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Doctoral Dissertation

**Three Essays on Banking, Capital Market Frictions
and Corporate Payout Policy**

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Submitted in partial fulfillment of the requirements for
Doctor of Philosophy in Management

at

Lazaridis School of Business and Economics

Wilfrid Laurier University

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Hosein Nooriaan

2017

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Declaration of Authorship

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- I have acknowledged all main sources of help.

Signed:

Date:

Acknowledgements

I would like to express my sincere gratitude to my dissertation committee chair, Dr. Si Li for her insightful feedback, supervision, and encouragement. In addition, I am indebted to my dissertation committee members, Professor Ben Amoako-Adu and Dr. Phelim Boyle for their guidance, insightful comments and support over the dissertation process.

I am grateful to the Laurier Finance faculty and my fellow Ph.D. students for their feedback and support. I also must thank Dr. Noori, Dr. Kalimipali, and Ms. Kristensen, who offered a great deal of support to all Ph.D. candidates during the program. All our activities as Ph.D. students were wonderfully coordinated by Dr. Smith, as finance program coordinator. I thank him so much.

I am also very grateful to all professors that I have had a chance to attend their classes. I must thank Dr. Nayak, Dr. Perez, Dr. Shkilko and Dr. Kalimipali, Dr. Amoako-Adu, Dr. Eid, Dr. Ziss and Dr. Johnson, for their memorable courses. I am specially indebted to Dr. Boyle. More important than his wonderful asset pricing courses was his extremely encouraging manner to all people around him.

Finally, I was blessed to have Dr. Amoako-Adu to the end of my dissertation and farewell him to his retirement. His kindness and care made this long journey much easier. I wish him a wonderful retirement.

I dedicate this dissertation to my beloved wife, Somayyeh, my two little daughters, Nika and Nora, and my wonderful parents, for their unconditional love throughout my entire life.

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Chapter 1

Introduction and Overview

1.1 Introduction

This dissertation is comprised of three essays on capital market frictions and corporate policy. The overall theme of the dissertation revolves around corporate payout policy and asset liquidity in the presence of capital market friction. A relatively extensive and well established area of financial research is dedicated to the link between supply of capital and corporate investment and capital structure policy. The discussions herein contribute to this literature by showing how the supply of capital may impact corporate payout policy during financial crises (first essay) and how anticipation of capital market friction can impact a bank's choice of asset liquidity (third essay). The second essay is an empirical investigation of contagion between investment banks and hedge funds.

The first essay, "Capital Market Friction and Corporate Payout Policy", examines the role that supply of capital plays in corporate payout policy. The classic framework of Modigliani & Miller (1958, 1961) considers capital market imperfections as irrelevant to corporate payout policy. In their framework, for signaling purpose, dividends are paid out of excess cash flow, which reduces free cash flow and/or caters to investors' liquidity needs. However, recent empirical studies, as well as anecdotal evidence, indicate that a significant proportion of publicly traded firms could not have funded their payout without relying on external financing (Farre-Mensa et al., 2014). This initial essay, therefore, examines the effect of supply of capital on payout policies and addresses whether and how changes in credit market conditions can impact corporate payout policy.

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The primary data source used in the first essay comes from the annual Compustat database for the period between 1973 and 2014. I use the local TED spread maximum as a proxy for capital market friction and investigate whether such events cause firms to change their payout policy. I find that in the event of extreme credit shocks, firms that rely more heavily on credit markets (experiment group) are more likely to reduce their payouts, mainly through repurchase mechanism, than firms that do not rely on credit markets. Interestingly, the experiment group, or firms with greater reliance on external capital to finance their payouts, consists of large and profitable firms. An important implication of this paper for investors is that large firms, which are presumably more resourceful at securing external finance in times of urgent need, are comparatively more likely to reduce their payouts in response to credit shocks than small firms. This is because their dependence on the external capital for financing payouts outweighs their capacity to find the sufficient funds.

The second essay, “Investment Bank Exposure to Hedge Funds and Financial Contagion”, empirically investigates the existence of contagion between hedge funds and investment banks. From a theoretical perspective, contagion between hedge funds and investment banks can occur in both directions. An initial shock to hedge funds can travel to investment banks through direct or indirect counterparty credit exposure. Conversely, an initial shock to investment banks can spread to hedge funds through the balance sheet of investment banks, or through the early withdrawal of cash or collaterals. My dataset consists of a panel of top five investment banks, that provide brokerage services to more than 60% of all hedge funds, and their affiliated hedge funds, as listed in the TASS database. By employing both parametric and non-parametric methods, I document that two sectors show excessive correlation for the lowest quantile (5% quantile) of residual

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returns. Through Granger causality, I also show that the direction of contagion is most likely from hedge funds to investment banks.

The third essay, “Bank Strategic Choice of Asset Liquidity”, seeks to answer why banks hold so much low-yield liquid assets while they can earn liquidity premiums from longer term and more risky assets. In addition to regulatory, transactional, precautionary, agency, or tax repatriation motives, banks have a somewhat unique motivation for holding liquid assets. The theoretical literature asserts that when aggregate liquidity in the financial system is scarce, financial institutions can make one of two strategic ex-ante choices: they can choose to maximize their invest in illiquid assets to maximize their profits from the liquidity premium; or they can choose to keep part of their portfolio liquid so that they can profit from asset fire sales (Allen & Carletti, 2004). The latter choice points to a unique motive for banks to hold liquid assets so as to take advantage of undervalued assets in fire sales (speculative motive). Despite rich theoretical underpinnings, there has been little empirical analysis of the speculative motive. This paper fills this gap by offering a range of univariate and regression analyses, and instrumental variable analyses.

In this final essay, I use U.S. banks call reports (reports of condition and income) for the period between 1985 and 2010 to build quarterly panel data of 34,000 samples. The period consists of five financial crises, three of which originated in the capital market (market crises) and two of which originated in the banking system (banking crises). The essay focuses on the impact of pre-crisis bank choice of liquid assets on gaining market share during crises. I show that banks can substantially benefit from pre-crisis choice of greater liquid assets. An increased level of pre-crisis

liquid assets statistically and economically improves bank competitiveness during financial crises, while undermining bank competitiveness during normal times. However, I find only a narrow definition of liquidity (cash and trading assets) is related to the bank performance. When the definition of bank liquid assets is broad enough to include available-for-sale securities and held-until-maturity securities, the relation either diminishes or reverses.

1.2 Overview of Dissertation

This dissertation is organized in 5 chapters. Following the introduction, the second chapter discusses the impact of capital market friction on corporate payout policy. While traditional theory of corporate payouts mainly focuses on demand determinants, in this chapter I examine the overlooked supply determinant of payout policy. I show that disruption in capital supply can have a significant impact on corporate payout policy.

Chapter three documents the existence of contagion between hedge funds and investment banks, analyzed at the firm level (top five investment banks and their affiliated hedge funds), as well as the index level (hedge funds index returns, HFR, and investment banks index returns). Empirically, I show that an initial negative shock to a hedge fund travels to its broker (investment bank) due to strong financial and liquidity links between the two.

Chapter four focuses on bank choice of asset liquidity in the presence of possible financial market frictions. I discuss two reasons why banks might retain excess liquid assets. First, banks might hold liquid assets to benefit from undervalued assets during market frictions; and second,

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liquid assets can signal safety during bank run episodes. I show empirically that banks with higher levels of liquidity pre-crisis gain greater market share during episodes of market friction.

The chapters that follow are presented as three independent essays that can be read in any order. For each chapter, I provide an abstract, an introduction, an overview of the related literature, a discussion of data and methodology, a complete analysis of results, and a conclusion.

Chapter 2

Capital Market Friction and Corporate Payout Policy

Abstract

Traditional payout policy theory argues that internally generated cash flow is the main source for financing corporate payout. Recent studies, however, suggest that firms may use external capital to finance payouts (Farre-Mensa, Michaely, & Schmalz, 2014). Building on this new insight, this paper uses global credit crunch events as natural experiments to examine the impact of credit supply on corporate payout policy. I find that during periods of capital market friction, firms that rely on external capital to finance their payouts are more likely to reduce payouts than firms that do not rely extensively on credit. The results indicate that firms which are more likely to cut payout tend to be large, and financially stable.

2.1 Introduction

It is well established that capital market friction influences corporate financing and investment policies. The literature shows that credit market shocks are associated with significant changes in leverage and investment (Hancock & Wilcox, 1998; Kashyap, Stein, & Wilcox, 1992; Leary, 2009; Lemmon & Roberts, 2010; Rauh, 2006; Sufi, 2009). A related but relatively underrepresented subject of analysis is the impact of capital market friction on corporate payout policy. Do firms adjust their payouts in response to credit shocks? If so, do they choose dividends or repurchase options to cope with the new credit environment? Does a change in funding liquidity (ease of access to the credit market) have an impact on corporate payout? Does payout reduction convey different information to investors during credit crunch times versus normal times?

The literature has shown that dividends are paid out of excess cash flows, for the reason of signaling, reducing free cash flows, or catering to investors' liquidity needs (Allen, Bernardo, & Welch, 2000; Jensen, 1986). As such, it is assumed that firms do not raise money externally to pay dividends because external financing would counteract the advantages of paying dividends, such as reducing information asymmetry and free cash flow (Miller & Rock, 1985). Recent anecdotal and empirical evidence, however, suggests that firms finance their payout with equity or debt issuances. For example, Apple, a firm with a cash balance of over \$150 billion, issued \$6.5 billion in bonds and used the proceeds mostly for repurchases and dividend payments (Eddings, 2015). Furthermore, Farre-Mensa et al. (2014) show that more than 36% of payers in their study could not have funded payouts without resorting to external financing. As a result, this essay examines

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the supply channel underlying corporate payout policy and addresses whether and how firms change their payouts if access to credit shrinks.

Herein, I use a range of macro credit tightening events as natural experiments to examine the issues noted above. I identify all macro credit events since 1973 (1974, 1980-1984, late 1990, 1998-1999, and 2007-2008) and employ a difference-in-differences analysis to examine changes in payout policies of the experiment group (firms that externally finance their payouts) versus the control group (firms that do not externally finance their payouts) in response to these events. The dependence on external funding to finance payouts is proxied by the ratio of net debt issuance to total payout ($NDITP_{it} = \frac{\text{Net Debt Issuance}_{it}}{\text{Total payout}_{it}}$), as introduced by Farre-Mensa et al. (2014).

Overall, I find that firms with a greater reliance on credit markets are more likely to reduce their payouts during extreme credit shocks. Firms choose to adjust their payouts by reducing repurchases rather than reducing dividends. Before 1990, when dividends are the main source of corporate payouts, credit shocks did not have an impact on the total payout of firms. Yet, after 1990, when repurchase become an important outlet for corporate payouts, firms react to shortages in the capital market by significantly reducing share repurchases. For example, in response to the 2007-2008 credit shock, firms that rely on the external credit market reduced share repurchases 10% more than firms that rely less heavily on external financing, with all other independent variables maintained at their expected values.

The above finding is not surprising if payout reductions are due to a shock to corporate cash flow, or more generally, a shock to demand, rather than a shock to capital supply. To address this

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concern, I use the possibility of having an external debt rating as an instrument for NDITP (degree of external financing of total payout). Firms that have external debt rating are larger and more profitable firms (Faulkender & Petersen, 2006) and hence less likely to reduce their payouts due to cash flow shocks(demand channel), however, I find that these firms(experiment group) are more likely to reduce their payouts in response to major shocks in supply of credit, compared to firms in control group(that do not have external debt rating). The finding challenges the view that corporate payouts are less influenced by capital market friction if the firms are larger, more profitable, and rely more on the capital market (Opler, Pinkowitz, Stulz, & Williamson, 1999). In other words, the supply side (capital market frictions) has a significant impact on firm payout policy after controlling for demand.

Next, I examine whether marginal changes in credit conditions, measured by National Financial Condition Index (NFCI) and cyclically adjusted NFCI, have an impact on corporate payout policy. To disentangle the demand from supply channels, I isolate the credit supply indices from macroeconomic indicators (e.g., GDP growth rate). The results show that an increase in the cost of funding (as proxied by higher NFCI index) is not significantly related to a greater likelihood of payout reduction.

Finally, I examine whether dividend reduction conveys different information content during tight credit conditions versus normal credit conditions for the experiment and control firms. If supply channel of payouts is an economically significant determinant of payout policy, dividend reductions should convey less information about future cash flows in the experimental group during periods when credit supply becomes an important determinant of payout policy. The results

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confirm that investor reactions to the announcement of dividend reductions are significantly less negative if investors believe that credit supply, rather than internal cash flow, is the reason for the reduction.

The main contribution of this study is to empirically show that availability of external funds is an important determinant of corporate payout policy. I find that firms in the experiment group (firms that mainly rely on credit for financing their payout) were 10% more likely to reduce their payouts than the control group in response to credit shocks following the 2007-2008 financial crisis. The supply perspective of payout policy is a valuable addition to the demand side of payout theories that mainly focus on signaling, clientele effect, and agency costs. In taking a different angle, I contribute to the growing body of literature that explores the real effect of financial market frictions. Previous studies show that difficulties in accessing external funds results in a reduction in capital spending (Campello, Graham, & Harvey, 2010). This study moves the ongoing discussion forward by showing that supply has a substantial impact on corporate payout policy in a financial crisis. From a macroeconomics perspective, aggregate payout reduction may reduce aggregate consumption. In particular, Baker, Nagel, & Wurgler (2006) find that investors are far more likely to consume dividends than capital gains.

2.2 Literature Review

The question at the center of this study exists at the confluence of two lines of research in the current literature. The first is the vast area of research that studies the impact of capital market imperfection on corporate policy, including investment and capital structure. The second is the

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well established literature on the determinants of payout policy. I extend the first line of research by focusing on the impact of capital market imperfection on corporate payout policy, and contribute to the second area by investigating whether supply of credit can be considered an independent determinant of corporate payout policy.

The classical framework of Modigliani & Miller (1958, 1961) considers capital market imperfections as irrelevant to corporate payout policy. However, thanks to a plethora of real-world evidence, it is now understood that capital market imperfections influence corporate financing and investment policy (Almeida, Campello, & Weisbach, 2011b; Campello et al., 2010; Hancock & Wilcox, 1998; Kashyap et al., 1992; Lemmon & Roberts, 2010; Rauh, 2006; Sufi, 2009)¹. These studies mostly address the impact of capital (credit) friction on investment and financing policy. On the other hand, the impact of credit friction on corporate payout policy is relatively poorly understood. Bliss, Cheng, & Denis (2013), studying the effects of the recent financial crisis on corporate payout policy, confirm that firms value cash when the external cost of financing rises. In their experimental setup, they show a sharp increase in the percentage of firms that either

¹ For example, Kashyap et al. (1992) find that tightening monetary policy changes the mixture of corporate external financing from bank loans to commercial papers. They also find that a shift in availability of credit negatively influences corporate investment. Hancock & Wilcox (1998) find that a shock in bank capital is transferred to loan availability for small businesses and their real economic activities. A recent wave of studies uses mostly natural experiments to investigate causality. For example, Rauh (2006) shows that firms with mandatory contributions to defined benefit pension (a proxy for exogenous shocks to funds available to firms), have lower investment and this is particularly the case for financially constrained firms. Sufi (2009) finds that the introduction of bank loan ratings leads to greater use of public debt, larger cash acquisitions, and higher asset growth by the rated firms. Campello et al. (2010) survey a large population of CFOs to find whether financial constraints influenced firms' choices of investment and real activities during the recent financial crisis. They find that financially constrained firms planned to substantially cut capital spending and employment and consume their cash holdings to survive. Finally Lemmon & Roberts (2010) investigate how shocks to credit supply influence corporate financing and investment by examining three exogenous contractionary shocks to the speculative bond market. They find that alternative sources of funding (e.g., equity, bank loan, and cash balances) are not able to offset the impact, leading to an almost one-for-one decline in net investment.

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eliminated or reduced payouts during the 2007-2008 crisis. Furthermore, they provide evidence that firms used the cash saved from their payout reduction in an economically meaningful way, funneling it into investments and/or cash balance. Although the current study uses the same natural event as that of Bliss et al., my perspective is substantially different. Whereas they conclude that demand side of dividend payout is more pronounced during the financial crisis, I show that supply of credit plays an important role during episodes of credit tightening.

2.2.1 Supply Determinants of Payout Policies

Admitting a great level of simplicity, the answer to the long standing question of how firms set their payout policy can be distilled down to three essential factors: signaling (Ambarish, John, & Williams, 1987); agency cost (Easterbrook, 1984); and clientele effect (tax) (Allen et al., 2000). Although these factors are inherently different, they all refer to the demand determinants of payout policies. In other words, firms adopt a particular payout policy because they want to signal the quality of their future cash flow, and/or lower the agency costs of free cash flow, and/or cater to the needs of their investors. The question is whether credit availability (supply) changes the intended outcomes of their payout policy.

This question has not been viewed as a particularly relevant issue in the payout policy literature, simply because payout policies, and in particular dividends, are assumed to be financed out of residual (i.e., after investment) cash flow. Although challenged by some early studies (Easterbrook, 1984), this long held axiom has not received sufficient empirical attention². Recent

² An exception is Lambrecht & Myers (2012) who argue that firms use external financing to smooth their payouts.

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studies, however, provide clear evidence that the traditional residual payout policy does not accurately reflect the actual practices of corporations: firms use external funds (mostly debt) extensively to finance their payout (Farre-Mensa et al., 2014). According to Farre-Mensa et al., less than half of U.S. industrial firms with positive payouts in a given year initiate an equity or net debt issue in the same year; yet, with all else being equal, most of the firms could not fund their payout without the proceeds of these issues.

If firms rely extensively and substantially on credit to finance their payout, the availability of credit can be regarded as an independent factor in determining a corporation's payout policy. In other words, any payout policy that firms might opt for as their ideal plan (based on traditional demand factors) may be hindered by the availability of credit. To investigate this possibility empirically, I examine whether exogenous shocks to credit availability have an extra explanatory power in determining corporate payout levels.

The caveat of using macro credit shocks in a natural experiment set-up is obvious; these exogenous credit events are usually concomitant with macroeconomic shocks that also affect the demand side of a payout policy. Before I address how to overcome this limitation (discussed further in the methodology, section 4), I briefly review how current theories can explain the impact of macroeconomic shocks on the demand side of corporate payout policy. The current literature is dominated by three competing theories that attempt to explain the main questions of this study. Agency theory suggests that firms pay out of their free cash flows to avoid costs associated with retaining excess cash reserves (Easterbrook, 1984; Jensen, 1986). The agency cost of cash is particularly acute when there is limited investment opportunity. Therefore, following a

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macroeconomic shock, firms tend to provide higher payouts to reduce potential costs associated with holding free cash flow. On the contrary, pecking order theory suggests that the marginal value of cash holdings increase as the cost of external financing increases (S. C. Myers & Majluf, 1984). Limited credit availability and uncertainty about future financing options accentuate the precautionary motive of cash holding. As a result, firms tend to hold more precautionary cash and reduce payouts so as not to miss any positive NPV investment (Bliss et al., 2013). Along the continuum between these two theories is the dividend signaling theory which suggests that firms do their best to maintain (or even increase) the current level of dividend in order to signal stable future cash flow (Bhattacharya, 1979; Kalay, 1980). There is also well established literature on dividend persistence, which indicates that dividend cut-down is the last thing that firms want to exert on cash flow shortfalls (Daniel, Denis, & Naveen, 2008). Recent evidence suggests that firms readily compromise investments over dividends and prefer other methods of payouts, such as share repurchases, to ensure flexibility. Brav, Graham, Harvey, & Michaely (2005) report that CFOs see dividends as on par with investments, while share repurchases are conducted using residual cash flow. More importantly, Daniel, Denis, & Naveen (2008) show that whenever firms face negative cash flow shocks, they mostly compromise investments, or use more debt financing. Therefore, with a shock in the credit market, firms might find it more convenient to sacrifice some profitable investments to preserve the signaling benefit of the dividend. In this case, the shock in the credit market should not affect payout policy, but will influence cash holding and investment policy.

The persistence of dividend payouts, as underscored in the above studies, is on the premise that dividend reductions provide investors with information about material future cash flow, thus

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enabling them to revise the stock price (Miller & Rock, 1985; Denis, Denis, & Sarin, 1994). While unconditional information content of dividend reductions has been widely examined in the empirical finance literature, few studies have explored whether dividend information content depends on business cycles. Below & Johnson (1996) examine the differential share price reaction to dividend increase and decrease announcements with respect to market phase. They find that information content of the dividend is more pronounced when it happens counter to the market phase. Further, Akron (2011) argues that business cycle is crucial in interpreting dividend announcement information. Examining the Tel Aviv Stock Exchange between 2000 and 2007, he finds that during a technology bust (2000-2003), a dividend announcement is perceived as a strong and reliable signal about the state of the corporation, compared to normal times.

Herein, I offer a new perspective by adding a further dimension to the conditional information content of dividend announcements³. I hypothesize that dividend reduction by firms that use credit extensively to finance their payouts conveys significantly different information than those that do not finance their dividends externally, especially when access to external finance is difficult. This is because firms in the former group are more likely to reduce dividends to cope with the shortage of external funds than firms in the latter group. In other words, when firms highly value balance sheet liquidity, investors may see dividend reductions as an effective liquidity management tool rather than a signal of reduced future cash flow. While the latter is a negative signal to investors, the former is an opportunistic act by managers, providing neutral information regarding the future state of the corporation. As a result, with all else being equal, firms in experiment group (i.e., those

³ I simultaneously condition for the type of firm and different credit. The purpose of adding a new dimension is to find additional evidence that supply of credit is a significant determinant of dividend payouts.

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with higher reliance on external capital to finance their payout) should have a smaller negative abnormal return to dividend reduction during tight credit periods than during normal times.

2.3 Hypotheses

H1.1: Firms reduce their payouts in response to major frictions in credit markets after controlling for all fundamental (i.e., demand) determinants of payout reductions.

H1.2: Firms that rely more on credit to finance their payouts further reduce payouts during episodes of the extreme credit tightening.

H2: Firms that rely more on credit to finance their payouts further reduce their payouts when credit conditions marginally worsen.

H3: During extremely tight credit conditions, investor reaction to dividend reduction announcements depends on whether or not firms use credit to finance their payouts: firms that use credit extensively to finance their payouts elicit a less negative reaction to dividend reduction announcements.

2.4 Data and Methodology

My primary data source comes from the annual Compustat database for the period between 1973 and 2014. As is common in the corporate finance literature, I exclude samples from financial and utility industries to avoid potential distortion due to regulatory cash holding and dividend policies. I eliminate samples with missing data on total assets, dividends, and market capitalization

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(PRCC_F in Compustat). Several other control variables are constructed from the Center for Research in Security Prices (CRSP) database, including stock return idiosyncratic volatility, buy and hold return, and total market return. The credit condition indicators, NFCI, TED spread, and ANFCI index are taken from the Chicago Federal Reserve (2014), while other macroeconomic variables are from the World Bank (2014) and the St. Louis Federal Reserve research web portal. Appendix 1 contains a complete discussion of the variables used in the study.

The credit condition indices are at the center of all experiments. I use the local maximum credit condition indicators to identify years of extreme credit tightening. The TED spread is the difference between the three-month Eurodollar rate and three-month Treasury bill. The NFCI index is the weighted combination of more than 30 sub-indices that are related to frictions in funding liquidity. Adjusted NFCI (ANFCI) is a component of the NFCI index uncorrelated to economic conditions.

Table 1 presents the summary statistics of the three indices. Given the similarity among the components that constitute all three indices, it is unsurprising that they are well correlated, with all pairs above 65%. The correlation between ANFCI and the other two indices is lower because ANFCI is orthogonalized from macroeconomic conditions. Furthermore, all NFCI sub-indices are normalized with a mean of 0 and standard deviation of 1; however, the standard deviation of TED is 0.91 and the mean value of TED is around 1. To present this visually, I show the development of NFCI indices and the TED spread over the study period in Figures 1 and 2, respectively. The highlighted dates are associated with local maximums (spike) of the indicators.

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The dependent variable in all regressions is reduction in corporate payout (share repurchase, dividend, or total payout). It is a binary variable, equal to 1 when the measure of corporate payout is reduced compared to previous years, and zero otherwise. The measure of share repurchase is the total expenditures for the purchase of common and preferred stocks (PRSTKC) minus any reduction in the value of the net number of preferred stocks outstanding (PSTKRV). Total payout is the sum of dividend and share repurchases. Dividend payers are firms that have positive average dividend payouts over the previous two years. Similarly, repurchasers and total payers are firms that have positive average repurchase payouts and total payouts over the previous two years. A firm is considered to have reduced its payout (dividend, repurchase, or total payout) if payout is at least 5% lower in a given year compared to the average payout of the previous two year. In all analyses, our samples are limited to payer firms. For example, when we test whether the credit liquidity shock had an impact on firm dividend levels, the samples include all dividend payer firms (that reduced or did not reduce dividend) and not all firms.

I measure the difference between payout reduction of the experiment and control groups in response to credit shocks after controlling for all demand related variables. The firms in the experiment group rely more on external funding to finance their payouts than the firms in the control group. The measure of “dependence on external funding to finance payout” is adopted from Farre-Mensa et al. (2014). The procedure to generate the control and experiment groups is as follows: each year, for each firm, I calculate NDITP, as the ratio of net debt issuance to total payout: $(NDITP_{it} = \frac{\text{Net Debt Issuance}_{it}}{\text{Total payout}_{it}})$. $NDITP_{it}$ represents the proportion of total payout that has been financed externally for firm i at year t . Net debt issuance is defined as the difference between the

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amount of debt issued (DLTIS) and the amount repaid (DLTR) if this difference is positive, and zero otherwise. Total payout includes total dividend plus total repurchase minus any reduction in the value of the net number of preferred stocks outstanding. Every year, I assign firms with the highest external payout financing (i.e., top 50th percentile of NDITP) to the experiment group, and those with lowest external payout financing (bottom 50th percentile of NDITP) to the control group.

2.4.1 Impact of capital market friction on firm payout

To test whether supply of credit is an independent determinant of payout policy, I use a difference-in-differences approach similar to that found in other corporate finance studies (e.g., Leary, 2009). I identify six credit market shocks using two criteria: first, a given year is identified as a credit supply event when there is a local maximum in the TED spread (and NFCI); and second, an economic story is required for the identified year, as described in Appendix 2⁴. The samples are split into two groups: experiment group, which includes firms in top 50th percentile of NDITP; and the control group, which includes firms in the bottom 50th percentile of NDITP⁵. I test whether firms in the experiment group show a greater reduction in their payout (dividend, repurchase, and total payout) in response to the identified credit events than the control group.

I form the following logistic regression:

$$Y_{it} = \alpha + \beta X_{it-1} + \gamma M_{t-1} + \theta_1 D_{it} + \theta_2 E + \theta_3 (D_{it} \cdot E) + e_{it} \quad (1)$$

⁴ I bundle credit events that occurred during 1979-1984 as one credit shock event. For 1971, I only use the first criteria (local TED spread maximum) to identify it as credit shock year.

⁵ The results hold for other splitting criteria.

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Y: Reduction in Payouts (binary variable,

= 1, if firms reduced payout compared to previous year,

= 0 otherwise)

X: Firm Control Variables

M: Macro Control Variables

D: dummy variable = 1 for experiment group

E: dummy variable = 1 for the event

the coefficient of interest is the interaction term (γ_3). The control variables are listed in Appendix 1.

2.4.2 Impact of marginal change of credit conditions on corporate payout

In this section, I examine whether firms reduce their payouts only in response to extreme supply shocks or if they reduce payouts when access to credit market only marginally deteriorates. I use two credit condition indices, namely Risk NFCI and Adjusted NFCI, and relate the index levels to probability of corporate payout reductions. Since all credit condition indices are highly correlated with economic conditions, a great deal of care must be taken with respect to separating demand, i.e., cutting payout due to shock to future cash flow, and supply, i.e., cutting payout due to difficulty in finding proper supply of funds. To this end, I follow a similar approach to that used in the previous section, by measuring the difference between the control and experiment group in response to changes in credit condition. However, to ensure the credit indices do not impound

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residual demand information, we use the isolated component of a credit condition index from the macroeconomic information, attained through equation (2), and use it in equation (3). Specifically, I use the residual of risk NFCI against GDP growth, total market returns, and aggregate corporate profit in equation (3). The variable of interest is the interaction term of $e_{t-1} \cdot D$ (experiment group times credit index). A positive value would indicate that firms in the experiment group, i.e., firms that use more credit to finance their payout, are more likely to change their payout in response to changes in the credit condition index.

$$\text{Credit Condition Index}_t = \alpha + \theta M_t + e_t \quad (2)$$

$$Y_{it} = \alpha + \beta X_{it-1} + \gamma_0 e_{t-1} + \gamma_1 D_{it} + \gamma_2 (e_{t-1} \cdot D_{it}) + u_{it} \quad (3)$$

Credit Condition Index_t : TED, NFCI, or ANFCI

Y: Reduction in Payouts (binary variable,

= 1, if firms reduced payout compared to previous year,

= 0 otherwise)

X: Firm Control Variables

M: Macro Control Variables

D: dummy variable = 1 for experiment group

e: residual from the equation (2)

2.4.3 Information content of dividend reductions

The testable hypothesis of this section is as follows: when credit conditions are tight, investor reactions to dividend reduction announcements are less negative for firms that finance their dividend externally than firms that do not finance externally. This is because the former group's decision to reduce dividends can be construed by investors as a strategic decision to safely weather the difficult credit crunch period, while the latter group's decision more likely conveys problems with future cash flow.

To test this hypothesis, I split the samples in two dimensions. The first dimension is the degree of dependence on external financing for payout: firms that are in the top 50th percentile of NDITP and those in the bottom 50th percentile⁶. The second dimension is the periods in which events occur, i.e., normal times versus stress times. As a result, there are four groups of firms: firms that highly depend on external funds to finance their payouts during normal times (experiment group in normal times); firms that do not depend on external funds to finance their payouts during normal times (control group in normal times); firms that highly depend on external funds to finance their payouts during stress times (experiment group during stress times); and firms that do not depend on external funds to finance their payouts during stress times (control group in stress times). Experiments are run on all dividend announcement events that occurred between 1986 and 2011. Stress times are identified as those years with local maximum TED spreads and NFCI: 1987, 1991,

⁶ For ease of understanding, this group is referred to as firms that do not rely on credit to externally finance their payout. However, this does not fully reflect reality, since the majority of the firms located in the bottom 50th percentile do not finance their payout at all.

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1998-2000, and 2007-2008. All other years are considered normal years, i.e., 1985-86, 1988-1989, 1993-1999, 2004-2007.

I employ classic event study methodology to estimate the surprise element of dividend reduction announcements. Further refinements to the event database, based on the current literature, are as follows: I restrict dividend distribution to regular quarterly cash dividends payable in U.S. dollars or with distribution code =1232. As a result, special dividends and non-quarterly dividends are excluded from the sample. Declaration date must be at least eight days before ex-dividend date to avoid an ex-dividend price reaction, as documented by Eades, Hess, & Kim (1984) and Kato & Loewenstein (1995). Reduction events that occurred simultaneously with other distribution events (e.g., stock split) have been excluded from the sample to avoid confounding event analyses. All events must have at least 250 trading days in the database before the event. Finally, events must be at least one year apart. I use 250 until ten days before the event as the period in which to estimate the market model parameters:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \quad (4)$$

The abnormal return is the residual returns of capital asset pricing model (CAPM) for the event window of one day before the event, the event day, and one day after the event (-1, 0, +1). I then calculate the average abnormal return for all events for all three-day event windows by:

$$\overline{AR}_t = \frac{1}{n} \sum_{i=1}^n AR_{it} \text{ for } \overline{AR}_{t-1}, \overline{AR}_t \text{ and } \overline{AR}_{t+1} \text{ and then find } \overline{CAR} \text{ as } \overline{CAR} = \sum_{t=-1}^{t=+1} \overline{AR}_t$$

(n: number of firm events).

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The variance of \overline{CAR} (cumulative abnormal return) is calculated as $\frac{3}{(n)^2} * \sum_{i=1}^{i=n} \epsilon_i^2$, in which, ϵ_i^2 is the residual variance from the statistical market model described above, and “n” is number of firms that have undergone the event (i.e., reduced dividend).

The goal is to measure the CAR of experiment and control groups in response to dividend reduction announcements in two different periods: when access to credit is easy, equation (5), and when access to credit is restricted, equation (6):

$$CAR_{(\text{experiment})(\text{normal times})} - CAR_{(\text{control})(\text{normal times})} \quad (5)$$

$$CAR_{(\text{experiment})(\text{stress times})} - CAR_{(\text{control})(\text{stress times})} \quad (6)$$

2.5 Results

2.5.1 Univariate analysis

I begin the analysis by offering some insights from the evolution of corporate payouts over the past 40 years. Figure 3 shows aggregate corporate payouts from 1971 to 2010 and Figure 4 depicts the average corporate payout ratio over the same period. As both Figures indicate, corporate payouts have soared in both absolute value (sum) and relative number (ratio) over time, except for some significant events during which firms substantially lowered their payouts. It is also worth noting that before 1990, dividend ratio slopes upward while after 1990, dividend ratio slopes downward. Furthermore, after 1990, share repurchases start to gain more importance in total payout ratio.

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To develop an overall understanding of corporate behavior during credit crunches, I show the number of firms that reduced their payouts during the liquidity shock periods. To identify liquidity shocks, I highlight the years in which the TED spread is associated with the local maximums, i.e., 1971, 1974, 1979-83, 1987, 1990, 1998-2000, and 2007-2008 (Figure 2). Figure 5 shows the percentage of firms that reduced their payouts since 1972. In the figure, I highlight the years associated with major macroeconomic credit shocks, similar to Figure 2. Since payout decisions are usually lagged (Bliss et al., 2013), the immediate adjacent year after a liquidity shock is highlighted. For example, according to the TED spread, a credit shock happened in 2007 and 2008, but we observe the payout adjustment in 2008-2009. As can be seen in Figure 5, firms dramatically reduce their payouts in response to increased liquidity tightness. Furthermore, we can note a significant change in the corporate payout patterns: before 1987, dividend reductions were the first choice in response to macroeconomic or credit shocks. For example, during the liquidity crisis of 1981-1983, firms mostly reduced dividend while the percentage of firms that reduced repurchases only slightly increased. The trend reverses after 1987, when firms prefer to reduce share repurchase as a means to exercise payout reduction.

Since all six credit events are associated with substantial cash flow shocks, it is difficult to conclude that the reduction of corporate payouts is solely due to shocks in available liquidity. To address this concern, I design a regression setup to measure the differential behavior of the experiment group (firms with greater reliance on credit market to finance their payout) and control group (firms with the least reliance on credit market to finance their payout) in response to credit shocks.

2.5.2 Regression analysis

2.5.2.1 Do firms adjust their payout policy in response to credit liquidity shocks?

Table 2, Panels A, B, and C, show the results of equation (1). The dependent variable is either dividend payout reduction, share repurchase reduction, or total payout (dividend + share repurchase) reduction. I control for firm-level factors (β) and macroeconomic factors (γ). Control variables are explained in Appendix 1. All control variables, except for TobinQ and Free Cash Flow that are used contemporaneously, are lagged for one period.

Separately, I run regressions for total payout, dividend, and repurchase reductions. Credit event year is listed at the top of each column, indicating the year that credit event shock is equal to 1 for equation (1). For each event year t , I use all samples between two credit events. For example, for the credit event of 1980-1984, I use samples from 1975 to 1987, and for credit event of 1987, I include samples between 1985 and 1990. The idea is that within samples there should be no other credit event except for the one specified at the top of the column. Samples include all non-financial and non-utility firms that have a positive average of dividend, repurchase, or total payout over the previous two years. For both dividend and repurchase reduction, the dependent variable (i.e., a firm reduced dividend or repurchase) is equal to one if payout is at least 5% lower than the previous two-year average payout, and zero otherwise. In each regression of each panel, the “credit shock event” variable is equal to 1 for the year indicated in the column and zero otherwise. For the sake of brevity, control variables only appear in Panel A, and in all panels the sign and significance of control variables do not contradict the current literature. I expect that firms with recent gains in their stocks (higher buy and hold returns) should have a lower probability of

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reductions, because higher buy and hold returns suggest greater future cash flow. On the other hand, idiosyncratic volatility has been used as a proxy for precautionary motive of cash holding and, thus, it is positively correlated with payout reductions. A higher ratio of free cash flow to assets suggests a lower likelihood that dividends will be reduced. Company size can also be a proxy for a firm's earning risk or financial constraints; therefore, it is negatively correlated with payout reductions. GDP growth should be negatively correlated with payout reduction as good economic conditions are associated with greater expected cash flow.

The variables of interest are the credit shock event, the experiment group, and the interaction term of "experiment group" with "credit shock event". A credit shock event is a dummy variable equal to 1 when TED or the risk component of NFCI has a local maximum, listed at the top of each column in Table 2. With the focus on the interaction term, it is expected that, after controlling for all demand determinants of corporate payouts, firms with more dependence on credit to finance their payouts (higher NDITP) are more likely to reduce their dividends in response to credit liquidity shocks. As a result, the sign and significance of the interaction term are critical.

I find that the interaction term (credit shock multiplied by experiment group) is significant for all credit shocks after 1991. That is, when the supply of credit is limited, firms that finance their payouts externally reduce their total payout more than firms that do not finance their payouts externally. In terms of economic significance, I find that firms in the experiment group (firms that rely the most on credit for payout financing) were 10% more likely to reduce their payout in response to credit shocks as a result of the 2007-2008 financial crisis, than the control group.

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In looking closely at Table 2, Panel A, we can see that credit shocks were not a significant determinant of total payout for the period before 1991. If we incorporate the insights offered by Panels B and C, we can better clarify this finding⁷. When decomposing total payouts into dividend and repurchase payouts, we can readily observe that most of the total payout reductions are due to reductions in repurchases and not reductions in dividends. This is not surprising given that the choice between dividend and repurchase reductions leans heavily toward the option that is less informationally charged. More interestingly, before 1990, when dividends were the main outlet of corporate payouts, firms did not reduce payouts even during the harsh credit crunch of the early 1980s. Indeed, as documented by Daniel, Denis, & Naveen (2008), less than 10% of firms cut dividends when they faced major economic shocks while the majority sacrificed positive NPV projects. On the other hand, as firms gradually adopted repurchasing as their main payout mechanism, a trend that began in the 1990s, they gained more flexibility in dealing with major economic shocks (Jagannathan, Stephens, & Weisbach, 2000), sacrificing payouts instead of positive NPV projects.

2.5.2.2 Impact of marginal credit tightness on firm payout policy

Table 4 presents the estimates of equation (3), in which I examine the impact of a marginal change in credit condition on corporate payout reductions. Although findings in the previous section clearly reflect that corporate payout is influenced by extreme shocks in credit supply, it is likely

⁷ The only anomaly that defies the supply theory of payout is for the crisis period of 1980-1984, when the coefficient of interaction term turns out to be negative for the repurchase reduction (Table 2, Panel B, Column 1980-1984). This is possibly due to the measurement error of repurchase before 1990, when the repurchase mechanism has not yet been adopted to be the main outlet of corporate payout.

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that firms dismiss small changes in the credit market, maintaining their payout policy. In this section, I examine this possibility by relating orthogonalized credit condition indicators to corporate payout reductions. The NFCI index is orthogonalized in equation (2) and the residual of this regression is used in equation (3), while the ANFCI is orthogonalized by construct. Table 4 shows the results of equation (3) for different indices and different payout methods. To save space, I do not discuss the control variables, whose sign and significance are similar to those reported in the previous sections (Table 2, Panel A). The variables of interest are credit condition index(e), experiment group which equals 1 if the firm falls in the top 50th percentile of NDITP (relies heavily on external financing for payout) and zero if the firm falls in the bottom 50th percentile of NDITP, and the interaction of experimental group with credit condition indices. The focus is on the interaction term.

The results indicate that marginal changes in credit conditions do not differentially impact the payout policy of experiment group versus the control group, i.e. the interaction terms are insignificant for both orthogonalized NFCI and ANFCI indicators. Given the importance of consistent payout policy in issuing a signal of healthy cashflow, it is plausible that firms do not change their payout policy in response to small deterioration of credit condition in the economy. The finding does not contradict the previous findings that credit shocks significantly influence corporate payout policy: The marginal deterioration of firms' access to credit is likely offset by their internal cash flow or reduction in investment policy (Brav, Graham, Harvey, & Michaely, 2005; Daniel, Denis, & Naveen, 2008), while the a significant constraint in access to external financing is most likely beyond firms' internal capacity.

2.5.3 Event study

Table 5, Panels A and B, demonstrate the differential cumulative abnormal return (CAR) formulated in equations (5) and (6). Panel A, Table 5, confirms that firms with greater reliance on external funds (experiment group) face less negative reactions by investors during times of stress. While insignificant during normal times, the difference between the control and experiment group are significantly different during credit shocks (1973, 1980-1984, 1987, 1998-2000, and 2007-2008). During stress periods, dividend reduction announcements elicit -2% returns for the control group while only eliciting -1.5% for the experiment group. Both numbers are significant, suggesting investors in the experiment group find that dividend reductions are related to tactical reasons (insufficient supply of credit to finance payouts) rather than fundamental reasons (poor future cash flow).

2.6 Robustness Test

2.6.1 Dealing with endogeneity

Admittedly, identifying the impact of supply through overarching macroeconomic shocks can be questioned due to endogeneity. The use of the experiment and control group in a difference-in-differences regression is a partial solution to this issue (Roberts & Whited, 2012) in that firms in the experiment group will react differently to macro credit events in the capital market. However, there is still a possibility that firms in the experiment group (firms with greater dependence on external financing for their payout) reduce their payouts not because of shortages in funding

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(supply explanation), but because of greater vulnerability to macroeconomic shocks (demand explanation). I attempt to rule out the possibility of a demand explanation by using the possibility of having a credit rating from a credit agency as an instrumental variable for the degree of dependence on external financing for payouts (NDITP).

A valid instrument satisfies two conditions. First it is correlated with the instrumented variable (relevance condition) and it excludes all other relations with dependent variables (i.e., probability of payouts) except for the one through which the instrumented variable is correlated with instrumental variable (exclusion condition). Fortunately, the first condition is empirically testable; however, the second condition mainly relies on the judgement of the researcher. Herein, the probability of having an external rating is used as an instrument for NDITP (degree of external financing of dividend). The instrument satisfies the requirements of a valid instrument in that the relevance condition is met: firms that can obtain external rating are expected to have easier access to credit and, hence, more dependence on the credit market to finance payouts. In other words, the instrument is correlated with NDITP. Table 3, Panel A, verifies the relevance condition. The exclusion condition is also satisfied: firms that can obtain external rating by credit agencies are more profitable, with a greater capacity to generate revenue, and larger physical assets (Faulkender & Petersen, 2006; Opler et al., 1999), characteristics that are either uncorrelated or negatively correlated with the dependent variable due to demand shock. If the instrument is expected to be negatively correlated with the dependent variable due to demand channel, a positive coefficient of the instrumental variable can be safely attributed to its relation with the instrumented variables through supply channel.

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To construct the instrument, I follow a two-stage process. In the first stage, I regress NDITP against the external rating indicator. The indicator, obtained from S&P Compustat credit rating database, is equal to 1 when a firm has at least one rated bond from the S&P credit rating agency:

$$\text{NDITP}_{it} = \alpha + \beta(\text{external rating})_{it} + u_{it} \quad (7)$$

$$\text{NDIPT}_{it} = \frac{\text{Min}(\text{Net Debt Issuance}_{it}, \text{Total Payout})}{\text{Total Payout}} \quad (8)$$

In the second stage, the estimated NDITP ($\widehat{\text{NDITP}}$), obtained through equation (7), is used in the main regression, equation (1), to form the control and experiment groups.

Table 3, Panels A presents the results of the coefficient estimates from equation (7). Panel B, Table 3, shows the results of the main regression, equation (1), in which the experiment and control groups are formed by estimated NDITP ($\widehat{\text{NDITP}}$) obtained in Panel A. To be concise, I exclude the results of all credit events before 1990, when the impact of credit events was found to be insignificant. The findings shown in Panel B corroborate the results in Table 2, with an anticipated diluted significance due to use of the instrument. In response to credit shocks, firms that rely heavily on credit for financing payout (top 50th percentile of NDITP) reduce their payout significantly more than firms in the bottom 50th percentile. I argue that the obtained coefficient is devoid of demand endogeneity for one important reason: compared with non-rated firms, firms with external rating are more stable, have a greater capacity to generate revenue, and have more physical assets, characteristics that are expected to be less affected by the precautionary motive of saving cash through payout reductions (Faulkender & Petersen, 2006; Opler et al., 1999). The key point in using this IV is to understand the different anticipations arising from whether supply or

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demand channel explain corporate payout policy: If demand was a factor, we would have observed that firms that have external rating (i.e., firms with more physical assets and higher revenue generation capacity) are less likely to reduce their payout in response to undesirable economic conditions. However, Table 3, Panel B, shows the opposite: firms that have external rating are more likely to reduce their payouts during macroeconomic shocks. This finding opens the plausibility of an alternative explanation (i.e. supply channel): firms that rely more on credit markets to finance their payouts are adversely affected by the shortage of credits during episodes of macroeconomic shocks.

2.6.2 Non-Macro events

Although the focus of this paper is on macro credit events, I also examine three non-macro events in 1989 that significantly affected the external financing of non-investment grade firms. The three events all occurred from late 1989 to early 1990 and include: the collapse of Drexel Burnham Lambert, Inc. (Drexel); the ratification of FIRREA (Financial Institutions Reform); and changes to the National Association of Insurance Companies (NAIC) credit rating guidelines. This chain of events was first used by Lemmon & Roberts (2010) to study the impact of shock in credit supply on corporate capital structure⁸. Similarly, I use these events as natural shocks to external financing of the treatment group (below investment grade firms) and investigate whether dividend ratio of the treatment group is affected by shock to external funds. Following Lemmon & Roberts' (2010) methodology, I develop a difference-in-differences regression model that measures the difference

⁸ Lemmon & Roberts (2010) discuss these events in great detail, arguing that these events are indeed exogenous shocks to the corporate financial policy. To save space, I do not repeat the arguments here.

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between dividend ratio of the treatment and control group before and after 1990 (1986 to 1989 and 1990 to 1993), when external financing for the treatment group became difficult. The model is shown in Table 6. While controlling for other regular determinants of dividend payment ratio, I find that the treatment group (speculative bond issuers) pays a significantly lower dividend ratio after 1990 than the control group. The results do not hold for repurchase ratios, which can be explained by the dominance of dividends in corporate payouts before 1990.

2.7 Discussion

When taken out of context, the implications of this study may sound counterintuitive to some readers. For example, I find that larger firms, which are presumably more resourceful at finding credit in times of need, are comparatively more likely to reduce their payouts in response to credit shocks than smaller firms. Consistent with the supply side of payout policies, I offer two explanations as to why the payout policies of smaller firms are less responsive to credit market frictions. First, firms with a smaller asset base are recognized as relying on their internally generated cash flow, rather than external capital, to finance dividends and repurchases (Farre-Mensa et al., 2014). That is, for small firms, less reliance on credit to finance payouts comparatively provides some immunity to major shocks in credit markets.

Secondly, aggregate lending of U.S. banks, which are the main providers of external financing to non-rated firms (smaller and less profitable firms), increases at the advent of credit market frictions. Figure 6 contrasts the percentage change in total corporate bonds outstanding (the main source of financing for large and rated firms) with percentage change in total loans outstanding

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(the main source of financing for small and non-rated firms) during the financial crisis of 2008 and a year after. It is interesting to note that total loans outstanding increased substantially since the financial crisis (highlighted in yellow), while at the same time the total bonds outstanding substantially decreased⁹. Similarly, Ivashina & Scharfstein (2010) report that the total loans outstanding during the peak of the financial crisis of 2007-2008 increase rather than decline, mostly due to increases in line of credit draw-downs. Regardless of the underlying reason, this observation serves to validate the empirical results found herein: firms that rely less on the credit market (i.e., firms that rely on banks, or alternatively, firms with a lower probability of an external credit rating) are relatively less affected by the supply of credit during credit market frictions than large firms that rely heavily on the credit market. Conversely, in an unreported experiment, I re-estimate equation (1) for the hypothetical event year of 2009 (highlighted in green, Figure 6) in which the total outstanding loans substantially declined compared to outstanding bonds. I find small firms (i.e., firms that rely less on the credit market) further reduce their payouts during this year, which can be attributed to declining access to credit markets, compared to larger firms.

2.8 Final Remarks

Although I have built the experimental framework on extreme credit events, I intend to put forward a general argument regarding the impact of supply of capital on corporate payout policy. I find that corporate payout policy, mostly through the repurchase mechanism, has a supply side

⁹ The finding in Figure 6 is also consistent with our observation of TED and NFCI development during the 2007-2008 financial crisis. The majority of NFCI components are capital market related and, therefore, the increase in the NFCI and TED spread is contemporaneous with lower growth in outstanding corporate bonds.

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determinant that has been overlooked. More specifically, firms that rely on credit markets to finance their payouts are 10% more likely to reduce share repurchases when access to credit is limited. This is an economically significant outcome, given that nearly 40% of industrial firms finance their payout externally. Interestingly, firms that rely more on the credit market are presumably more resourceful in finding capital at times of urgent needs. However, I find that a greater dependence on credit market for financing payouts outweighs a firm's capacity to find sufficient funds. An immediate implication of this finding for investors is that larger firms are more likely to change their payout policies during poor economic states, even though their cash flow is more stable.

Nevertheless, it appears that this effect was non-existent three decades ago when dividends were the principle means of payout. As firms shift their payouts toward less informationally charged mechanisms (i.e., share repurchases), they can flexibly react to supply problems by postponing their payouts to a later time when external capital is more affordable.

2.9 References

- Aharony, J., & Swary, I. (1980). Quarterly Dividend and Earnings Announcements and Stockholders' Returns: An Empirical Analysis. *The Journal of Finance*, 35(1), 1–12.
- Akron, S. (2011). Market Reactions to Dividend Announcements under Different Business Cycles. *Emerging Markets Finance and Trade*, 47(0), 72–85.
- Allen, F., Bernardo, A. E., & Welch, I. (2000). A Theory of Dividends Based on Tax Clienteles. *The Journal of Finance*, 55(6), 2499–2536. <https://doi.org/10.1111/0022-1082.00298>
- Almeida, H., Campello, M., & Weisbach, M. S. (2011). Corporate financial and investment policies when future financing is not frictionless. *Journal of Corporate Finance*, 17(3), 675–693.
- Amihud, Y., & Li, K. (2006). The Declining Information Content of Dividend Announcements and the Effects of Institutional Holdings. *Journal of Financial and Quantitative Analysis*, 41(03), 637–660.
- Bajaj, M., & Vijh, A. M. (1990). Dividend clienteles and the information content of dividend changes. *Journal of Financial Economics*, 26(2), 193–219.
- Baker, M., Nagel, S., & Wurgler, J. (2006). The effect of dividends on consumption. National Bureau of Economic Research.
- Bates, T. W., Kahle, K. M., & Stulz, R. M. (2009). Why do US firms hold so much more cash than they used to? *The Journal of Finance*, 64(5), 1985–2021.
- Below, S. D., & Johnson, K. H. (1996). An Analysis of Shareholder Reaction to Dividend Announcements in Bull and Bear Markets. *Journal of Financial And Strategic Decisions*.
- Bessler, W., & Nohel, T. (2000). Asymmetric information, dividend reductions, and contagion effects in bank stock returns. *Journal of Banking & Finance*, 24(11), 1831–1848.
- Bhattacharya, S. (1979). Imperfect information, dividend policy, and “the bird in the hand” fallacy. *The Bell Journal of Economics*, 259–270.
- Bliss, B., Cheng, Y., & Denis, D. (2013). Corporate Payout, Cash Retention, and the Supply of Credit: Evidence from the 2008-09 Credit Crisis. SSRN, April 2013.
- Brav, A., Graham, J. R., Harvey, C. R., & Michaely, R. (2005). Payout policy in the 21st century. *Journal of Financial Economics*, 77(3), 483–527.

- Brave, S., & Butters, A. (2011a). Diagnosing the Financial System: Financial Conditions and Financial Stress. *International Journal of Central Banking*, June 2012 Issue.
- Brave, S., & Butters, A. (2011b). Monitoring financial stability: A financial conditions index approach, *Economic Perspectives*, Vol. 35, No. 1, p. 22, 2011.
- CBOE. (2014). VIX Index. CBOE. Retrieved from <http://www.cboe.com/micro/vix/historical.aspx>
- Chicago Federal Reserve. (2014). NFCI. Retrieved from <http://www.chicagofed.org/webpages/publications/nfci/>
- Cornett, M. M., McNutt, J. J., Strahan, P. E., & Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, 101(2), 297–312.
- Daniel, N. D., Denis, D. J., & Naveen, L. (2008). Sources of financial flexibility: Evidence from cash flow shortfalls. Unpublished Working Paper, Drexel University, Purdue University and Temple University.
- DeAngelo, H., & DeAngelo, L. (1990). Dividend Policy and Financial Distress: An Empirical Investigation of Troubled NYSE Firms. *The Journal of Finance*, 45(5), 1415–1431.
- DeAngelo, H., DeAngelo, L., & Skinner, D. J. (1992). Dividends and Losses. *The Journal of Finance*, 47(5), 1837–1863.
- Denis, D. J., Denis, D. K., & Sarin, A. (1994a). The information content of dividend changes: Cash flow signaling, overinvestment, and dividend clienteles. *Journal of Financial and Quantitative Analysis*, 29(4).
- Denis, D. J., Denis, D. K., & Sarin, A. (1994b). The information content of dividend changes: Cash flow signaling, overinvestment, and dividend clienteles. *Journal of Financial and Quantitative Analysis*, 29(4).
- Dittmar, A., & Mahrt-Smith, J. (2007). Corporate governance and the value of cash holdings. *Journal of Financial Economics*, 83(3), 599–634.
- Eades, K. M., Hess, P. J., & Kim, E. H. (1984). On interpreting security returns during the ex-dividend period. *Journal of Financial Economics*, 13(1), 3–34.
- Easterbrook, F. H. (1984). Two Agency-Cost Explanations of Dividends. *The American Economic Review*, 74(4), 650–659.
- Eddings, C. (2015). Apple Plans \$5 Billion Bond Sale; Fourth Since 2013. Bloomberg. Retrieved

- from <http://www.bloomberg.com/news/articles/2015-02-02/apple-said-to-plan-5-billion-bondoffering-in-fourth-since-2013>
- Farre-Mensa, J., Michaely, R., & Schmalz, M. C. (2014). Financing Payouts. Available at SSRN 2535675. Retrieved from http://papers.ssrn.com/sol3/Papers.cfm?abstract_id=2535675
- Faulkender, M., & Petersen, M. A. (2006). Does the source of capital affect capital structure? *Review of Financial Studies*, 19(1), 45–79.
- Ghosh, C., & Woolridge, J. R. (1988). An Analysis of Shareholder Reaction to Dividend Cuts and Omissions. *Journal of Financial Research*, 11(4), 281.
- Grullon, G., & Michaely, R. (2002). Dividends, share repurchases, and the substitution hypothesis. *The Journal of Finance*, 57(4), 1649–1684.
- Grullon, G., & Michaely, R. (2004). The information content of share repurchase programs. *The Journal of Finance*, 59(2), 651–680.
- Guay, W., & Harford, J. (2000). The cash-flow permanence and information content of dividend increases versus repurchases. *Journal of Financial Economics*, 57(3), 385–415.
- Hancock, D., & Wilcox, J. A. (1998). The “credit crunch” and the availability of credit to small business. *Journal of Banking & Finance*, 22(6), 983–1014.
- Ivashina, V., & Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3), 319–338.
- Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76(2), 323–329.
- Kalay, A. (1980). Signaling, information content, and the reluctance to cut dividends. *Journal of Financial and Quantitative Analysis*
- Kashyap, A. K., Stein, J. C., & Wilcox, D. W. (1992). Monetary policy and credit conditions: Evidence from the composition of external finance. *National Bureau of Economic Research*.
- Kato, K., & Loewenstein, U. (1995). The ex-dividend-day behavior of stock prices: the case of Japan. *Review of Financial Studies*, 8(3), 817–847.
- Leary, M. T. (2009). Bank loan supply, lender choice, and corporate capital structure. *The Journal of Finance*, 64(3), 1143–1185.

- Lemmon, M., & Roberts, M. R. (2010). The response of corporate financing and investment to changes in the supply of credit. *Journal of Financial and Quantitative Analysis*, 45(03), 555–587.
- Lintner, J. (1956). Distribution of incomes of corporations among dividends, retained earnings, and taxes. *The American Economic Review*, 46(2), 97–113.
- Labrecht, B.M., & Myers, S.C. (2012). A Lintner model of payout and managerial rents. *The Journal of Finance*, 67(5), 1761–1810
- Miller, M. H., & Rock, K. (1985). Dividend policy under asymmetric information. *The Journal of Finance*, 40(4), 1031–1051.
- Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187–221.
- Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of Financial Economics*, 52(1), 3–46.
- Pinkowitz, L., & Williamson, R. (2003). What is a dollar worth? The market value of cash holdings. Unpublished working paper.
- Rauh, J. D. (2006). Investment and financing constraints: Evidence from the funding of corporate pension plans. *The Journal of Finance*, 61(1), 33–71.
- Sufi, A. (2009). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *Review of Financial Studies*, 22(4), 1659–1691.
- Watts, R. (1973). The Information Content of Dividends. *The Journal of Business*, 46(2), 191–211.
- World Bank. (2014). U.S Annual GDP Growth. World Bank.

2.10 Appendices

Appendix 1

Definition of variables

Variable	Description
Loss	Corporate Loss in the last five years. Number of years a firm has experienced negative net income within the past five years. DeAngelo, DeAngelo, & Skinner (1992) show that an earning loss is a necessary condition for dividend reductions. Furthermore DeAngelo & DeAngelo (1990) document that firms with lasting financial distress tend to reduce dividends.
Idiosyncratic Volatility	Standard deviation of residuals from Fama-French three-factor model using monthly returns from the fiscal year.
Asset	Natural logarithm of total assets
PPE	Physical Asset: Property, Plant, and Equipment Buildings (PPENB)
NYSE	Equal to 1 if the stock is listed in the NYSE exchange
Sales	Natural logarithm of firm revenue (REVT)
Profitability	Operating Income Before Depreciation (OIBDP) divided by assets

Free Cash Flow	Operating income before depreciation (OIBDP) minus total interest related expenses (XINT) minus total income taxes (TXT) divided by total assets (AT)
Debt Rating	Equal to 1 if the firm has at least one rated bond from S&P credit agency, derived from the COMPUSTAT: ADSPRATE database
Cash Holding	Cash and short term investments (CHE) divided by total assets (AT)
Leverage	Book leverage: long-term debt (DLTT) plus the short-term debt (DLC) divided by total assets
TobinQ	Market value of common equity (CSHO*PRCC_F) + book value of short term debt (DLC) and book value of long-term debt (DLTT) divided by total assets (AT)
CAPEX	Capital expenditure item (CAPX)+ R&D(XRD) divided by total assets (AT)
Total Payout	Absolute value of Dividend + Repurchase divided by assets
GDP Growth	Yearly GDP growth rate
Age	How long the firms have been in Compustat (Current Date – Starting Date or date when firm appears in Compustat)

NDITP	$NDIPT_{it} = \frac{\text{Min}(\text{Net Debt Issuance}_{it}, \text{Total Payout})}{\text{Total Payout}}$ Net debt issuance is defined as the difference between the amount of debt issued (DLTIS) and the amount repaid (DLTR) if this difference is positive, and zero otherwise
Credit Shock Event	Years identified as local maximum of TED spread in Figure 2 (1974, 1979-1984, 1987, late 1990, 1998-2000, 2007-2008). The variable becomes 1 during one these listed event years and zero otherwise
Experiment Group	1 when the firm belongs to the top 50 th percentile of NDITP firms, and 0 when firm belongs to the bottom 50 th percentile of NDITP

Appendix 2

Timeline of U.S major macroeconomic and liquidity downturns (Brave & Butters, 2011b)

Year	Narrative	Credit Crunch	Negative Market Condition
1973-74	<ul style="list-style-type: none"> Sharp increase in oil price National Bank of San Diego declared insolvent 	Yes	Yes
1979	<ul style="list-style-type: none"> Dramatic policy change by Fed, resulted from the start of Reagan presidency; policy resulted in a short term stagflation (1979-1983) U.S. dollar begins a steep decline against major foreign currencies 	Yes	No
1980-81	<ul style="list-style-type: none"> Carter Announces credit control program Pennsylvania National Bank insolvency 	Yes	Yes

1982-83	<ul style="list-style-type: none"> • Mexico Debt Default • Penn Square Bank fails 	Yes	NO
1984	<ul style="list-style-type: none"> • Run on Continental Illinois, which borrows \$3.6 billion from discount window 	Yes	NO
1987	<ul style="list-style-type: none"> • Saving & Loan Crisis 	Yes	No
1991	<ul style="list-style-type: none"> • Tax hike, rate tightening, and increase in oil price 	Yes	Yes
1998-2000	<ul style="list-style-type: none"> • Asian Market Crisis • Russian Federation defaults on debt • Collapse of LTCM 	Yes	NO
2007-2008	<ul style="list-style-type: none"> • Subprime Financial Crisis 	Yes	Yes

2.11 Table and Figures

Table 1: Summary statistics of three funding liquidity measures

TED spread covers years starting from 1971 to 2014, but NFCI indices start from 1973. The numbers are based on weekly measures for Risk NFCI and ANFCI and monthly for TED spread. Risk NFCI and ANFCI, by design, have the standard deviation of 1 and mean zero.

	TED	ANFCI	Risk NFCI
MEAN	0.99	0.03	0.05
STD	0.91	1.00	1.02
CORR (TED)	1.00	0.66	0.96
CORR (ANFCI)	0.66	1.00	0.65
CORR (Risk NFCI)	0.96	0.65	1.00

Table 2: Logistic regression of corporate payout reductions

In Panel A, the dependent variable is “total payout reduction”, in the Panel B, the dependent variable is “repurchase reduction”, and in the Panel C, the dependent variable is “dividend reduction”. Liquidity event years are listed in columns. For each event year t , I use all samples between two liquidity events in a pooled panel data and do the following Logit regression:

$$\begin{aligned} \text{payout reduction}_{it} = & \alpha + \beta_2 \cdot \text{idiosyncratic volatility}_{i(t-1)} + \beta_3 \cdot \text{age}_i + \beta_4 \cdot \text{asset}_{i(t-1)} + \beta_5 \cdot \text{Loss}_{it-1} + \beta_6 \cdot \text{Capex}_{i(t-1)} \\ & + \beta_7 \cdot \text{TotalPayout}_{i(t-1)} + \beta_8 \cdot \text{leverage}_{i(t-1)} + \beta_9 \cdot \text{TobinQ}_{it} + \beta_{10} \cdot (\text{FreeCashFlow})_{it} \\ & + \gamma_1 \cdot (\text{GDP Growth})_{(t-1)} + \theta_1 \cdot \text{Credit Shock Event} + \theta_2 \cdot \text{Experiment Group} \\ & + \theta_3 \cdot \text{Experiment Group} \cdot \text{Credit Shock Event} + \text{Industry Fixed Effect} + \epsilon_{it} \end{aligned}$$

For the sake of brevity, I present coefficients of the control variable only for panel A. The samples include all non-financial and non-utility firms that have a positive average of dividend or repurchase from the previous two years. For dividend payers, repurchasers, and total payers, the dependent variable is equal to one (i.e., firms are considered to have reduced dividend, repurchases, or total payout) if the payout decreases at least 5% from the previous two-year average payout, zero otherwise. In each regression of each panel, “Credit Shock Event” is equal to 1 for the year indicated in the column and zero otherwise. The experiment and control group are based on the degree of dependence of firms on credit to finance their payout, measured by NDITP (Net Debt Issuance divided by Total Payout). The experiment group includes firms in the top 50th percentile of NDITP and control group are firms in the bottom 50th percentile of NDITP. All independent variables (firm level and macro level) are lagged one year except TobinQ and Free Cash Flow (FCF). All independent variables are winsorized at the 1% and 99% level. P value (in parentheses) is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Standard errors (p value in parentheses) are heteroscedasticity-robust and clustered by firm.

Panel A: Total Payout Reduction

	1974	1980-1984	1987	1991	1998-2000	2007-2008
Idiosyncratic volatility	1.3509*** (<.0001)	1.1092*** (<.0001)	0.9629*** (<.0001)	1.2895*** (<.0001)	1.0692*** (<.0001)	1.2613*** (<.0001)
Age	-0.00036 (0.9541)	0.00112 (0.7614)	0.000171 (0.9596)	-0.0113*** (<.0001)	-0.00829*** (<.0001)	-0.00482*** (0.0008)
Log Asset	-0.262*** (<.0001)	-0.1821*** (<.0001)	-0.1348*** (<.0001)	-0.1063*** (<.0001)	-0.1227*** (<.0001)	-0.0529*** (<.0001)
Loss	0.7806*** (<.0001)	0.6558*** (<.0001)	0.2987*** (<.0001)	0.2586*** (<.0001)	0.2232*** (<.0001)	0.1429*** (<.0001)
CAPEX	2.4426*** (0.0001)	1.0231*** (0.0059)	0.9736** (0.0183)	1.088*** (0.0003)	1.2906*** (<.0001)	1.9776*** (<.0001)
Total Payout to Asset	14.1421*** (<.0001)	11.8216*** (<.0001)	9.2558** (<.0001)	8.5348*** (<.0001)	7.3915*** (<.0001)	8.1896*** (<.0001)
Leverage	1.655*** (<.0001)	1.6003*** (<.0001)	1.4809*** (<.0001)	1.1147*** (<.0001)	1.1339*** (<.0001)	0.8887*** (<.0001)
TobinQ	-0.9209*** (<.0001)	-0.1298** (0.0255)	-0.1023** (0.0348)	-0.1211*** (<.0001)	-0.113*** (<.0001)	-0.1762*** (<.0001)
FCF	-7.6967*** (<.0001)	-5.9579*** (<.0001)	-3.9644*** (<.0001)	-2.6623*** (<.0001)	-2.2276*** (<.0001)	-3.194*** (<.0001)

Panel A(Continue)	1974	1980-1984	1987	1991	1998-2000	2007-2008
Cash	-1.9973*** (0.0001)	-1.2357*** (<.0001)	-1.0892 (<.0001)	-0.7867*** (<.0001)	-0.939*** (<.0001)	-0.8033*** (<.0001)
GDP Growth	-0.0296** (0.0416)	-0.0145* (0.0551)	-0.0515*** (0.0071)	-0.0716*** (<.0001)	-0.1898*** (<.0001)	-0.1715*** (<.0001)
Credit Event	0.3748*** (0.0001)	0.2207 (0.0001)	0.089 (0.207)	0.1308** (0.0398)	0.6135*** (0.0001)	0.3559*** (0.0001)
Experiment Group	-0.3916*** (0.0001)	-0.4601 (0.0001)	-0.5297*** (0.0001)	-0.5365*** (0.0001)	-0.5226*** (0.0001)	-0.4477*** (0.0001)
CreditEvent* Experiment	-0.1943 (0.294)	-0.0869 (0.3834)	0.1666 (0.2887)	0.2602* (0.0707)	0.1723** (0.0434)	0.2347** (0.0254)
N	6350	14516	8911	15858	26167	17553
R Squared	0.2263	0.1941	0.1855	0.1455	0.1339	0.1461

Panel B: Repurchase Reduction

	1974	1980-1984	1987	1991	1998-2000	2007-2008
Credit Event	0.9898*** (0.000)	-0.1163 (0.180)	0.1089 (0.33)	0.3128*** (0.000)	0.4773*** (0.000)	0.2882*** (0.000)
Experiment Group	0.3358** (0.040)	0.0512 (0.650)	-0.2874*** (0.0053)	-0.314*** (0.000)	-0.385*** (0.000)	-0.3843*** (0.000)
Credit Event* Experiment	-0.4524 (0.210)	-0.3247** (0.045)	0.1463 (0.5300)	0.4448* (0.070)	0.2284** (0.037)	0.3688*** (0.005)

Panel C: Dividend Reduction

	1974	1980-1984	1987	1990	1998-2000	2007-2008
Liquidity Event	0.1253 (0.2434)	0.3645*** (<.0001)	-0.00405 (0.9664)	0.0281 (0.7413)	0.5036*** (<.0001)	0.1918** (0.011)
Experiment Group	-0.7803*** (<.0001)	-0.8981*** (<.0001)	-0.9602*** (<.0001)	-0.7147*** (<.0001)	-0.5459*** (<.0001)	-0.3804*** (<.0001)
Credit Event * Experiment	0.2297 (0.3877)	0.0747 (0.6171)	0.1442 (0.5929)	-0.1786 (0.4498)	0.1798 (0.1721)	0.2084 (0.1638)

Table 3: Instrumental variables analysis

Panel A and B report results of two-stage least square, using external debt rating (“Debt Rating”) as an instrument for NDITP (Net Debt Issuance divided by Total Payout) in equation (1). “Debt Rating” is 1 if the firm receives any rating from any credit agencies, and 0 otherwise.

Panel A GLM (Generalized Linear Model) regression with a logit link:

$$\text{NDITP}_{it} = \alpha + \text{DebtRating}_{it} + u_{it}$$

Coefficients of Panel A and B regression are estimated based on samples from 1986 to 2014. The samples include all non-financial and non-utility firms that have a positive average of dividend or repurchase from the previous two years. For dividend payers, repurchasers, and total payers, the dependent variable is equal to one (i.e. the firms are considered to have reduced its dividend, repurchase or total payout) if the payout decreases at least 5% from the previous two-year average payout, and zero otherwise. For brevity, we do not report control variables in Panel C. All independent variables are winsorized at the 1% and 99% level. P value (in parentheses) is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Standard errors (p value in parentheses) are heteroscedasticity-robust and clustered by firm.

Panel A

Intercept	-1.801*** (0.0001)
DebtRating	1.011*** (0.0001)
N	82535

Panel B

	Total Payout			Repurchase			Dividend		
	1991	1998-2000	2007-08	1991	1998-2000	2007-08	1991	1998-2000	2007-08
Event	0.27*** (0.001)	0.61*** (<0.0001)	0.32*** (<.0001)	0.37*** (0.001)	0.45*** (0.0001)	0.26*** (<.0001)	0.1775 (0.13)	0.57*** (0.001)	0.19** (0.013)
Experiment	-0.56*** (0.0001)	-0.67*** (0.0001)	-0.69*** (0.0001)	-0.39*** (0.0001)	-0.51*** (0.0001)	-0.52*** (0.0001)	-0.51*** (0.001)	-0.43*** (0.0001)	-0.36*** (<.0001)
Event*Experiment	0.38** (0.01)	0.24*** (<.0001)	0.38*** (<.0001)	0.51** (0.0101)	0.13* (.08)	0.32*** (.0012)	0.0128 (0.95)	0.1089 (0.31)	0.2083 (0.12)

Table 4: Impact of marginal credit change on payout reductions

I regress payout reduction on funding liquidity indices (Risk NFCI residual, and ANFCI) and their interaction with experiment group (a higher value of funding liquidity index is associated with increased credit market friction). First, I find the residual of funding liquidity index against macroeconomic variables and then use the residual from this regression in the payout reduction:

$$\text{Credit Tightness Index Index}_t = \beta_1 \cdot \text{GDP}_t + \beta_2 \cdot (\text{Market Return})_t + \beta_3 \cdot (\text{Aggregate Corporate Profit})_t + \epsilon_t$$

$$\begin{aligned} \text{payout reduction}_{it} = & \alpha + \beta_1 \cdot \text{idiosyncratic volatility}_{i(t-1)} + \beta_2 \cdot \text{age}_i + \beta_3 \cdot \text{asset}_{i(t-1)} + \beta_4 \cdot \text{Loss}_{it} + \beta_5 \cdot \text{Capex}_{i(t-1)} + \beta_6 \cdot \text{TotalPayout}_{i(t-1)} + \beta_7 \cdot \text{leverage}_{i(t-1)} \\ & + \beta_8 \cdot \text{TobinQ}_{it} + \beta_9 \cdot (\text{FreeCashFlow})_{it} + \gamma_1 \cdot (\text{GDP Growth})_{(t-1)} + \theta_0 \cdot \text{CreditCondition Index} + \theta_1 \cdot \text{Experiment Group} + \theta_2 \cdot \text{Experiment Group} \cdot \epsilon_{t-1} \\ & + u_{it} \end{aligned}$$

The rest of conventions and variables are inherited from Table 2.

	Credit Tightness Index=NFCI			Credit Tightness Index=ANFCI		
	Total Payout	Repurchase	Dividend	Total Payout	Repurchase	Dividend
Credit Condition Index	0.0824 (0.4853)	0.0392 (0.1005)	0.0486 (0.5005)	-0.00554 (0.895)	-0.027 (0.547)	0.0896 (0.1869)
Experiment Group	-0.31*** (<.0001)	-0.23*** (<.0001)	-0.22*** (<.0001)	-0.30*** (<.0001)	-0.23*** (<.0001)	-0.22*** (<.0001)
Experiment Group* Credit Condition Index	0.0655 (0.0075)	0.0842 (0.0807)	0.0282 (0.0256)	0.041 (0.0001)	0.027 (0.0556)	0.00735 (0.1301)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	60819	42099	42949	62036	42656	44326
R	0.1552	0.0886	0.2197	0.1524	0.0835	0.2166

Table 5: Event Study

Table 5 shows the cumulative abnormal return of dividend reduction announcements in normal and stress periods for experiment and control groups.

	CAR	t value	# Events	CAR	t value	# Events
	Good Times (NDITP)			Stress Times (NDITP)		
Control Group	-0.5%	-1.6	185	-2%***	-3.34	61
Experiment Group	-0.49%	-1.2	101	-1.5%*	-1.5	22

CAR: Cumulative Abnormal Return

Std: standard error of CAR

t: t value(=CAR/std)

#Event: number of dividend cut announcement

Table 6: Non-Macro credit events

I test whether the dividend ratio of the experiment group (speculative bond issuers) changes due to negative shocks to their financing supply. I estimate the following model:

$$\frac{\text{Divident}_{it}}{\text{Asset}_{it}} = \alpha + \beta_1 \cdot \text{idiosyncratic volatility}_{i(t-1)} + \beta_2 \cdot \text{age}_i + \beta_3 \cdot \text{asset}_{i(t-1)} + \beta_4 \cdot \text{Cash}_{i(t-1)} + \beta_5 \cdot \text{TobinQ}_{it} \\ + \beta_6 \cdot (\text{FreeCashFlow})_{it} + \theta_1 \cdot \text{Experiment Group} + \theta_2 \cdot \text{After1990} \\ + \theta_3 \cdot \text{ExpereimentGroup} * \text{After1990} + u_{it}$$

Samples include all non-financial and non-utility firms that have a positive dividend average from the previous two years. We estimate regression for the period between 1986 and 1993. "After1990" is a dummy variable equal to "1" for the period between 1990 until 1993 (after the three credit events) and "0" for 1986 until 1989 (before three credit events). The variable of interest is interaction of "After1990" and Experiment Group. All independent variables (firm level and macro level) are lagged one year except TobinQ and Free Cash Flow (FCF). All independent variables are winsorized at the 1% and 99% level. P value (in parentheses) is reported below the coefficients. ***, **, or * indicate that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Standard errors (p value in parentheses) are heteroscedasticity-robust and clustered by firms

Intercept	-0.023 (0.38)
Idiosyncratic volatility	-0.02 (0.12)
Age	-0.0038 (0.55)
Assets	0.006 0.33
Cash	0.032** (0.044)
TobinQ	0.0013 (0.14)
FreeCashFlow	0.16*** (0.00016)
ExperimentGroup	-0.00012 (0.91)
After1990	0.00012 (0.66)
After1990*ExperimentGroup	-0.009*** (0.0085)
N	2567
Adjusted R Squares	0.2322
Firm Fixed Effect	Yes

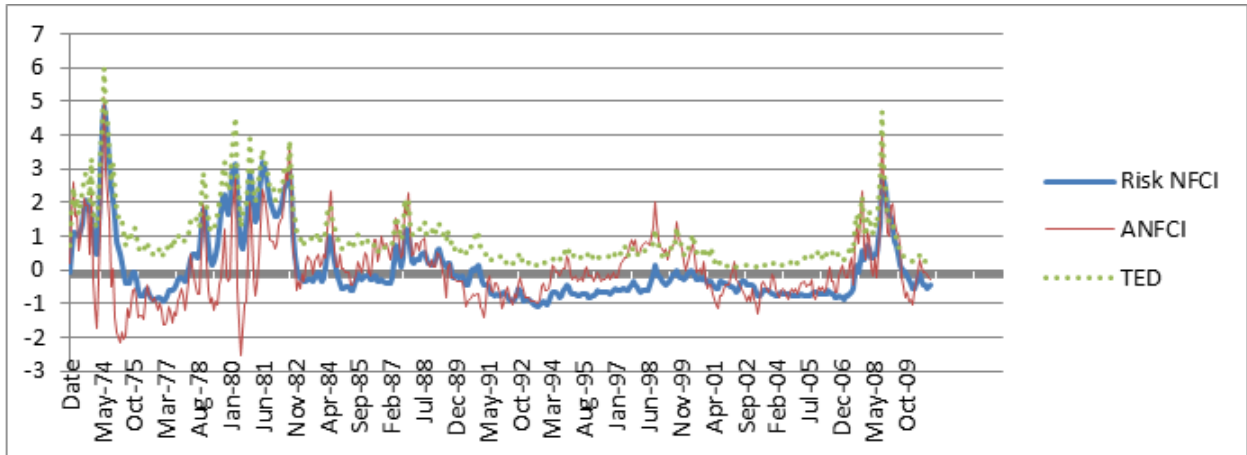


Figure 1: Monthly time series of three funding liquidity indicators.

Risk component of NFCI, Adjusted NFCI, and TED spread are plotted for the period from 1974 to 2010. TED spread is calculated from Eurodollar Rate – Treasury Rate for three-month maturity instruments. Risk NFCI and ANFCI are composed of 30 and 100 sub-indices compiled by the Chicago Fed on a weekly basis.

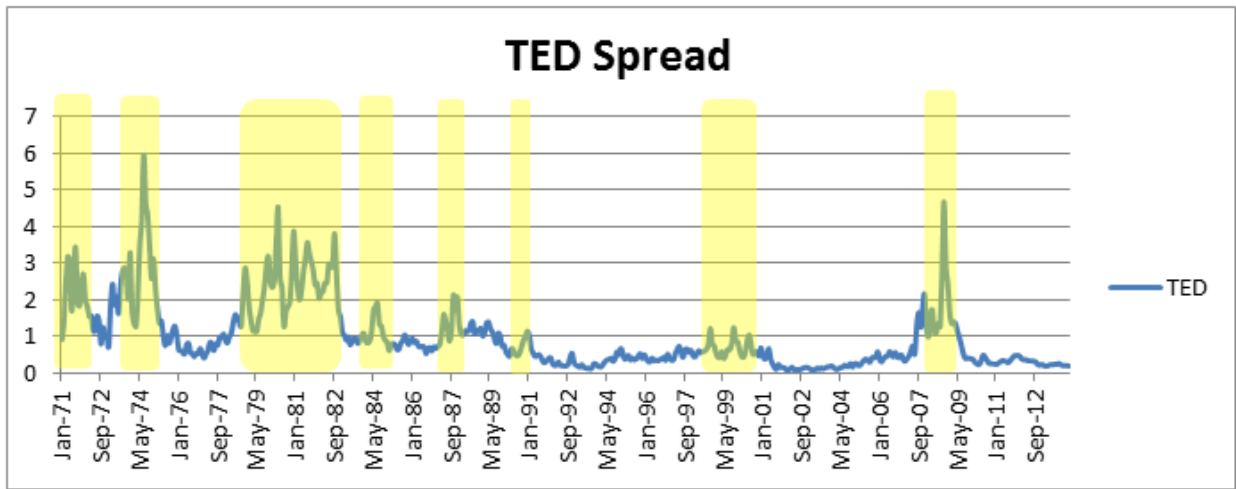


Figure 2: Monthly time series of TED spread.

TED spread is defined as difference between Eurodollar rate and Treasury rate for three-month maturity instruments ($\text{Eurodollar}_{3\text{ month}} - \text{Treasury}_{3\text{ month}}$). The highlighted bars are associated with local maximums of TED spread. Highlighted dates are liquidity shock events.

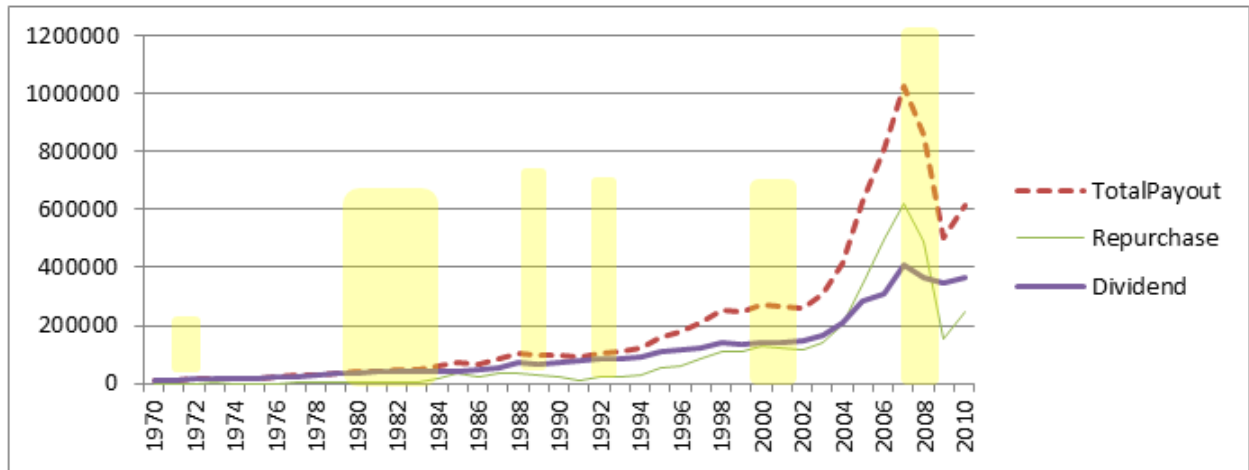


Figure 3: Time series of corporate payouts.

Figure 3 shows the sum of dividend payout, share repurchase, and total payout are plotted for non-financial and non-utility firms from 1970 to 2010. The highlighted bars are years with associated friction in the credit market.

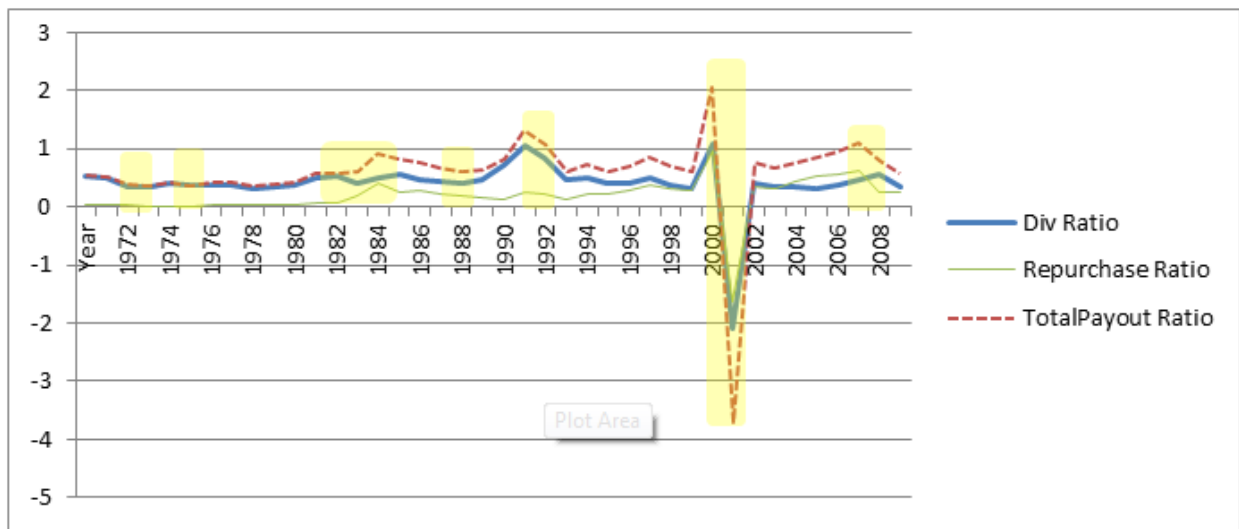


Figure 4: Time series of yearly payout ratios.

Figure 4 shows the time series of payout ratios. Dividend ratio at year “t” is defined the ratio of total dividends of all non-financial and non-utility firms to total corporate income that year. Similarly share repurchase ratio and total payout ratio are defined as total repurchase/total payout [i.e., dividend + repurchase] of all non-financial and non-utility firms to total corporate income that year. The highlighted years are associated with a spike in TED spread.

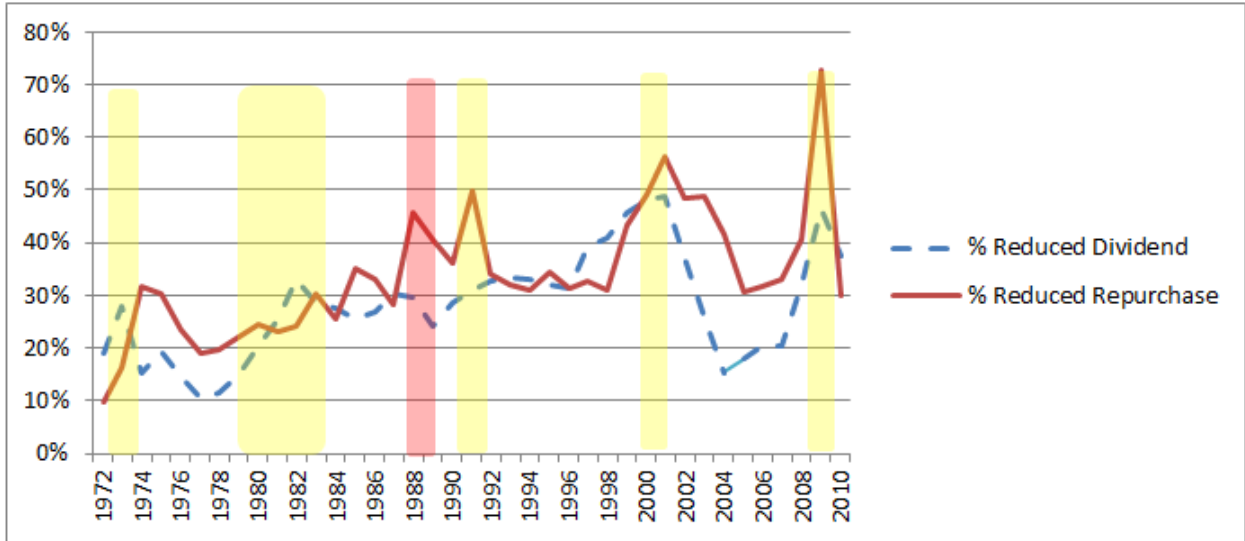


Figure 5: Percentage of firms with reduced payouts

Figure 5 shows the Percentage of firms with reduced payouts (repurchases or dividends) between 1972 and 2010. The sample includes all Compustat firms except financial firms and utilities. Firms that have negative repurchase in a given year were eliminated. Dividend payers are firms that have positive average dividend in the previous two years. Similarly, repurchasers and total payers are firms that have positive repurchase and total payouts in the previous two years. A firm reduced its payout (dividend, repurchase, or total payout) if its payout is at least 5% lower in a given year compared to an average of the previous two years. Highlighted years are associated with a substantial increase in credit tightness. The pink bar indicates year 1990, when the choice of repurchase reduction becomes more prevalent.

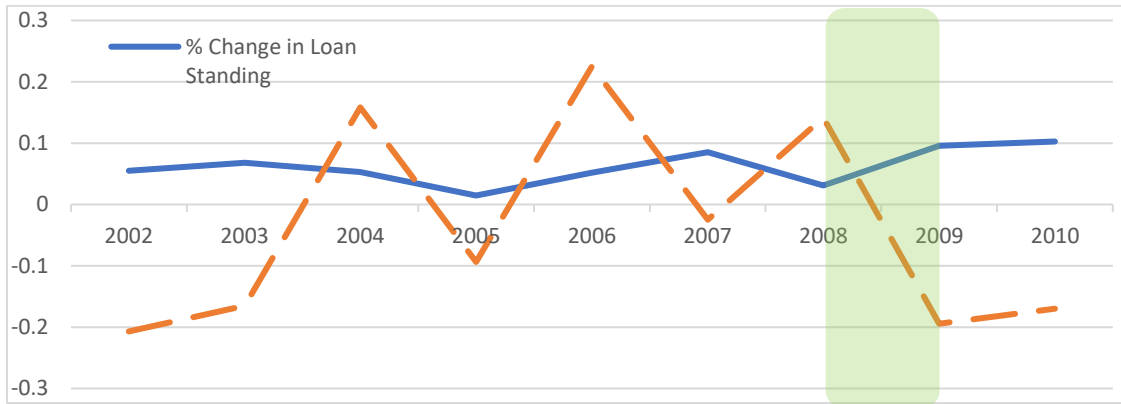


Figure 6: Percentage change of aggregate corporate debt outstanding

Figure 6 Depicts the percentage change in aggregate corporate bonds versus percentage change in aggregate corporate loans outstanding during the financial crisis of 2008 and one year later (2009). The aggregate corporate loans data are taken from the Saint Luis Federal Reserve web portal, while the aggregate corporate bond data are obtained from Securities Industry and Financial Markets Association (SIFMA). The peak of the 2008 financial crisis is highlighted with yellow, and the year after the financial crisis, 2009, is highlighted in green. During the peak of financial crisis, total outstanding loans increased substantially, in sharp contrast with the total outstanding corporate debt. The trend reverses in 2009.

Chapter 3

Investment Bank Exposure to Hedge Funds and Financial Contagion

Abstract

This essay investigates the existence of contagion between investment banks and hedge funds using firm-level information. The data used includes information on the top five investment banks (that provide brokerage services to more than 60% of all hedge funds) and their affiliated hedge funds, for the period from 1990 to 2011. By employing both parametric and non-parametric approaches, I demonstrate that the two sectors show excessive correlation for the extreme lowest quantile (5% quantile) of returns that cannot be explained by their fundamentals. I also show that the direction of contagion is most likely from hedge funds to investment banks. The results further suggest that contagion is the result of direct or indirect credit exposure of investment banks to their affiliated hedge funds.

3.1 Introduction

The aggregate assets under management (AUM) in the hedge fund industry is less than 2% of aggregate financial assets; however, their impact on financial markets reaches far beyond their AUM. This is due to their massive trading activities and liquidity provision in the market, their essential role in some specific markets such as the distress debt market, and their strategic relationships with other essential financial institutions such as investment banks. Hedge funds account for 40% of trades in the leveraged loan market and 80% of credit derivatives. More importantly, they are the most profitable customers of investment banks' prime brokerage business line (GAO, 2008; Mustiers & Dubois, 2007; King & Maier, 2009). The latter point provides sufficient motivation to investigate the systemic role of hedge funds, considering that the advent of the 2007-2008 financial crisis is attributed to the systemic malfunction of the largest investment banks. In this paper, my goal is to understand whether the systemic malfunction of investment banks is partially triggered by their close relationship with hedge funds.

Beyond providing hedge funds with trading and sales settlement services, investment banks offer prime brokerage services to hedge funds. As such, investment banks provide funding services to hedge funds mostly through collateralized short and long term debt. At the same time, both hedge funds and investment banks pose a counterparty credit risk to one another through their derivatives exposure and collateralized loans. The connection becomes more significant from a systemic risk perspective when we consider that both hedge funds and investment banks are highly concentrated financial institutions.

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Theoretically, both hedge funds and investment banks can be the initial source of contagion. On one side, through direct or indirect exposure, the failure of hedge funds may result in the failure of investment banks (Figure 2) (Ferguson & Laster, 2007; Rubin, Greenspan, Levitt, & Born, 1999)¹⁰. On the other, the failure of investment banks may affect hedge funds through reductions in collateralized loans (Adrian & Shin, 2010) or early withdrawal of collateral and cash from troubled investment banks (Duffie, 2010). The most recent example of such systemic contagion was the failure of Lehman Brothers, which led to substantial losses in its affiliated hedge funds (Aragon & Strahan, 2012). These mechanisms are examined thoroughly in the literature review (section 2).

Investigating contagion between investment banks and hedge funds is important for several reasons: first, if there is a possibility of contagion between traditional asset classes, like investment banks and hedge funds, the benefits of diversification may be significantly limited, especially when it is needed the most. More importantly, policy makers and regulators are interested in gaining a better understanding of how interlinkages across major financial institutions can endanger the stability of the financial system as a whole. Furthermore, understanding the direction of contagion also matters. Within the discipline, a lively discussion has developed as to whether or not hedge funds increase systemic risks through their trading behavior and high leverage (Kambhu, Stiroh, & Schuermann, 2007; Ang, Gorovyy, & Van Inwegen, 2011; Lewis, 2014). This essay contributes to this discussion by assessing whether contagion is initiated by hedge funds or investment banks.

¹⁰ This channel of contagion has been widely discussed following the near collapse of Long Term Capital Management (LTCM).

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Following recent trends in contagion research, I use the definition of contagion introduced by Bekaert, Harvey, & Ng (2005). In their framework, contagion is defined as the excess correlation of returns over and above that which can be explained by fundamental risk factors. To employ this concept, I identify hedge fund residual returns by filtering raw returns from the factors introduced by Fung & Hsieh (2001) and Agarwal & Naik (2004). Furthermore, I filter hedge fund returns for the well-documented serial correlation. Investment bank raw returns are filtered using the risk factors outlined by Fama & French (1993). My goal is to show whether the filtered returns demonstrate an excessive correlation during times of economic stress. I start by visually presenting the pattern of correlation in different percentiles (dynamic correlation, Engle (2002)), and graduate to formal tests of contagion, including semi-parametric (quantile regression) and parametric approaches (probit and condition correlation model).

The results provide ample evidence of excessive correlation between investment banks and hedge funds. The probability of investment banks to have extremely low returns (i.e., below 5% quantile) increases as hedge funds experience extremely low returns, confirmed by probit models and quantile regression. The Engle's dynamic conditional correlation confirms that residual returns are excessively correlated during the stress periods of the tech bubble crisis (2000-2002) and subprime mortgage crisis (2007-2008). Finally, by conducting a Granger causality test and impulse response function, I find that contagion starts in hedge funds and runs through investment banks.

This essay contributes to the literature of contagion in several ways. First, to the best of my knowledge, the possibility of contagion between the two sectors has not been thoroughly examined in previous studies. Most research about the relationship between investment banks and hedge funds are either qualitative (Duffie, 2010; King, 2008; Hildebrandfung, 2007) or do not focus on

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the relationship between the two sectors (Billio, Getmansky, Lo, & Pelizzon, 2010; Boyson, Stahel, & Stulz, 2010). Second, my analysis is conducted at the firm level rather than at the industry level (index level). By employing a panel of investment banks paired with their affiliated hedge funds (hedge funds whose prime broker is that investment bank), I am able to directly relate each investment bank with the most probable financially interlinked hedge funds. Finally, I seek to identify the direction of contagion; that is, I investigate whether an initial shock that leads to contagion originates from investment banks or hedge funds. This is an important question given that the answer may indicate which is the most dominant channel of contagion (Figures 2, 3, 4).

This paper is organized into six sections. In section 2, I provide a brief review of the literature on contagion in financial institutions. Section 3 addresses the data and methodology and section 4 discusses the empirical results. Several robustness tests are reported in section 5 and I finish with concluding remarks in section 6.

3.2 Literature Review

3.2.1 Contagion in financial markets

Financial contagion is defined as a significant increase in interlinkage among two or more financial markets, financial asset classes, or financial institutions. The excessive¹¹ comovement of two markets falls into two broad categories. The first category, fundamental (real) channel of contagion (Figure 1(A)), explains how two markets comove because they are exposed to common fundamental drivers. A common theme in all variations of the fundamental contagion channel is

¹¹ Throughout the paper, I use the word “excessive” to indicate “more than normal”. Herein, the word “normal”, means, normal status (i.e., correlation driven by common risk factors), that happens in normal times (i.e., non-crises times). Thus, normal correlation between two markets is the correlation driven by common risk factors in normal times.

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the transfer of a negative shock from one entity to another due to fundamental economic connections between the two entities. Borrowing from the asset pricing literature, we might say that asset prices in market B follows those of market A, because either the expected cash flow of market B, or the required rate of return of market B, changes subsequent to a shock in market A. An important characteristic of the fundamental channel of contagion is that entities with strong comovement during bad times share strong commonality in their returns process during normal times. In a series of influential papers, Forbes & Rigobon (2000, 2001, 2002) suggest that many seemingly excessive asset price comovements during bad times should be excluded from the definition of contagion because excessive comovement is most likely due to the more influential role of common risk factors during times of stress. Consequently, two entities (for example, two financial markets in two countries) show excessive correlation that is not due to transfer of shock from one country to another, but rather to similar exposures to common fundamental risk factors. As suggested by Bekaert et al. (2005), and subsequently adopted in the contagion literature, to avoid incorrectly identifying common risk exposures as contagion, I define contagion as excessive correlation that is over and above what fundamental risk factors can explain.

The financial channel of contagion is the second mechanism through which a negative shock to one entity may spread to another. The Financial channel of contagion can be subcategorized into three channels: balance sheet, asset fire sale, and financial interlinkage (Figure 1(B)). The balance sheet channel of contagion (Figure 1(B)) refers to the amplification of initial negative shocks due to disruptions in supply of bank loans (Bernanke, Gertler, & Gilchrist, 1996)¹². In the

¹² The disruption in bank supply can be due to banks' internal risk management or regulatory requirements on bank capital or liquidity. Bernanke & Gertler (1989), Kiyotaki & Moore (1997), and Bernanke, Gertler, & Gilchrist, (1996) discuss mechanisms through which the initial shock to the economy is amplified and persists for a long period of time. To summarize, following an initial shock in an economy, the collaterals submitted by small firms lose their value; the

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liquidity channel (Figure 1(B)), excessive demand for market liquidity, as well as limited supply of funding liquidity, cause sharp decreases in asset prices (Brunnermeier & Pedersen, 2009). Finally, through financial interlinkage (Figure 1(B)) failure of a firm with direct credit or derivative exposures leads counterparties to suffer losses. It is important to note that the three subchannels interact intimately during episodes of financial contagion (as illustrated by dashed lines in the figure), which makes it extremely difficult to accurately identify the single most important source of contagion in each scenario.

At the core of the liquidity channel of contagion is the occurrence of asset fire sales. The earliest documented liquidity contagion dates back to the 1763 crisis in northern Europe in which high leverage of market participants triggered distress sales of assets, leading to a severe liquidity crisis (Schnabel & Shin, 2004). Two years before the advent of the 2007-2008 financial crisis, Cifuentes, Ferrucci, & Shin (2005) demonstrated the important role of liquidity risk in a system of interconnected financial institutions when these institutions are subject to regulatory capital constraints. They argued that a small fundamental shock to leveraged financial institutions induces a new round of endogenously generated asset sales, depressing prices and inducing further sales. In their model, the liquidity channel of contagion (i.e., fire sales) can convert small fundamental shocks to full-fledged contagion.

3.2.2 Relationship between hedge funds and investment banks

Hedge funds account for 40% of trades in the leveraged loan market and 80% of credit derivatives. More significantly, hedge funds are the most profitable customers of investment banks' prime

banks, which are motivated by a more conservative risk management approach following the initial negative shock, subsequently stop extending loans to those firms.

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brokerage business line (GAO, 2008; Mustiers & Dubois, 2007). Thus, there is a clear need to investigate the systemic role of hedge funds, particularly since the catalyst of the 2007-2008 financial crisis has been attributed to systemic malfunction of large investment banks. Arguably, the crisis unfolded when two of the biggest investment banks, Bear Stearns and Lehman Brothers, collapsed¹³ and quickly morphed into one of the most devastating financial crises since the Great Depression.

Other than being interconnected by sharing similar portfolios or cross derivative exposures, the two sectors are prominently linked through liquidity channels, in which investment banks' prime brokerage business line lend to hedge funds on short or long term basis (Duffie, 2010; King, 2008; King & Maier, 2009; Rubin, Greenspan, Levitt, & Born, 1999). At the same time, both hedge funds and investment banks pose counterparty credit risk to one another through derivatives exposure and collateralized loans. The connection becomes more significant from a systemic risk perspective when we consider that both hedge funds and investment banks are highly concentrated. At the end of 2006, the top three (10) investment banks account for more than 58% (84%) of broker services to hedge funds, and the largest 100 hedge funds account for 75% of all hedge fund assets in 2007, up from 53% in 2003 (King & Maier, 2009). Considering that a negative fundamental shock to one sector transfers to another through the complex relationship between them, the two sectors show symptoms of possible financial contagion.

There are two mechanisms through which a negative shock can transfer from one sector to the other. First, the failure of a hedge fund can cause an investment bank with direct or indirect exposure to incur significant financial losses. Direct exposure of investment banks includes

¹³ Bear Stearns did not technically default as the Federal Reserve arranged a deal to sell the entity to JP Morgan.

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secured or unsecured lending, derivative exposures, and other forms of counterparty credit exposure. Even though most credit counterparty risk is collateralized, the failure of a hedge fund makes its collateral less valuable, leading to a net loss in collateral pledged to the investment bank. During the near collapse of LTCM, 17 counterparties could have lost between \$3 and \$5 billion if LTCM had not been bailed out¹⁴ (Ferguson & Laster, 2007; Rubin et al., 1999).

Beyond directly exposing investment banks to financial losses, hedge funds can indirectly expose investment banks to market risk and asset fire sales. Failure or near failure of big hedge funds can disrupt the liquidity of financial markets, with spillover into portfolios of both investment banks and other hedge funds. As explicitly stated by Timothy Geithner (2004), the president of the New York Federal Reserve in 2004:

It is not enough to simply manage the firm's direct potential future credit exposure to hedge funds within prudently low limits. This has to be complimented with a more exacting approach to the evaluation of a firm's overall vulnerability to market risk that includes full consideration of the potential impact of a large shock, including one that involves hedge funds.

What Geithner refers to is the indirect exposure of big investment banks to hedge funds through market risk. Due to heavy use of leverage by a number of hedge fund styles, if funds are forced to sell their securities, the impact may go far beyond their AUM, prompting asset fire sales and disrupting market liquidity. This effect is aggravated when juxtaposed with the recent findings that hedge funds are themselves subject to contagion (Boyson et al., 2010; Dudley & Nimalendran, 2010). For example, if there is a negative shock to one style of hedge fund, it may cause a domino effect to other styles. In this regard, investment banks, with considerable reliance on proprietary

¹⁴ Compared to the equity capital of big investment banks, this is a large number. In 1998, \$5 billion would have constituted about 80% of the equity capital of Lehman Brothers.

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trading, may suffer from market illiquidity caused by the failure of one or more hedge fund. The direct and indirect counterparty risk exposure is depicted in Figure 2.

Conversely, failure of investment banks may cause their affiliated hedge funds to incur losses. As illustrated in Figures 3 and 4, this can materialize in two separate ways. First, balance sheet interdependence of investment banks and hedge funds can be a source of financial contagion. Financial intermediaries (and in particular investment banks) immediately react to changes in their net worth (shock to their asset prices) by reducing their leverage and asset size (Adrian & Shin 2008, 2010). In the case of investment banks, they reduce their asset size by limiting credit services to their customers, including hedge funds. Such a dependence on balance sheets by both hedge funds and investment banks is conducive to a rapid transmission of a fundamental shock from the financier (i.e., investment bank) to the borrower (i.e., hedge fund). When an investment bank voluntarily or forcibly reduces its leverage, the affiliated hedge funds, in response, would need to shrink their asset size by selling off some of their assets in fire sales. Aragon & Strahan (2012) argue that assets held by hedge funds whose prime broker was Lehman Brothers faced substantial illiquidity, thus resulting in the hedge funds incurring losses following the bank's collapse. I have summarized this mechanism in Figure 3.

The second mechanism through which shock is transferred from investment banks to hedge funds is through the early withdrawal of collateral and/or cash by hedge funds from their prime brokerages. To understand this mechanism we need to understand how the prime brokerage business works in relation to hedge funds, as outlined by Duffie (2010). A typical course of action by the prime broker to provide financing to hedge funds is through the repo market or secured margin lending. A U.S. prime brokerage can re-pledge collateral promised by hedge funds to a

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third party that in turn uses this collateral to finance the prime brokerage. The prime brokerage passes a portion of the obtained fund (essentially collateralized by hedge funds' assets) to hedge funds. This process, called rehypothecation, can theoretically provide an infinite lending chain from a single item of actual collateral. According to regulation T, for every \$140¹⁵ that a prime brokerage obtains from posting hedge funds' collateral to a third party, it can lend up to \$100 to a client (hedge fund). Therefore, for every dollar they lend out to hedge funds, they find 40 cents funding surplus. Naturally, the difference can be used by investment banks to finance their own assets or other unsecured hedge funds. The problem starts when dealer banks come under financial distress and bankruptcy becomes imminent. Because the value of assets that have been rehypothecated by dealers are more than the loan offered to hedge funds (i.e., these are marginal secured loans), when a dealer's bankruptcy is foreseen, hedge funds may demand their assets from the investment bank (or ban investment banks from re-pledging their assets) to avoid their assets being used as a claim by a third party on the dealer's loan. A failure to demand assets (collateral and cash) from the troubled investment bank, as Lehman Brothers' (London Based) clients learned, could result in the inability to claim their own assets (Duffie, 2010). A preemptive run by hedge funds can cause investment banks to experience a potentially severe liquidity crunch. As a result, investment banks have two options: they can reduce other non-secured lending or they can sell some of their existing assets. The first approach can have an adverse impact on other hedge funds' balance sheets, forcing them to liquidate assets; the second option forces investment banks to

¹⁵ Federal Reserve Regulation T (Reg T) states that "margin equity security, except for an exempted security, money market mutual fund or exempted securities mutual fund, warrant on a securities index or foreign currency or a long position in an option: 50 percent of the current market value of the security or the percentage set by the regulatory authority where the trade occurs, whichever is greater" (e-CFR, n.d., sec. Part 220—Credit by Brokers and Dealers (regulation T)). By establishing offshore investment or using portfolio margining, hedge funds can obtain levels greater than those allowed by regulation T (Ang, Gorovyy, & Van Inwegen, 2011).

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liquidate existing assets in a fire sale. It is important to note that during the recent crisis even non-bankrupt investment banks experienced such a run scenario by hedge funds. Sorkin (2010) and Aitken & Singh (2009) show how Morgan Stanley experienced an extreme liquidity crunch following the flight of its prime brokerage clients (mostly hedge funds) in August 2008. Similarly, Bear Stearns experienced hedge fund runs in March 2008 when hedge funds, that typically park a sizable amount of liquid wealth with their prime brokers, recalled those funds (Brunnermeier, 2008). I outline the rehypothecation process during normal and stress times in Figure 4.

To summarize, contagion between hedge funds and investment banks can occur in both directions: first, an initial shock to hedge funds can travel to investment banks through direct or indirect counterparty credit exposure of investment banks to hedge funds. This channel was the focus of scholars and policy makers after the collapse of LTCM and before the 2007-2008 crisis. Conversely, an initial shock to investment banks can spread to hedge funds through the balance sheet of investment banks, or through the early withdrawal of cash or collateral. Therefore, determining which direction (and therefore which contagion channel) is dominant in the relationship between the two sectors is an empirical question.

3.2.3 Recent studies

In the wake of the 2007-2008 financial crisis, several studies have tried to quantify the interconnectedness of financial institutions within financial markets. Chan et al. (2005) conducted the earliest study on the relationship between the returns of publicly traded commercial banks and hedge funds. They construct equally weighted and value weighted portfolios of firms with SIC codes 6000-6199 and 6710 (commercial banks), and regress the raw returns against the S&P index and Tremont hedge funds index. Their results indicate that the commercial banking sector

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(especially smaller institutions) is exposed to risk from hedge funds. Billio et al. (2010) introduce a new methodology based on principal component analysis (PCA) to measure interconnectedness of four financial institutions, including insurance, investment banks, commercial banks, and hedge funds. They show that the first principal component of returns increased during the 2007-2008 financial crisis, confirming that the connection between the four institutions increased during the crisis. Boyson et al. (2010) investigate contagion between hedge funds for the period from 1990 to 2008 and show that there is strong evidence that hedge fund returns are clustered in the worst returns. Furthermore, they show large negative shocks to hedge fund assets and funding liquidity strongly increase the probability of contagion across hedge funds. Adrian & Brunnermeier (2011) introduce an alternative measure of financial institutions interconnectedness, namely CoVaR, that measures the sensitivity of whole financial systems (for return below a certain quantile) to the failure of each (or portfolio of) financial institution.

3.3 Data and Methodology

3.3.1 Data

I use monthly returns of hedge funds and investment banks from 1990 to 2014 for the index based analyses, and from 1990 to 2011 for firm level analyses, for which data is available. Hedge fund data is obtained from two sources: Hedge Fund Research (HFR) provides the return information for the value weighted portfolio of all hedge funds (HFRI index), as well as different hedge fund styles; Lipper Hedge Fund Dataset, TASS, provides return information for individual hedge funds. I focus on live¹⁶ and levered hedge funds, whose prime brokerage is not the same company as the

¹⁶ The impact is presumably stronger for graveyard datasets.

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sponsor firm¹⁷. Return information for individual investment banks was obtained from the Center for Research in Security Prices (CRSP). Since the investment bank sector is highly concentrated (with the top three banks owning around 60% of all investment bank assets), I limit the samples to the top five investment banks and their affiliated hedge funds. Furthermore, the investment bank index is the value (equally) weighted portfolio of the top five (10) investment banks each year with SIC codes between 6200 and 6299.

For firm level analyses, the dataset is constructed as follows: I create pooled panel data that consists of returns for the top five investment banks, including Morgan Stanley, Goldman Sachs, Lehman Brothers, Bear Stearns, and Merrill Lynch. I then pair returns of each investment bank with returns of a portfolio of hedge funds whose prime brokerage is that investment bank. For example, Goldman Sachs served as prime broker for 13 hedge funds in May 2001. I find the portfolio returns for all 13 hedge funds and pair the portfolio returns with Goldman Sachs' returns for that month. Forming panel data of hedge funds and investment banks is a new approach that has statistical and economic advantages over index level analyses: first, by forming paired returns, the investment bank returns are related only to those hedge funds to which they provide liquidity; second, I can increase the sample size of the number of investment banks. I use the paired dataset in quantile, probit, as well as comovement box analyses.

3.3.2 Methodology

The main question of this study is whether investment bank and hedge fund returns become more correlated at times when one faces financial distress. However, as discussed in the literature

¹⁷ This is to exclude hedge funds that are owned by investment banks.

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review, even without the existence of contagion, it is natural to have excess correlation during periods of financial distress because systematic factors can explain the greater portion of institutions' returns during those periods (Forbes & Rigobon, 2002). Contagion, however, must be recognized when excess correlation of returns cannot be explained by the increasing impact of systematic factors on total returns. To account for this, I filter out returns for systematic risk factors that each institution is exposed to and investigate excess correlation between return residuals. I filter hedge fund returns for broad market exposures (return on S&P 500 and Russell 3000), trend following factors (lookback straddle factors for bonds, currencies, commodities, short term interest rates, and equities), bond market factors (return on BAA rated corporate bonds), equity size factors, currency factor (change in the FRB Dollar), default factors (BAA – 10 year TBill), 10 year TBill yield change, and the negative portion of the S&P 500 index as a proxy for put option risk, as suggested by Fung & Hsieh (2004) and Agarwal & Naik (2004). Since hedge funds have serially correlated returns, I augment the return process with an AR (1) term. Investment bank returns are filtered based on Fama & French (1993) three-factor models. Since choosing the relevant return process is essential to reach any credible conclusion, the majority of robustness tests are dedicated to examining alternative return processes. For example, I augment the investment banks' return process with hedge fund factors and add liquidity risk factors. I discuss the sensitivity of the results to modified asset pricing models in section 6.

After defining the filtered returns, I find conditional probability of return comovement for different quantiles of returns for each investment bank with their portfolio of affiliated hedge funds. Next, I use a quantile regression analysis to examine whether the relationship between the two sectors is different at the lowest quantile (5% quantile) than at other quantiles. I then use the

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probit model to test whether the probability of having low residuals in one sector increases when the other sector experiences low residuals of returns. Finally, I employ the Granger causality test and impulse response function to determine whether contagion goes from investment banks to hedge funds or the other way around. I discuss each approach in the results section.

3.4 Results

3.4.1 Summary statistics and univariate analysis

The analysis begins with a brief look at the raw returns of investment banks and hedge funds. Table 1 shows the median return, standard deviation, skewness, and excess kurtosis, and extremely good (95% percentile) and poor (5% percentile) returns. To reduce survivorship bias in the reported numbers, I limit the time span to the period from 1990 to 2008. A quick scan of returns and risk may offer some valuable insights about the characteristics of the two sectors. First, the median monthly return and standard deviation of investment banks are substantially higher than those of hedge funds and market returns. The difference is partially explained by the fact that the average leverage of big investment banks is more than 25 (King, 2008), compared to recent estimates of the average leverage of hedge funds of less than 2 (Ang et al., 2011) and average market leverage of about 1.6¹⁸. Second, as can be seen through excess kurtosis, investment banks are substantially more susceptible to tail risk than firms in the market index and hedge funds. Alternatively, the hedge fund index is substantially better shaped in terms of conventional risk measures (standard deviation) as well as tail risks. For every unit of standard deviation¹⁹, hedge fund investors earn a monthly median rate of 0.55%, while market portfolio investors earn 0.318%,

¹⁸ Leverage = Total Asset / Total Equity Capital

¹⁹ (Monthly Median)/(Monthly Standard Deviation)

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and investors in investment banks earn 0.315%. More importantly, the tail risk of hedge funds is substantially lower than the other two. Figure 5 shows the compounding return of the four major hedge fund styles along with the investment bank index, market index, and value weighted hedge fund index. Investment banks have performed significantly better than other indices at the expense of greater variability in returns and substantial tail risk.

I also include the summary statistics for each individual investment bank used in the analyses and all hedge funds whose prime brokerage is the corresponding investment bank. For example, all hedge funds whose prime brokerage is Goldman Sachs have a monthly median return of 0.4%, while the return for Lehman Brothers' affiliated hedge funds is substantially higher (1.4%). Interestingly, the standard deviation of the surviving investment banks (Morgan Stanley and Goldman Sachs) is not significantly different with that of failed investment banks, suggesting that their failure cannot be attributed to their ex-ante conventional risk taking. Perhaps the most interesting observation is that hedge funds associated with the two of the failed investment banks (Lehman Brothers and Merrill Lynch) have significantly higher risk measures than hedge funds affiliated with the two surviving investment banks (Goldman Sachs and Morgan Stanley). These numbers suggest that hedge fund risk taking (rather than investment bank risk taking) might contribute to the failure of the investment banks.

Table 2 shows the correlation matrix of hedge fund and investment bank raw returns. Panel A presents the correlation at the index level, while Panel B shows the correlation of each investment bank with its affiliated hedge funds. As can be seen from Panel A, the hedge fund index is significantly correlated with both the market and investment banks (corr = 0.81 and 0.7, respectively). This number is greatest for the "event" style hedge fund and lowest for the "equity

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neutral” style (that simultaneously takes a short and long position in the equity market). Interestingly, raw returns of event style and relative value style funds share the most commonality with the investment bank index ($\rho = 0.9$ and 0.76 , respectively), suggesting that they are the dominant type of business activities for investment banks. At the individual firm level, Panel B shows that the correlation between each investment bank and its affiliated hedge funds is much smaller than at the index level. For example, the correlation between Bear Stearns and its affiliated hedge funds is 0.44 , compared to an index level correlation of 0.7 . More interestingly, the correlation of an investment bank’s returns with its affiliated hedge funds is not necessarily greater than its correlation with non-affiliated hedge funds. For example, the correlation between Goldman Sachs and its affiliated hedge funds is 0.37 , while the correlation between Goldman Sachs with the affiliated hedge funds of Bear Stearns is even higher (0.59). This may suggest that, at the lowest decile, a greater correlation between each investment bank and its affiliated hedge funds might not be the result of shared risk factors (e.g., sharing common asset portfolios). In an unreported table, I repeat Table 2 for the filtered returns (instead of raw returns); the correlation of each individual investment bank with its affiliated hedge funds becomes insignificant at any confidence level, confirming that asset pricing models used to filter raw returns are effective.

Table 3 provides the first evidence for the existence of contagion between the two sectors. The test is conducted on a pooled panel of individual investment banks paired with their affiliated hedge funds. For every percentile, I present the number of common days (relative to total days in that percentile) that the returns of both investment banks and hedge funds are below the stated

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percentile²⁰. I include numbers for both residual and total returns (raw return). For example, for 20% of days, both banks and hedge funds experience returns greater than the top 5% percentile returns, while for 30% of days, both banks and hedge funds experience returns lower than the bottom 5% percentile returns. This implies that co-movement between the two sectors is more frequent when returns are in the lowest percentile than the highest. Interestingly, in moving upward toward higher percentiles, the difference between the lowest and the top percentile declines, suggesting that contagion between the two sectors only occurs during periods of extremely low returns. Finally, total returns show little difference in any percentile, suggesting that the common risk factors that drive returns for both sectors act relatively uniformly across high and low percentiles of returns.

3.4.2 Conditional correlation

Before conducting the inferential analyses, it is helpful to visualize the dynamic relationship between hedge funds and investment banks. I estimate the conditional correlation between hedge funds and investment banks index residual returns based on Engle's (2002) multivariate GARCH model:

$$C_{ij,t} = \alpha_1 + \alpha_2 C_{ij,(t-1)} + \alpha_3 \frac{\epsilon_{i,t-1}}{\sigma_{i,t-1}} * \frac{\epsilon_{j,t-1}}{\sigma_{j,t-1}} \quad (1)$$

$$\sigma_{i,t}^2 = \beta_1 + \beta_2 \epsilon_{i,t-1}^2 + \beta_3 \sigma_{i,t-1}^2 \quad (2)$$

$$\sigma_{j,t}^2 = \gamma_1 + \gamma_2 \epsilon_{j,t-1}^2 + \gamma_3 \sigma_{j,t-1}^2 \quad (3)$$

$$\rho_{ij,t} = \frac{C_{ij}}{\sqrt{C_{ii,t} * C_{jj,t}}} \quad (4)$$

²⁰ For example, for the 5% lowest quantile, I collect all days that either investment banks or hedge funds are in the lowest 5% quantile (k days). Then, I determine how many common days both hedge funds and the investment banks are in that quantile (p). The percentage (p/k *100) is shown in the table.

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$C_{ij,t}$: dynamic covariance between hedge funds and investment banks;

$\sigma_{i,t}^2, \sigma_{j,t}^2$: GARCH variance of hedge funds and investment banks, respectively;

$\epsilon_{i,t}$ and $\epsilon_{j,t}$: residual returns of hedge funds and investment banks, respectively;

$\rho_{ij,t}$: dynamic correlation between residual returns of hedge funds and investment banks.

Figure 6 depicts the dynamic development of correlation $\rho_{ij,t}$, between two residuals, for the period from 1990 and 2010. While the average correlation is 0.18, the correlations show significant fluctuations around the mean throughout the entire period. It is easily discernable that the two sectors demonstrate excessive correlation during the LTCM crisis (1998) and the financial crisis of 2007-2008. During the LTCM crisis, when hedge funds were the original source of extreme market shortfalls, the correlation between the two sectors jumped to 0.48 from the average correlation of 0.18. Similarly, during the financial crisis of 2007-2008, when investment banks were the source of financial system turmoil, the correlation level spiked to 0.37.

3.4.3 Comovement box

The comovement box is an intuitive approach to summarize the conditional probability of two variables in a square with unit side (Figure 7). The idea was first introduced by Cappiello et al. (2005, 2010) to investigate contagion across emerging equity markets. It has since been replicated in recent studies on contagion, including the study by Boyson et al. (2010) investigating contagion across hedge funds. For each quantile θ , I measure the probability of comovement of each investment bank with its affiliated hedge fund portfolio without imposing any particular structure on the relationship between the two variables. To make inferences about contagion from the

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comovement box, we need to understand a basic characteristic of conditional probability. By definition, if two variables (Y and X) are independent, the probability of Y condition on X for the quantile θ of X and Y is $P(Y \leq q_\theta | X \leq q_\theta) = P(Y \leq q_\theta) = \theta$ ²¹. It follows that if two variables are positively correlated, $P(Y \leq q_\theta | X \leq q_\theta) > (P(Y \leq q_\theta) = \theta)$, and if they are negatively correlated, $P_\theta(Y|X) < \theta$. Hence, after calculating the conditional probability of Y on X for a given quantile, any probability that is more than θ indicates that for that quantile, the two variables are more correlated than would be expected from an independent relationship. The conditional probability of Y (investment bank returns) on X (hedge fund returns) for each quantile, $P_\theta(Y|X)$, can be determined as follows: I run a quantile regression of Y on X for each quantile θ to find the estimated quantile of investment bank residual returns for a given quantile of hedge fund residual returns. I then find an exceedance indicator for both investment banks and hedge funds. For investment banks, the exceedance indicator is 1 when the investment bank's residual is less than the estimated quantile, and zero otherwise. For hedge funds, the indicator is 1 when the hedge fund's residual is less than the unconditional quantile of hedge funds. The co-exceedance indicator is the product of two exceedance indicators. Finally, I find the average co-exceedance indicator, which is the conditional probability of investment banks on hedge funds.

I construct the comovement box separately for each investment bank and its portfolio of hedge funds (Figure 8). The line with dots (red) is the calculated conditional probability of the investment bank on hedge funds and the solid line (black) is the conditional probability if the two are

²¹ A quantile is defined as, $P(Y \leq q_\theta) = \theta$ and $P(Y \leq q_\theta | X \leq q_\theta) = \frac{P(Y \leq q_\theta \text{ and } X \leq q_\theta)}{P(X \leq q_\theta)}$. If Y and X are independent, $P(Y \leq q_\theta \text{ and } X \leq q_\theta) = P(Y \leq q_\theta) \times P(X \leq q_\theta)$, therefore, $P(Y \leq q_\theta | X \leq q_\theta) = \frac{P(Y \leq q_\theta) \times P(X \leq q_\theta)}{P(X \leq q_\theta)} = P(Y \leq q_\theta) = \theta$.

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independent. Except for Merrill Lynch, the other four banks show positive correlation at the lowest percentiles (below 20% percentile). The calculated conditional probability of residual returns of Morgan Stanley on its affiliated hedge funds suggest that there is a positive correlation (i.e., a correlation beyond what is expected from two independent variables) for quantiles below 20%, and a negative correlation for any decile between 20% and 60%. Similarly, the comovement box for Lehman Brothers indicates that there is a positive correlation in all deciles below 50% and a negative correlation for deciles above 50%. Except for Merrill Lynch, which shows negative correlation for almost all deciles, the other investment banks demonstrate that the residual returns of the two sectors are positively correlated at low quantiles. This finding suggests that the residual returns of the two sectors are not independent.

3.4.4 Quantile regression

While the comovement box is simple and intuitive, any inference from the results is extremely sensitive to sample size, particularly in the lowest and highest quantiles for which the number of exceedance indicators is limited²². If we use quantile regression directly, this limitation may be overcome. Quantile regression models the relationship between an independent variable and the conditional quantile of a dependent variable²³. I test whether hedge fund shocks (X) and investment bank shocks (Y) are related in different quantiles. Thus, for a given month and a given investment bank, I find the number of hedge funds whose residual returns fall below q% quantile. Following

²² For the comovement box, I use each investment bank separately with its own portfolio of affiliated hedge funds; hence, the power is lower than what could be obtained by increasing the sample size and pooling all investment banks with their affiliated hedge funds.

²³ It is better understood when compared with OLS regression, which models the relationship between X (independent variable) and the conditional mean of Y (dependent variable). One would expect that estimates of quantile regression of 50% quantile (i.e., median) of Y on X should yield similar results to OLS estimates if the median and mean of the dependent variable (Y) are similar.

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Boyson et al. (2010), I use this proxy for negative shocks in hedge fund returns in any given month. The measure is intuitive and more granular than a dummy variable (that is 1 if hedge fund returns fall below $q\%$ quantile and zero otherwise). Quantile regression can be interpreted as the impact of the number of hedge funds that experience financial distress (i.e., their returns fall below $q\%$ quantile) on the financial distress of their prime brokerage.

$$IB_{i,t,q\%} = \alpha + \beta NHFFQ_{i,t,q\%} + \epsilon_{i,t,q\%} \quad (5)$$

$IB_{i,t,q\%}$: $q\%$ quantile of residual returns of investment bank “i” at month “t”;

$NHFFQ_{i,t,q\%}$: number of hedge funds of investment bank “i” at month “t” whose returns fall below $q\%$ quantile.

The estimates of beta for all quantile assortments are reported in Table 4. The first column (quantile Y) corresponds to different quantiles of investment bank returns and all other columns (quantile X) correspond to different quantiles of hedge fund returns. The table can be read as follows: if the number of affiliated hedge funds of an investment bank that experience shocks at $q_x\%$ quantile (in columns X) increases by 1 unit, the $q_y\%$ quantile returns for their investment banks changes by the coefficients presented in the table. For example, when the number of hedge funds whose returns fall under the 20% quantile increases by 1 unit, the median return (50% quantile) of investment banks changes by -0.0005 (and is insignificant)²⁴. To avoid clutter, the standard error is not included in the table and only significant coefficients are marked with an asterisk.

²⁴ A more accurate interpretation is as follows: when the number of affiliated hedge funds [of an investment bank] whose returns fall under their 20% quantile increases by 1 unit, the median return (50% quantile) of the investment bank will change by -0.0005.

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The results provide clear evidence of contagion between the two sectors. As can be seen in Table 4, the only significant estimate is found when hedge fund returns are below their extreme lowest (5% X quantile) and investment banks returns are below their extreme lowest (5% Y quantile). This is a very promising result, given that all other possibilities are thoroughly examined in the table. More importantly, the sign of the coefficient is negative, as expected, and economically significant: when the number of hedge funds whose returns fall below the 5% quantile increases by one unit, the investment bank residuals in the lowest quantile (5%) fall by 2.6%.

Figure 9 summarizes the information presented in Table 4. For each quantile of hedge fund residuals, it shows the estimated coefficient of quantile regression of investment bank returns on hedge fund returns within a 95% confidence interval. Therefore, estimates of the impact of the number of hedge funds whose residual returns fall below 10% on different quantiles of investment bank returns can be found in the second diagram from the top left. A quick scan of the figure demonstrates that the only confidence interval that does not encompass the horizontal axis is the very first diagram, where both the hedge fund and investment bank returns are below the 5% quantile (circled with a red dashed line).

3.4.5 Probit model

An alternative approach to assess contagion is to impose a logit or probit structure on the relationship between investment bank and hedge fund returns as introduced by Bekaert et al. (2005) and widely used in the contagion literature. My objective is to determine whether low returns of the affiliated hedge fund portfolio are associated with a higher probability that their prime brokerage also has low returns. I use a probit model in two different setups: in the first setup,

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I create a portfolio of affiliated funds for any given investment bank (i) at each month (t). The dummy variable equals 1 when the hedge fund portfolio returns or investment bank returns fall below their q% quantile. I regress the two dummy variables for all quantiles from 5% to 100%.

The formal equation is:

$$IBDummy_{it} = HFDummy_{it} + \epsilon_{it} \quad (6)$$

$HFDummy_{it}$: dummy variable, = 1 if the return of the value weighted portfolio of hedge funds affiliated with investment bank “i” at month “t” falls below q% quantile (negative shock to hedge fund returns);

$IBDummy_{it}$: dummy variable, = 1 if the return of investment bank “i” at month “t” is below q% quantile (negative shock to investment bank i).

In the second setup, I use the number of hedge funds whose residual returns fall below q% quantile as a proxy for shock in the hedge fund sector (Boyson et al., 2010). The formal equation is:

$$IBDummy_{it} = NHFFQ_{it} + \epsilon_{it} \quad (7)$$

$IBDummy_{it}$: dummy variable, = 1 if the return of investment bank “i” at month “t” is below q% quantile (negative shock to investment bank i);

$NHFFQ_{it}$: number of hedge funds affiliated with investment bank “i” at month “t” whose returns fall below their q% quantile.

Table 5 shows the results from equation (6). The table can be read as follows: when hedge fund returns fall below the q% quantile, the probability of investment bank returns to fall below

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q% quantile changes by the coefficients reported in the table²⁵. For example, when hedge fund returns fall below the 20% quantile, the probability of an investment bank's returns to fall below the 20% quantile is insignificant (coefficient of probit model 0.13, P value of 0.67)²⁶. The only significant result is reported at the lowest 5% quantile, confirming that when hedge fund returns fall below the lowest value (i.e., less than 5% quantile), the probability that investment bank returns will fall below their extreme low value (5% quantile) increases.

The results of equation (7) are presented in Table 6. The interpretation of the table is similar to Table 4, except I use a different proxy for negative shocks on hedge funds. For example, when the number of hedge funds whose returns fall below 20% quantile increases by 1 unit, the probability that their prime brokerage's returns will fall below 20% quantile is insignificant (coefficient of probit model 0.017, P value of 0.23). When the number of hedge funds whose returns are at their extreme lowest value (i.e., less than 5% quantile) increases by 1 unit, the probability that an investment bank's returns will fall below the 5% quantile increases. In other situations, i.e., when the number of hedge funds with returns at higher percentiles increases, there is no relationship between residuals of investment bank and hedge fund returns.

Finally, I examine the economic significance of the results reported in Tables 4, 5, and 6. The results of quantile regression, Table 4, suggest an economically significant impact of distress in hedge fund returns on investment bank returns, i.e., one unit increase in the number of hedge funds that experience extremely low returns is associated with a reduction of -2.6% in investment bank

²⁵ The interpretation is admittedly inaccurate. Since it is a probit regression, the correct interpretation is that when hedge fund returns fall below q% quantile, the probability that investment bank returns fall below q% quantile changes by beta times the normal function, i.e., $\beta * \phi(\beta)$.

²⁶ Similar to quantile regression, I could provide an exhaustive table in which the impact of every $q_x\%$ on $q_y\%$ is reported. Here in Tables 3 and 4, I only include the impact of shocks of X on Y when both shocks happen in the same quantile. An exhaustive table would add little information to the analysis.

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returns. Nevertheless, the probit regression shows less significant impacts. If hedge fund returns fall below their lowest quantile (5% quantile), the probability that investment bank returns fall below their lowest quantile increases by around 3%. The difference between the economic significance of the two tests (Table 4 and 5) may not necessarily indicate inconsistency when we consider that the two tests correspond to two different measures: the former (Table 4) indicates the magnitude of impact of hedge fund failure on prime brokerage returns; the latter (Table 5 and 6) refers to the probability of investment bank failure given the failure of their affiliated hedge funds. In light of this difference, we can see that the probability of failure of investment banks given failure of their affiliated hedge funds may not increase substantially (Table 5 and 6), but the magnitude of this impact can be significant (Table 4).

3.4.6 Direction of contagion

3.4.6.1 Vector Auto Regression(VAR) and Granger Causality

In this section, I examine if hedge funds or investment banks are the initial source of contagion which may help to identify which is the most likely channel of contagion (Figures 2, 3, and 4). Since investment banks supply liquidity to hedge funds, if disruption to liquidity (through balance sheet or asset withdrawal) is the main channel of contagion (Figure 4), we may see contagion begin in investment banks and run through hedge funds. On the other hand, if the dominant channel of contagion is counterparty risk exposure (Figure 2), we may see that failing hedge funds cause investment banks to fail. To investigate this, I model the relationship between the two sectors using a Vector Auto Regression (VAR), the Granger Causality test, and impulse response function.

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I create a portfolio of all hedge funds affiliated with the top five investment banks and a portfolio of the top five investment banks. I run the following system of equations:

$$IBClipped_t = \sum_{k=1}^4 \alpha_k IBClipped_{(t-k)} + \sum_{k=1}^4 \theta_k HFClipped_{(t-k)} + u_t$$

(8)

$$HFClipped_t = \sum_{k=1}^4 \gamma_k HFClipped_{(t-k)} + \sum_{k=1}^4 \beta_k IBClipped_{(t-k)} + \epsilon_t$$

(9)

$HFClipped_t$ = return of equally weighted portfolio of all hedge funds at month “t” when it is below 5% quantile (negative shock to hedge fund returns), zero otherwise;

$IBClipped_t$ = return of equally weighted investment banks at month “t” when it is below 5% quantile, zero otherwise.

Construction of the dependent and independent variables (HFClipped and IBClippedP) is as follows: I build an equally weighted portfolio of all hedge funds (affiliated with the top five investment banks) as the independent variable, and an equally weighted index of the top five investment banks as the dependent variable. However, I insert zero for any return greater than 5% quantile, i.e., zero represents any return above the 5% quantile²⁷. The question that equation (8) addresses is as follows: if returns of the hedge fund portfolio during previous periods falls to the lowest quantile (i.e., falls from zero to a return that is smaller than the 5% quantile), does this cause investment bank returns to fall below the lowest quantile in the contemporaneous period? (i.e., fall from zero to a return that is smaller 5% quantile)? Similarly, for equation (9), if the returns of investment banks during previous periods fall to their lowest quantile, does this contemporaneously cause the returns of hedge fund portfolio to fall to its lowest quantile? The

²⁷ If I do not insert zero, the VAR estimates would be for normal and extreme periods combined, but we only need VAR estimates for extreme conditions.

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significance of β in equation (9) indicates that the direction of contagion is from investment bank to hedge funds, while the significance of θ coefficient in equation (8) indicates the direction of contagion is from hedge funds to investment banks.

The result of the Granger causality test, equation (8) and (9), is presented in Table 7. In the first test, the null hypothesis is that the current value of investment bank returns at their lowest quantile (5% quantile) are only influenced by their lagged values and not by lagged hedge fund returns. As Table 7 shows, this hypothesis is strongly rejected (p value =0.0021) suggesting that a negative shock may travel from hedge funds to investment banks. In the second test, the null hypothesis is that hedge fund returns at the 5% quantile are self-influenced and not influenced by investment banks lagged residual returns. This hypothesis cannot be rejected (p value =0.844). The results suggest when hedge funds experience extremely low returns they may cause investment banks to experience the extremely low returns in the next period, but not the other way around. In other words, when investment banks experience extremely low returns they do not cause hedge funds to also experience extremely low returns (i.e., below 5% quantile) in the subsequent periods.

3.4.6.2 Impulse Response Function

Impulse response function (IRF) is an alternative test of causality between two time series variables. At its core, IRF can be used to investigate the impact of an impulse (a shock) in one variable on another variable. In this analysis, I use equations (8) and (9) to find the impact of one unit change in residual of hedge fund return innovation (ϵ_{it}) on investment bank return innovation at the 5% quantile. At the same time, I find the impact of one unit change in residual of hedge fund return innovation (u_{it}) on investment bank residual return at the 5% quantile. It is important to note that ϵ_{it} and u_{it} are residuals of return residuals (the returns are filtered by common risk

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factors and filtered again by residuals of another sector). This ensures that the results are not the outcome of omitted factors (i.e., not captured by formal asset pricing models) that drive both returns.

The results of simple IRF and orthogonalized IRF are shown in Table 8. In the simple IRF, it is assumed that shocks (u_{it} and ϵ_{it}) happen one at a time. This assumption is reasonable when shocks in different variables are independent. In an orthogonalized IRF, this assumption is relaxed: I assume innovation in one variable can happen simultaneously in another. Panel A shows the results of simple IRF and Panel B presents the result of orthogonalized IRF. An impulse in hedge fund residual returns, i.e., one unit change in ϵ_{it} , causes investment bank residuals to change by 0.667 unit. However, an impulse in investment bank residual returns, i.e., one unit change in u_{it} , does not significantly change hedge funds' residuals. We can also see that coefficients of all lags greater than the first lag, are not significant for both investment banks and hedge funds. Panel B shows the results of orthogonalized IRF. Similar to simple IRF, an impulse in hedge fund residual returns significantly causes investment bank residuals to change by 0.008 unit. However, an impulse in investment bank residual returns does not significantly change hedge fund residuals.

Figure 10 presents graphically the information in Panel A of the Table 8. Figure 10 (a) shows the response of hedge fund residuals (H) to an impulse in investment bank residuals (I), and Figure 10 (b) shows the response of investment bank residuals to an impulse in hedge fund residuals. We can see in Figure 10 (A and B) that the 95% confidence interval encompasses the zero line for the response of hedge funds to an impulse in investment bank residuals, while it does not encompass the zero line for the response of investment bank returns to a shock in hedge fund return residuals.

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Thus, with 95% confidence we can say that only an impulse in hedge fund residuals has an impact on investment bank residuals.

The results of the impulse response function (IRF) and VAR tests point to hedge funds as the origin of contagion, however, from theoretical perspective, the contagion can also originate from investment banks due to reasons portrayed in figures 3 and 4. The question is, why do we empirically observe that hedge funds have stronger chance to initiate the contagion? Two explanations might exist: first, investment banks, particularly those famously known as Too-Big-To-Fail (TBTF) have a subsidized access to liquidity, and therefore, negative liquidity shocks as illustrated in the figures 3 and 4, can be partially prevented from spreading out to their counterparties. More specifically, during the financial crisis of 2007-8, two (out of 5) of investment banks used in our samples, namely, Morgan Stanley and Goldman Sachs, filed to become bank holding companies(BHC), in order to use the liquidity facilities provided by Federal Reserves. The very fact that that they have access to liquidity when they face significant liquidity constraints forebodes well for their counterparties, specially hedge funds, whose liquidity needs depends upon the liquidity provision of these banks.

A different but related reason to why hedge funds are the original source of contagion is that they are usually prone to failure without benefitting from any government intervention or bailout. The yearly attrition (failure) rate of hedge funds is estimated to be 8.7%(3.1%) , which points to significant counterparty risks they pose to all bilateral contracts they have with their prime brokerages (Liang and Park , 2010). In contrast, the failure of investment banks is much less frequent. Investment banks benefit from a de-facto diversification of U.S. universal banking system that allows investment banking activities to constitute a fairly small portion of banking

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services offered by bank holding companies (BHC). More importantly, being chartered as BHC, many investment banks have used government bailout or subsidies in different capacity in the past. For example, except for the Lehman Brothers that actually failed, two of other troubled investment banks, namely, Bear Sterns and Merrill-Lynch were absorbed by other entities, advocated by Federal Reserves attempts to contain the spillover of failure of those investment banks. The lower rate of investment bank failure than hedge funds is perhaps the most likely reason that contagion most likely materialize through the mechanism illustrated in figure 2 rather than those portrayed in figures 3 and 4.

3.5 Robustness Tests

3.5.1 Omitted variables

Historically, investigating contagion has been plagued by misidentification of econometric models²⁸. In this section, I address some of the potential econometric concerns that might influence the results. One of the main concerns that refrains many scholars and policy makers to jump to any conclusion regarding contagion is the possibility of omitted variables in filtering out common risk factors. In the other words, if asset pricing models fail to capture all common risk factors, two sectors may show a false contagious relationship, when in fact the two sectors share an omitted common risk factor. The following discussion outlines various robustness tests conducted in this study.

²⁸ For a good discussion , see Forbes & Rigobon (2001).

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First, recent research emphasizes the influence of liquidity risk on a cross section of hedge fund returns (Sadka, 2010). However, in the original model presented by Fung & Hsieh (2004), liquidity risk is not embedded as a separate systematic factor. Following Boyson et al. (2010), I use the TED spread (difference between Eurodollar rate and Treasury rate for three-month maturity) as a proxy for liquidity risk. Throughout the paper, I augment the seven-factor model introduced by Fung & Hsieh (2004), with the TED spread to filter hedge fund raw returns.

Second, to the extent that investment banks share similar business models with hedge funds (mostly through proprietary trading), they may reasonably be exposed to similar risk factors. In such a case, traditional Fama-French three-factor models might underestimate the systematic risk processes and thus, overestimate the correlated residuals with affiliated hedge funds. I address this concern by experimenting with several asset pricing models, starting with the Fama-French three-factor model and evolving into a return process that fully resembles those of hedge funds. Shifting asset pricing models from Fama-French to Fung-Hsieh-Naik fifteen-factor models indeed strengthens the significance of the results presented herein. For example, the results of the probit model, previously significant at 5% level, become significant at 0.001 confidence level.

Third, some might argue that two institutions show excess correlation at a 5% quantile, as occurred in all tests, because these return quantiles are associated with extreme financial crises that can cause all sectors to experience extremely poor returns. At the core of this argument is the assumption that the asset pricing models used herein do not capture all systematic factors to which both institutions are exposed, particularly during a crisis period. I deal with this challenge in two different ways. First, a typical scenario of financial crises is accompanied by a substantial tension in financial firms' ease of access to credit markets. The time series of the monthly TED spread,

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Figure 11, indicates that all financial crises since 1990 are strongly correlated with a surge in TED spread. If omitted variables related to financial crises are the driving factors behind excessive correlation between investment bank and hedge fund returns, we should observe that after adding TED to the returns process of the two sectors, they do not demonstrate a contagious relationship. However, after adding the TED spread to both investment bank and hedge fund returns processes, all results regarding existence of contagion and direction of contagion hold as significant and in some cases become even more significant.

Second, and perhaps more interestingly, I attempt to exclude the possibility of financial crises omitted variables by designing a counterfactual test. I create portfolios of hedge funds whose prime brokerage is *not* their actual prime brokerage, i.e., instead of forming panel data in which each investment bank is paired with the hedge funds to which it provides liquidity, I pair each investment bank with hedge funds to which it does not provide liquidity. If omitted variables and a non-specific relationship (through liquidity and/or credit risk exposure) between two sectors are the cause of contagion, we should still see contagion. The result, however, shows there is no contagion between an investment bank and hedge funds to which it does not supply liquidity. This suggests that the driving force of contagion is the specific relationship between the two sectors and not omitted risk factors.

3.5.2 Non-Bankrupt banks

The 2007-2008 financial crisis caused three of the five investment banks used in this analysis to face insolvency. This may trigger a valid concern that the results are driven by specific considerations concerning the bankruptcy of those banks. To address this, I trimmed the samples to only two banks that did not face bankruptcy, namely, Morgan Stanley and Goldman Sachs, and

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dropped the bankrupt banks, Bear Stearns, Merrill Lynch, and Lehman Brothers. I repeated all tests with only non-bankrupt samples and all tests remain significant, except for the result presented in Table 4 that becomes nonsignificant.

3.6 Conclusions

Herein, I examine the possibility of contagion between two of today's most important financial sectors, investment banks and hedge funds. These two sectors are highly interconnected; the prime brokerage businesses of the top five investment banks act as the liquidity engine for the majority of hedge funds, while hedge funds pose substantial counterparty credit risk to investment banks. It seems reasonable that two sectors with such strong financial ties would demonstrate a contagious relationship. To avoid misidentifying interdependence as contagion, I use the methodology introduced by Bae, Karolyi, & Stulz (2003) to separate the systematic components of raw returns. Contagion in this framework is an excessive correlation between residual returns. I investigate this possibility by applying both a non-parametric and parametric approach. I find that the probability of an investment bank's returns to fall below the lowest quantile (5%) if their affiliated hedge funds' returns fall below the lowest quantile is more than what two independent variables warrant. Similarly, the parametric test concludes that if hedge fund returns fall below the lowest quantile, there is an increased probability that their prime brokerage will also fall below the lowest quantile. The results are also economically significant: when the number of affiliated hedge funds that experience extremely low returns increases by one unit, the returns of an investment bank fall by 2.6%.

Investment Bank Exposure to Hedge Funds and Financial Contagion

In order to identify the channel of contagion, I use Vector Auto Regression (VAR). Based on Granger causality test, I show that an initial negative shock to hedge funds leads to a negative shock to investment banks. The causality implies that the possible channel of contagion is more likely direct (credit or derivative exposure posed by hedge funds to investment banks) or indirect (asset fire sales) rather than through deficiency in liquidity provision by investment banks. In robustness test, I explore several measures to reduce the probability that the results are driven by omitted variables. The majority of the results remain significant even after using conservative asset pricing models and several other controls.

3.7 References

- Adrian, T., & Brunnermeier, M. K. (2011). CoVaR. National Bureau of Economic Research. Retrieved from <http://www.nber.org/papers/w17454>
- Adrian, T., & Shin, H. S. (2008). Liquidity and Financial Contagion. *Financial Stability Review*, Banque de France.
- Adrian, T., & Shin, H. S. (2010). Liquidity and leverage. *Journal of Financial Intermediation*, 19(3), 418–437.
- Agarwal, V., & Naik, N. Y. (2004). Risks and portfolio decisions involving hedge funds. *Review of Financial Studies*, 17(1), 63–98.
- Aitken, J., & Singh, M. (2009). Deleveraging After Lehman--Evidence from Reduced Rehypothecation. International Monetary Fund.
- Ang, A., Gorovyy, S., & Van Inwegen, G. B. (2011). Hedge fund leverage. *Journal of Financial Economics*, 102(1), 102–126.
- Aragon, G. O., & Strahan, P. E. (2012). Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. *Journal of Financial Economics*, 103(3), 570–587.
- Bae, K.-H., Karolyi, G. A., & Stulz, R. M. (2003). A New Approach to Measuring Financial Contagion. *Review of Financial Studies*, 16(3), 717–763.
- Bekaert, G., Harvey, C. R., & Ng, A. (2005). Market Integration and Contagion.
- Bernanke, B., & Gertler, M. (1989). Agency Costs, Net Worth, and Business Fluctuations. *The American Economic Review*, 79(1), 14–31.
- Bernanke, B., Gertler, M., & Gilchrist, S. (1996). The Financial Accelerator and the Flight to Quality. *The Review of Economics and Statistics*, 78(1), 1–15.
- Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2010). Econometric measures of systemic risk in the finance and insurance sectors. National Bureau of Economic Research.
- Boyson, N. M., Stahel, C. W., & Stulz, R. M. (2010). Hedge fund contagion and liquidity shocks. *The Journal of Finance*, 65(5), 1789–1816.
- Brunnermeier, M. K. (2008). Deciphering the liquidity and credit crunch 2007-08. National Bureau of Economic Research. Retrieved from <http://www.nber.org/papers/w14612.ack>

- Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, 22(6), 2201–2238.
- Cappiello, L., Gérard, B., & Manganelli, S. (2005). Measuring comovements by regression quantiles. Retrieved from <http://ideas.repec.org/p/ecb/ecbwps/20050501.html>
- Cappiello, L., Kadareja, A., & Manganelli, S. (2010). The impact of the euro on equity markets. Retrieved from http://journals.cambridge.org/abstract_S0022109010000086
- Chan, N., Getmansky, M., Haas, S. M., & Lo, A. W. (2005). Systemic risk and hedge funds. National Bureau of Economic Research.
- Cifuentes, R., Ferrucci, G., & Shin, H. S. (2005). Liquidity Risk and Contagion. *Journal of the European Economic Association*, 3(2–3), 556–566.
- Dudley, E., & Nimalendran, M. (2010). Funding Risk and Hedge Fund Returns. SSRN eLibrary. Retrieved from <https://northernfinance.org/2010/NFAPapers2010/papers/138.pdf>
- Duffie, D. (2010). The Failure Mechanics of Dealer Banks. *Journal of Economic Perspectives*, 24(1), 51–72. <https://doi.org/10.1257/jep.24.1.51>
- e-CFR part 220, 2015, Electronic Code of Federal Regulations § Part 220—Credit by Brokers and Dealers (regulation T). Retrieved from http://www.ecfr.gov/cgi-bin/retrieveECFR?gp=&SID=ad7616bc70f2ec935b7cdbfa6cd8f4ef&n=pt12.3.220&r=PART&ty=HTML#se12.3.220_17
- Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics*, 20(3), 339–350.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56.
- Ferguson, R., & Laster, D. (2007). Hedge funds and systemic risk. Banque de France, *Financial Stability Review: Special Issue Hedge Funds*, 45–54.
- Forbes, K. J., & Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. *The Journal of Finance*, 57(5), 2223–2261.
- Forbes, K., & Rigobon, R. (2000). Contagion in Latin America: Definitions, Measurement, and Policy Implications (Working Paper No. 7885). National Bureau of Economic Research.

- Forbes, K., & Rigobon, R. (2001). Measuring contagion: conceptual and empirical issues. In *International financial contagion* (pp. 43–66). Springer.
- Fung, W., & Hsieh, D. A. (2001). The risk in hedge fund strategies: theory and evidence from trend followers. *Review of Financial Studies*, 14(2), 313–341.
- Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal*, 65–80.
- GAO. (2008, January). *Hedge Funds*. United States Government Accountability Office Report to Congressional Requesters.
- Geithner. (2004). *Hedge Funds and Their Implications for the Financial System*. Retrieved from <http://www.newyorkfed.org/newsevents/speeches/2004/gei041117.html>
- Hildebrandfung, P. M. (2007). Hedge funds and prime broker dealers: steps towards a “best practice proposal.” *Financial Stability Review*, (10), 67–76.
- Kambhu, J., Stiroh, K. J., & Schuermann, T. (2007). *Hedge Funds, Financial Intermediation, and Systemic Risk* (SSRN Scholarly Paper No. ID 995907). Rochester, NY: Social Science Research Network. Retrieved from <http://papers.ssrn.com/abstract=995907>
- King, M. (2008). *Are the brokers broken*. Report, Citigroup European Quantitative Credit Strategy and Analysis.
- King, M. R., & Maier, P. (2009). Hedge funds and financial stability: Regulating prime brokers will mitigate systemic risks. *Journal of Financial Stability*, 5(3), 283–297.
- Kiyotaki, N., & Moore, J. (1997). Credit Cycles. *Journal of Political Economy*, 105(2), 211–248. <https://doi.org/10.1086/262072>
- Lewis, A. (2014, April 20). *The Systemic Risk of Hedge Funds*. Wall Street Journal. Retrieved from <http://www.wsj.com/articles/SB10001424052702303626804579505673648422470>
- Mustiers, J. P., & Dubois, A. (2007). Risks and return of banking activities related to hedge funds. *Financial Stability Review*, (10), 85–94.
- Rubin, Greenspan, Levitt, & Born. (1999). *Hedge Funds, Leverage, and the Lessons of Long-Term Capital Management*. Reports of The Presidential Working Group.
- Sadka, R. (2010). Liquidity risk and the cross-section of hedge-fund returns. *Journal of Financial Economics*, 98(1), 54–71. <https://doi.org/10.1016/j.jfineco.2010.05.001>

Schnabel, I., & Shin, H. S. (2004). Liquidity and Contagion: The Crisis of 1763. *Journal of the European Economic Association*, 2(6), 929–968.

Sorkin, A. R. (2010). *Too Big to Fail: The Inside Story of How Wall Street and Washington Fought to Save the Financial System--and Themselves* (Updated edition). New York: Penguin Books.

3.8 Tables and Figures

Table 1: Summary statistics

The table, panel A and B, presents the median return, standard deviation, skewness, excess kurtosis, and extreme positive (95% percentile) and poor (5% percentile) returns of the top 20 investment banks value weighted index, hedge funds value weighted index, market index (CRSP), four of the main hedge fund styles (Macro, Relative Value, Equity Neutral, and Event), the five major investment banks, and finally, all hedge funds whose prime brokerage is the corresponding investment bank. Panel A's summary statistics are reported for the period between 1990 and 2008. Panel B's statistics report the average market value of investment banks for the period of 1990 to 2013, and the NAV of hedge funds affiliated with each investment bank for the period between 1990 and 2011.

Panel A

	Median	Std Deviation	Skewness	Excess Kurtosis	P5%	P95%
Investment Banks Index	2.4%	7.6%	0.17	1.76	-10.4%	14.8%
Hedge Funds Index	1.1%	2.0%	-0.69	2.55	-2.3%	3.7%
Market Index(CRSP)	1.4%	4.4%	-0.74	1.44	-7.7%	7.5%
Macro Style	0.7%	2.2%	0.57	1.05	-2.0%	5.2%
Relative Value Style	0.9%	1.3%	-2.13	13.80	-0.8%	2.5%
Equity Neutral Style	0.5%	0.9%	-0.26	1.65	-1.0%	2.2%
Event Style	1.2%	1.9%	-1.31	4.15	-2.5%	3.6%

Panel B

	Median	Std Deviation	Skewness	Excess Kurtosis	P5%	P95%	Mktvalue/NAV (Mean, \$)
Bear Stearns	1.9%	10.7%	-2.53	20.09	-12.3%	15.6%	\$5.8B
Goldman Sachs	1.5%	10.4%	0.24	0.88	-15.0%	16.6%	\$57.4B
Lehman Brothers	1.8%	12.6%	-0.25	1.91	-16.5%	22.6%	\$15.4B
Merrill Lynch	2.0%	10.4%	-0.42	0.53	-16.0%	17.3%	\$30.3B
Morgan Stanley	1.8%	10.8%	-0.11	2.73	-16.3%	17.9%	\$37.7B
Goldman Sachs Hedge Funds	0.4%	2.9%	2.73	12.26	-3.2%	3.8%	\$0.965B
Lehman Brothers Hedge Funds	1.4%	5.2%	-0.22	1.43	-7.8%	9.7%	\$1.67B
Merrill Lynch Hedge Funds	1.6%	8.3%	0.85	4.38	-10.2%	15.1%	\$3.34B
Morgan Stanley Hedge Funds	1.1%	3.7%	1.59	8.14	-3.6%	7.5%	\$1.46B
Bear Stern Hedge Funds	1.1%	3.3%	-0.02	2.77	-3.9%	6.2%	\$2.4B

Table 2: Correlation matrix of hedge funds and investment banks

Panel A shows the correlation at the index level between hedge funds value weighted index, investment bank value weighted index, CRSP value weighted index, and Macro, Relative, Equity Neutral and Event Style value weighted indices. Panel B presents the correlation of each investment bank with its affiliated hedge funds. The first column includes the listed investment banks, followed by hedge funds whose prime brokerage is that investment bank. The rows present abbreviated names from the first column: **BS**: Bear Stearns; **GS**: Goldman Sachs; **LB**: Lehman Brothers; **ML**: Merrill Lynch; **MS**: Morgan Stanley; **HF**: affiliated Hedge Funds. All correlations are significant at 1%.

Panel A							
	HF Index	IB Index	CRSP	Macro	Relative Value	Equity Neutral	Event
Hedge Fund Index	1						
Investment Banks Index	0.70	1					
CRSP Index	0.81	0.81	1				
Macro Style	0.34	0.64	0.37	1			
Relative Value Style	0.46	0.73	0.55	0.34	1		
Equity Neutral Style	0.22	0.46	0.28	0.33	0.41	1	
Event Style	0.63	0.90	0.76	0.51	0.76	0.41	1

Panel B										
	BS	GS	LB	ML	MS	BS HF	GS HF	LB HF	ML HF	MS HF
Bear Stearns	1									
Goldman Sachs	0.49	1								
Lehman Brothers	0.71	0.73	1							
Merrill Lynch	0.53	0.66	0.69	1						
Morgan Stanley	0.44	0.82	0.77	0.75	1					
Bear Stearns Hedge Funds	0.41	0.59	0.47	0.47	0.50	1				
Goldman Sachs Hedge Funds	0.18	0.37	0.20	0.35	0.37	0.64	1			
Lehman Brothers Hedge Funds	0.32	0.47	0.45	0.52	0.53	0.65	0.64	1		
Merrill Lynch Hedge Funds	0.20	0.30	0.25	0.20	0.25	0.66	0.53	0.53	1	
Morgan Stanley Hedge Funds	0.20	0.43	0.26	0.21	0.35	0.75	0.81	0.57	0.70	1

Table 3: Percent of days both hedge funds and investment banks fall below q% quantile

For every quantile, I present the number of common days (relative to total days in that percentile) that returns of both investment banks and hedge funds are below that percentile. This provides intuitive evidence of excessive comovement in the lowest percentiles relative to highest percentiles. I include numbers for both residuals and total return (raw return). For example, in 20% of days, both investment banks and hedge funds experience returns higher than the top 5% percentile return, while in 30% of days, both investment banks and hedge funds experience returns lower than the bottom 5% percentile return.

	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
	5%	5%	10%	10%	20%	20%	30%	30%	40%	40%	50%	50%
Residuals	20%	30%	44%	51%	54%	62%	81%	82%	96%	92%	100%	100%
Total Return	50%	50%	66%	69%	89%	88%	92%	92%	100%	100%	100%	100%

Table 4:Quantile Regression

For a given month and given investment bank, I find the number of hedge funds whose residual returns fall below q% quantile in the following quantile model:

$$IB_{i,t,q\%} = \alpha + \beta NHFFQ_{i,t,q\%} + \epsilon_{i,t,q\%}$$

$IB_{i,t,q\%}$: q% quantile of residual returns of investment bank “i” residual at month “t”;

$NHFFQ_{i,t,q\%}$: number of hedge funds of investment bank “i” at month “t” that falls below q% quantile.

The first column (Quantile Y) includes different quantiles of investment bank residual returns and all other columns (Quantile X) are different quantiles of hedge fund returns. The results should be read as such: when the number of hedge funds whose residual returns fall under the 20% quantile increases by 1 unit, the median return (50% quantile) of investment banks will not change significantly (-0.0005). To avoid clutter, I do not include standard errors and only show the significance with ***,**, or * corresponding with 1%, 5%, or 10% level, respectively.

Quantile (Y)	Quantile (X)											
	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%	99%
5%	-0.026**	-0.007	-0.0001	-0.0001	-0.0001	0.0002	0.001	0.001	0.001	0.000	0.000	-0.005
10%	-0.015	-0.001	-0.0009	-0.0004	0.0003	-0.0001	0.000	0.001	0.001	0.001	0.001	-0.002
20%	-0.005	-0.001	-0.0011	-0.0003	-0.0002	-0.0002	0.000	0.000	0.000	0.000	-0.001	-0.001
30%	-0.004	-0.001	-0.0008	-0.0003	-0.0002	-0.0002	0.000	0.000	-0.001	-0.001	-0.001	-0.002
40%	-0.002	0.000	-0.0005	0.0003	0.0003	0.0002	0.000	-0.0006	0.000	0.000	0.000	0.000
50%	-0.002	-0.001	-0.0005	-0.0002	-0.0002	-0.0002	0.000	0.000	0.000	0.000	0.000	0.000
60%	-0.001	0.000	0.0001	0.0001	-0.0001	-0.0001	0.000	0.000	0.000	0.000	0.000	0.001
70%	0.000	0.000	-0.0002	-0.0001	-0.0001	-0.0002	0.000	0.000	0.000	0.000	0.000	0.000
80%	0.004	0.003*	0.0003	0.0002	-0.0001	-0.0004	0.000	0.000	0.000	0.000	0.000	0.001
90%	0.003	0.002	0.0005	0.0001	-0.0001	-0.0003	0.000	0.000	0.000	0.000	0.001	0.003
95%	0.003	0.001	0.0009	0.0001	-0.0007	-0.0007	-0.001	-0.001	0.001	0.003	0.003	0.003
99%	0.043	0.018	0.0145	0.0093	0.0085	0.0072	0.006	0.008	0.010	0.014	0.021	0.020

Table 5: Contagion Test Using Probit Model

I examine the conditional probability of investment banks on returns of hedge funds using a probit model. I form a portfolio of hedge funds affiliated with any given investment bank “i” at month “t”. I then use dummy variables equal to 1, when hedge fund portfolio returns or investment bank returns fall their below q% quantiles. I then regress the two dummy variables for the entire range of quantiles from 5% to 100%. The equation is:

$$IBDummy_{it} = \beta HFDummy_{it} + \epsilon_{it}$$

HFDummy_{it} : dummy variable, = 1 if the return of the value weighted portfolio of hedge funds affiliated with investment bank “i” at month “t” is below their q% quantile (negative shock to hedge fund returns);

IBDummy_{it} : dummy variable, = 1 when return of investment bank “i” at month “t” is below q% quantile (negative shock to investment bank “i”).

The table can be read as follows: when hedge fund returns fall below the 10% quantile, the impact on the probability of investment banks to fall below 10% is insignificant at $\beta = -0.003$. P value is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Percentile	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%	100%
Estimate	0.075**	-0.003	0.013	0.005	0.008	0.03	0.029	0.005	0.014	.0.02	-0.017	-0.06
P value	(0.020)	(0.91)	(0.67)	(0.86)	(0.77)	(0.31)	(0.3)	(0.85)	(0.56)	(0.52)	(0.51)	(0.85)

Table 6: Contagion Test Using Probit Model: Second Approach

I assess conditional probability of investment banks on hedge fund returns using a logistic model. I form a portfolio of hedge funds affiliated for any given investment bank. I then use dummy variables equal to 1, when investment bank returns fall below q% quantile. The number of hedge funds whose residual returns fall below q% quantile is a proxy for shock in the hedge fund sector. I then regress the two dummy variables for all quantiles from 5% to 100%. The formal equation is:

$$IBDummy_{it} = \beta NHFFQ_{it} + \epsilon_{it}$$

IBDummy_{it} : dummy variable, = 1 if the return of investment bank “i” at month “t” is below q% quantile (negative shock to investment bank “i”);

NHFFQ_{it} : dumber of hedge funds affiliated with investment bank “i” at month “t” whose returns fall below their q% quantile.

The table can be read as follows: when the number of hedge funds whose returns fall below the 10% quantile increases by 1 unit, the impact on the probability of investment banks returns to fall below 10% has the insignificant coefficient of $\beta = 0.03$. P value is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

Percentile	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%	100%
Estimate	0.11***	0.03	0.017	0.003	-0.003	0	-0.0001	0.005	-0.0008	.0004	0.038**	0.054*
P value	0.01	0.25	0.23	0.72	0.6	0.97	0.93	-0.85	0.93	0.69	0.049	0.06

Table 7: Granger Causality Test

I run the Vector Auto Regression (VAR) for the following models:

$$IBClipped_t = \sum_{k=1}^4 \alpha_k IBClipped_{(t-k)} + \sum_{k=1}^4 \theta_k HFClipped_{(t-k)} + u_t \quad (4)$$

$$HFClipped_t = \sum_{k=1}^4 \gamma_k HFClipped_{(t-k)} + \sum_{k=1}^4 \beta_k IBClipped_{(t-k)} + \epsilon_t \quad (5)$$

$HFClipped_t$ = returns of equally weighted portfolio of all hedge funds at month “t” when it is below 5% quantile (negative shock to hedge fund returns), zero otherwise;

$IBClipped_t$ = returns of equally weighted investment banks at month “t” when it is below 5% quantile, zero otherwise.

HFClipped and IBclipped correspond with H and I respectively in the table. The estimates of interests are θ (impact of lagged hedge fund residuals on investment bank residuals) and β (impact of lagged investment bank residuals on hedge fund residuals) that correspond with coefficients of different lags of H and I in the table below. P value is reported in a separate column. ***, **, or * indicate that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

In the first test, the null hypothesis is that investment bank residual returns at their lowest quantiles are only influenced by themselves (i.e., their lagged values influence their current value) and not by hedge fund residual returns. In the second test, the null hypothesis is that hedge fund residual returns at the lowest quantiles are only influenced by themselves and not by investment bank residual returns.

Granger Causality Wald Test			
Test	DF	Chi-Square	Pr > ChiSq
1	4	14.73	0.0021
2	4	0.82	0.844

Table 8: Impulse Response Function

I describe the results of simple IRF in Panel A and orthogonalized IRF in Panel B. The models are:

$$IBClipped_t = \sum_{k=1}^4 \alpha_k IBClipped_{(t-k)} + \sum_{k=1}^4 \theta_k HFClipped_{(t-k)} + u_t \quad (4)$$

$$HFClipped_t = \sum_{k=1}^4 \gamma_k HFClipped_{(t-k)} + \sum_{k=1}^4 \beta_k IBClipped_{(t-k)} + \epsilon_t \quad (5)$$

$HFClipped_t$ = return of equally weighted portfolio of all hedge funds at month “t” when it is below 5% quantile (negative shock to hedge funds return), zero otherwise;

$IBClipped_t$ = return of equally weighted investment banks at month “t” when it is below 5% quantile, zero otherwise.

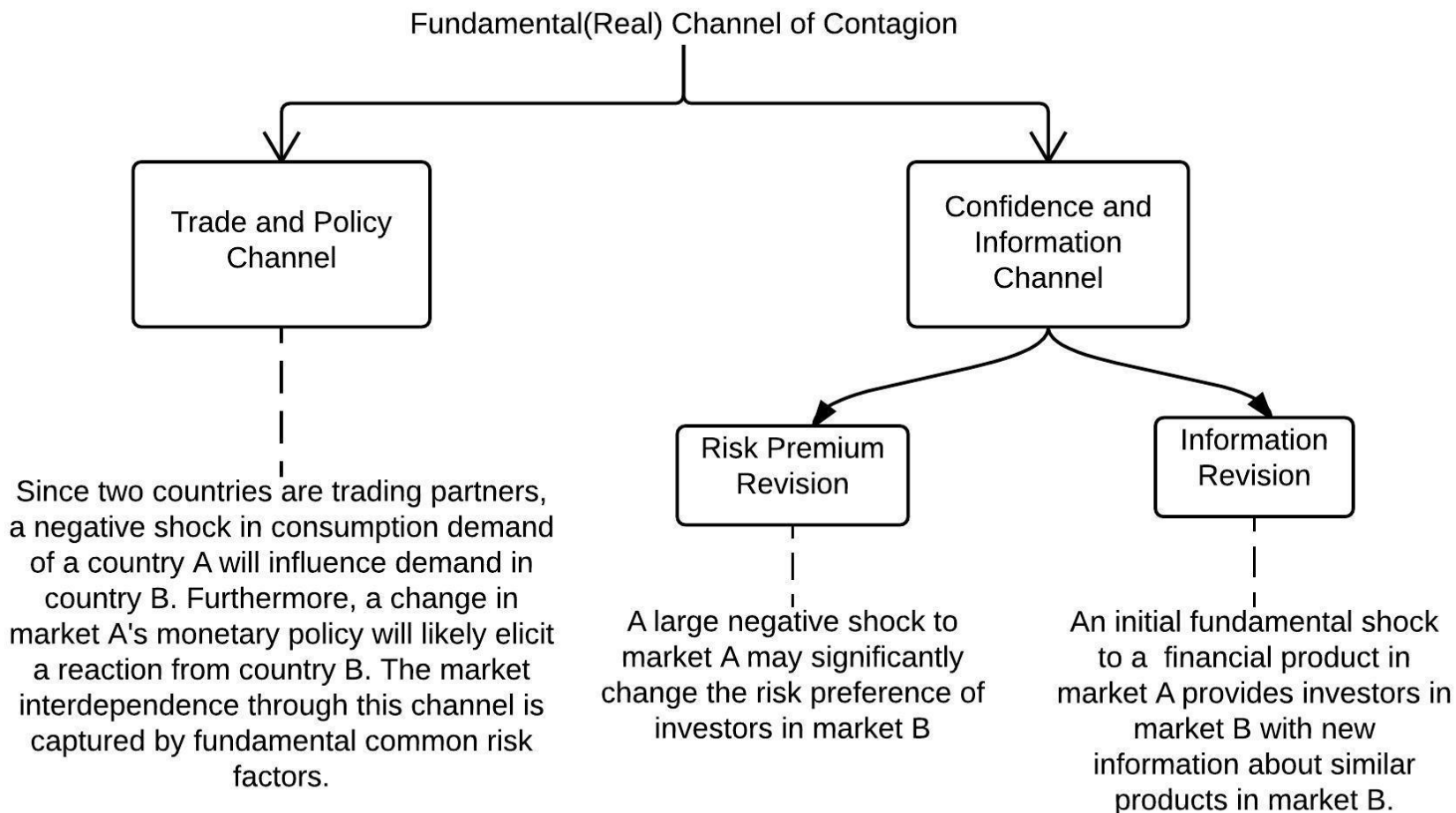
I examine the impact of a unit shock in the residual return of one sector (a unit change in u_{it} or ϵ_{it}) on residuals of another sector. In the simple IRF, I assume that shocks (u_{it} and ϵ_{it}) happen one variable at a time. In orthogonalized IRF (Panel B), I assume a shock in one variable can happen simultaneously with a shock in another variable.

Panel A: Simple Impulse Response Function			
Lag	Variable	I	H
	Response\Impulse		
1	I	0.070 (0.063)	0.667*** (0.178)
	H	0.006 (0.022)	-0.047 (0.063)
2	I	0.043 (0.064)	-0.001 (0.183)
	H	-0.006 (0.022)	-0.043 (0.063)
3	I	0.152 (0.063)**	0.163 (0.183)
	H	-0.018 (0.022)	0.150 (0.063)**

Panel B: Orthogonalized Impulse Response Function

Lag	Variable	I	H
	Response\Impulse		
0	I	0.034*** (0.002)	0.000 (0.000)
	H	0.001 (0.002)	0.012 (0.001)
1	I	0.003 (0.002)	0.008*** (0.002)
	H	0.000 (0.001)	-0.001 (0.001)
2	I	0.001 (0.002)	0.000 (0.002)
	H	0.000 (0.001)	-0.001 (0.001)
3	I	0.005** (0.002)	0.002 (0.002)
	H	-0.001 (0.001)	0.002** (0.001)

(1A)



(1B)

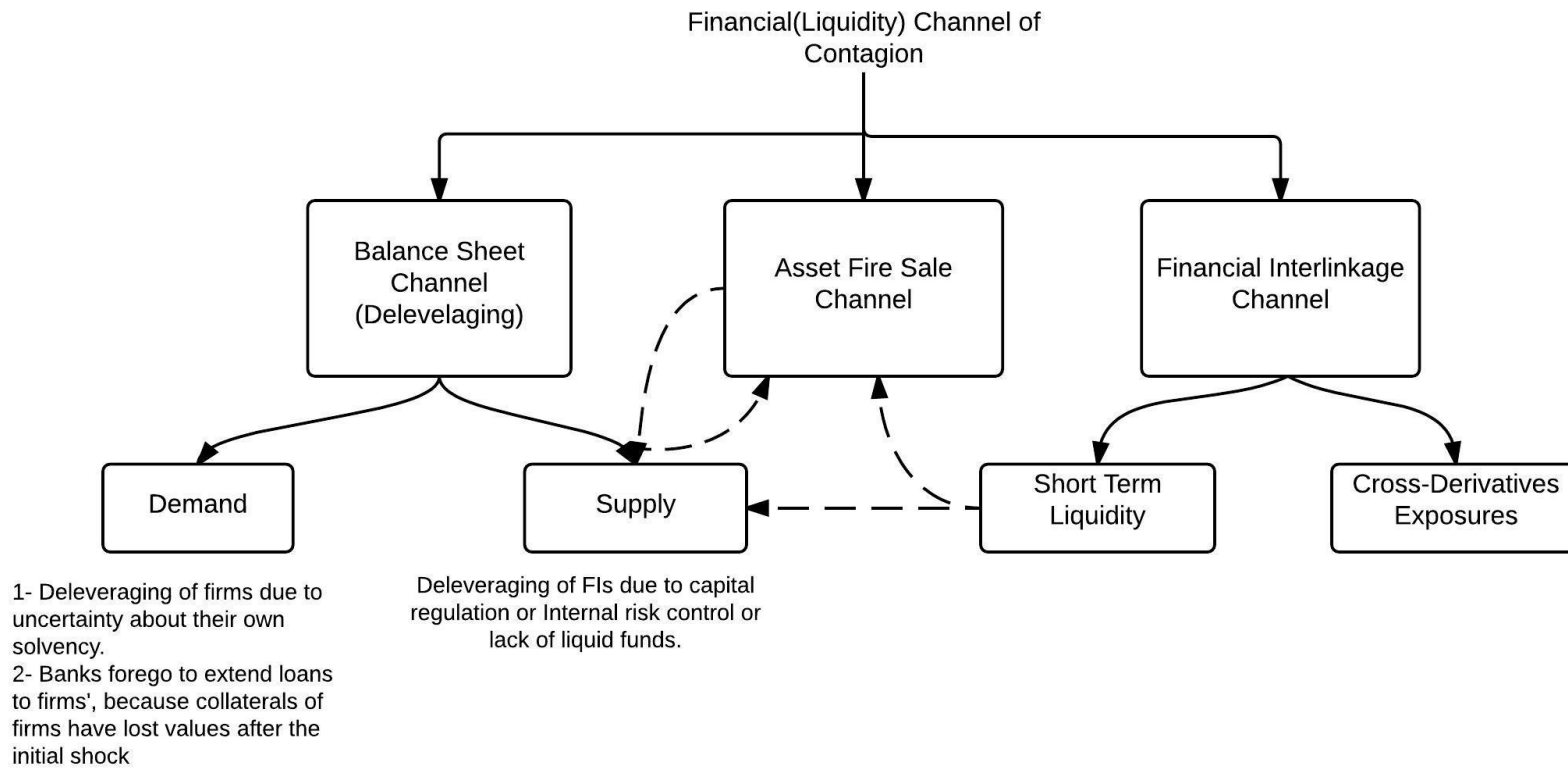
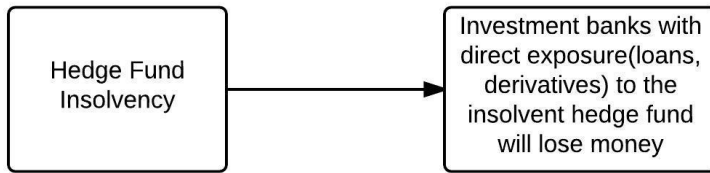


Figure 1: Channels of financial contagion.

Figure 1(A) shows the real channels of contagion, i.e., trade and policy channels, risk premium channel, and information channel. Figure 1(B) shows the financial channels of contagion. I outline three major channels of financial contagion: balance sheet, asset fire sale, and financial interlinkage channel. At the core of financial channels is asset fire sales through which the impact of the other two channels (balance sheet and interlinkage) is magnified. I have identified the potential causality relationship with dashed arrows. For example, a disruption in short term liquidity in institution A can cause financier in institution B to face liquidity shortage, leading to the liquidation of their assets in a fire sale.

(2A) Direct Channel of Credit Risk Exposure: failure of a firm with direct credit or derivative exposures leads counterparties to suffer losses.



(2B) Indirect Channel of Credit Risk Exposure

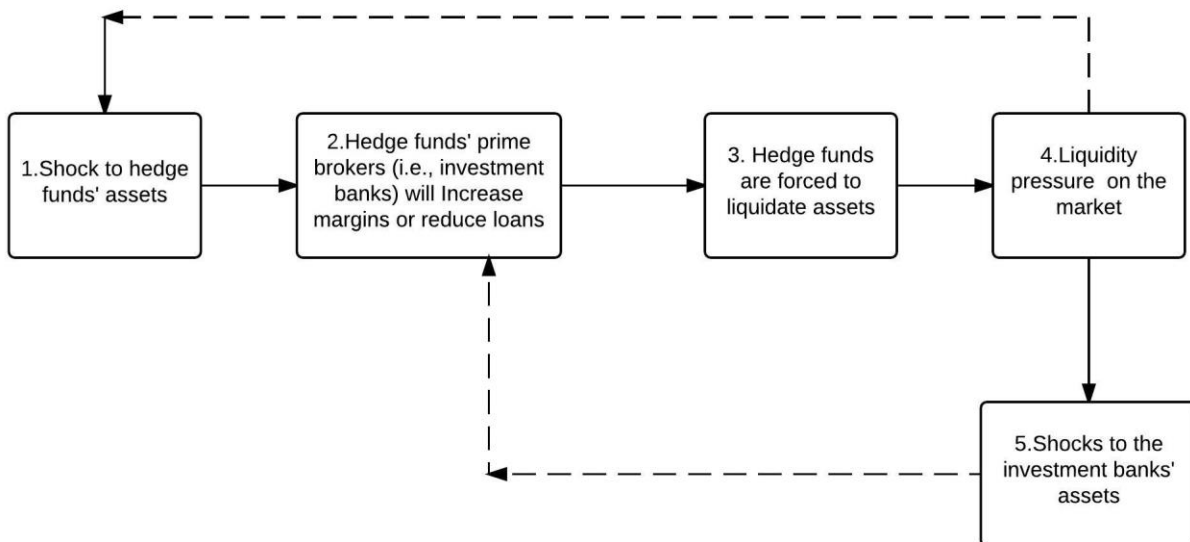


Figure2 : Direct and indirect channels of contagion by counterparty credit risk exposure.

(A) shows the direct channel and (B) shows the indirect channel of contagion. The dashed line shows the feedback effect.

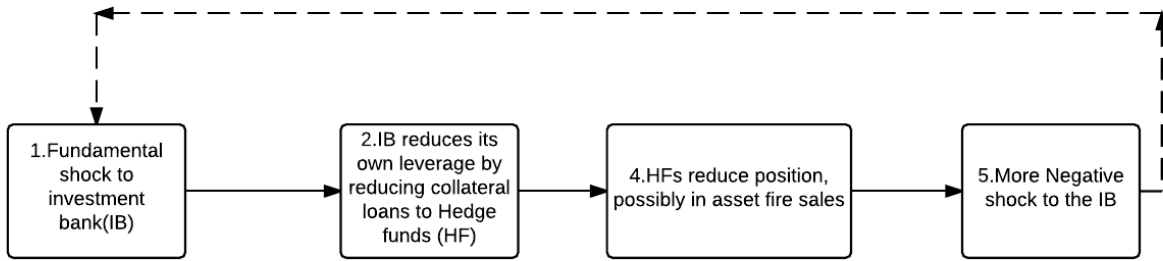
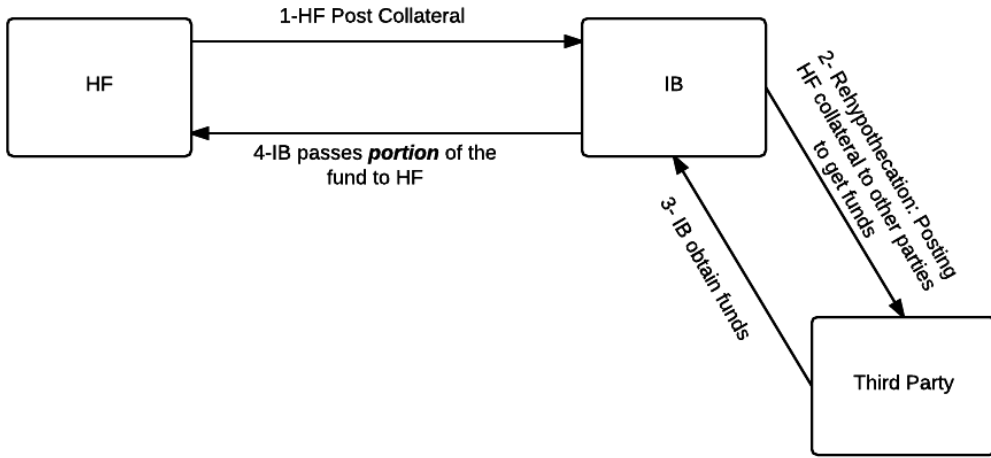


Figure 3: Contagion between investment banks and hedge funds.

The contagion is initiated by negative shock to investment bank. The dashed line shows feedback effect.

(4A) Normal times



(4B) Distress times

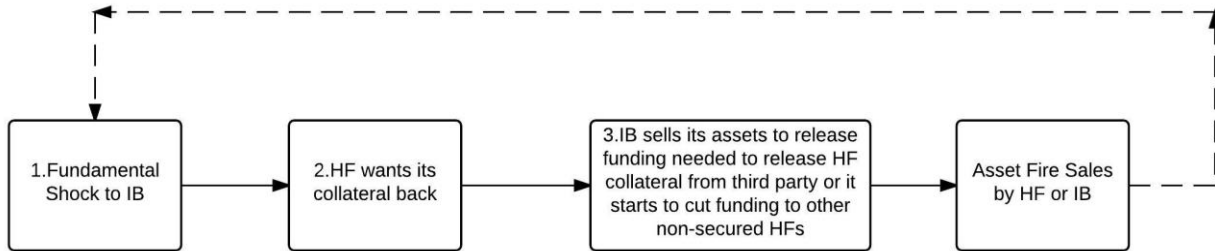


Figure 4: Normal and distress times liquidity connection between hedge funds and investment banks.

(A) shows the relationship between the two sectors in normal times, and (B) shows their relationship in times of stress. The dashed line shows feedback effect.

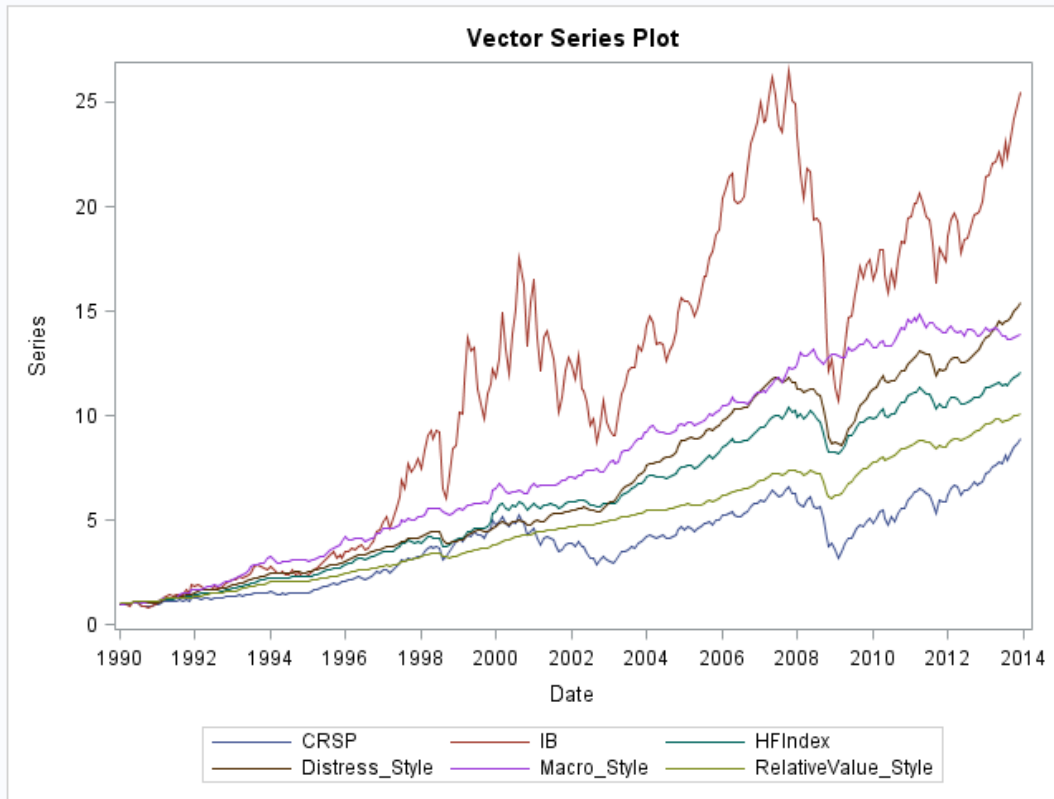


Figure 5: Hedge funds and investment bank return index.

IB stands for investment banks; CRSP is the value weighted portfolio of all firms in the CRSP database, a proxy for market portfolio; HFIndex is the value weighted portfolio of all hedge funds in HFR database. Distress Style are hedge funds whose main trading strategy is on corporate fixed income instruments, trading at significant discounts to their value; Macro Styles are predicated on movements in underlying economic variables and the impact these have on equity, fixed income, hard currency, and commodity markets; Relative Value Style is predicated on the realization of a valuation discrepancy in the relationship between multiple securities (Resource: Hedge Fund Research website).

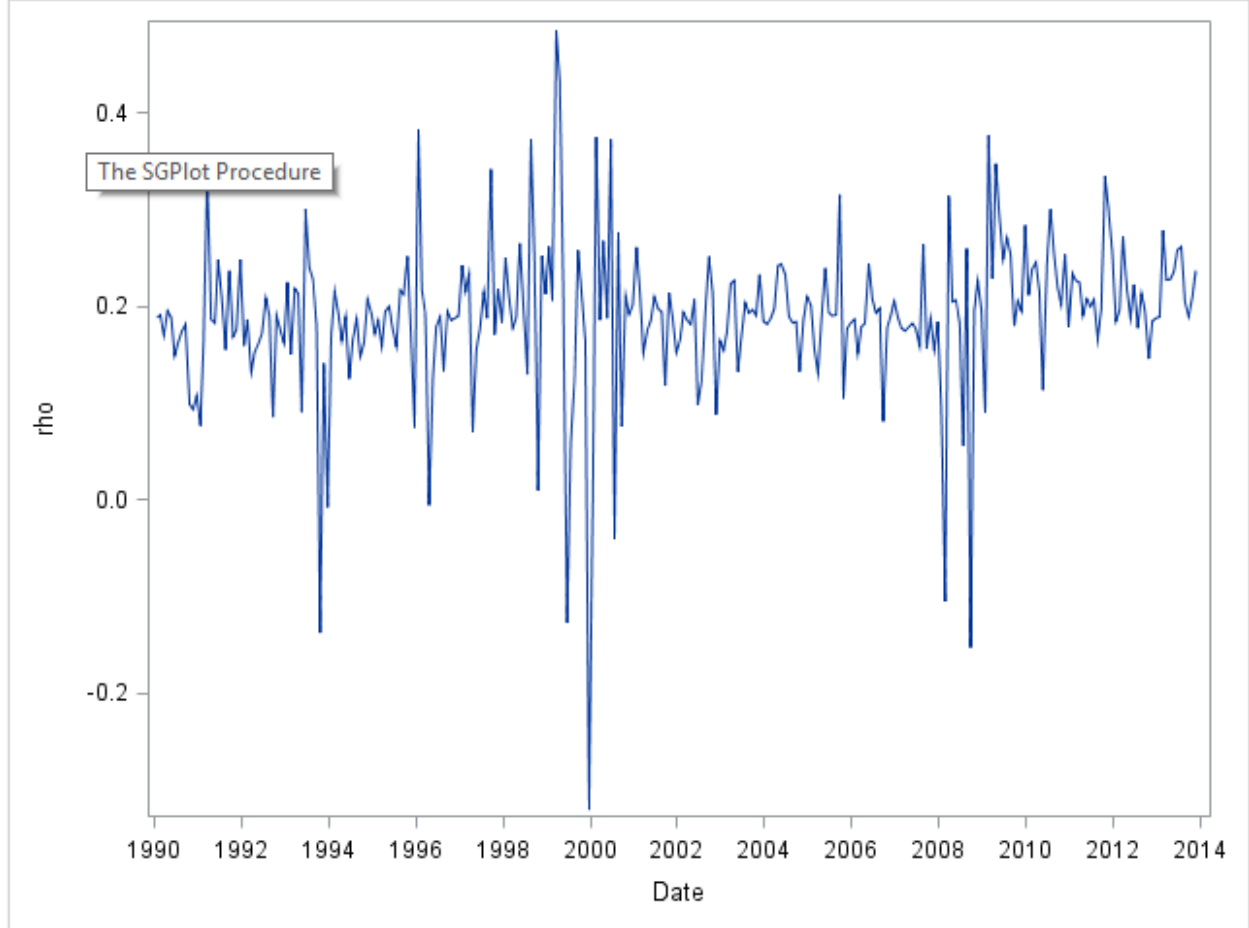


Figure 6: Conditional correlation between hedge funds and investment banks residual returns.

The figure shows the time varying correlation, $\rho_{ij,t}$, between hedge funds index and investment banks index residual returns. I use Engle's (2002) multivariate GARCH model to parsimoniously capture the time varying development of covariance, $C_{ij,t}$, between hedge fund residuals, $\epsilon_{i,t}$, and investment bank residuals, $\epsilon_{j,t}$, as follows:

$$C_{ij,t} = \alpha_1 + \alpha_2 C_{ij,(t-1)} + \alpha_3 \frac{\epsilon_{i,t-1}}{\sigma_{i,t-1}} * \frac{\epsilon_{j,t-1}}{\sigma_{j,t-1}}$$

$$\sigma_{i,t}^2 = \beta_1 + \beta_2 \epsilon_{i,t-1}^2 + \beta_3 \sigma_{i,t-1}^2$$

$$\sigma_{j,t}^2 = \gamma_1 + \gamma_2 \epsilon_{j,t-1}^2 + \gamma_3 \sigma_{j,t-1}^2$$

$$\rho_{ij,t} = \frac{C_{ij}}{\sqrt{C_{ii,t} * C_{jj,t}}}$$

$\sigma_{i,t}^2$ and $\sigma_{j,t}^2$ are GARCH conditional variance of hedge funds and investment banks, and $\rho_{ij,t}$ is the dynamic correlation between the two returns.

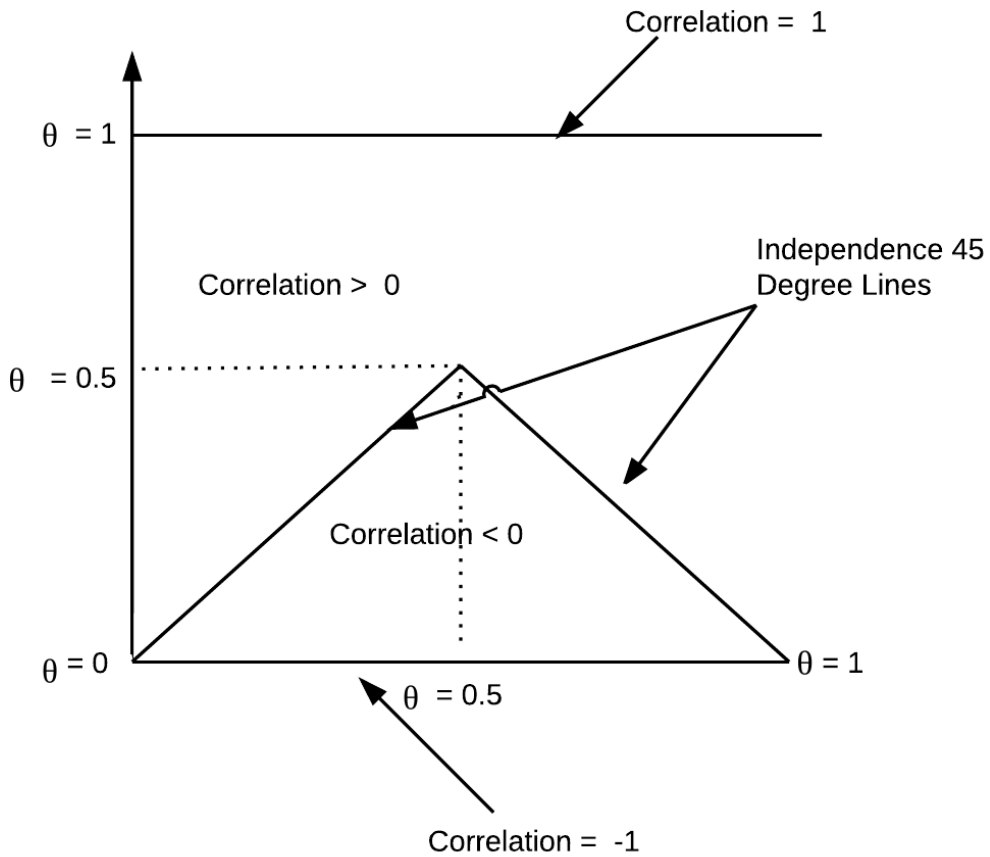


Figure 7: Comovement Box.

The comovement box concisely summarizes the conditional probability of comovement of two variables for any given quantile θ . By definition, if the two variables (Y and X) are independent (i.e., correlation = 0), the probability of Y condition on X for the quantile θ is $P_{\theta}(Y < q_{\theta}|X < q_{\theta}) = P_{\theta}(Y) = \theta$. This independence structure for different quantiles is shown by two intersecting 45-degree lines. The first line ($\theta < 0.5$) shows probability of comovement of two independent variables for $P_{\theta}(Y < q_{\theta}|X < q_{\theta})$, and the second ($\theta > 0.5$) shows $P_{\theta}(Y > q_{\theta}|X > q_{\theta})$ for two independent variables. It follows that if two variables are positively correlated, $P_{\theta}(Y|X) > \theta$, and if they are negatively correlated, $P_{\theta}(Y|X) < \theta$. Any points below (above) the 45 degree lines indicate that the two assets show more (less) correlation than what an independent relation between the two variables warrants.

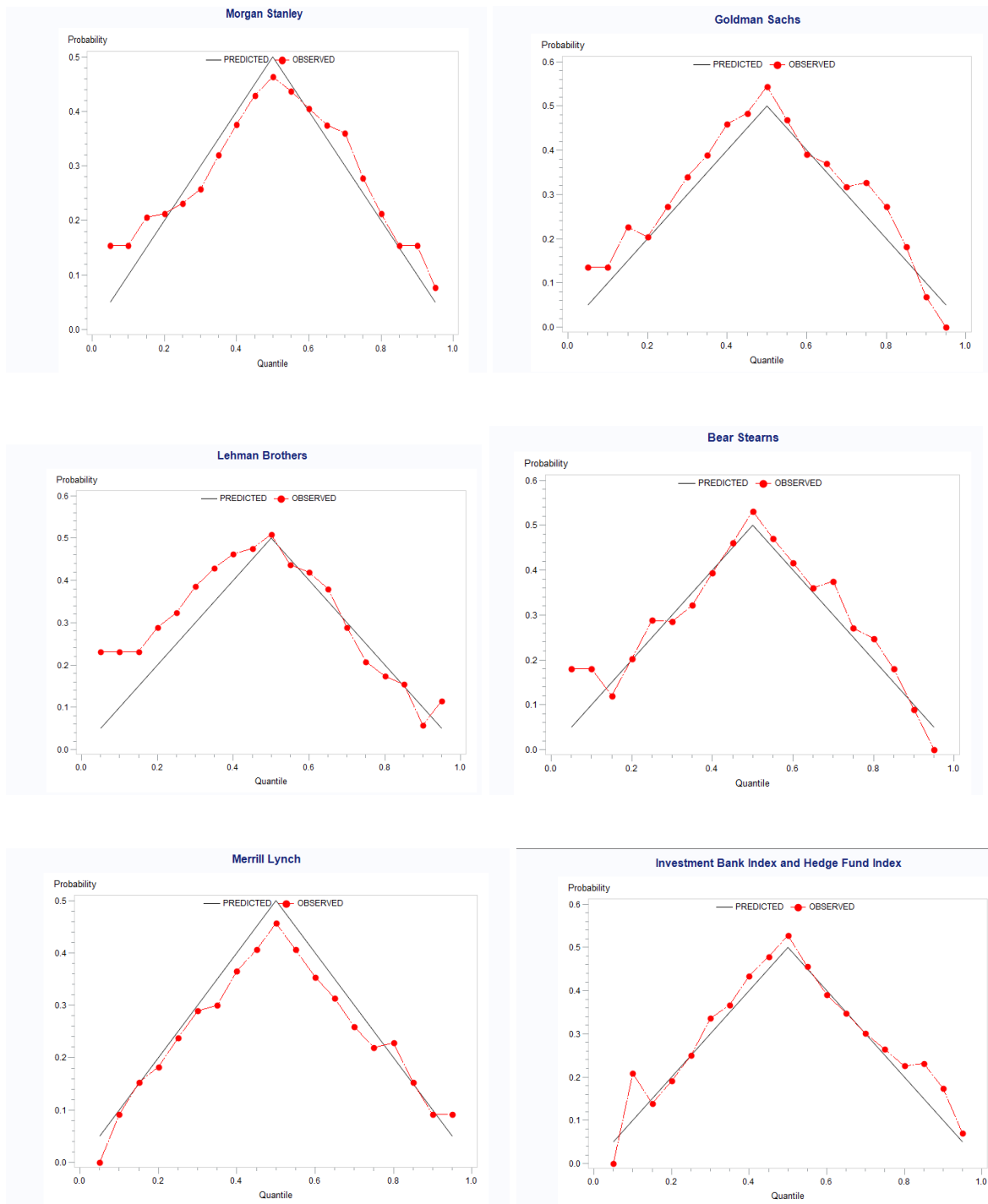


Figure 8: Comovement box diagram for each investment bank and affiliated hedge funds.

The comovement box of residual returns for five investment banks and their affiliated hedge funds. The line with dots (red) is the realized conditional probability between investment banks and hedge funds, and the solid line (black) is the expected correlation if the two variables are independent. For example, realized conditional probability of residual returns between Morgan Stanley and its affiliated hedge funds suggest that the two variables are positively correlated (the lines cross what is expected at the 45 degree line) for decile below 20%, and there is a negative correlation for any decile between 20% and 60%.

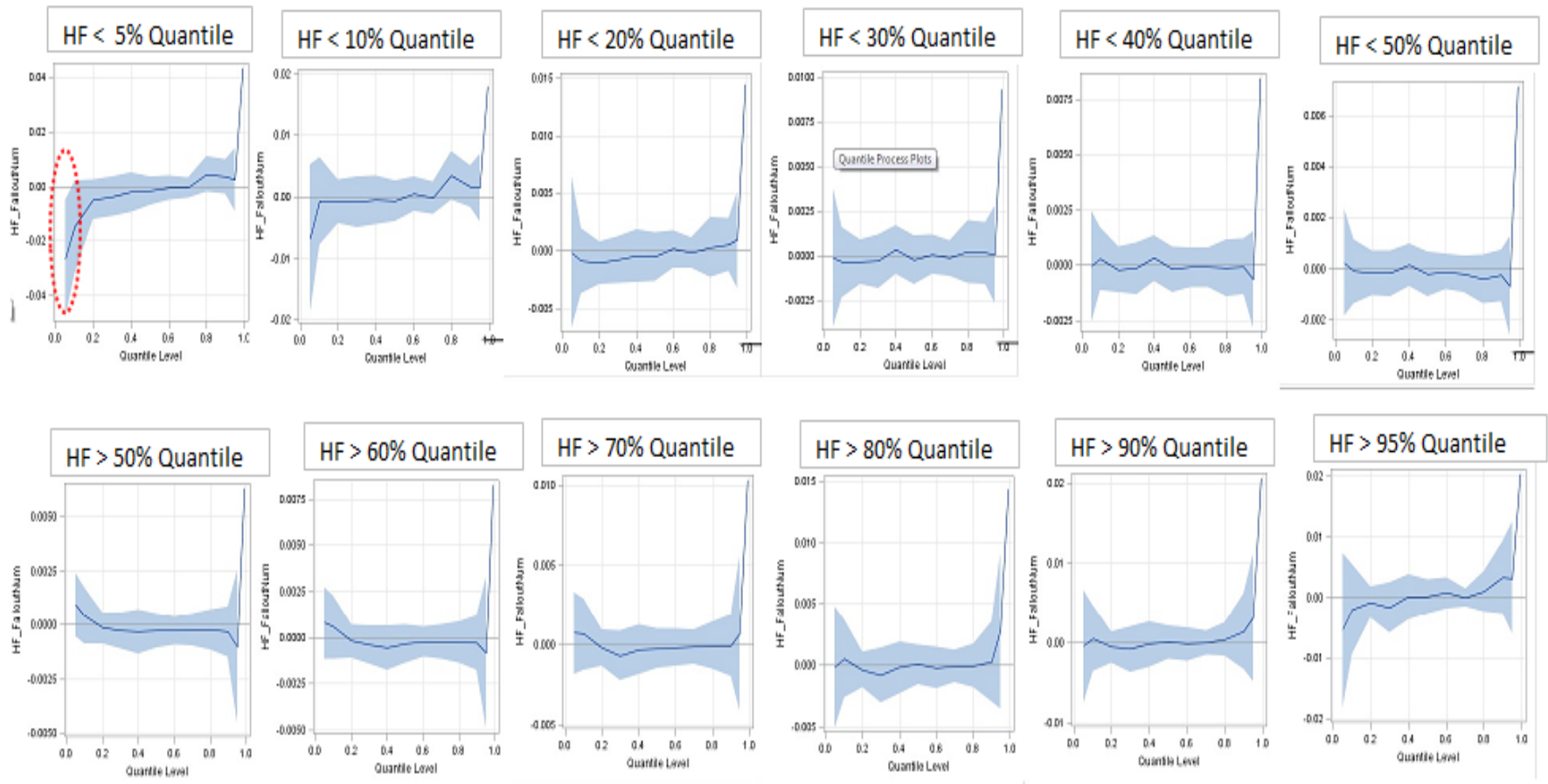
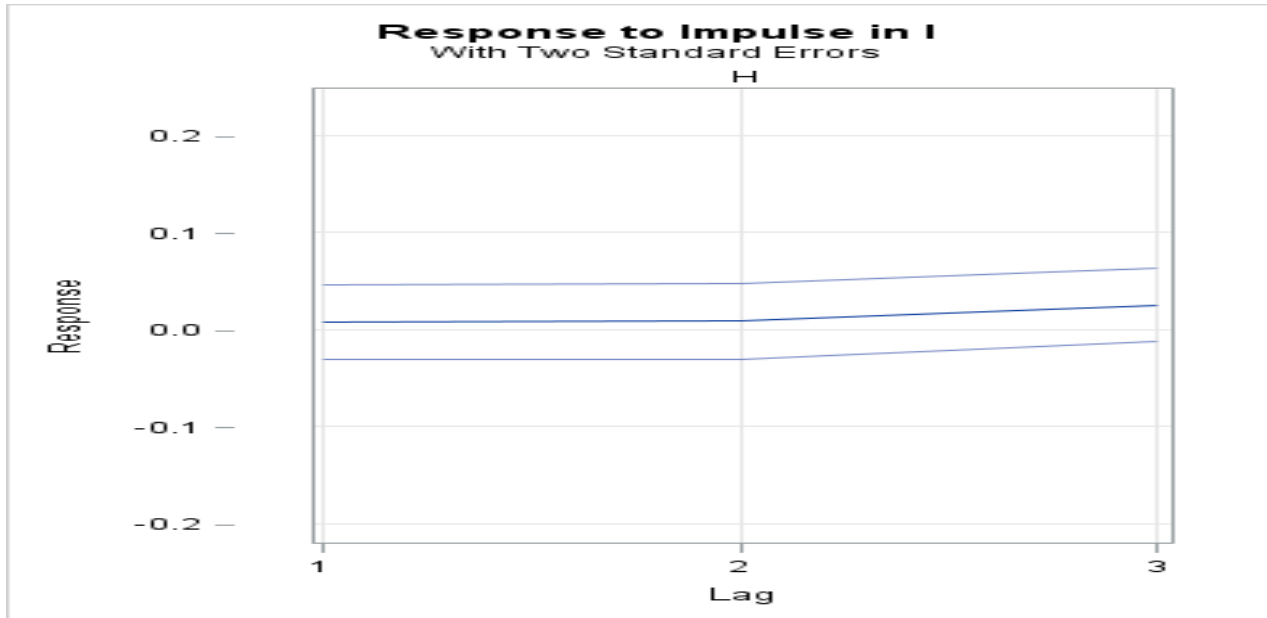


Figure 9: Quantile regression confidence interval of estimated coefficients.

A graphic summary of information presented in Table 4. For each quantile of hedge fund residuals, it shows the estimated coefficient of quantile regression of hedge fund returns on investment banks residual returns within a 95% confidence interval. Therefore, the impact of the number of hedge funds whose residual returns fall below 10% on different quantiles of investment banks returns can be found on the second diagram from the top left. The red circle indicates the only significant interval (not encompassing zero) among all diagrams and all investment bank quantiles.

(A)



(B)

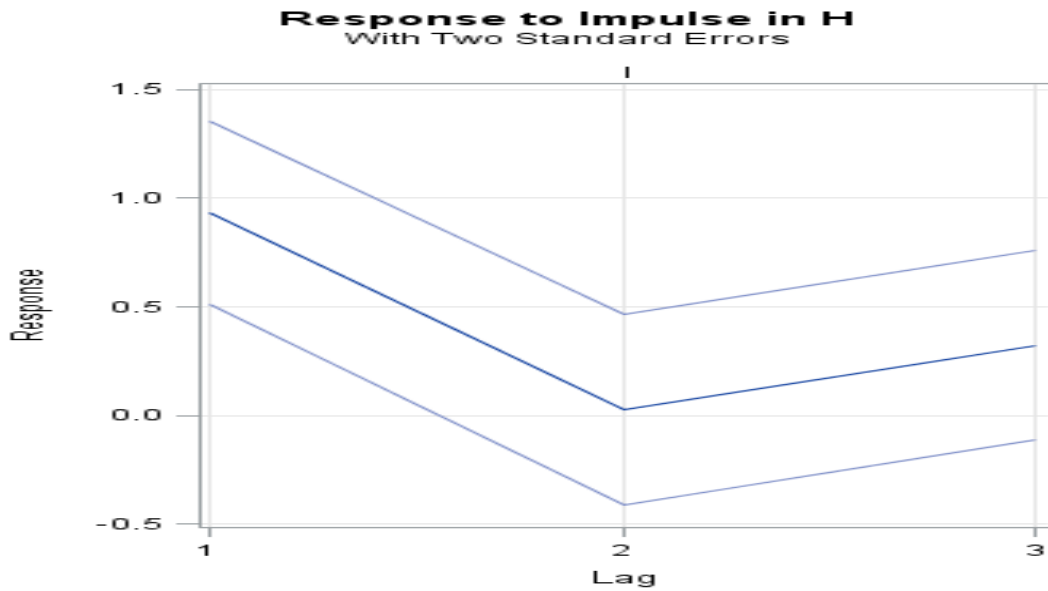


Figure 10: Impulse response function

The impulse response function (IRF) of investment bank (hedge funds) residual return on hedge fund (investment banks) residual returns. (A) shows the response to impulse in I (investment bank shock) by hedge funds, and (B) shows the response to impulse in H (hedge funds) by investment banks with a 95% confidence interval.

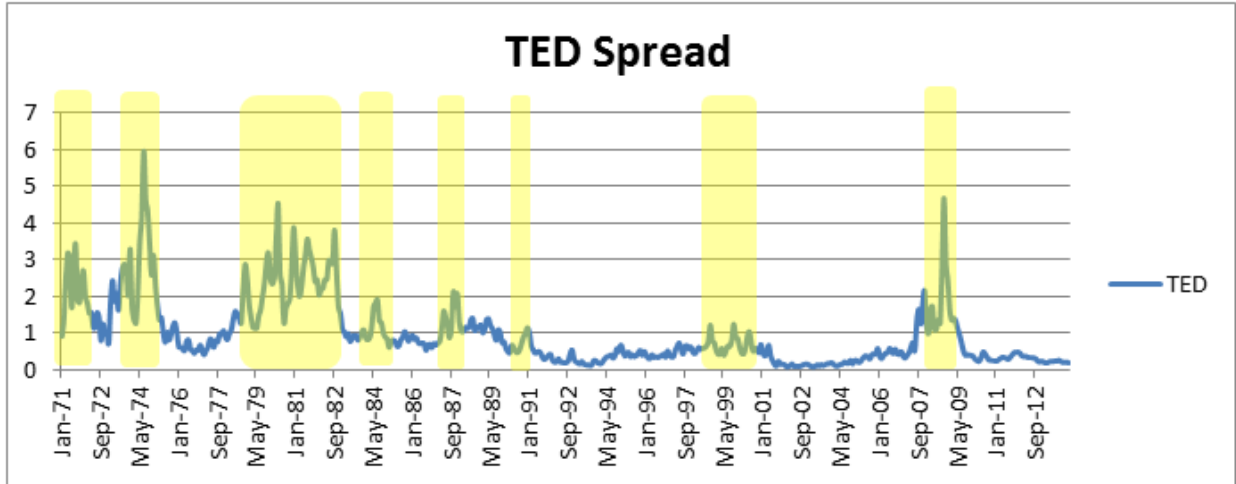


Figure 11: Monthly time series of TED spread.

TED spread is defined as the difference between Eurodollar rate and Treasury rate for three-month maturity instruments ($\text{Eurodollar}_{3\text{ month}} - \text{Treasury}_{3\text{ month}}$). The highlighted bars are associated with local maximum TED spreads. These periods coincide with periods of financial crises, as identified by NBER.

Chapter 4

Bank Strategic Choice of Asset Liquidity

Abstract

This essay examines the impact of pre-crisis bank asset liquidity levels on competitive advantage during bank crises. The theoretical literature predicts that, in equilibrium, bank liquidity may have an important strategic determinant, which is the opportunity to make significant profit during asset fire sales (speculative motive). Additionally, banks may hold excess liquidity to signal safety and incentive alignment to depositors (signaling motive). Herein, I investigate the theoretical predictions empirically and find that banks with higher pre-crisis liquidity levels gain greater market share, indicated by an increase in revenue, during banking crises but not market crises. However, not all sources of liquidity help banks gain a competitive advantage. While cash balance is conducive to maintaining an advantage, marketable securities do not provide the same benefits. The results are robust to “Too big to fail” financial institutions and alternative measures of bank performance.

4.1 Introduction

From 1976 to 2009, banks held on average 6.5% (24%) of their assets in cash (cash plus available for sale securities), far exceeding the reserve requirement of less than 1% of assets^{29, 30}. Thus, the question remains: why do banks hold so much low-yield liquid assets when they can earn liquidity premiums from longer term, higher risk assets?

Beyond regulatory requirements, the incentives for holding liquid assets are similar across banks and other non-financial corporations. They are either transactional, precautionary, agency driven, or related to tax repatriation. In this paper, I study an alternative motive that is somewhat unique to financial institutions. The central question is whether there is any strategic advantage for banks to maintain liquid assets to benefit from fire sales of other banks' assets (speculative motive) and/or to safeguard against a fire sale economic environment (signaling motive).

The theoretical background for my empirical analysis comes from two lines of discussion in the literature. The first, which is rooted in the asset pricing literature, stems from the seminal paper of Shleifer & Vishny (1992), and its follow-up Shleifer & Vishny (2010), in which they highlight the role of asset fire sales in corporate financial policy. The core idea is that because bank assets

²⁹ The reserve requirement is calculated based on the guideline published in the Federal Reserve website: <https://www.federalreserve.gov/monetarypolicy/reservereq.htm>.

³⁰ It is useful to highlight that the unprecedented hoarding of liquidity starting from the last quarter of 2008 has a radically different motive than those mentioned above. Beginning on Oct 5th 2008, the US Federal Reserve pays interest of 25 basis points on excess reserves held with the Federal Reserve. The rationale behind this decision has been discussed in detail by Kashyap & Stein (2012). To summarize, the Federal Reserve can respond to a rising interest rate environment using two major strategies: reduce reserves through open market operations (selling government bonds); or increase the floor interest rate paid on excess reserves. The former runs the significant risk of government bond fire sales if it happens quickly and widely. As a result, the latter strategy of paying interest on excess reserves is a viable tool in that it guarantees the lower bound of interest rates can be quickly and easily managed by the Federal Reserve. However, this is not the focus of the current study.

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are special (James, 1991; Hanson, Shleifer, Stein, & Vishny, 2015)³¹, their ex-ante choice of leverage and other financial policies is significantly influenced by fire sale prices during times of distress. Building upon this core idea, and incorporating many particular characteristics of financial corporations, Allen & Gale (1994, 1998, 2000, 2004, 2005) developed a series of papers in which they relate the endogenous liquidity choice of financial firms to the possibility of profit making during times of crisis.

As summarized in Allen & Carletti (2008), when markets are incomplete (i.e., banks are unable to buy contracts that provide liquidity contingent on the state of the economy), liquidity is achieved by selling assets. When aggregate liquidity in the financial system is scarce, asset prices are determined by the available liquidity, in other words the available “cash in the market.” In this situation, financial institutions can make either of two strategic choices in determining ex-ante liquidity of their portfolio: they can choose to maximize investment in illiquid assets to maximize their profit from the liquidity premium; or they can keep part of their portfolio liquid so as to profit from asset fire sales. The latter group (i.e., suppliers of liquidity during asset fire sales) is not compensated for the opportunity cost of providing liquidity during good states of the banking system. Instead, the cost must be compensated on average across all states. For agents to be willing to supply liquidity during bad states, they must be able to make a profit when the banking system is in bad states.

³¹ If bank assets are assumed bank specific (rather than banking system specific), the impact of fire sales is even more acute (Acharya, Gromb, & Yorulmazer, 2012). The idea of bank specific assets hinges on the premise that banks may have assets that are worth more under current owners rather than alternative owners, because alternative owners do not have the expertise of current owners (Diamond & Rajan, 2001).

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From an equilibrium perspective, if all agents decide to fully invest in illiquid assets, the price of those assets would collapse to zero during bad states (because bad states are characterized by cash-in-the-market pricing), thus providing an incentive for some agents to hold liquidity so as to acquire assets cheaply. However, profit cannot be too high or all agents would choose to hold excess liquidity. In equilibrium, the bid price of assets will level out to where profit during bad states (in which all banks face high liquidity demand) is sufficient to compensate liquidity providers for all other states during which they were subjected to opportunity costs of holding excess liquidity. Allen & Gale, however, suggest that a speculative motive embodies market failures and can be partly cured by regulation and central planning interventions. I discuss a normative aspect of the speculative motive later in this paper³².

Another line of research, which is embedded in the corporate finance literature, links asset liquidity to the ability of firms to signal quality of fundamentals and lower risk taking incentives (Calomiris, Heider, & Hoerova, 2015). To the extent that bank runs are a run on poor fundamentals, cash balance can play a prominent role in creating a competitive advantage during downturns. First, cash is an asset and a clear sign of safety, due to its verifiability and lack of risk. (On the other hand, equity is on the liability side of the balance sheet and difficult to verify because its

³² Acharya, Shin, and Yorulmazer (2010) have proposed a similar but distinct view from Allen, Gale and Carletti, about the role of liquidity in financial crises. Their theoretical framework is based on the higher pledgeability of bank liquid assets in times of financial crises. In this framework, banks do not use their existing liquid assets to purchase troubled assets, as proposed by Allen and Gale, but they are able to borrow against those liquid assets and hence, have higher financial flexibility to purchase fire-sold assets at times of financial crises. Either of these propositions is consistent with the empirical hypotheses of my paper that pre-crises liquidity provides a competitive advantage for the holders during the crises: This competitive advantage is obtained by purchasing troubled assets either directly by existing liquid assets (Allen and Gale) or indirectly through the higher pledgeability of liquid assets in distress times (Acharya, Shin, and Yorulmazer). I have elaborated the Acharya, Shin, and Yorulmazer (2010)'s framework in literature review section.

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value depends on the observation and valuation of assets.) Cash as an asset is therefore particularly helpful during periods when the presence of information asymmetry in financial markets is driving investor decision making. Because cash is observable and verifiable, banks with higher liquid assets are less adversely affected by asset fire sales triggered by investor perceptions about a bank's fundamentals³³. As such, cash replaces the role of capital in preventing investors from fleeing (Diamond & Rajan, 2000).

Second, and perhaps more interestingly, holding liquid assets can signal an alignment of incentive between owners and debt holders. When fire sales happen, senior debt holders are paid out in cash, the most liquid assets, while owners and junior debt holders earn post-fire sale residual payouts. In other words, during market conditions in which the first movers have an advantage, holding cash is equivalent to granting senior debt holders an embedded put option³⁴ that increases the relative value of their claims in relation to other junior claims, including equity holders. If the expected residual loss from fire sales is large enough, the issuer of the put option (the banker) has the incentive to budget their risk-taking activities as long as option holders (senior claimants) do not exercise their options. Hence, a higher ex-ante cash balance is indicative of a greater incentive for owners to avoid excessive risk taking³⁵. To summarize, if the expected loss in fire sales is

³³ Banking literature is divided on whether bank runs are triggered by weak fundamentals (Gorton, 1988), if they are random events due to mob psychology (Kindleberger & Aliber, 2011), or the result of coordination failures of depositors (Diamond & Dybvig, 1983). The speculative motive of holding liquid assets (Allen & Gale's perspective) is consistent with all views; however, the signaling motive is only consistent with the fundamentals view of bank runs.

³⁴ This is a put option because the senior debt holders of liquid banks are insured against fire sale losses, while the issuer of the option, the bank, suffers from the residual losses of fire sales.

³⁵ The disciplining role of cash holding, as described above, does not necessarily contradict the agency cost of cash widely documented by traditional corporate finance literature. It is important to note that agency cost of free cash flow, as pioneered by Jensen (1986), highlights the conflict of interest between managers and owners (i.e., cash increases the agency cost of type I), while the above mentioned agency benefits of holding cash highlights the incentive alignment between owners and senior debt holders (i.e., cash decreases the agency cost of type II). Moreover, the disciplining role of cash (liquidity) in this paper is also different from that documented by Diamond & Rajan (2001),

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significant, cash can be an effective substitute for equity to prevent bank runs and attract more deposits³⁶.

The above discussion highlights the role of liquidity in creating a competitive advantage during episodes of asset fire sales and leads to the following two hypotheses:

H1: *Banks with higher liquid assets pre-crisis gain greater market share during a crisis.*

H2: *Tradeable securities are not a substitute for cash in providing competitive advantage during a crisis.*

Despite the rich theoretical underpinnings of these issues, no studies have empirically tested these hypotheses. This paper fills this gap by presenting a range of univariate, regression analyses and instrumental variable analyses to assess the impact of pre-crisis bank choice of liquid assets on gaining market share during a crisis. To address this objective, I follow the methodology suggested by Berger & Bouwman (2013) by grouping eight quarters before each financial crisis as the pre-crisis period and evaluating the average value of all independent variables (liquid asset measures and control variables) for that period. The dependent variable is the percentage change in bank market share between pre- and during crisis periods. The primary goal of regression is to

as the disciplining role in their model originates from liability side liquidity (demand deposits), while herein it is based on asset side liquidity.

³⁶ The role of equity in creating a competitive advantage for banks has been theoretically and empirically investigated (Allen, Carletti, & Marquez, 2011; Diamond & Rajan, 2000).

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relate the average percentage change of market share during a crisis to liquid assets pre-crisis. The time of analyses and grouping strategy is shown in Figure 1 and Appendix 2.

The results support the theoretical predictions. Both economically and statistically, the choice of greater pre-crisis liquid assets improves bank competitiveness during financial crises, while undermining bank competitiveness during normal times. This finding is consistent with Allen & Gale's (2005) proposition that productivity of bank liquidity must be state-dependent; in normal states banks lose liquidity premium, while in bad states they are compensated for the foregone liquidity premium. Drilling down further, I show that not all types of financial crises are the same. Financial crises that do not originate from the banking system (i.e., market crisis) are indifferent toward a bank's choice of liquid assets. On the other hand, banking crises significantly reward banks that choose a greater pre-crisis liquidity. Finally, I find that only a narrow definition of liquidity (cash and trading assets) is related to bank competitiveness. When the definition of bank liquid assets is expanded to include available-for-sale securities and held-until-maturity securities, the relation between liquidity and increased competitiveness is either eliminated or reverses. These findings, discussed in detail in the results section (section 4), are consistent with both asset pricing theory (Allen & Gale's proposition) and corporate finance theory (Calomiris et al., 2015). The results are robust even when excluding "Too big to fail" samples.

As is the legitimate concern of every corporate finance study, endogeneity may undermine assertions regarding the "causality" of the relation between liquidity and competitiveness. Identifying whether both market share and liquidity choices are determined by a third omitted variable, such as managerial discretion and competency, is not an easy task. Furthermore, it is

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possible that the choice of asset liquidity is indeed caused by improved competitiveness of a bank rather than the other way around. The principal methodology of this paper is to relate the average value of the pre-crisis independent variable (which is a lagged independent variable) to an average of crisis period dependent variables (contemporaneous). Nevertheless, this does not definitively address the issue of endogeneity³⁷. To deal with the first source of endogeneity, that is the observed impact caused by the fixed effect of managerial discretion, I employ panel data analyses, controlling for both firms (banks) as well as time fixed effects.

I use two instrumental variables for the bank choice of asset liquidity. First, I use the ratio of cash deposited in foreign banks or foreign branches to total cash balance as an instrument for cash holding. The choice of this instrument is inspired by the literature on tax repatriation motives related to cash holdings (Foley, Hartzell, Titman, & Twite, 2006). The greater relative portion of cash deposited in foreign countries is associated with larger tax incentives of holding cash balances, while unrelated to bank efficiency or market share through other channels.

Second, I construct an innovative instrument using information on heteroscedasticity of endogenous variables, following a recently developed econometric technique (Lewbel, 2012). Because the relation between “bank percentage change in market share” and “assets liquidity” is highly heteroscedastic, a heteroscedasticity based instrument is a viable choice. Accordingly, I build four instruments, each corresponding with one presumed exogenous variable in the model, and estimate an over-identified equation using Generalized Method of Moments (GMM). The

³⁷ Using the lag variable may help rule out reverse causality; however, it is not a definitive solution because if liquidity is highly persistent, lagging for one period cannot rule out the possibility that the market share in previous period (t-1) caused the liquidity in previous period (t-1), which in turn, caused the liquidity in the next period.

results of all instrumental variable experiments lend support to the results obtained using panel data.

4.2 Literature Review

In this section I examine the role of liquidity in asset pricing in an imperfect capital market (speculative motive) and discuss the signaling feature of liquid assets during financial crises.

4.1.1 Imperfect capital market and role of liquidity

Although the recognition of speculative motive of liquidity preference dates back to Keynes' general theory (Keynes, 1936)³⁸, the impact of speculative motive on a firm's choice of financial policies has not been an active area of research, mostly due to the strong assumption that supply of liquidity is elastic to changes in demand. In the world of perfectly elastic liquidity supply, the ex-ante demand for liquid assets would be zero; firms could find liquidity by pledging the future returns of their long-term, non-liquid assets (Holmström, 2011; Holmström & Tirole, 1998). However, if this assumption is violated, that is if firms are forced to either raise costly debt or equity, or have to sell their assets in fire sales to meet urgent needs for liquidity, there is significant room for rent seeking through hoarding liquidity. In such an environment, a bank can hoard liquidity to benefit from assets priced based on cash-in-the-market rather than their fundamental

³⁸ It is important to note that Keynes discusses liquidity preference in the context of households and consumers rather than firms.

value. This “vulture behavior,” as termed by Tirole (2010), is only possible when access to external financing diverges from the established assumption of perfect capital markets.

The assumption of perfect supply of credits, or perfect pledgeability of a firm’s future income, has been challenged both theoretically, through microeconomic models (moral hazard and information asymmetry), and empirically, through a plethora of evidence documenting the significant cost of external financing. From a theoretical perspective, firms (entrepreneurs) are not able to fully pledge the future returns of their assets for two simple reasons: first, investors need their entrepreneurs to have a sufficient stake in the initiated endeavor (Diamond & Rajan, 2001; Holmström & Tirole, 1998); and second, investors face a preventative information gap regarding the intention and ability of borrowers to provide fair returns on their investment (information asymmetry)³⁹. Importantly, the information asymmetry component of costly external financing is the common mechanism through which traditional and modern macro-finance theories explain why initially small, fundamental shocks turn into big and/or persistent macroeconomic agitations⁴⁰ (Bernanke, Gertler, & Gilchrist, 1996; M. K. Brunnermeier & Pedersen, 2009; Stiglitz & Weiss, 1981).

Parallel to the theoretical arguments, empirical research has reached a definitive conclusion regarding the covariation of availability and cost of external financing with market conditions. In

³⁹ The banking literature, in general, offers three solutions to alleviate this information gap (Flannery, 1994): secured debts (collateralized debts), short-term debts, and strict covenants. It is worth noting that while short-term debt plays an important role in assuring incentive alignment between borrowers and lenders, it can be a source of vulnerability and bank runs when the fundamentals of borrowers deteriorate (He & Xiong, 2012).

⁴⁰ However, the treatment of information asymmetry is different in traditional macro-finance models such as Bernanke’s model and modern macro-finance models such as Brunnermeier (2009, 2014). In the former, the information asymmetry is between banks (as suppliers of liquidity) and small corporations (as demand for liquidity), while in the latter, the information asymmetry is between financiers and financial institutions.

the context of our discussion, a financial firms' access to uncollateralized funding is dramatically reduced during episodes of financial stress, as best seen in the TED spread (rate spread between interbank loans and T-Bill). The issue exists even in secured financing (collateralized funding) where the information gap is supposedly less of an issue (Flannery, 1994). For example, a 10% haircut of asset-backed securities that provided a sufficient protection during normal times (Spring 2007) increases to 30% during stress times (Fall 2008) (Krishnamurthy, 2009). Needless to say, the 200% increase in lending margin suggests the borrower needs to either raise new equity, which is particularly difficult during crisis periods, or to resort to asset fire sales to continue financing old assets.

4.1.2 Asset fire sales and bank portfolio choice

With limited pledgeability of assets, a bank's choice of portfolio rests on the trade-off between liquidity premium (i.e., the opportunity cost of investing in liquid assets) and the present value of excess returns from purchasing assets in fire sales. This trade-off has been meticulously modeled in Acharya, Shin, and Yorulmazer (2010). In a two-period model, as depicted in Figure 2, banks initially choose the liquidity level of their portfolio based on the trade-off between opportunity cost of liquidity premium and expected profit from buying assets at time 1, if a fire sale happens. At time 1, when the actual returns on risky assets are realized, there are two possible states: first, a relatively small proportion of banks fail due to excessive investment in risky, illiquid assets, in which asset prices still reflect fundamental values; and second, there is a sufficient number of failing banks whose low return on risky assets force them to sell their assets to withstand liquidity shocks. The high number of failures causes cash-in-the-market pricing rather than fundamental value pricing, and as a result, assets fall below their fundamentals. The surviving banks can use

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this opportunity to purchase assets at bargain prices. However, the surviving banks need external financing to take advantage of this unique opportunity. The amount of external financing they find depends on the pledgeability of their assets, which in turn, depends on the liquidity of their assets, chosen at time 0.

Several studies have explicitly used the speculative motive of holding liquid assets to explain recurrent liquidity disruptions during the financial crisis of 2007-2008⁴¹. In an attempt to explain credit market freeze, Diamond & Rajan (2011) argue that a necessary consequence of fire sales, in which the limited resources of potential buyers drive asset prices much below their fundamental value, is that the return on buyers' liquid assets are "extraordinarily high." In such situations, the buyers [liquidity providers] have the private motivation to delay purchasing assets (to benefit from further divergence from fundamental values) and the sellers [liquidity demanders] have the private motivation to delay selling their assets (due to risk shifting motives and limited liability). The end result is that no agents actively trade in the credit market. The fact that potential buyers may want to delay buying assets during fire sales, waiting for assets to diverge further from fundamentals, indicates how the optimal choice of portfolio liquidity can lead to utility maximization in the long term. Similarly, Brunnermeier & Sannikov (2014) argue that when endogenous risk (i.e., risk self-generated by the financial system through fire sale mechanisms) dominates volatility dynamics, asset market price is determined by endogenous risk rather than fundamental risk. This, in turn,

⁴¹ Following the financial crisis of 2007-8, with an unprecedented disruption in liquidity provision channels, speculative motives of liquidity preference received a great deal of attention as an alternative to other explanations for why the financial system failed to smoothly channel excess liquidity into the economy. Among major channels that contributed to the disruption of credit markets, precautionary motives (Acharya & Merrouche, 2012), information asymmetry and counterparty risk (Heider, Hoerova, & Holthausen, 2015; Malherbe, 2014), and Knightian uncertainty (Caballero & Simsek, 2013) have been widely discussed in the literature.

creates an incentive for market participants to hold onto cash to benefit from the non-fundamentally driven risks in the market. Acharya, Gromb, & Yorulmazer (2012) show how surplus liquidity holders may use their market power to exploit those banks with high liquidity demands. Their model includes two types of banks: those with surplus liquid assets and those in dire need of liquidity. The former may have market power in times when access to external liquidity is tight. Banks with surplus liquidity use this power to impose higher interest rates on interbank borrowing for banks in need. Eventually, when the cost of borrowing is too high, needy banks are discouraged from borrowing from the surplus banks, and asset sales become an attractive option despite the inherent loss in value⁴². The implication of this model is that banks can have a rent seeking motive in choosing the liquidity of their portfolio. In equilibrium, banks with surplus must be able to charge needy banks at a price equal to the opportunity cost of liquidity premium. Other studies have also discussed assumptions or implications related to the speculative motive of liquidity holding, including: Gale & Yorulmazer (2013), in which they show that a speculative motive can dominate a firm's decision to hoard liquidity during a financial crises; and Diamond and Rajan (2006) who indicate that in episodes of fire sale pricing, banks are likely to pay higher rates to depositors to attract more deposits (and hence increase their cash balance) because the purchase of cash goods becomes more lucrative during those times.

4.1.3 Liquid assets as substitute for capital

⁴² Importantly, their model does not necessarily need the fire sale assumption, as they assume assets are bank specific (not banking system specific), and hence, they lose value as they are transferred (sold) even when market conditions are normal.

Bank Strategic Choice of Asset Liquidity

Is it strategically sound to hold liquid assets to signal safety and resilience to depositors when there is a high possibility of a bank run? A similar question in the context of a bank's capital has been answered positively in numerous empirical and theoretical studies (Berger & Bouwman, 2013; Diamond & Rajan, 2000). However, the desirability of liquid assets in helping banks gain market share is insufficiently addressed in the literature, particularly with regards to empirical studies. As I have discussed the supporting views in the first section (Calomiris et al., 2015), in this section I examine several alternative views that challenge Calomiris et al.'s (2015) proposition.

Myers and Rajan (1998) argue that holding liquid assets can limit the external financing capability of a financial intermediary. Liquid assets give a financial firm the freedom to readily change its risk profile by shifting the risk of current liquid assets to other liquid or illiquid assets with considerably higher risk. As a result, creditors of the firm may not be able to accurately predict the risk profile of the firm during their extended loan. Hence, the pledgeability of illiquid assets (amount of external financing that a bank can earn by using the illiquid assets as collateral) declines with a higher portion of liquid assets. From this perspective, banks are better off obtaining external financing if they are more invested in illiquid assets. More recently, Malherbe (2014) proposed an alternate explanation for why liquidity can be detrimental to a firm's ability to avoid fire sales. In his model, when firms hold liquid assets, their decision to sell assets is construed more as holding private information and less as the need to raise liquidity for financing new projects. As a result, holding more liquid assets may diminish a firm's ability to gain market share during a crisis as their ability to raise new funds is more limited than firms with lower liquidity.

The relation between balance sheet liquidity and bank performance has been the subject of several empirical studies. Not surprisingly, most of these studies follow the financial crisis of 2007-2008, in which the malfunction of the short term funding was one of the most critical cause of the crisis. In general, banks with a higher reliance on stable funds are shown to fare better during financial crises and perform their banking functions more effectively shortly after the crisis (Cornett, McNutt, Strahan, & Tehranian, 2011; Fahlenbrach, Prilmeier, & Stulz, 2012; Ivashina & Scharfstein, 2010). The focus of my paper, however, is not on funding liquidity, but rather on asset liquidity. Although from a stability perspective, the illiquidity of liability (i.e., stable source of funding) may be a good substitute for assets liquidity in preventing fire sales, from a strategic perspective they are not quite the same. In particular, the pledgeability of liquid assets is a unique aspect of banks⁴³.

4.2 Data and methodology

I use U.S. bank reports of condition and income (call reports) for the period between 1985 and 2010 to build quarterly panel data with a total of 34,000 bank-quarter samples. The period consists of five financial crises (Figure 1, Appendix 2), three of which originated in the capital market

⁴³ For this reason, the liquidity measures used in this table are different from those introduced in the new Basel III NSFR (Net Stable Funding Ratio) and LCR (Liquidity Coverage Ratio). Specifically, NSFR does not distinguish between liability liquidity and assets liquidity, devising a ratio that measures the discrepancy between assets liquidity and liability illiquidity (the higher liquid asset and lower liability liquidity, the higher NSFR). Instead, asset liquidity used in this paper (Eq (2) - Eq(5)), focus merely on the liquidity of bank assets, rather than the discrepancy between bank assets and liability liquidity.

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(market crises)⁴⁴ and two that originated in the banking system (banking crises)⁴⁵. To enrich the pseudo-experimental design, I add two placebo periods and test whether the detected impact holds for those periods. To account for outliers and idiosyncratic changes in bank financial policy, I average all independent variables over eight quarters before each financial crisis (and placebo crises) and relate them to the average dependent variable during the crisis period. Thus, the panel encompasses seven periods (T=7) with five financial crises and two placebos. I reexamine the results for flexible change in pre-crisis periods using robustness tests.

The first hypothesis concentrates on the impact of pre-crisis bank choice of liquid assets on its market share during the crises. The following model is used:

$$\begin{aligned} \% \Delta \text{Market Share}_{i,t} = & \beta_0 + \sum_1^4 \beta_k \text{Control Variables}_{k,i,\text{precrisis}-t} + \\ & \beta_5 * \text{Financial Crises Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \\ & \beta_6 * \text{NormalTime Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \epsilon_{it} \end{aligned}$$

Eq (1A)

⁴⁴ We can define market crisis periods as those associated with a significant drop in capital market asset prices in a relatively short period of time. Specifically, between 1987(Q3) and 1988(Q1) (Black Friday) the S&P 500 dropped more than 50%. Similarly, between 1998(Q2) and 1999(Q1) (Asian Crisis) and 2000(Q1) and 2002(Q2) (technology crisis) the S&P lost 25% and 80% respectively.

⁴⁵ Alternatively, we may define banking crisis periods as those periods associated with significant increases in the number of bank failures. Specifically, starting from the fourth quarter of 1988, 488 banks failed, more than twice that of a similar period. The trend continued until 1992. The next banking crisis is associated with the subprime mortgage (third quarter of 2007 until end of 2009) in which the number of bank failures increased ten times from 2006 numbers, FDIC (2017).

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Alternatively, the percentage change in bank revenue is regressed against bank choice of pre-crisis liquidity. The total bank revenue is defined as total interest income (RIAD4107) plus total non-interest income (RIAD4079), as represented by the following regression:

$$\begin{aligned} \% \Delta \text{Revenue}_{i,t} = & \beta_0 + \sum_1^4 \beta_k \text{Control Variables}_{k,i,\text{precrisis}-t} + \\ & \beta_5 * \text{Financial CrisesDummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \\ & \beta_6 * \text{NormalTime Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \epsilon_{it} \end{aligned}$$

Eq (1B)

The variables of interest are the interaction of bank liquidity ratio with crises dummy as well as the interaction of bank liquid assets with normal time dummy. The bank liquidity ratio is measured as the total liquid assets scaled by total assets. The dependent variable, percentage change in market share, is defined as the average bank market share during the crisis minus the average bank market share over the eight quarters pre-crisis, divided by its pre-crisis average market share (the eight quarters before the crisis)⁴⁶. Market share is defined as total bank assets divided by aggregate total bank assets.

The proxy for bank liquid assets can be as narrow and as simple as bank excess reserves, to as wide as securities that are barely traded. In particular, I employ four measures of liquidity sorted by the extent of the liquidity of underlying assets. The first measure includes solely cash (excess reserves) which is the purest form of liquidity. As discussed in section 1, signaling hypotheses

⁴⁶ The reason for using “percentage change” in market share rather than “change” in market share is obvious. It is more convenient to assume that change in market share against its determinants is a convex curve, in that one percent change in low market share (e.g., change from 1% to 2%) is much harder than one percent change in high market share (e.g., change from 20% to 21%).

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mostly hinge on cash, ruling out other types of liquid assets to fulfill its prediction. The second liquidity measure adds assets held in trading accounts to the first measure. Trading assets are short term securities intended to be held for less than one fiscal year. Importantly, only very large banks have sizeable trading accounts, making this measure economically very similar to the first measure (Table 1). The third and fourth liquidity measures include assets held in investment accounts. Securities that are purchased with the intent of being sold prior to their maturity are called available for sale securities, forming the third measure of liquidity⁴⁷. Similarly, hold-to-maturity securities make up the fourth proxy of bank liquid assets.

$$\text{Bank Liquidity Ratio 1} = \frac{\text{Excess Reserve}}{\text{Total Assets}}$$

Eq (3)

$$\text{Bank Liquidity Ratio 2} = \frac{\text{Excess Reserve} + \text{Trading Assets}}{\text{Total Assets}}$$

Eq (4)

$$\text{Bank Liquidity Ratio 3} = \frac{\text{Excess Reserve} + \text{Trading Assets} + \text{Securities AvailableForSale}}{\text{Total Assets}}$$

Eq (5)

⁴⁷ Trading assets and available for sale securities are both evaluated at their fair value at the end of each quarter; however, the realized gain/loss is reported in “income statement” for the former, while it is reported in “comprehensive income statement” for the latter.

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Bank Liquidity Ratio 4

$$= \frac{\text{Excess Reserve} + \text{Trading Assets} + \text{Securities HeldToMaturity} + \text{Securities AvailableForSale}}{\text{Total Assets}}$$

Eq (6)

In quarters when there is an ongoing market crisis or banking crisis, FinancialCrisisDummy equals one: fourth quarter of 1987 (sharp stock market decline: market crisis); first quarter of 1990 until fourth quarter of 1992 (credit crunch of early 1990s: banking crisis); third quarter of 1998 and fourth quarter of 1998 (LTCM and spillover of Russian and East Asian crisis: market crisis); second quarter of 2000 until third quarter of 2002 (dot.com bubble: market crisis); and finally, the third quarter of 2007 until third quarter of 2009 (subprime mortgage defaults: banking crisis). The normal time dummy is used as a placebo to form a pseudo-experimental test, for which I use the same grouping methodology applied to assess financial crises. The identified normal times are the first quarter of 1995 until the second quarter of 1996 and the fourth quarter of 2004 until the second quarter of 2005.

The control variables are chosen from extant banking literature on bank performance and financial policy. However, the strategy is to avoid cluttering models with several control variables that may be redundant or readily nested within existing variables. Overall, I select a handful of control variables that likely simultaneously drive both bank liquidity policy as well as bank performance. The list of the control variables are as follows:

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Size: Bank size is a proxy for many variables that can affect firm performance as well as its choice of financial policy. Bank size is a well-known proxy for the extent of access to external financing, as larger banks are known to be safer and bear lower information asymmetry than small or mid-sized banks. Moreover, owing to economies of scale and scope (dimension of activities), large banks have more diversified cash flows and lesser need to hold cash for transaction and precautionary motives (Opler et al., 1999). As a result, the expectation is that larger banks would need a lower equilibrium level of liquid assets. From a performance perspective, larger banks are expected to have diminishing rates of return for their size (Bertay, Demirgüç-Kunt, & Huizinga, 2013). However, it is not obvious whether the well-documented tendency of governments to save large banks (particularly for mega size banks), can change the statistical inference. Bank size is measured by the log of total assets (RCFD2170). Because the variables are winsorized at 1%, the samples are devoid of “Too big to fail” (TBTF) banks. In the robustness test, I include TBTF samples and evaluate whether their inclusion changes the inferences.

Credit Risk: Previous studies show that banks may simultaneously choose their level of liquidity, risk taking, and capital (Jokipii & Milne, 2011; Kochubey & Kowalczyk, 2014). That is, bank choice of liquid assets may be driven by common factors that are related to credit risk. A common proxy for bank credit risk is the ratio of risk-weighted assets (RWA) to total assets. RWAs are calculated as the risk-adjusted weighted average of all assets, in which riskier assets (such as asset-backed securities or junk corporate bonds) receive higher weights (close to 1) and safe assets (such as cash and government bonds) receive lower weights (in the case of cash and treasuries, the weight is zero)⁴⁸. The proxy is widely used in banking literature (see for example, Jokipii & Milne

⁴⁸ Admittedly, the proxy is not perfect, as it overlooks the risks taken through off balance sheet activities.

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(2011) and Rime (2001)). However, there are two practical problems with using this measure: first, reporting information for RWA in call reports (RCFDA223) begins only in 1990, while experiments used in this study date back to 1985; secondly, there are many missing values in the RCFD series. To overcome these limitations, the existing RWA is regressed based on its determinants (size, allowance ratios, liquidity ratios, equity capital ratios, and core deposits) for the period after 1990 (first stage). Subsequently, I use the coefficients obtained in the first stage to estimate RWA for the missing period (1985-1990) as well as missing values. The bank asset allowance ratio, calculated as total loan allowances (RCFD3123) divided by total assets (RCFD2170), is used as an alternative measure of credit risk.

Capital Ratio: The impact of capital on bank survival and performance has been the subject of numerous theoretical and empirical studies. Banks with a higher capital base may attract more customers (borrowers) by signaling safety and resilience toward fundamental shocks (Diamond & Rajan, 2000). Berger & Bouwman (2013) investigate the impact of capital on bank survival and market share during normal times and financial crises. They find that bank capital is a statistically and economically significant determinant of a bank's ability to gain market share during a crisis, but not during normal times⁴⁹. I measure bank capital as the ratio of bank equity capital (RCFD3210) to total assets.

Core Deposits: Core deposits are traditional retail deposits, consisting of demand deposits, small saving and short time deposit accounts. The ratio of core deposits to total assets is a measure

⁴⁹ There is no consensus in the literature regarding the impact of capital on bank competitive advantage: it is seen either as expensive and, therefore, counter-productive; or it creates a competitive edge for holders (Allen et al., 2011; Kwan & Eisenbeis, 1977).

of funding stability that can affect bank choice related to liquid assets as well as its performance. A higher ratio of core deposits to total assets can be associated with lower liquid assets through substitution effects: banks with greater liquid assets can more effectively manage the early withdrawal of funds than those with lower liquid assets, and vice versa.

Large core deposits are also expected to be positively correlated with bank performance, as banks with more stable sources of lending are less likely to face early withdrawal of valuable funds during times of liquidity stress (Gatev & Strahan, 2006). Recent findings indicate that banks with stable sources of funding are more active lenders post-crisis (Cornett et al., 2011; Ivashina & Scharfstein, 2010). On the other hand, public guarantee of bank core deposits by deposit insurance structures can lead to a distorted motivation to take higher risks (Gropp, Gruendl, & Guettler, 2013). As a result, the impact of stable funding on bank market share is most likely determined in combination with their choice of credit risks. Core deposit ratio is measured as the sum of transaction accounts (defined as the sum of current deposits (RCON3485) and demand deposits (RCON6631)), with time deposits below 100k (RCON6648), and savings accounts (RCON6810), scaled by total assets.

4.3 Results

4.3.1 Summary statistics

Table 1 shows the summary statistics of the main variables during banking crises, market crises, and normal times. Although the average changes in market share do not show a discernable difference in crises versus normal times, variation of change (standard deviation) in banking crises (19%) is significantly higher than in normal times (13.8%).

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Bank liquidity ratio, the treatment variable, has substantially dispersed mean values, depending on the definition of liquidity. Comparing the average liquidity ratio 1 with liquidity ratio 4 (Eq (3) and Eq (6)) reveals that most of the bank liquid assets are held through marketable securities rather than cash. Comparing liquidity ratio 1 and 2 also reveals useful information; when securities in trading accounts are added to excess cash reserves, the liquidity ratio is practically unchanged. This is because the majority of banks maintain a very small trading account, with the exception of very large banks that have sizable trading accounts.

4.3.2 Univariate analysis

In this section, I illustrate how average market share can change with different quantiles of pre-crisis liquid assets in different periods. Of course, the purpose of the test is to merely provide useful insight, rather than serve as a formal statistical test. Figure 3 (Panel A, B, and C) presents the covariation of the percentage change in average market share with different quantiles of liquidity ratio in normal and crisis periods. Although average market share during financial crises has an uninterrupted ascending pattern in relation to liquidity quantiles (Panel B), there is no observable pattern during normal times (Panel A). Panel B is consistent with the speculative theory of holding liquid assets, in that banks would only benefit from liquidity when there is a good opportunity to use the liquid assets to purchase undervalued assets in fire sales. However, Panel A may not be fully consistent with Allen & Gale's theoretical framework that suggests holding liquidity in normal times must be detrimental to a holder's competitive position. Nevertheless, the findings of both panels are consistent with the signaling theory of holding liquid assets: while holding liquid assets during periods of heightened information asymmetry plays a positive role in attracting more deposits (Panel B), it is irrelevant during normal times (Panel A). Panel C

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demonstrates the broadest definition of asset liquidity: cash and all marketable securities. Strikingly, the relation between liquidity and market share trends downward during crisis times. This may be explained by the fact that firms with higher marketable securities suffer a greater [fire sale] loss during financial crises, suggesting that not all sources of liquid assets can help banks gain competitive advantage.

Table 2, Panels A and B, shows the average percentage change in market share for 25 groups of observations during financial crises. In the first panel, groups are formed based on the intersection of liquidity ratio 1 and equity capital ratio. Moving from the lowest liquidity quantile to the highest, the average percentage change in market share increases continuously in almost every quantile of the equity ratio. For example, maintaining equity ratio at quantile 3, the average percentage change in market share for the liquidity ratio increases by 5.32% when we slide from the lowest liquidity quantile (-8.67%) to the highest (-3.35%).

Similarly, Panel B presents the formation of groups based on the intersection of liquidity ratio 1 and bank size. Interestingly, the average percentage change in market share accompanies asset size (columns) as well as asset liquidity (rows). If we keep the size constant, the average percentage change in market share increases with bank liquidity ratio. For example, for the fifth quantile of bank size, moving from lowest quantile of liquidity ratio to the highest can increase the percentage change in market share by 4.5%.

4.3.3 Regression Analysis

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Table 3 presents results of estimating Eq 1 (Eq1A and Eq1B) by ordinary least square, time fixed effect, and time and firm fixed effects. The significance of control variables is consistent with the theoretical literature and previous empirical studies. Specifically, size is negatively related to change in market share (revenue), as the larger banks have diminishing rates of return. The return of bank performance on equity ratio is significantly positive, as predicted by competitive advantage theories of equity capital. Core deposits are also negatively correlated with bank performance, supporting the moral hazard theories of stable funds. Finally, higher pre-crisis credit risk is positively related to increases in market share.

Herein, the focus is on the interaction between the bank liquidity and normal and crises dummy variables. In all regression setups, I find that, during the normal times, the impact of bank liquid assets on bank market share (revenue) is negative (OLS and Time fixed effects) or insignificant (Firm and Time Fixed Effect Model), while the impact of liquidity on market share is statistically and economically significant during the crisis times. In the baseline model (OLS), one standard deviation increase in liquid assets is associated with a 16% increase in market share (revenue) percentage change. In the rest of the analyses, the time and bank fixed effect model (third column of Table 3, Panel A and B) are used because, despite being less efficient, the fixed effect model is more robust to endogeneity. Moreover, the Hausman fixed/random effect test strongly rejects the hypothesis that the estimate of coefficients is equal, with or without the inclusion of firm fixed effects.

Next, I differentiate the two types of crises (market and banking) and estimate the model (Eq (7)). The two types of crises may have significantly different dynamics that can impact the results.

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Market crises are characterized by systematically large declines in equity and/or debt markets, which can also affect the banking system through the marketable securities portfolio. However, price pressure does not affect bank specific assets, and thus, fire sale dynamics are not a major driver of bank economic behavior. In contrast, banking crises feature substantial price declines in assets specific to the banking systems (such as mortgage-related products), triggering asset fire sales of many liquidity-constrained banks⁵⁰. The three crises of 1987, 1998, and 2000-2 are grouped as market crises, while the crises of 1990-2 and 2007-9 are grouped as banking crises:

$$\begin{aligned} \% \Delta \text{Market Share}_{i,t} = & \beta_0 + \sum_1^4 \beta_k \text{Control Variables}_{k,i,\text{precrisis}-t} + \\ & \beta_5 * \text{BankingCrisesDummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \\ & \beta_6 * \text{MarketCrisesDummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \\ & \beta_6 * \text{NormalTime Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \epsilon_{it} \end{aligned}$$

Eq (7)

Table 4 (column 1) provides the estimated coefficients of Eq (7). Interestingly, maintaining a higher level of liquidity only results in greater competitive advantage during banking crises when banks desperately seek new sources of liquidity to avoid bankruptcy. During market crises, when the equity and/or debt markets are the origins of the market stress, holding liquid assets does not provide any competitive edge to holders because bank specific assets are not subject to fire sales.

⁵⁰ Admittedly, holding 25% available for sale securities, Table 1, can result in enough exposure to market crises. However, the composition of available marketable securities is needed to determine the level of vulnerability to market crises. Nevertheless, the contrast between banking crises and market crises is still relevant as the relative proportion of a bank's marketable securities is less than half of their specific assets.

In establishing that only banking crises make excess liquidity fruitful for the holders, I ask whether the two banking crises included in this study (i.e., the credit crunch of the early 1990s and subprime mortgage crisis 2007-8) have different impacts on the results.

Table 4, Column 2 and 3, present the estimates of the 1990s and 2007 banking crises, respectively. The impact of liquidity is significant for both crises; however, the impact is stronger, both economically and statistically, for the 1990s crisis. The difference between the two time periods may be explained by Gale & Yorulmazer's (2013) proposition that a bank's speculative motives for hoarding liquidity is diminished if a central planner aggressively injects liquidity into the market. The unprecedented liquidity infusion by the Federal Reserves during the financial crisis of 2007-8⁵¹ could partially diminish the impact of privately chosen liquidity level on bank competitiveness during the crisis.

4.4 Robustness tests

In this section, I discuss the results of several robustness tests. I preserve Eq (7), with separate market and banking crises, while maintaining the same control variables.

4.4.1 Alternative measures of bank liquid assets

Bank liquid assets include a wide range of assets, from cash balances held in vaults for day to day transactions, to marketable securities intended to be held until they mature. It is important to know which sources of liquidity help banks gain a competitive advantage during financial crises.

⁵¹ Including, but not limited to, expanding discount window, term auction facility, security lending, and TARP.

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Alternative measures of bank liquid assets, as introduced through Eq (4) to Eq (6), are used to answer this question. The first two measures of liquidity, liquidity ratio 1 and liquidity ratio 2, are based on excess cash flow and excess cash flow plus trading assets, respectively. Liquidity 3 adds “available for sale securities” to the previous measure and liquidity 4 adds “held to maturity securities” to bank liquidity 3. There are two important points regarding the difference between these measures. First, only a few large banks hold a sizable trading account, thus the difference between liquidity ratio 1 and liquidity ratio 2 is minimal. The summary statistics reveal that a bank’s average excess cash (liquidity ratio 1) is indistinguishable from excess cash plus trading assets (liquidity ratio 2). Hence, it is expected that the coefficients of interaction terms in Eq (1), estimated from liquidity measure 1, are insignificantly different from those estimated using liquidity measure 2. Second, although marketable securities are sufficiently liquid in normal times, they may not be as liquid during periods of stress. As a result, marketable securities might not perform an economically similar function as cash holdings during a fire sale. If marketable securities lose their value in stress times, due to cash-in-the-market pricing, a higher portion of pre-crisis marketable securities may predict a reduction in market share during the crisis.

In Table 5 (columns 1 to 4) we can see the impact of excess cash, trading assets, available for sale securities and held until maturity securities on the percentage change in market share. Column 1 replicates the base model in Table 3, with Eq (3) as bank liquidity ratio. Adding trading assets to the benchmark liquidity ratio, Eq (3), does not statistically and economically change the results because the two ratios, Eq (3) and Eq (4), are similar. For the reasons discussed in the previous paragraph, considering marketable securities as liquid assets, as defined in Eq (5) and Eq (6), yields totally different results from those reported for Eq (3) and Eq (4). While banks gain higher market

share by holding cash (Eq (3)), they lose market share by holding liquid assets in the form of marketable securities. Economically, one standard deviation increase in pre-crisis holding of marketable securities (Eq (6)) can negatively affect its change in market share by 13% during a financial crisis.

4.4.2 Size and Too Big to Fail (TBTF) banks

Reasonably, small commercial banks, which operate across few branches with substantial locality in their business model, are dissimilar entities to large, multinational, and tremendously diversified banks, especially in terms of access to and use of liquidity. Moreover, it is likely that banks described as “Too Big to Fail” (TBTF) have an economically significant influence on the econometric inference, which has nothing to do with their private, pre-crisis choice of liquidity. The financial crisis of 2007-2008 made a strong case for this possibility when TBTF banks received special treatment from government authorities, particularly in terms of access to uniquely cheap liquidity. The bank database (Call Reports) contains all samples ranging from the small Tricentury bank with assets worth \$3 million in 2009, to the mega large banks of JP Morgan with \$1.7 trillion in assets. This highlights the fact that econometric care is needed when generalizing the results.

In this section, I test whether the results obtained in section 4 can be generalized to all size categories and whether TBTF is helping or undermining the results⁵². The benchmark analyses shown in Table 3 include winsorized samples at 1%, effectively eliminating very small and very

⁵² In this study, a bank is identified as TBTF when its total assets are greater than \$5 billion.

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large banks, including TBTF banks. Thus, I rebuild the samples by adding all banks, including TBTF banks, and replicate the analyses presented in Table 3.

All things being equal, one would expect large banks to have less private motivation to hold liquidity (cash) for the sake of speculation. Large banks have easier access to external liquidity as well as government-sponsored liquidity than smaller banks. In particular, TBTF banks are expected to undermine the findings reported in Table 3 because they are more resourceful in finding external liquidity, whenever and for whatever purpose, than small or medium sized banks. I test this possibility by re-estimating Eq (1) for different size quantiles as well as for TBTF banks (Table 6). In the first column, the benchmark model is repeated (Table 3, Panel A, column 3). Column 2 presents the results for all samples, including TBTF banks⁵³. Columns 3, 4, and 5, present the estimate of Eq (1) for small banks (less than 20% quantile), medium sized banks (20% to 80% quantile), and large banks (greater than 80% quantile), respectively. The numbers confirm our expectation that large banks undermine the impact of liquidity on market share. Including all large banks does not change the statistical significance, yet the economic significance of the interaction term is reduced by 31% (Column 2). Moving through different size quantiles (Columns 3 to 5), there is no evidence that bank size has a significant impact on the results reported in the benchmark (Column 1); The magnitudes of coefficients reported for small and medium sized banks remain consistent with those in the benchmark. Finally, an exclusive examination of TBTF

⁵³ In the benchmark, the dependent variable and all independent variables are winsorized, while in Column 2 of Table 6 only the dependent variable is winsorized. The resulting dataset used for the estimates in Column 2 incorporates all large banks including TBTF.

(Column 6) does not reject the hypothesis that higher liquidity cannot provide a competitive advantage for holders. Admittedly, the inconclusive result of the latter may be due to lack of power.

4.4.3 Alternative pre-crisis period definition

Finally, I examine whether the results for Eq (1) are sensitive to the length of pre-crisis periods. As discussed in section 3, all treatment and control variables are averaged over eight quarters before each banking, market, or placebo crisis, to smooth transitory variations. I allow the pre-crisis period to flexibly change down to two quarters, averaging all independent variables to a shorter period of time. The results (unreported) are robust to the choice of pre-crisis length.

4.5 Instrumental variable analysis

To substitute the demand for cash balance, I construct two instrumental variables. The first instrument is the ratio of foreign cash holdings to total excess cash reserves, as defined by cash deposited in foreign banks (RCFD0074) or foreign branches of the bank (RCFD0073) divided by total excess cash holdings. The relevance of the instrument is based on the study of Foley et al. (2006), in which they show that U.S. corporate demand for cash is partly driven by the tax costs associated with repatriating foreign income. Foley et al. estimate that one standard deviation increase in tax burden from repatriating foreign income is associated with a 7.9% increase in the ratio of cash to net assets. A relevance condition test in the first stage supports their finding. In particular, a one standard deviation increase in the foreign cash ratio is associated with a 21% increase in bank cash balance. Like all instruments, the internal validity of the instrument (i.e., whether the higher foreign cash ratio is orthogonal to a firm's performance in any other way except

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the cash holding channel), is not statistically testable. I estimate the following 2SLS model for normal time and banking crisis periods. In the first stage, Eq (8), I estimate the liquidity ratio using the foreign cash ratio as an instrument for bank liquidity ratio. Secondly, I use the estimated liquidity ratio, Eq (9), and estimate β_2 for banking crisis and normal times separately.

$$\text{Liquidity Ratio}_{1it} = \alpha_0 + \alpha_1 \text{control variables}_{it} + \alpha_2 \frac{\text{Foregin Cash}_{it}}{\text{Total Cash}_{it}} + u_{it}$$

Eq (8)

$$\begin{aligned} \% \Delta \text{MarketShare}_{i,t} &= \beta_0 + \sum_1^4 \beta_k \text{Control Variables}_{k,i,\text{precrisis-t}} + \beta_5 \widehat{\text{Liquidity Ratio}}_{1,i,\text{precrisis-t}} \\ &+ \epsilon_{it} \end{aligned}$$

Eq (9)

Table 7 presents the results of Eq (9) for normal (Column 1) and crisis periods (Column 2). The results confirm the previous findings.

The second instrument derives from a recently developed technique that uses information available on the heteroscedasticity of a dependent variable to build an instrument for an endogenous variable (Lewbel, 2012). The advantage of this method is that it constructs a relevant and valid instrument based on existing exogenous variables that can substitute the suspected endogenous independent variable. The relevance of the instrument depends on the degree of

heteroscedasticity of the dependent variable and the validity of the instrument is mathematically proven if few reasonable assumptions hold (Appendix 1). Given the abundance of heteroscedastic series in finance and economics, the application of this approach is growing in economics studies (see for example, Lanne & Lütkepohl (2008)). The first step is to show that the dependent variable, percentage change in market share, is heteroscedastic with regards to the other independent variables (i.e., size, credit risk, core deposits, capital and liquidity ratios). The result of a Baruch Pagan test rejects that percentage change in market share is homoscedastic. Next, I build four instruments, each based on one of the exogenous variables in the main regression, to collectively act as instruments for bank choice of liquid assets (Appendix 1). I use a Generalized Method of Moments (GMM) to estimate the main regression. The use of GMM over 2SLS is preferred for two reasons: first, since the model is heteroscedastic, using 2SLS without knowing the functional form of conditional variance is inefficient. In GMM an optimal weighting matrix is used to overcome the estimation inefficiency of the ordinary least square method. Second, having three extra instruments enables us to use J-statistics to test if any of the extra instrumental variables are not orthogonal to error terms (validity of over-identification test). The results presented in Table 8 confirm that the choice of greater liquid assets has a positive influence on the competitiveness of the bank during crisis periods.

4.6 Conclusions

The research was designed to investigate the impact of pre-crisis levels of bank asset liquidity on its competitive advantage during bank crises. The theoretical literature asserts that when aggregate liquidity in the financial system is scarce, financial institutions can make either of two

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strategic choices (ex-ante): they can choose to invest in illiquid assets to maximize profit from the liquidity premium; or they can choose to keep part of their portfolio liquid so as to profit from asset fire sales. The latter choice may point to a unique motive for banks to hold liquid assets in normal times to take advantage of undervalued assets in fire sales (speculative motive). Despite rich theoretical underpinnings, no empirical analyses have assessed this speculative motive. This paper fills this gap by offering a range of univariate and regression analyses and instrumental variable analyses to determine the impact of pre-crisis bank choice of liquid assets on market share during a crisis.

The results are consistent with the theoretical predictions. While insignificant or negatively significant during normal times, higher levels of pre-crisis bank liquidity have a statistically and economically positive impact on bank market share over the course of a financial crisis: one standard deviation increase in liquid assets is associated with a 16% increase in market share percentage change. This finding is consistent with Allen & Gale's (2005) proposition that the productivity of bank liquidity must be state-dependent. Banks lose liquidity premium in normal times, but are compensated for the lost liquidity premium in bad times. However, I find that not all types of financial crises are the same. Financial crises that do not originate in the banking system (i.e., market crises) are indifferent toward a bank's choice of liquid assets. On the other hand, banking crises significantly reward banks with higher levels of pre-crisis liquidity. Finally, I find only a narrow definition of liquidity (cash and trading assets) is related to bank performance during bank crisis periods. A broad definition of liquid assets, encompassing available-for-sale securities and held-until-maturity securities, reverse or eliminate these results. The results are robust to exclusions of "Too big to fail" banks and various other performance measures.

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Overall, the findings shed light on an important determinant of a financial firm's choice related to cash holdings. I find equilibrium of bank cash levels has an important strategic determinant, which is the possibility of making a large profit during crises. The private motive of holding liquid assets prior crises, however, may be inconsistent with any liquidity regulations, e.g., Basel III NSFR, aiming to increase the aggregate level of liquidity in normal times; That is, the chance of making profits during crises periods lessens when all banks maintain liquid balance sheet in normal times. From this perspective, the liquidity requirement substitutes the private motive and hence, ineffectual. The impact of liquidity requirements on equilibrium levels of liquid assets has been investigated in previous studies, such as Bonner, van Lelyveld, & Zymek, (2015) and Holmström & Tirole (1998)⁵⁴.

⁵⁴ From the perspective of Allen & Gale, the speculative motive may not avoid cash-in-the-market pricing, as those with high liquidity do not provide liquidity until fire sales actually happen, hence the reason they forego the liquidity premium in the first place. However, even if the cash-in-the-market pricing cannot be avoided, with higher levels of aggregate liquidity in the banking system, we can hope that banks' specific assets are exchanged within the banking system, rather than being sold to non-expert financial firms (such as hedge funds).

4.7 References

- Acharya, V. V., Gromb, D., & Yorulmazer, T. (2012). Imperfect Competition in the Interbank Market for Liquidity as a Rationale for Central Banking. *American Economic Journal: Macroeconomics*, 4(2), 184–217.
- Acharya, V. V., & Merrouche, O. (2012). Precautionary Hoarding of Liquidity and Interbank Markets: Evidence from the Subprime Crisis. *Review of Finance*.
- Acharya, V. V., Shin, H. S., & Yorulmazer, T. (2010). Crisis Resolution and Bank Liquidity. *Review of Financial Studies*.
- Allen, F., & Carletti, E. (2008). The Role of Liquidity in Financial Crises (SSRN Scholarly Paper No. ID 1268367). Rochester, NY: Social Science Research Network.
- Allen, F., Carletti, E., & Marquez, R. (2011). Credit Market Competition and Capital Regulation. *Review of Financial Studies*, 24(4), 983–1018.
- Allen, F., & Gale, D. (1994). Limited Market Participation and Volatility of Asset Prices. *American Economic Review*, 84(4), 933–55.
- Allen, F., & Gale, D. (1998). Optimal Financial Crises. *The Journal of Finance*, 53(4), 1245–1284.
- Allen, F., & Gale, D. (2000). Financial Contagion. *Journal of Political Economy*, 108(1), 1–33.
- Allen, F., & Gale, D. (2004). Financial Fragility, Liquidity, and Asset Prices. *Journal of the European Economic Association*, 2(6), 1015–1048.
- Allen, F., & Gale, D. (2005). From Cash-in-the-Market Pricing to Financial Fragility. *Journal of the European Economic Association*, 3 (2–3), 535–546.
- Berger, A. N., & Bouwman, C. H. (2013). How does capital affect bank performance during financial crises? *Journal of Financial Economics*, 109 (1), 146–176.
- Bernanke, B., Gertler, M., & Gilchrist, S. (1996). The Financial Accelerator and the Flight to Quality. *The Review of Economics and Statistics*, 78 (1), 1–15.

- Bertay, A. C., Demirgüç-Kunt, A., & Huizinga, H. (2013). Do we need big banks? Evidence on performance, strategy and market discipline. *Journal of Financial Intermediation*, 22 (4), 532–558.
- Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, 22 (6), 2201–2238.
- Brunnermeier, M. K., & Sannikov, Y. (2014). A Macroeconomic Model with a Financial Sector. *American Economic Review*, 104 (2), 379–421.
- Caballero, R. J., & Simsek, A. (2013). Fire Sales in a Model of Complexity. *The Journal of Finance*, 68 (6), 2549–2587.
- Calomiris, C. W., Heider, F., & Hoerova, M. (2015). *A Theory of Bank Liquidity Requirements*. Rochester, NY: Social Science Research Network.
- Cornett, M. M., McNutt, J. J., Strahan, P. E., & Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, 101 (2), 297–312.
- Diamond, D. W., & Dybvig, P. H. (1983). Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy*, 91 (3), 401–19.
- Diamond, D. W., & Rajan, R. G. (2000). A Theory of Bank Capital. *The Journal of Finance*, 55 (6), 2431–2465.
- Diamond, D. W., & Rajan, R. G. (2001). Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking. *Journal of Political Economy*, 109 (2), 287–327.
- Diamond, D. W., & Rajan, R. G. (2006). Money in a Theory of Banking. *American Economic Review*, 96 (1), 30–53.
- Diamond, D. W., & Rajan, R. G. (2011). Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes. *The Quarterly Journal of Economics*, 126 (2), 557–591.
- Fahlenbrach, R., Prilmeier, R., & Stulz, R. M. (2012). This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent Financial Crisis. *The Journal of Finance*, 67 (6), 2139–2185.

- Flannery, M. J. (1994). Debt Maturity and the Deadweight Cost of Leverage: Optimally Financing Banking Firms. *The American Economic Review*, 84 (1), 320–331.
- Foley, C. F., Hartzell, J. C., Titman, S., & Twite, G. (2006). Why do firms hold so much cash? A tax-based explanation National Bureau of Economic Research.
- Gale, D., & Yorulmazer, T. (2013). Liquidity hoarding. *Theoretical Economics*, 8 (2), 291–324.
- Gatev, E., & Strahan, P. E. (2006). Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market. *The Journal of Finance*, 61 (2), 867–892.
- Gorton, G. (1988). Banking Panics and Business Cycles. *Oxford Economic Papers*, 40 (4), 751–781.
- Gropp, R., Gruendl, C., & Guettler, A. (2013). The Impact of Public Guarantees on Bank Risk-Taking: Evidence from a Natural Experiment*. *Review of Finance*.
- Hanson, S. G., Shleifer, A., Stein, J. C., & Vishny, R. W. (2015). Banks as patient fixed-income investors. *Journal of Financial Economics*, 117(3), 449–469.
- He, Z., & Xiong, W. (2012). Dynamic Debt Runs. *Review of Financial Studies*, 25(6), 1799–1843.
- Heider, F., Hoerova, M., & Holthausen, C. (2015). Liquidity hoarding and interbank market rates: The role of counterparty risk. *Journal of Financial Economics*, 118(2), 336–354.
- Holmström, B. (2011). *Inside and Outside Liquidity* (Reprint edition). The MIT Press.
- Holmström, B., & Tirole, J. (1998). Private and Public Supply of Liquidity. *Journal of Political Economy*, 106(1), 1–40.
- Ivashina, V., & Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3), 319–338.
- Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76(2), 323–329.
- Jokipii, T., & Milne, A. (2011). Bank capital buffer and risk adjustment decisions. *Journal of Financial Stability*, 7(3), 165–178.

- Keynes, J. M. (2014). *The General Theory of Employment, Interest and Money*. Business and Leadership Publishing.
- Kindleberger, C. P., & Aliber, R. Z. (2011). *Manias, panics and crashes: a history of financial crises*. Palgrave Macmillan.
- Kochubey, T., & Kowalczyk, D. (2014). *The Relationship between Capital, Liquidity and Risk in Commercial Banks*. Center for Economic Research and Graduate Education.
- Krishnamurthy, A. (2009). *How Debt Markets have Malfunctioned in the Crisis* (NBER Working Paper No. 15542). National Bureau of Economic Research, Inc.
- Kwan, S., & Eisenbeis, R. A. (n.d.). *Bank Risk, Capitalization, and Operating Efficiency*. *Journal of Financial Services Research*, 12(2–3), 117–131.
- Lewbel, A. (2012). *Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models*. *Journal of Business & Economic Statistics*, 30(1), 67–80.
- Malherbe, F. (2014). *Self-Fulfilling Liquidity Dry-Ups*. *The Journal of Finance*, 69(2), 947–970.
- Myers, S. C., & Rajan, R. G. (1998). *The Paradox of Liquidity*. *The Quarterly Journal of Economics*, 113(3), 733–771.
- Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). *The determinants and implications of corporate cash holdings*. *Journal of Financial Economics*, 52(1), 3–46.
- Rime, B. (2001). *Capital requirements and bank behaviour: Empirical evidence for Switzerland*. *Journal of Banking & Finance*, 25(4), 789–805.
- Shleifer, A., & Vishny, R. (1992). *Liquidation Values and Debt Capacity: A Market Equilibrium Approach*. *Journal of Finance*, 47(4), 1343–1366.
- Shleifer, A., & Vishny, R. W. (2010). *Fire Sales in Finance and Macroeconomics* (Working Paper No. 16642). National Bureau of Economic Research.
- Stiglitz, J. E., & Weiss, A. (1981). *Credit Rationing in Markets with Imperfect Information*. *The American Economic Review*, 71(3), 393–410.
- Tirole, J. (2010). *Illiquidity and all its friends* (BIS Working Paper No. 303). Bank for International Settlements.

FDIC (2017), Failure and Transaction Assistance Query,

<https://www5.fdic.gov/hsob/SelectRpt.asp?EntryTyp=30&Header=1>

4.8 Appendices

Appendix 1 : Heteroscedasticity driven instrumental variable (Lewbel, 2012)

Assume we have the following model, in which x_1 is exogenous and x_2 is endogenous:

$$y = \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

We can build the instrumental variable in two stages:

1) We regress the endogenous variable on all exogenous variables and estimate the residuals

$$x_2 = \beta_1 x_1 + u$$

We find \hat{u} .

2) We construct an instrumental variable based on $Z = (x_1 - \bar{x}_1) \cdot \hat{u}$

In my model, I regress liquidity ratio 1 (i.e., endogenous variable) on all exogenous variables (i.e., size, credit risk, core deposits ratio, and equity ratio) and construct four instrumental variables, Z_1, Z_2, Z_3, Z_4 , each corresponding with one exogenous variables.

One can easily show that the instrument is not correlated with error term (validity condition)

$$\begin{aligned} Cov(Z, \epsilon) &= E(Z \cdot \epsilon) - E(Z) \cdot E(\epsilon) = E(Z \cdot \epsilon) = E(x_1 u \cdot \epsilon) - E(\bar{x}_1 u \cdot \epsilon) \\ &= E(x_1)E(u \cdot \epsilon) - \bar{x}_1 E(u \cdot \epsilon) = 0 \end{aligned}$$

The only assumption needed is to have $x_1 \perp u \cdot \epsilon$.

Lewbel (2012) show that the relevance condition depends on the heteroscedasticity of the model, i.e., if $Cov(x_1, \epsilon^2) \neq 0$ then, Z is correlated with x_1 .

Appendix 2 : Timeframe of analysis

Name	Date	Length	Description
Pre-crisis Period	1985: Q4 until 1987: Q3	8 quarters	
Market Crisis	1987: Q4	1 quarters	Black Monday, Sharp stock market decline
Pre-crisis Period	1988: Q1 until 1989: Q4	8 quarters	
Banking Crisis	1990: Q1 until 1992: Q4	8 quarters	The credit crunch of the early 1990s
Pre-crisis Period	1993: Q1 until 1994: Q4	8 quarters	
Placebo Crisis (Normal Time)	1995: Q1 until 1996: Q2	6 quarters	Placebo crises represent normal times. I apply this methodology to test the robustness of the results.
Pre-crisis	1996: Q3 until 1998: Q1	8 quarters	
Market Crisis	1998: Q3 until 1998: Q4	2 quarters	LTCM crisis and spillover of Russian and Asian crisis
Pre-crisis	1999: Q1 until 2000: Q1	5 quarters	
Market Crisis	2000: Q2 until 2002: Q3	10 quarters	Technology bubble crisis
Pre-crisis	2002: Q3 until 2004: Q3	8 quarters	
Placebo Crisis (Normal Time)	2004: Q4 until 2005: Q2	3 quarters	
Pre-crisis	2005: Q3 until 2007: Q2	8 quarters	
Banking Crisis	2007: Q3 until 2009: Q4	10 quarters	Subprime mortgage crisis

4.9 Figure and Tables

Table 1: Summary Statistics

Table presents the mean (standard deviation/t-stat) of bank variables used in the analyses. % Change in Market Share is defined as the bank's average market share during the crisis minus the bank's average market share over the eight quarters before the crisis, divided by its pre-crisis average market share (the eight quarters before the crisis). Market share is defined as a bank's total assets divided by aggregate total assets at any given quarter. Bank Liquidity ratio 1 is defined as bank excess cash reserves scaled by total assets. The excess reserve is defined as total cash minus Federal Reserve required reserve. Bank Liquidity ratio 2 is defined as excess reserve plus trading assets scaled by total assets. Bank Liquidity ratio 3 and 4, add "available for sales security" and "held to maturity securities" to the numerator of liquidity ratio 2, respectively. Size is measured by the natural log of total assets. Equity Capital Ratio is the ratio of bank capital (RCFD 3210) scaled by total assets. Bank Credit Risk is measured by risk-weighted assets divided by total assets. Finally, Core Deposits is the sum of transaction accounts, time deposits below 100k, and saving accounts, scaled by total assets. The last three columns show difference between normal times and financial crisis, market crisis, and banking crisis, respectively. The numbers in parentheses for these three columns report p-value, and for other columns report standard deviations. Information is derived from banks' quarterly data samples, between 1985 and 2010, winsorized at 1%.

	All	Financial Crisis (1)	Market Crisis (2)	Banking Crisis (3)	Normal Times (4)	(1) - (4)	(2) - (4)	(3) - (4)
% Change in Market Share	-9.01 (14.4)	-7.96 (16.85)	-7.33 (15.46)	-9.13 (19.15)	-8.95 (13.87)	0.99 (0.0001)	1.62 (0.012)	-0.19 (0.02)
Bank Liquidity Ratio1	0.05 (0.03)	0.04 (0.03)	0.05 (0.03)	0.04 (0.03)	0.05 (0.01)	-0.01 (0.002)	-0.01 (0.002)	-0.01 (0.001)
Bank Liquidity Ratio2	0.05 (0.03)	0.04 (0.03)	0.05 (0.03)	0.04 (0.03)	0.05 (0.03)	-0.01 (0.002)	0.00 (0.51)	-0.01 (0.001)
Bank Liquidity Ratio3	0.24 (0.14)	0.24 (0.13)	0.25 (0.14)	0.23 (0.13)	0.23 (0.14)	0.01 (0.001)	0.02 (0.001)	0.00 (0.64)
Bank Liquidity Ratio4	0.32 (0.14)	0.31 (0.13)	0.33 (0.12)	0.27 (0.14)	0.35 (0.15)	-0.04 (<0.000)	-0.02 (<0.000)	-0.08 (<0.000)
Total Assets (\$ Million)	160 (281)	159 (275)	125 (208)	221 (362)	140 (254)	19.00 (0.01)	-15.00 (<0.000)	81.00 (<0.000)
Size	11.36 (1.04)	11.35 (1.04)	11.18 (0.99)	11.68 (1.06)	11.23 (1.04)	0.12 (0.001)	-0.05 (0.002)	0.45 (0.001)
Equity Capital Ratio	0.11 (0.03)	0.11 (0.04)	0.11 (0.04)	0.11 (0.04)	0.11 (0.09)	0.00 (0.14)	0.00 (0.45)	0.01 (0.001)
Credit Risk	0.65 (0.11)	0.65 (0.12)	0.63 (0.11)	0.69 (0.11)	0.65 (0.03)	0.00 (0.31)	-0.02 (0.001)	0.04 (0.001)
Core Deposits	0.73 (0.09)	0.73 (0.09)	0.75 (0.08)	0.69 (0.1)	0.76 (0.09)	-0.03 (0.001)	-0.01 (0.002)	-0.07 (<0.000)

Table 2 : Two-way mean analyses

Table 2 presents the average change in percentage market shares for 25 groups of observations during the financial crises. Groups in Panel A are formed by the intersection of liquidity ratio1 (=excess cash reserve divided by total assets) and equity capital ratio (=equity capital divided by total assets). Groups in Panel B are formed by the intersection of liquidity ratio 1 and bank size (= log of total assets). p-value is reported in parentheses. Information is derived from banks' quarterly data samples, between 1985 and 2010, winsorized at 1%.

Panel A : bank average percentage change in market share in financial crises period

		Liquidity ratio Quantile				
Equity Ratio Quantile		1(Low)	2	3	4	5(High)
1(Low)		-6.71	-4.45	-3.33	-1.26	-0.82
		(<.001)	(<.001)	(<.001)	(.01)	(0.34)
2		-8.09	-6.01	-5.14	-3.12	-2.01
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
3		-8.67	-7.88	-6.53	-5.26	-3.35
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
4		-9.55	-9.18	-7.21	-6.46	-3.93
		(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
5(High)		-5.01	-6.67	-4.81	-2.98	1.90
		(0.002) **	(0.002) **	(0.004) **	(0.01)	(0.04)

Panel B: Bank average percentage change in market share in financial crisis periods

Liquidity ratio Quantile

Size Quantile	Liquidity ratio Quantile				
	1(Low)	2	3	4	5(High)
1(Low)	-5.57 ($<.001$)	-2.79 (0.006)	-2.09 (0.008)	-0.07 (0.7)	-0.05 (0.8)
2	-5.60 (0.004)	-6.19 (0.003)	-4.44 (0.003)	-3.50 (0.005)	-1.71 (0.01)
3	-6.01 (0.003)	-6.84 ($<.001$)	-5.75 ($<.001$)	-3.63 (0.004)	-2.42 (0.006)
4	-8.63 ($<.001$)	-8.97 ($<.001$)	-7.37 ($<.001$)	-5.40 ($<.001$)	-3.85 ($<.001$)
5(High)	-8.95 ($<.001$)	-8.54 ($<.001$)	-7.34 ($<.001$)	-6.26 ($<.001$)	-4.46 ($<.001$)

Table 3 : Impact of bank holding of liquidity pre-crises on market share during crises

Table 3 (Panel A and B) present the results of estimating the effect of pre-crises bank liquidity ratio on its market share (panel A) and revenue change (panel B) during crises:

%Δ Market Share_{i,t}

$$= \beta_0 + \sum_1^4 \beta_k * \text{Control Variables}_{k,i,\text{precrisis}-t} + \beta_5 \text{Financial Crises Dummy}_t \\ * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \beta_6 \text{NormalTime Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \epsilon_{it}$$

%Δ Banks Revenue_{i,t}

$$= \beta_0 + \sum_1^4 \beta_k * \text{Control Variables}_{k,i,\text{precrisis}-t} + \beta_5 \text{Financial Crises Dummy}_t \\ * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \beta_6 \text{NormalTime Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \epsilon_{it}$$

The dependent variable in Panel A is percentage change in market share, which is the market share during the crisis minus market share pre-crisis, divided by market share pre-crisis. The dependent variable in panel B is percentage change in bank revenue, which is the bank revenue during the crisis minus bank revenue pre-crisis, divided by bank revenue pre-crisis. The liquidity ratio is defined as bank excess cash divided by total assets (Bank Liquidity Ratio1). Financial Crises Dummy is one for the quarters marked in Figure 1 and Appendix 2, and zero otherwise. Normal Time Dummies are placebo financial crisis, also marked in Figure 1. Control variables, as well as treatment variables, are lagged and averaged during eight quarters prior each crisis. All variables are winsorized at level of 1% and 99%. P value (in parentheses) is reported below the coefficients. ***, **, or * indicates the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Standard errors (p-value in parentheses) are heteroscedasticity robust and clustered by firm.

Panel A

	OLS	Time Fixed Effect	Time & Firm Fixed Effect
Intercept	-10.89*** (<0.001)	1.37 (0.4308)	100.7729*** (<.0001)
Size	-1.21*** (<0.001)	0.01 (0.907)	-10.4544*** (<.0001)
Equity Ratio	70.95*** (<0.001)	44.87*** (<.0001)	84.62905*** (<.0001)
Credit Risk	27.28*** (<0.001)	26.36 (<.0001)	15.5182*** (<.0001)
Core Deposits	-12.25*** (<0.001)	-26.59*** (<.0001)	-16.3838*** (<.0001)
Normal Times * Liquidity Ratio	-2.60 (<0.001)	3.83 (0.3184)	-13.30*** (0.0002)
Crisis Times * Liquidity ratio	63.22*** (<0.001)	32.04*** (<.0001)	14.36*** (<.0001)
Firms Fixed Effect	No	No	Yes
Time Fixed Effect	No	Yes	Yes
N	30460	30184	25142
R Squares	0.08	0.13	0.49

Panel B

	OLS	Time Fixed Effect	Time & Firm Fixed Effect
Intercept	35.99 (<0.0001)	122.17 (<0.0001)	296.50 (<0.0001)
Size	-1.77 (<0.0001)	-6.63 (<0.0001)	-13.30 (<0.0001)
Equity Ratio	190.61 (<0.0001)	222.82 (<0.0001)	278.56 (<0.0001)
Credit Risk	26.55 (<0.0001)	13.41 (<0.0001)	-18.52 (<0.0001)
Core Deposits	-35.15 (<0.0001)	-44.94 (<0.0001)	-47.27 (<0.0001)
Normal Times * Liquidity Ratio	-309.05 (<0.0001)	41.68 (<0.0001)	-387.45 (<0.0001)
Crisis Times * Liquidity ratio	168.61 (<0.0001)	18.29 (.0004)	49.34 (<0.0001)
Firms Fixed Effect	No	No	Yes
Time Fixed Effect	No	Yes	Yes
N	30472	30180	25133
R Squares	0.20	0.08	0.45

Table 4: Market crises and banking crises

Table 4 demonstrates the estimates of the impact of pre-crisis levels of bank asset liquidity on its market share during the crises for banking crises, market crises, and for each banking crisis, separately.

$$\% \Delta \text{Market Share}_{i,t} = \beta_0 + \sum_1^4 \beta_k \text{Control Variables}_{k,i,\text{precrisis}-t} + \beta_5 \text{Market Crisis Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \beta_6 \text{Banking Crisis Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \beta_7 \text{Normal Time Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis}-t} + \epsilon_{it}$$

The dependent variable is percentage change in market share, which is the market share during the crisis minus market share pre-crisis, divided by market share pre-crisis. The liquidity ratio is defined as a bank's excess cash divided by total assets. Banking Crises Dummy and Market Crises Dummy are equal to 1 for the quarters marked in Figure 1, and zero otherwise. Normal Time Dummy is a placebo financial crisis, also marked in Figure 1. Control variables, as well as the treatment variables, are lagged and averaged over eight periods prior to each crisis. Model 1, presents the results of grouping all banking crises, while model 2 and 3 report the estimation of the model for the banking crisis of 1990-1992 and subprime banking crisis of 2007-2009 respectively. All variables are winsorized at the 1% and 99% level. P value (in parentheses) is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Standard errors (p-value in parentheses) are heteroscedasticity-robust and clustered by firm.

	(1): All Banking crises	(2): 1990-2	(3): 2008-9
Intercept	98.71*** (<.0001)	199.83*** (<.0001)	94.78*** (<.0001)
Size	-10.13*** (<.0001)	-13.14*** (<.0001)	-9.48*** (<.0001)
Equity Ratio	88.58*** (<.0001)	19.60** (0.0383)	61.16*** (<.0001)
Credit Risk	14.01*** (<.0001)	17.08*** (<.0001)	11.23*** (<.0001)
Core Deposits	-16.75*** (<.0001)	-19.64*** (<.0001)	-13.52*** (<.0001)
Normal Times * Liquidity	-16.75*** (<.0001)	-15.16** (0.0039)	-1.36 (0.82)
Market Crisis * Liquidity	-4.84 0.1241		
Banking Crisis * Liquidity	30.31*** (<.0001)	36.46*** (<.0001)	24.50** (<.0011)
Firms Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
N	25141	7913	8613
R Squares	0.501	0.6	0.57

Table 5: Alternative liquidity measures

Table 5 shows the estimates of regressing percentage change in bank market share on pre-crisis levels of bank liquid assets and control variables for alternative measures of liquidity:

$$\% \Delta \text{ Market Share}_{i,t} = \beta_0 + \sum_1^4 \beta_k * \text{Control Variables}_{k,i,\text{precrisis-t}} + \beta_5 \text{Financial Crises Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis-t}} + \beta_6 \text{Normal Time Dummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis-t}} + \epsilon_{it}$$

percentage change in market share is defined as total interest income divided by total assets (equity capital). To save space, I only report the results of banking crisis dummy interacting with a bank’s liquidity ratio, as well as normal crisis dummy interacting with liquidity ratio. Column 1 to 4 show the alternative measures of bank liquidity ratio as defined in 3, Eq (3), Eq (4), Eq (5), and Eq (6). Banking Crises Dummy is equal to 1 for the quarters marked in **Figure 1**, and zero otherwise. Normal Time Dummies are placebo financial crises, also marked in **Figure 1**. All variables are winsorized at the 1% and 99% level. P value (in parentheses) is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Standard errors (p-value in parentheses) are heteroscedasticity-robust and clustered by firm.

	Bank Liquidity 1	Bank Liquidity 2	Bank Liquidity 3	Bank Liquidity 4
Normal*Liquidity	-13.30*** (0.0002)	-9.3*** (<0.0001)	-8.14*** (0.0093)	-18.81 (<0.0001)
Crisis * Liquidity	14.36*** (<0.0001)	9.27*** (<0.0001)	-3.5*** (0.001)	-16.91*** (<0.0001)
N	25142	17555	17551	15551
R Square	0.49	0.55	0.56	0.56

Table 6: Different size quantile and TBTF

Table 6 shows the estimate of regressing percentage change in bank market share on pre-crisis levels of bank liquid assets and control variables for different size quantiles.

$$\begin{aligned} \% \Delta \text{Market Share}_{i,t} &= \beta_0 + \sum_1^4 \beta_k \text{Control Variables}_{k,i,\text{precrisis-t}} + \beta_5 \text{Financial CrisesDummy}_t * \text{Liquidity Ratio}_{i,\text{precrisis-t}} + \beta_6 \text{NormalTime Dummy}_t \\ &\quad * \text{Liquidity Ratio}_{i,\text{precrisis-t}} + \epsilon_{it} \end{aligned}$$

In the first column, I repeat the benchmark model (reported in Table 3, column 3), that includes winsorized samples. Column 2 includes all samples, including TBTF banks. Column 3, 4, and 5 report the estimates of the equation for small banks (less than 20% quantile), medium sized banks (20% to 80% quantile), and large banks (greater than 80% quantile), respectively. Column 6 demonstrates the results for TBTF (Too Big to Fail) banks. P value (in parentheses) is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Standard errors (p-value in parentheses) are heteroscedasticity-robust and clustered by firm.

	(1)	(2)	(3)	(4)	(5)	(6)
Normal*Liquidity	-13.30*** (0.0002)	-12.87*** (<0.0001)	-11.14*** (0.0093)	-17.81 (<0.0001)	-16.8 0.1334	1.56 (0.96)
Crisis * Liquidity	14.36*** (<0.0001)	11.45*** (<0.0001)	7.93** (0.0434)	10.91*** (<0.0001)	17.98** (0.035)	24.11 (0.45)
N	25142	27156	4852	15790	5097	221
R Square	0.49	0.49	0.51	0.50	0.4	0.38

Table 7 : Instrumental variable analysis (1)

Table 8, reports the estimation of regressing bank percentage change in market shares on bank's pre-crisis level of liquid assets using the ratio of foreign cash to total cash as an instrument for bank assets liquidity. We estimate the following model for banking crises and normal times separately,

$$Liquidity\ Ratio1_t = \alpha_1 control\ variables_t + \alpha_2 \frac{ForeignCash_t}{Total\ Cash_t} + u_t \quad (1)$$

$$\% \Delta Market\ Share_{i,t} = \beta_1 Control\ Variables_{i,precrisis-t} + \beta_2 \widehat{Liquidity\ Ratio1}_{i,precrisis-t} + \epsilon_{it} \quad (2)$$

We use the estimated liquidity ratio1 from the first stage in the second equation. The first column reports the estimation of second equation for crises period, and second column reports the estimation of second equation for the normal times. All variables are winsorized at the 1% and 99% level. P value (in parentheses) is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively.

	Crises Periods	Normal Times
Intercept	-34.89*** (<0.0001)	-21.37*** (<0.0001)
Size	-0.45* (<0.06)	-0.11 (0.55)
Equity Ratio	105.9*** (<0.001)	48.65*** (<.0001)
Credit Risk	24.48*** (<0.001)	25.20*** (<.0001)
Core Deposits	-1.48*** (<0.001)	-11.79*** (<.0001)
Bank Liquidity ratio	117.27*** (<0.001)	26.04 (0.13)
N	9665	9799
R Squares	0.084	0.064

Table 8: Instrumental analysis (2)

Table 8 provides the estimates of regressing percentage change in bank market share on pre-crisis level of bank liquid assets based on the instrumental variables constructed on heteroscedastic information, as described in Appendix 1.

$$\% \Delta \text{ Market Share}_{i,t} = \beta_0 + \sum_1^4 \beta_k \text{ Control Variables}_{k,i,\text{precrisis}-t} + \beta_5 \text{ liquidity ratio}_{i,\text{precrisis}-t} + \epsilon_{it}$$

The model is estimated by Generalized Method of Moments (GMM), using four instruments constructed on each control variable (see Appendix 1). To save space, coefficients of control variables are not reported. All variables are winsorized at the 1% and 99% level. P value (in parentheses) is reported below the coefficients. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. The J-Statistic is reported in the last row.

	Crisis Period	Normal Time
Bank Liquidity ratio	18.10*** (0.0057)	5.549599 (0.41)
N	9665	9799
Over-Identification Test Prob	0.15	0.22

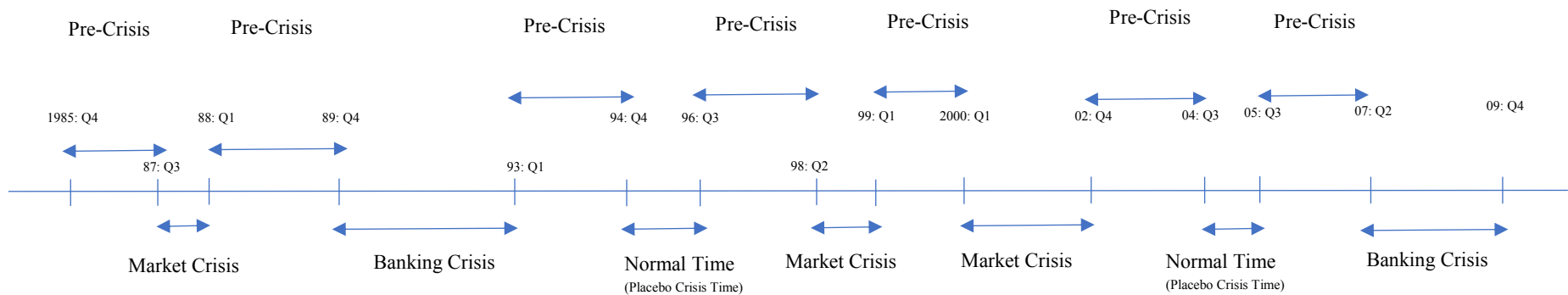


Figure 1: Timeline of analyses.

The figure shows pre-crisis, market crises, banking crises, and placebo crises for the period between 1985 and 2010. For every financial crisis, either market, banking, or placebo, eight prior quarters are identified as a pre-crisis period. To avoid overlap with the previous market crisis, I average over 5 quarters for the market crisis that starts at 2000: Q2. The independent variables, including the control variables and the main bank liquidity measures, are averaged over the pre-crisis quarters. The dependent variable, the percentage change in market share, is the percentage change in average market share during the pre-crises from average market share during the crisis periods. Two placebo financial crises are called normal times. The samples include three market crisis (1987: Q4, sharp stock market decline; 1998:Q3-1998:Q4, LTCM crisis and spillover of Russian and Asian crisis; 2000:Q2-2002:Q3, bubble tech crisis) and two banking crisis(1990:Q1-1992:Q4, credit crunch of early 1990s; 2007:Q3-2009:Q3, subprime mortgage crisis)(Berger & Bouwman, 2013).

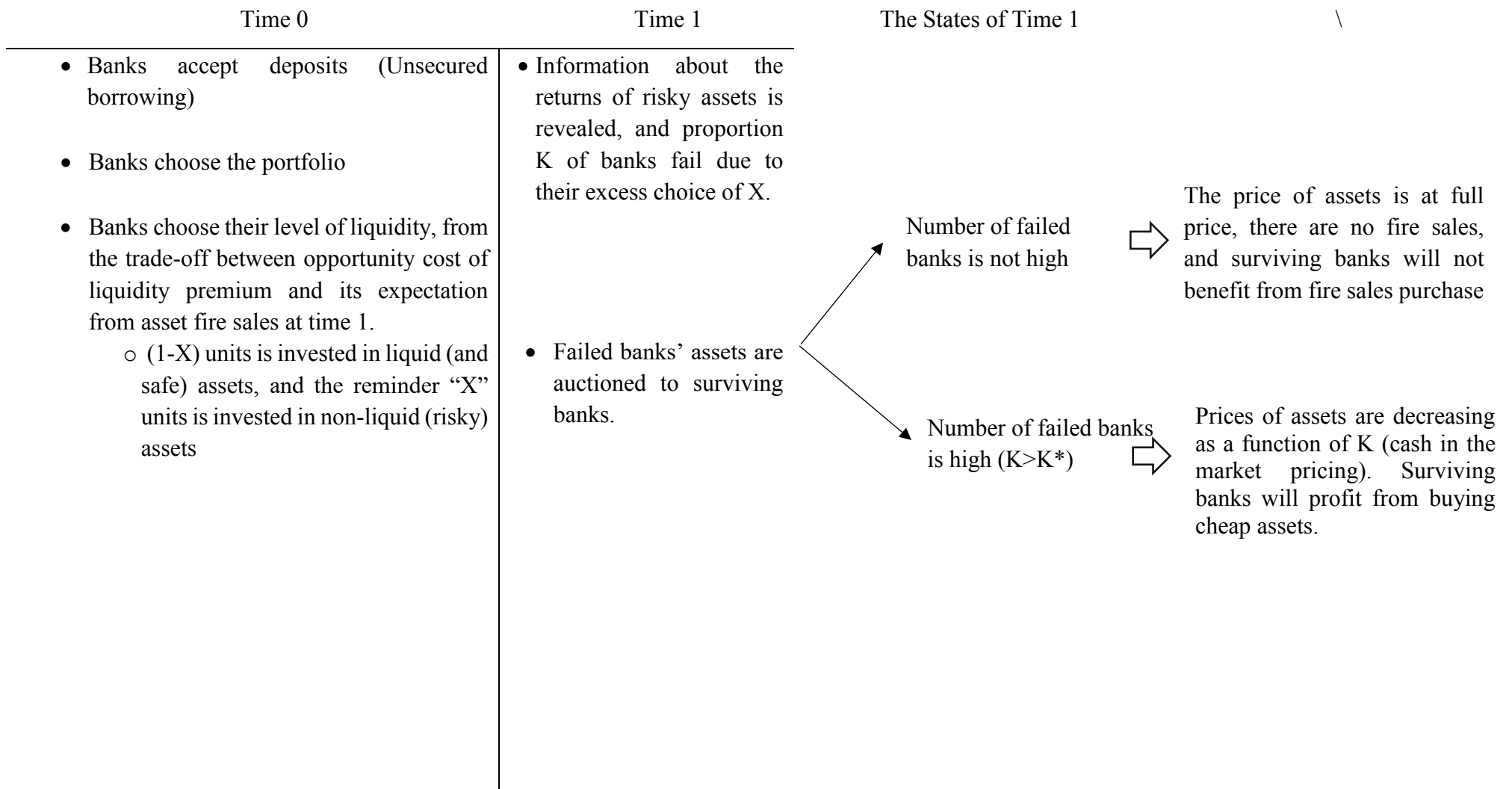
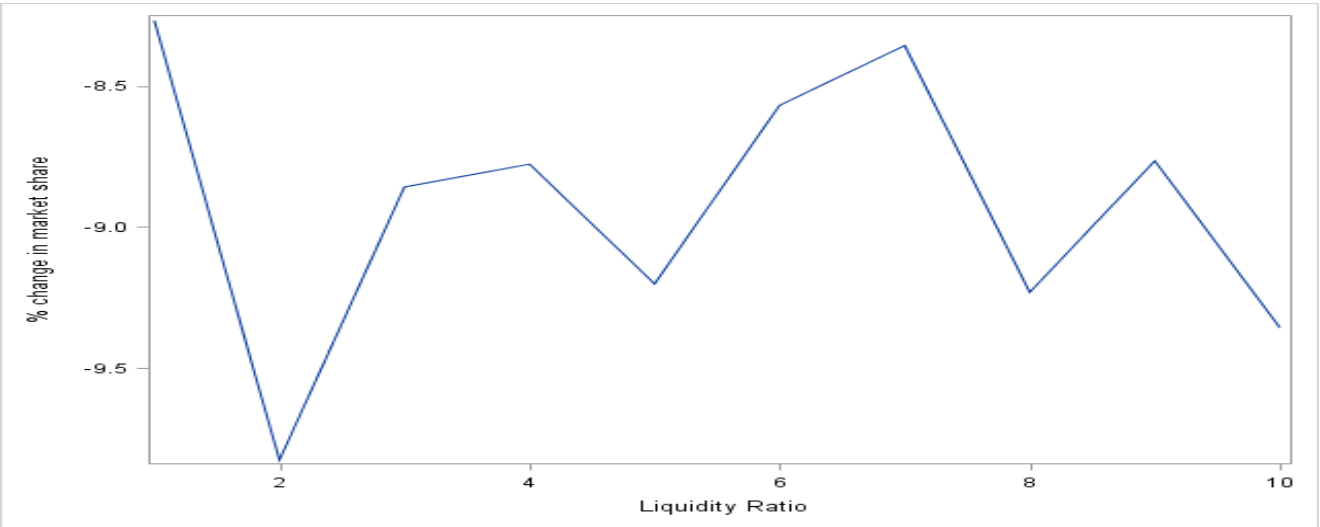
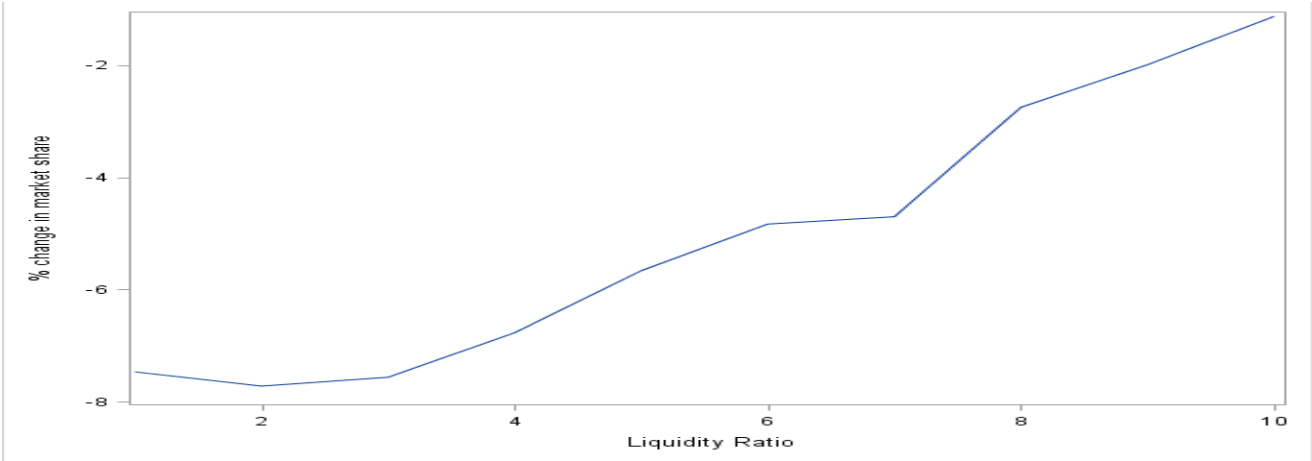


Figure 2: Theoretical Timeline of Speculative Motives of Cash Holding
 Acharya, Shin, Yorulmazer (2012)

Panel A: % change in market share vs. Liquidity Ratio1 (lagged), in normal times.



Panel B: % change in market share vs. Liquidity Ratio1 (prior crisis), in crisis times.



Panel C: % change in market share vs. Liquidity Ratio4 (prior crisis), during crises period.

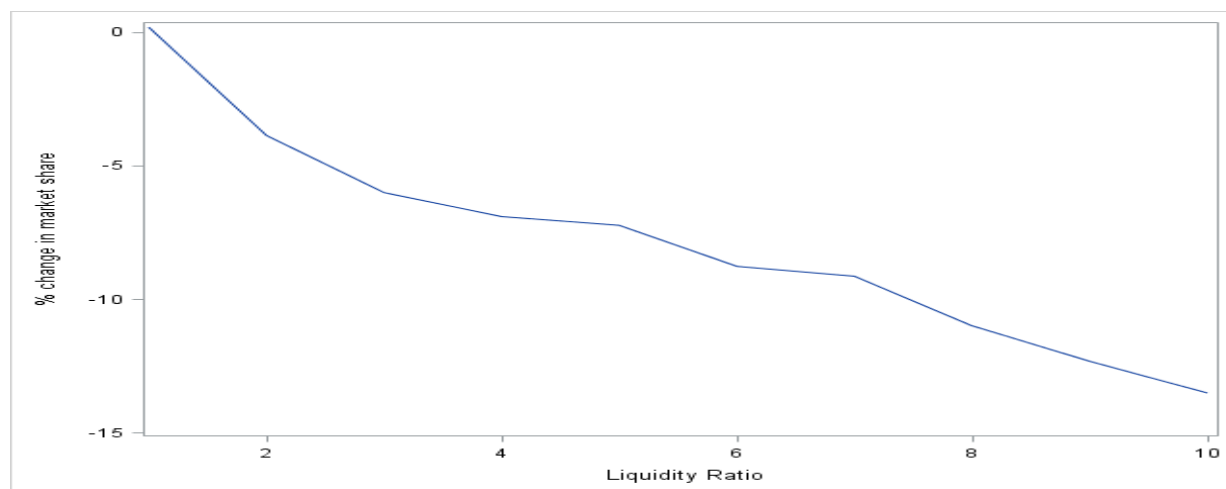


Figure 3: Percentage change of market share with bank liquidity

Figure 3 (Panel A, B, and C) presents the covariation of the average percentage change in market share with different quantiles of pre-crisis liquidity ratio in normal and crisis periods. Panel A represents the percentage change in market share against liquidity ratio 1 in normal times (placebo financial crisis). Percentage change in market share is defined by the average bank market share during the crisis minus the average bank market share over the eight quarters before the crisis divided by its pre-crisis average market share. Liquidity ratio 1, as defined by excess cash reserve scaled by total assets. Panel B presents the same measures in financial crisis periods. Panel C presents the percentage change in market share against liquidity ratio 4 in financial crisis times. Liquidity ratio 4 is defined as excess cash plus trading assets plus available for sales securities plus held until maturity securities divided by total assets.

Chapter 5

3 Conclusions and Contributions

The prevalence of financial market frictions is far from uncommon. Between 1970 and 2011, Laeven & Valencia (2012) identify 147 banking crises, along with 218 episodes of currency crisis, and 66 episodes of sovereign debt default. Thus, understanding a firm's behavior in the presence of financial crisis is an important issue for future financial research. My dissertation explores corporate payout and liquidity policy either during a financial market crisis, or in anticipation of financial market crisis.

In the first essay, "Capital Market Friction and Corporate Payout Policy", I focus on the role of supply of capital on corporate payout policy. I include a comprehensive record of capital market frictions, spanning from 1970 to 2010, and examine whether an extreme shock to, or a marginal change in, global credit conditions has any impact on a firm's choice of payouts. I find that during global credit shocks, firms that rely more heavily on credit markets to finance payouts (experiment group) are more likely to reduce their payouts, mainly through repurchase mechanisms, than firms that do not rely on credit markets. Some of the findings in this essay challenge the traditional wisdom of payout policies. For example, I find that larger firms, that are presumably more resourceful at finding credit in times of need, are comparatively more likely to reduce their payouts in response to credit shocks than smaller firms. This reveals a unique aspect of firm behavior during financial market frictions that is dissimilar to their behavior in normal times.

Conclusions and Contributions

In the second essay, “Investment Bank Exposure to Hedge Funds and Financial Contagion”, I examine the possibility of contagion between two of the most important financial sectors, namely, investment banks and hedge funds. Understanding the systemic role of hedge funds and investment banks is particularly important when we consider that the initiation of the 2007-2008 financial crisis has been mainly attributed to systemic malfunction of investment banks along with many other non-bank financial institutions. Using firm-level information from the five largest investment banks and their affiliated hedge funds, I find that while uncorrelated during normal times, the residual returns of the two sectors become excessively correlated in times of financial distress. In other words, the two sectors show signs of financial contagion. Moreover, the direction of contagion is most likely from a hedge fund to its prime brokerage, and not the other way around. The results of the analyses are of particular interest to policy makers looking to regulate the prime brokerage business of investment banks in relation to systemically important hedge funds.

In the third essay, “Bank Strategic Choice of Asset Liquidity”, I explore a bank’s optimal choice of holding liquid assets in the presence of financial market frictions. The theoretical literature suggests that the equilibrium level of bank liquid assets in normal times may be partially driven by the motive to purchase undervalued assets in fire sales (speculative motive). The essay is an empirical test of this speculative motive and focuses on the impact of pre-crisis bank choice of liquid assets on gaining market share during crises. I show that an increased level of pre-crisis liquid assets statistically and economically improves bank competitiveness during financial crises, while undermining bank competitiveness during normal times. The private motive of holding liquid assets prior crises, however, may be inconsistent with any liquidity regulations, e.g., Basel III NSFR, aiming to increase the aggregate level of liquidity in normal times; That is, the chance of making profits during crises periods lessens when all banks maintain liquid balance sheet in

Conclusions and Contributions

normal times. From this perspective, the liquidity requirement substitutes the private motive and hence, ineffectual.

Overall, the three essays in the dissertation contribute to the growing literature on financial policies that do not consider the supply of capital as completely elastic.