram G. Rajan, 2001, Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking, *Journal of Political Economy* 109, 287–327.

Dichev, Ilia D., 1998, Is the Risk of Bankruptcy a Systematic Risk?, *Journal of Finance* 53, 1131–1147.

Dow, James, and Jungsuk Han, 2018, The Paradox of Financial Fire Sales: The Role of Arbitrage Capital in Determining Liquidity, *Journal of Finance* 73, 229–274.

Fahlenbrach, Rüdiger, Robert Prilmeier, and René M. Stulz, 2012, This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent Financial Crisis, *Journal of Finance* 67, 2139–2185.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 2015, A Five-Factor Asset Pricing Model, *Journal of Financial Economics* 116, 1–22.

Fontaine, Jean-Sébastien, and René Garcia, 2012, Bond Liquidity Premia, *Review of Financial Studies* 25, 1207–1254.

Frazzini, Andrea, Ronen Israel, and Tobias J. Moskowitz, 2015, Trading Costs of Asset Pricing Anomalies, *Working Paper* .

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting Against Beta, *Journal of Financial Economics* 111, 1–25.

Fung, William, and David A. Hsieh, 2001, The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers, *Review of Financial Studies* 14, 313–341.

Furlong, Frederick T., and Michael C. Keeley, 1989, Capital Regulation and Bank Risk-Taking: A

Note, *Journal of Banking and Finance* 13, 883–891.

Gandhi, Priyank, and Hanno Lustig, 2015, Size Anomalies in U.S. Bank Stock Returns, *Journal of Finance* 70, 733–768.

Garel, Alexandre, Arthur Petit-Romec, and Rudi Vander Vennet, 2018, Institutional Shareholders and Bank Capital, *Working Paper* .

Garlappi, Lorenzo, Tao Shu, and Hong Yan, 2008, Default Risk, Shareholder Advantage, and Stock Returns, *Review of Financial Studies* 21, 2743–2778.

Gârleanu, Nicolae, and Stavros Panageas, 2015, Young, Old, Conservative, and Bold: The Implications of Heterogeneity and Finite Lives for Asset Pricing, *Journal of Political Economy* 123, 670–685.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2011, Margin-based Asset Pricing and Deviations from the Law of One Price, *Review of Financial Studies* 24, 1980–2022.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2015, Neglected Risks: The Psychology of Financial Crises, *American Economic Review* 105, 310–314.

George, Thomas J., and Chuan-Yang Hwang, 2010, A Resolution of the Distress Risk and Leverage Puzzles in the Cross Section of Stock Returns, *Journal of Financial Economics* 96, 56–79.

Gorton, Gary, and Andrew Winton, 2017, Liquidity Provision, Bank Capital, and the Macroeconomy, *Journal of Money, Credit and Banking* 49, 5–37.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary Asset Pricing: New Evidence from Many Asset Classes, *Journal of Financial Economics* 126, 1–35.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary Asset Pricing, *American Economic Review* 103, 732–770.

He, Zhiguo, and Arvind Krishnamurthy, 2018, Intermediary Asset Pricing and the Financial Crisis, *Annual Review of Financial Economics* 10, 173–197.

Hendershott, Terrence, Dmitry Livdan, and Norman Schürhoff, 2015, Are Institutions Informed about News?, *Journal of Financial Economics* 117, 249–287.

Holmstrom, B., and J. Tirole, 1997, Financial Intermediation, Loanable Funds, and The Real Sector, *Quarterly Journal of Economics* 112, 663–691.

Hutton, Amy P., Lian Fen Lee, and SUSAN Z. SHU, 2012, Do Managers Always Know Better? The Relative Accuracy of Management and Analyst Forecasts, *Journal of Accounting Research* 50, 1217–1244.

Irvine, Paul, Marc Lipson, and Andy Puckett, 2007, Tipping, *Review of Financial Studies* 20, 741–768.

Jagannathan, Ravi, and Yong Wang, 2007, Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns, *Journal of Finance* 62, 1623–1661.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

Johnson, Shane A., Theodore C. Moorman, and Sorin Sorescu, 2009, A Reexamination of Corporate Governance and Equity Prices, *Review of Financial Studies* 22, 4753–4786.

Keskek, Sami, Senyo Tse, and Jennifer Wu Tucker, 2014, Analyst Information Production and the Timing of Annual Earnings Forecasts, *Review of Accounting Studies* 19, 1504–1531.

Koehn, Michael, and Anthony M. Santomero, 1980, Regulation of Bank Capital and Portfolio Risk, *Journal of Finance* 35, 1235–1244.

Kolasinski, Adam C., Adam Reed, and Jacob R. Thornock, 2013, Can Short Restrictions Actually Increase Informed Short Selling?, *Financial Management* 42, 155–181.

Livnat, Joshua, and Richard R. Mendenhall, 2006, Comparing the Post-Earnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts, *Journal of Accounting Research* 44, 177–205.

Lyon, John D., Brad M. Barber, and Chih-Ling Tsai, 1999, Improved Methods for Tests of Long-Run Abnormal Stock Returns, *Journal of Finance* 54, 165–201.

Ma, Sai, 2018, Heterogeneous Intermediaries and Asset Prices, *Working Paper* .

Mehran, Hamid, and Anjan Thakor, 2011, Bank Capital and Value in the Cross-Section, *Review of Financial Studies* 24, 1019–1067.

Miles, David, Jing Yang, and Gilberto Marcheggiano, 2013, Optimal Bank Capital, *Economic*

Journal 123, 1–37.

Modigliani, F., and M.H. Miller, 1963, Corporate Income Taxes and the Cost of Capital: A Correction, *American Economic Review* 53, 433–443.

Muravyev, Dmitriy, Neil D. Pearson, and Joshua Matthew Pollet, 2016, Is There a Risk Premium in the Stock Lending Market? Evidence from Equity Options, *Working Paper* .

Pástor, Ä¡uboš, and RobertÂăF. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642–685.

Pérignon, Christophe, David Thesmar, and Guillaume Vuillemey, 2016, Wholesale Funding Runs, *Working Paper* .

Rosenberg, Joshua V., and Robert F. Engle, 2002, Empirical Pricing Kernels, *Journal of Financial Economics* 64, 341–372.

Santos, Tano, and Pietro Veronesi, 2018, Habits and Leverage, *Working Paper* .

Scholes, Myron, and Joseph Williams, 1977, Estimating Betas from Nonsynchronous Data, *Journal of Financial Economics* 5, 309–327.

Schwert, G William, 1989, Why Does Stock Market Volatility Change Over Time?, *Journal of Finance* 44, 1115–1153.

Thakor, Anjan V., 2014, Bank Capital and Financial Stability: An Economic Trade-Off or a Faustian Bargain?, *Annual Review of Financial Economics* 6, 185–223.

Thakor, Anjan V., 2015, Lending Booms, Smart Bankers, and Financial Crises, *American Economic Review* 105, 305–309.

Thakor, Anjan V., 2016, The Highs and the Lows: A Theory of Credit Risk Assessment and Pricing through the Business Cycle, *Journal of Financial Intermediation* 25, 1–29.

Thomas, Jacob, and Frank X. Zhang, 2011, Tax Expense Momentum, *Journal of Accounting Research* 49, 791–821.

van Rooij, Maarten, Annamaria Lusardi, and Rob Alessie, 2011, Financial Literacy and Stock Market Participation, *Journal of Financial Economics* 101, 449–472.

Vassalou, Maria, and Yuhang Xing, 2004, Default Risk in Equity Returns, *Journal Finance* 59, 831–868.

Veronesi, Pietro, 1999, Stock Market Overreactions to Bad News in Good Times: A Rational Expectations Equilibrium Model, *Review of Financial Studies* 12, 975–1007.

Vissing-Jorgensen, Annette, 2003, Perspectives on Behavioral Finance: Does "Irrationality" Disappear with Wealth? Evidence from Expectations and Actions, *NBER Macroeconomics Annual* 18, 139–194.

Vuolteenaho, Tuomo, 2002, What Drives Firm-Level Stock Returns?, *Journal of Finance* 57, 233–264.

APPENDIX A

PROOFS OF PROPOSITIONS

Proof of Proposition 1. Equation (2.6.7) implies that $\Gamma_1^H = \dfrac{\gamma}{S_1^H}$ and $\Gamma_1^L = \dfrac{\gamma}{S_1^L}$. From (2.6.4) and $\Delta c_1 = g + \sigma_c \varepsilon_1$, the surplus consumption ratio of specialist H (S_1^H) is lower than that of specialist L (S_1^L) at $t = 1$:

$$S_1^H = \frac{C_1^H - X_1^H}{C_1^H} = 1 - \eta\phi^H \frac{C_0^H}{C_1^H} < S_t^L = \frac{C_t^L - X_1^L}{C_1^L} = 1 - \eta\phi^L \frac{C_0^L}{C_1^L}. \tag{A.0.1}$$

Thus, specialist H has higher risk aversion than specialist L at $t = 1$, or $\Gamma_1^H > \Gamma_1^L$.

In addition, a more risk-averse specialist will require higher risk premium (i.e., expected return) against per unit risk (i.e., variance) for her portfolio than a risk-tolerant specialist. This implies that:

$$\frac{E_1\left[r_2^H - r_2^f\right]}{Var_1\left(r_2^H\right)} = \frac{\alpha_1^H E_1\left[r_2^a - r_2^f\right]}{\left(\alpha_1^H\right)^2 Var_1\left(r_2^a\right)} > \frac{E_1\left[r_2^L - r_2^f\right]}{Var_1\left(r_2^L\right)} = \frac{\alpha_1^L E_1\left[r_2^a - r_2^f\right]}{\left(\alpha_1^L\right)^2 Var_1\left(r_2^a\right)}. \tag{A.0.2}$$

Therefore, specialist L allocates a higher portion of her wealth into the risky asset than specialist H at $t = 1$, or $\alpha_1^H < \alpha_1^L$. ■

Proof of Proposition 2. From the first order conditions of (2.6.15) and (2.6.16), $E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\left(\alpha_t^H \psi_t^H + \alpha_t^L \psi_t^L\right) Var_t\left[r_{t+1}^a\right] = 0$ or, equivalently, $\alpha_t^H \psi_t^H + \alpha_t^L \psi_t^L = \dfrac{1}{A}\dfrac{\mu_t - r_t^f}{\sigma_t^2}$. Let $Y_t \equiv \dfrac{1}{A}\dfrac{\mu_t - r_t^f}{\sigma_t^2}$. Using (2.6.12), I obtain that

$$\psi_t^L = \frac{Y_t - \alpha_t^H \psi_t^H}{\alpha_t^L} \geq \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - \psi_t^H \text{ and } \psi_t^H = \frac{Y_t - \alpha_t^L \psi_t^L}{\alpha_t^H} \geq \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - \psi_t^L.$$

If further rearranged, then

$$\psi_t^H \geq \frac{\alpha_t^L \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - Y_t}{\alpha_t^L - \alpha_t^H} \quad \text{and} \quad \psi_t^L \leq \frac{Y_t - \alpha_t^H \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}}}{\alpha_t^L - \alpha_t^H}. \tag{A.0.3}$$

When the minimum capital $\tilde{\kappa}^* \equiv w_t^{hh} \dfrac{2Y_t}{\alpha_t^H + \alpha_t^L} + \left(w_t^H + w_t^L\right)$, the household's allocation is that:

$$\psi_t^{H*} \geq \frac{\alpha_t^L \frac{\tilde{\kappa}^* - w_t^H - w_t^L}{w_t^{hh}} - Y_t}{\alpha_t^L - \alpha_t^H)} = \frac{\alpha_t^L \frac{2Y_t}{\alpha_t^L + \alpha_t^H} - Y_t}{\alpha_t^L - \alpha_t^H} = \frac{Y_t}{\alpha_t^L + \alpha_t^H}$$
$$\psi_t^{L*} \leq \frac{Y_t - \alpha_t^H \frac{\tilde{\kappa}^* - w_t^H - w_t^L}{w_t^{hh}}}{(\alpha_t^L - \alpha_t^H)} = \frac{Y_t - \alpha_t^H \frac{2Y_t}{\alpha_t^L + \alpha_t^H}}{\alpha_t^L - \alpha_t^H} = \frac{Y_t}{\alpha_t^L + \alpha_t^H}.$$

Thus, if $\tilde{\kappa} > \tilde{\kappa}^*$, $\psi_t^H > \psi_t^L$, that is the household purchases more equity capital from intermediary H than from intermediary L. ■

Proof of Proposition 3. From (2.6.6), $\partial C_0^I / \partial \phi^I < 0$, $C_0^H < C_0^L$ and $C_1^H < C_1^L$, and from (2.6.3), $w_1^I = \left(e^I - C_0^I\right)\left(1 + r_1^I\right) - C_1^I$. This implies that specialist H has larger wealth to form an intermediary than specialist L at $t = 1$, or $w_1^H > w_1^L$. Combined with Proposition 2 that if $\tilde{\kappa} > \tilde{\kappa}^*$, $\psi_t^H > \psi_t^L$, the following inequality holds:

$$\kappa_1^H = w_1^H + \psi_1^H w_1^{hh} > \kappa_1^L = w_1^L + \psi_t^L w_1^{hh}. \tag{A.0.4}$$

Therefore, if the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^*$, the specialist who has higher (lower) risk aversion forms an intermediary with higher (lower) capital. ■

Proof of Proposition 4. Let me derive the percentage change of intermediary capital to the shock at $t = 2$. For specialist H,

$$\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} = \frac{\kappa_1^H\left[1+r_2^H\right] - E\left[\kappa_1^H\left[1+r_2^H\right]\right]}{E\left[\kappa_1^H\left[1+r_2^H\right]\right]}$$

$$= \frac{\kappa_1^H\left[1+\alpha_1^H\left(r_2^a - r_2^f\right)+r_2^f\right] - E\left[\kappa_1^H\left[1+\alpha_1^H\left(r_2^a - r_2^f\right)+r_2^f\right]\right]}{E\left[\kappa_1^H\left[1+\alpha_1^H\left(r_2^a - r_2^f\right)+r_2^f\right]\right]} = \frac{\alpha_1^H\sigma_2\varepsilon_2}{1+\alpha_1^H\left(\mu_2 - r_2^f\right)+r_2^f}.$$

Similarly, for specialist L, $\frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} = \frac{\alpha_1^L\sigma_2\varepsilon_2}{1+\alpha_1^L\left(\mu_2 - r_2^f\right)+r_2^f}$. Therefore, the difference in their responses is that:

$$\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} = \frac{\alpha_1^H\sigma_2\varepsilon_2}{1+\alpha_1^H\left(\mu_2 - r_2^f\right)+r_2^f} - \frac{\alpha_1^L\sigma_2\varepsilon_2}{1+\alpha_1^L\left(\mu_2 - r_2^f\right)+r_2^f}$$

$$= \frac{\alpha_1^H\sigma_2\varepsilon_2\left[1+\alpha_1^L\left(\mu_2 - r_2^f\right)+r_2^f\right] - \alpha_1^L\sigma_2\varepsilon_2\left[1+\alpha_1^H\left(\mu_2 - r_2^f\right)+r_2^f\right]}{\left[1+\alpha_1^H\left(\mu_2 - r_2^f\right)+r_2^f\right]\left[1+\alpha_1^L\left(\mu_2 - r_2^f\right)+r_2^f\right]}$$

$$= \frac{\sigma_2\varepsilon_2\left(\alpha_1^H - \alpha_1^L\right)\left(1+r_2^f\right)}{\left[1+\alpha_1^H\left(\mu_2 - r_2^f\right)+r_2^f\right]\left[1+\alpha_1^L\left(\mu_2 - r_2^f\right)+r_2^f\right]}$$

Consequently, when $\varepsilon_2 > 0$, $\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} < 0$, and when $\varepsilon_2 < 0$, $\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} > 0$. This is summarized as follows:

$$\varepsilon_2\left(\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]}\right) < 0 \tag{A.0.5}$$

Note that a consumption function is a monotonic transformation of wealth. Thus, $\frac{\kappa_2^H - E\left[\kappa_2^H\right]}{E\left[\kappa_2^H\right]} - \frac{\kappa_2^L - E\left[\kappa_2^L\right]}{E\left[\kappa_2^L\right]} = \frac{w_2^H - E\left[w_2^H\right]}{E\left[w_2^H\right]} - \frac{w_2^L - E\left[w_2^L\right]}{E\left[w_2^L\right]} \propto \frac{C_2^H - E\left[C_2^H\right]}{E\left[C_2^H\right]} - \frac{C_2^L - E\left[C_2^L\right]}{E\left[C_2^L\right]}$. This results in the following relationship between the shock in the risky asset and the dispersion in consumption changes between the two specialists.

$$\varepsilon_2 \left(\frac{C_2^H - E\left[C_2^H\right]}{E\left[C_2^H\right]} - \frac{C_2^L - E\left[C_2^L\right]}{E\left[C_2^L\right]} \right) < 0 \tag{A.0.6}$$

■

Proof of Proposition 5. First, I prove that if a negative shock arrives in the risky asset, $\varepsilon_2 < 0$, then aggregate risk aversion rises:

$$\text{If } \varepsilon_2 < 0, \text{ then } \frac{C_2^H - E\left[C_2^H\right]}{E\left[C_2^H\right]} > \frac{C_2^L - E\left[C_2^L\right]}{E\left[C_2^L\right]}$$

$$\begin{aligned}
\Leftrightarrow \quad & E\left[C_2^L\right]\left(C_2^H - E\left[C_2^H\right]\right) > E\left[C_2^H\right]\left(C_2^L - E\left[C_2^L\right]\right) \\
\Leftrightarrow \quad & \left\{E\left[C_2^L\right]\left(C_2^H - E\left[C_2^H\right]\right) - E\left[C_2^H\right]\left(C_2^L - E\left[C_2^L\right]\right)\right\}\frac{1}{\Gamma_2^L} \\
> \quad & \left\{E\left[C_2^L\right]\left(C_2^H - E\left[C_2^H\right]\right) - E\left[C_2^H\right]\left(C_2^L - E\left[C_2^L\right]\right)\right\}\frac{1}{\Gamma_2^H} \\
\Leftrightarrow \quad & \left\{\begin{array}{c} E\left[C_2^L\right]\left(C_2^H - E\left[C_2^H\right]\right) - \left(E\left[C_2\right] - E\left[C_2^L\right]\right)\left(C_2^L - E\left[C_2^L\right]\right) \\ +E\left[C_2\right]E\left[C_2^L\right] - E\left[C_2\right]E\left[C_2^L\right] \end{array}\right\}\frac{1}{\Gamma_2^L} \\
> \quad & \left\{\begin{array}{c} \left(E\left[C_2\right] - E\left[C_2^H\right]\right)\left(C_2^H - E\left[C_2^H\right]\right) - E\left[C_2^H\right]\left(C_2^L - E\left[C_2^L\right]\right) \\ +E\left[C_2\right]E\left[C_2^H\right] - E\left[C_2\right]E\left[C_2^H\right] \end{array}\right\}\frac{1}{\Gamma_2^H} \\
\Leftrightarrow \quad & \left\{\begin{array}{c} E\left[C_2^L\right]\left(E\left[C_2\right] + C_2^H - E\left[C_2^H\right] + C_2^L - E\left[C_2^L\right]\right) \\ -\left(E\left[C_2^L\right] + C_2^L - E\left[C_2^L\right]\right)E\left[C_2\right] \end{array}\right\}\frac{1}{\Gamma_2^L} \\
> \quad & \left\{\begin{array}{c} -E\left[C_2^H\right]\left(E\left[C_2\right] + C_2^H - E\left[C_2^H\right] + C_2^L - E\left[C_2^L\right]\right) \\ +\left(E\left[C_2^H\right] + C_2^H - E\left[C_2^H\right]\right)E\left[C_2\right] \end{array}\right\}\frac{1}{\Gamma_2^H} \\
\Leftrightarrow \quad & \left(E\left[C_2^L\right]C_2 - C_2^L E\left[C_2\right]\right)\frac{1}{\Gamma_2^L} > \left(-E\left[C_2^H\right]C_2 + C_2^H E\left[C_2\right]\right)\frac{1}{\Gamma_2^H}
\end{aligned}$$

$$\Leftrightarrow \quad E\left[C_2^H\right] C_2 \frac{1}{\Gamma_2^H} + E\left[C_2^L\right] C_2 \frac{1}{\Gamma_2^L} > C_2^H E\left[C_2\right] \frac{1}{\Gamma_2^H} + C_2^L E\left[C_2\right] \frac{1}{\Gamma_2^L}$$

$$\Leftrightarrow \quad \frac{E\left[C_2^H\right]}{E\left[C_2\right]} \frac{1}{\Gamma_2^H} + \frac{E\left[C_2^L\right]}{E\left[C_2\right]} \frac{1}{\Gamma_2^L} > \frac{C_2^H}{C_2} \frac{1}{\Gamma_2^H} + \frac{C_2^L}{C_2} \frac{1}{\Gamma_2^L} \quad \left(\textit{use } \Gamma_2^I > E\left[\Gamma_2^I\right]\right)$$

$$\Leftrightarrow \quad \frac{E\left[C_2^H\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]} \frac{1}{E\left[\Gamma_2^H\right]} + \frac{E\left[C_2^L\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]} \frac{1}{E\left[\Gamma_2^L\right]} > \frac{C_2^H}{C_2^H + C_2^L} \frac{1}{\Gamma_2^H} + \frac{C_2^L}{C_2^H + C_2^L} \frac{1}{\Gamma_2^L}$$

where $C \equiv C^H + C^L$ and $E\left[C\right] \equiv E\left[C^H\right] + E\left[C^L\right]$. Therefore, if $\varepsilon_2 < 0$, then

$$\frac{1}{\Gamma_2} \equiv \frac{C_2^H}{C_2^H + C_2^L} \frac{1}{\Gamma_2^H} + \frac{C_2^L}{C_2^H + C_2^L} \frac{1}{\Gamma_2^L} < \frac{1}{E\left[\Gamma_2\right]} \equiv \frac{E\left[C_2^H\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]} \frac{1}{E\left[\Gamma_2^H\right]} + \frac{E\left[C_2^L\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]} \frac{1}{E\left[\Gamma_2^L\right]}. \quad \text{(A.0.7)}$$

On the other hand, if a positive shock arrives in the risky asset, $\varepsilon_2 > 0$, then aggregate risk aversion falls:

$$\frac{1}{\Gamma_2} \equiv \frac{C_2^H}{C_2^H + C_2^L} \frac{1}{\Gamma_2^H} + \frac{C_2^L}{C_2^H + C_2^L} \frac{1}{\Gamma_2^L} > \frac{1}{E\left[\Gamma_2\right]} \equiv \frac{E\left[C_2^H\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]} \frac{1}{E\left[\Gamma_2^H\right]} + \frac{E\left[C_2^L\right]}{E\left[C_2^H\right] + E\left[C_2^L\right]} \frac{1}{E\left[\Gamma_2^L\right]}. \quad \text{(A.0.8)}$$

Finally, combining (A.0.7) and (A.0.8) gives:

$$\varepsilon_2 \Gamma_2 < 0. \quad \text{(A.0.9)}$$

As such, the shock in the risky asset and aggregate risk aversion are inversely related at $t = 2$. ■

Proof of Proposition 6. Proposition 4 implies that the dispersion of intermediary capital and the shock at $t = 2$ is negatively related. More formally, I prove this relation as follows:

$$\begin{aligned}
&\frac{\partial DISP_2^{Capr}}{\partial \varepsilon_2} \\
&= \partial \left\{ \frac{\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] - \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]}{\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] + \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]} \right\} / \partial \varepsilon_2 \\
&= \frac{\left(\kappa_1^H \alpha_1^H - \kappa_1^L \alpha_1^L\right) \sigma_2}{\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] + \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]} \\
&- \frac{\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] - \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]}{\left(\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] + \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]\right)^2} \left(\kappa_1^H \alpha_1^H + \kappa_1^L \alpha_1^L\right) \sigma_2 \\
&= \frac{\sigma_2}{\left(\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] + \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]\right)^2} \\
&\times \left\{ \begin{array}{ll} & \left(\kappa_1^H \alpha_1^H - \kappa_1^L \alpha_1^L\right) \left(\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] + \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]\right) \\ - & \left(\kappa_1^H \alpha_1^H + \kappa_1^L \alpha_1^L\right) \left(\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] - \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]\right) \end{array} \right\}
\end{aligned}$$

$$\begin{aligned}
&= \frac{\sigma_2}{\left(\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] + \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]\right)^2} \\
&\times \left(\kappa_1^H \alpha_1^H \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] - \kappa_1^L \alpha_1^L \kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]\right) \\
&= \frac{\sigma_2}{\left(\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] + \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]\right)^2} \\
&\times \left[\kappa_1^H \kappa_1^L \left(1 + r_2^f\right) \left(\alpha_1^H - \alpha_1^L\right)\right] \\
&= \frac{\kappa_1^H \kappa_1^L \left(1 + r_2^f\right) \sigma_2}{\left(\kappa_1^H \left[1 + \alpha_1^H (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right] + \kappa_1^L \left[1 + \alpha_1^L (\mu_2 + \sigma_2 \varepsilon_2) + r_2^f\right]\right)^2} \times \left(\alpha_1^H - \alpha_1^L\right) < 0.
\end{aligned}$$

Together with the countercyclical variation in aggregate risk aversion in Proposition 5, I obtain the following result:

$$\left(\frac{\kappa_2^H - \kappa_2^L}{\kappa_2}\right)\Gamma_2 > 0. \tag{A.0.10}$$

At $t = 2$, the dispersion of intermediary capital is *positively* associated with the aggregate risk aversion of the market. ■

APPENDIX B

OTHER CASES OF THE HOUSEHOLD PROBLEM IN SECTION 2.6.3

In this section, I consider the cases where the minimum capital requirement in (2.6.12) and/or the capital constraints in (2.6.13) are not slack. That is, at least one of θ_t^C, θ_t^H, and θ_t^L is nonzero.

Case 1: $\theta_t^H > 0$ and $\theta_t^L > 0$

In this case, capital constraints for both intermediaries hold, so the solution is immediate from (2.6.18) and (2.6.19); $\psi_t^H = m\frac{w_t^H}{w_t^{hh}} > \psi_t^L = m\frac{w_t^L}{w_t^{hh}}$. Thus, the household allocates larger wealth to intermediary H than to intermediary L.

Case 2: $\theta_t^H > 0$ and $\theta_t^L = 0$

I considers the case where the capital constraint for specialist H binds, but that for specialist L does not. If $\theta_t^C = 0$, then from Equation (2.6.16), $E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right] = 0$. Equation (2.6.15) implies that $\theta_t^H = 0$, so this case does not have a feasible solution. If $\theta_t^C > 0$, then $\psi_t^H = m\frac{w_t^H}{w_t^{hh}}$ from (2.6.18), and $\psi_t^L = \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - m\frac{w_t^H}{w_t^{hh}}$ from (2.6.17). Since $\psi_t^L < m\frac{w_t^L}{w_t^{hh}}$ and $m\frac{w_t^H}{w_t^{hh}} > m\frac{w_t^L}{w_t^{hh}}$, I have that $\psi_t^H > \psi_t^L$. Again, the household purchases more equity capital from intermediary H than from intermediary L.

Case 3: $\theta_t^H = 0$ and $\theta_t^L > 0$

Suppose that the capital constraint for specialist L binds, but that for specialist H does not. If $\theta_t^C = 0$, then from Equation (2.6.15), $E_t\left[r_{t+1}^a - r_{t+1}^f\right] - A\left(\alpha_t^H\psi_t^H + \alpha_t^L\psi_t^L\right)Var_t\left[r_{t+1}^a\right] = 0$. From Equation (2.6.16), $\theta_t^L = 0$, so this case does not have a feasible solution, similar to Case 2. If $\theta_t^C > 0$, then $\psi_t^L = m\frac{w_t^L}{w_t^{hh}}$ from (2.6.19), and $\psi_t^H = \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - m\frac{w_t^L}{w_t^{hh}}$ from (2.6.17). There is a minimum capital $\tilde{\kappa}^{**} \equiv 2mw_t^L + \left(w_t^H + w_t^L\right)$ that satisfies $\psi_t^H = \psi_t^L$. Thus, if the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^{**}$, the household allocates a larger portion of her wealth to intermediary H than to intermediary L (i.e., $\psi_t^H > \psi_t^L$).

Case 4: $\theta_t^H = 0$ and $\theta_t^L = 0$

Finally, I examine the case where capital constraints for both intermediaries does not bind, but the minimum capital requirement binds. Because $\theta_t^C > 0$, (2.6.15) and (2.6.16) can be rewritten as follows: $\alpha_t^H E_t \left[r_{t+1}^a - r_{t+1}^f\right] - A\alpha_t^H \left(\alpha_t^H \psi_t^H + \alpha_t^L \psi_t^L\right) Var_t \left[r_{t+1}^a\right] = \alpha_t^L E_t \left[r_{t+1}^a - r_{t+1}^f\right] - A\alpha_t^L \left(\alpha_t^H \psi_t^H + \alpha_t^L \psi_t^L\right) Var_t \left[r_{t+1}^a\right]$, which further implies that $\alpha_t^H \psi_t^H + \alpha_t^L \psi_t^L = \frac{1}{A}\frac{\mu_t - r_t^f}{\sigma_t^2}$. Next, from (2.6.17), I obtain that

$$\psi_t^H = \frac{\alpha_t^L \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}} - Y_t}{\left(\alpha_t^L - \alpha_t^H\right)} \quad \text{and} \quad \psi_t^L = \frac{Y_t - \alpha_t^H \frac{\tilde{\kappa} - w_t^H - w_t^L}{w_t^{hh}}}{\left(\alpha_t^L - \alpha_t^H\right)}.$$

Let $Y_t \equiv \frac{1}{A}\frac{\mu_t - r_t^f}{\sigma_t^2}$. The minimum capital $\tilde{\kappa}^*$, defined in Proposition 2, satisfies $\psi_t^H = \psi_t^L$. Again, if the minimum capital requirement is sufficiently high, say $\tilde{\kappa} > \tilde{\kappa}^*$, the household purchases more equity capital from the intermediary H than the intermediary L (i.e., $\psi_t^H > \psi_t^L$).

APPENDIX C

APPENDIX TABLE

Table C.1
List of Intermediaries

This table lists 118 intermediaries in the sample. The intermediaries are identified as all firms listed on NYSE, AMEX, or NASDAQ whose *header* SIC code or *historical* SIC code is 6000-6200 or 6712. The largest 30 intermediaries are identified based on their market capitalization at the end of each quarter from 1973/Q1 to 2016/Q4. The nonfinancial firms are identified as all firms listed on NYSE, AMEX, or NASDAQ excluding financial firms (*header* SIC code or *historical* SIC code 6).

Intermediary Name	Intermediary Name	Intermediary Name
AFFILIATED MANAGERS GROUP INC	FEDERAL NATIONAL MORTGAGE ASSN	NEW YORK COMMUNITY BANCORP INC
ALLY FINANCIAL INC	FIRST CHARTER FINL CORP	NORTH FORK BANCORPORATION NY INC
AMERICAN EXPRESS CO	FIRST CHICAGO CORP	NORTHERN TRUST CORP
AMERIPRISE FINANCIAL INC	FIRST CHICAGO N B D CORP	P N C FINANCIAL SERVICES GRP INC
AMERITRUST CORP	FIRST FIDELITY BANCORP	PAINE WEBBER INC
ASSOCIATES FIRST CAPITAL CORP	FIRST INTL BANCSHARES INC	PEOPLES UNITED FINANCIAL INC
B B & T CORP	FIRST PENNSYLVANIA CORP	PROVIDIAN FINANCIAL CORP
BACHE GROUP INC	FIRST REPUBLIC BANK S F	PRUDENTIAL FINANCIAL INC
BANK NEW ENGLAND CORP	FIRST SECURITY CORP DE	REGIONS FINANCIAL CORP
BANK OF AMERICA CORP	FIRST TENNESSEE NATIONAL CORP	REPUBLICBANK CORP
BANK OF NEW YORK MELLON CORP	FIRSTAR CORP	RYDER SYSTEMS INC
BANK ONE CORP	FLEETBOSTON FINANCIAL CORP	S & P GLOBAL INC
BANKAMERICA CORP	FRANKLIN RESOURCES INC	S L M CORP
BANKBOSTON CORP	GOLDEN WEST FINANCIAL CORP	SALOMON INC
BANKERS TRUST CORP	GOLDMAN SACHS GROUP INC	SCHWAB CHARLES CORP
BEAR STEARNS COMPANIES INC	GREAT WESTERN FINANCIAL CORP	SHAWMUT NATIONAL CORP
BLACKROCK INC	HARRIS BANKCORP INC	SHEARSON LOEB RHOADES INC
BLOCK H & R INC	HOUSEHOLD INTERNATIONAL INC	SOCIETY CORP
C & S SOVRAN CORP	HUDSON CITY BANCORP INC	SOUTHTRUST CORP
C I T GROUP INC	HUTTON E F GROUP INC	SOUTHWEST BANCSHARES INC
C M E GROUP INC	I T T HARTFORD GROUP INC	SOVRAN FINANCIAL CORP
CAPITAL ONE FINANCIAL CORP	INTERCONTINENTALEXCHANGE GRP INC	STATE STREET CORP
CHARTER COMPANY	JPMORGAN CHASE & CO	SUNAMERICA INC
CHARTER NEW YORK CORP	KEYCORP	SUNTRUST BANKS INC
CHASE MANHATTAN CORP	LEGG MASON INC	T D AMERITRADE HOLDING CORP
CITICORP	LEHMAN BROTHERS HOLDINGS INC	T ROWE PRICE GROUP INC
CITIGROUP INC	M & T BANK CORP	TEXAS COMMERCE BANCSHARES INC
CITIZENS & SOUTHERN CORP GA	M B N A CORP	U S BANCORP DEL
CITIZENS FINANCIAL GROUP INC	M CORP	UNION BANCORP INC
COMERICA INC	M N C FINANCIAL INC	UNIONBANCAL CORP
CONCORD E F S INC	MANUFACTURERS HANOVER CORP	UNITED VIRGINIA BANKSHARES INC
CONTINENTAL ILL CORP	MARINE MIDLAND BKS INC	VALLEY NATIONAL CORP AZ
CORESTATES FINANCIAL CORP	MELLON FINANCIAL CORP	VISA INC
COUNTRYWIDE FINANCIAL CORP	MERCANTILE BANCORPORATION INC	WACHOVIA CORP
CROCKER NATIONAL CORP	MERRILL LYNCH & CO INC	WACHOVIA CORP NEW
DEAN WITTER DISCOVER & CO	MORGAN STANLEY DEAN WITTER & CO	WASHINGTON MUTUAL INC
DISCOVER FINANCIAL SERVICES	N Y S E EURONEXT	WELLS FARGO & CO
DREYFUS CORP	NASDAQ INC	WELLS FARGO & CO NEW
FEDERAL HOME LOAN MORTGAGE CORP	NATIONAL CITY CORP	WESTERN BANCORPORATION
		WESTERN UNION CO