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Three essays on bailout banks during 2007-2009 financial crisis

Daphne Shu Nu Wang
University of Texas-Pan American

THREE ESSAYS ON BAILOUT BANKS DURING 2007-2009 FINANCIAL CRISIS

A Dissertation
by
DAPHNE SHU NU WANG

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COMMITTEE MEMBERS

Dr. Diego A. Escobari
Chair of Committee

Dr. Dave O. Jackson
Committee Member

Dr. Andre V. Mollick
Committee Member

Dr. Thanh N. Ngo
Committee Member

Dr. Surendranath Jory
Committee Member

May 2015

ABSTRACT

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In the wake of the financial crisis 2007-2009, the government injected approximately $604 billion into the financial sector to increase liquidity and improve capital base for the bailout banks, in order to restore market confidence and to prevent bank runs and possible contagion effects.

The main purpose of this dissertation is to assess the appropriateness and effects of the bailout program between 2008 and 2009. Chapter 1 introduces the causes and the effects of the recent financial crisis. Chapter 2 explains the bailout program-Capital Purchase Program (CPP) and discusses the sample selection method. There is limited empirical research focus on the bailout effects by the government as a lender of last resort. How effective the government intervention is on the banking industry becomes an ongoing open question which needs to be answered.

In Chapter 3, I find that the increased liquidity injected by the government bailout to the banking industry has reduced firm's cost of equity. I also document the moderating effect of institutional ownership on the impact of government bailout on banks' cost of equity; the reduction in cost of equity brought about with the government bailout is larger in magnitude among banks with higher institutional investor shareholding, especially for banks dominated by

domestic and grey institutional investors.

In Chapter 4, I revisit the idiosyncratic volatility (IVOL)-return puzzle using alternative measures of idiosyncratic volatility and investigate the determinants of the change in IVOL using a unique group of bailout banks. Return is positively related to the lagged realized IVOL. The findings show that the financial bailout does not deter the risk-taking behavior among banks to the fullest, especially for the banks with highest IVOL. Furthermore, I document the important role of corporate governance and information asymmetry on banks' IVOL.

In Chapter 5, I investigate how institutional ownership stability and aggregate shareholding affect bailout banks' decision on CPP bailout exit. I document that firms with better institutional ownership stability and high institutional ownership shareholding tend to pay back bailout funds in a shorter timeframe. The results are robust with control of size, non-performing loan, efficiency, profitability and capital ratio.

DEDICATION

The completion of my doctoral studies would not have been possible without the love and support of my family. I dedicate this dissertation to my family. Thank you for your unconditional love and support.

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CHAPTER I

INTRODUCTION

1.1 Recent Financial Crisis 2007-2009

The recent financial crisis of 2007-2009 is considered the worst downturn since the Great Depression. House prices depreciated by more than 30 percent; the unemployment rate surged to ten percent in October 2009[1] (or 15.382 million in labor force). At the same time, the number of bank failures hit the newest peak since 1990s; more than 400 banks failed between 2008 and 2011[2].

Several factors have been suggested by researchers and practitioners as the causes of the 2007-2009 banking crisis. The very first cause is the "too-big-to-fail" myth. It is a result of the passage of Gramm-Leach-Bliley Act (or Financial Services Modernization Act) in 1999, which repealed the Glass-Steagall (1933) and removed barriers between commercial banking and investment banking. This act completely changes the landscape for insurance activities as it allows bank holding companies to open insurance underwriting affiliates and allows insurance companies to offer commercial banking services. Many argue that this act should be responsible for the creation of several financial giants that take on more risk.

[1] Source: United States Department of Labor, Bureau of Labor Statistics at http://data.bls.gov/cgi-bin/surveymost
[2] There are 414 banks bank failed during 2008 to 2011. Source: FDIC at http://www.fdic.gov/bank/individual/failed/banklist.html

The second factor is the low interest rate introduced by Greenspan, former Federal Reserve Chairman, in response to the post September 11th recession and the collapse of the high-tech bubble. Traditionally, a bank makes profits from the interest margin between lending and deposit by issuing loans and holding them until maturity. However, the interest margin is getting thinner as the short-term interest rates have gone down to one percent, the lowest level in fifty years. Low returns on traditional investments force banks to look for ways to improve revenues. Therefore, many banks change from the traditional banking model of "originating and holding" to "originating and distributing" in which loans are pooled, trenched, and then resold through securitization. These securities, or subprime mortgage, are composed of various qualities of mortgage loans and other assets. When put together as a security, they are considered to be of investable quality by credit rating agencies. It appears to be a widespread consensus that periods of rapid credit growth tend to be accompanied by loosening lending standards. Credit-boom-and-bust-cycle theory affirms that the rise in popularity of securitized products has led to a flooding of cheap credits and lower lending standards. The quality of such mortgage is doubtful, especially subprime lenders reduced down payment or even offered mortgage with zero money down, and loosen rules about borrower' income. If the house prices kept rising, subprime loans would work out. But real estate is an industry of extreme cycles. The holders of subprime mortgage did not feel safe, so they protected their investment through credit default swap (CDS). The risk was then shifted to those who wished to bear it, and it was spread among many market participants. As real estate price fell, the default on a significant fraction of subprime mortgage produced spillover effects. In August 2007, many quantitative hedge funds suffered large losses, triggering margin calls and fire sales. Crowned trades caused high correlation across quant trading strategies. This liquidity crisis impacted the entire financial system: financial institutions failed, the stock market declined; source of equity dried up; confidence was low and there was not even an inter-banking lending until the government intervened.

In summary, the recent financial crisis resulted from loosened lending practices in the banking and mortgage industry, inappropriate regulation and supervision on CDS, and poor risk management at banks and financial institutions (Brunnermeier, 2008; Eichengreen et al., 2012; Veronesi and Zingales, 2010; Voinea and Anton, 2009).

In the wake of this financial crisis, the Congress allocated $700 billion to the financial sector in the Emergency Economic Stabilization Act of 2008 (EESA). The EESA authorizes the U.S. Department of the Treasury to establish the Troubled Asset Relief Program (TARP) to bail out the financial industry. Under the EESA section 111(b), there are strict requirements on corporate governance and executive compensation for bailout banks during bailout period. Later, the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act), was signed into law on July 21, 2010. The Dodd-Frank Act affects almost every aspect of the U.S. financial services industry. The objectives ascribed to the Dodd-Frank Act include restoring public confidence in the financial system, protecting consumers, reining in Wall Street and big bonus, ending bailouts and too-big-to-fail, and preventing another financial crisis etc.

1.2 Motivation

The main purpose of this dissertation is to assess the appropriateness and effects of the bailout program between 2008 and 2009. There is limited empirical research focus on the bailout effect by the government as a lender of last resort. How effective the government intervention is on the banking industry becomes an ongoing open question which needs to be answered.

There are three possible economic predictions on the impact of government bailout on firm's risk-taking behavior as summarized by Duchin and Sosyura (2014). First, financial bailout could be implicitly interpreted as a government protection from future financial distress, which may encourage banks' risk-taking and promote moral hazard issues. Second, government intervention will increase the value of banks by reducing the refinancing costs and the probability of bankruptcy; therefore, the bailout will reduce the risk-taking behavior of bailout banks. The last prediction asserts that the bailout will have little effect on banks' risk-taking behavior since the costs and benefits will offset each other.

For example, Brei and Gadanecz (2012) assess the soundness of government bailout programs in the G10 and four other developed countries (87 large internationally active banks) in the pre-crisis (2000-2007) and during-crisis (2008-2010) periods. They compare the lending practices (particularly on syndicated loans) between bailout banks and non-bailout banks and document that, after receiving public funds, bailout banks involve more risky lending than non-bailout banks. These findings suggest that government bailout programs do not deter banks from conducting risky lending. However, Brei and Gadanecz do not examine stock-related risk measures.

The conventional wisdom states that the "too-big-to-fail" policy encourages risk-taking behavior in larger banks. Black and Hazelwood (2013) examine the effect of TARP on bank risk-taking activities and find that the average risk of loan origination increases among large TARP-banks, but decreases among small TARP-banks. However, their sample consists only of 37 TARP-banks; therefore, it is difficult to draw a general conclusion about the government intervention effect on bailout banks. Huerta et al. (2011) study the short-term impact of TARP bailout on stock volatility and find that stock market volatility (i.e. a proxy for firm's total risk) is significantly reduced on the bailout-funding date and the day after. Unlike my focus on Capital Purchase Program (CPP) recipients' cost of equity, they emphasize on the market volatility changes for four TARP recipient groups: banking, insurance, finance and automotive industries. Duchin and Sosyura (2014) analyze the effect of government capital infusions on CPP banks and find that bailout improves the capitalization level of recipient banks, but induces their risk-taking behavior in both lending and investment.

Veronesi and Zingales (2010) investigate the costs and benefits of the U.S. government intervention plan to the ten largest banks[3] in the recent financial bailout and find that the value of banks' financial claims increases by $130 billion with a cost for tax payers of about $21 billion. Fratianni and Marchionne (2013) apply an event study methodology to estimate the value creation/destruction for 122 banks following government bailout programs in 19 countries. They identify general announcements as those associated with government intervention plans such as capital injection and asset/debt guarantees program, and specific announcements as the announcements about specific banks to receive government financial support. They find different market reactions across regions and by type of rescue announcements. General announcements tend to bring about positive cumulative abnormal returns (CARs), while specific announcements often generate negative CARs. Interestingly, Fahlenbrach et al. (2012) connect recent financial crisis with previous ones and show that a bank's stock performance during the 1998 crisis can predict its own stock performance and probability of failure in the 2008-2009 financial crisis. These findings suggest that banks' risk culture and business model make their performance sensitive to future crises.

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[3] Nine largest banks are Citigroup, Bank of America, JP Morgan Chase, Wells Fargo, Bank of NY Mellon, State Street Corp, Goldman Sachs, Morgan Stanley, and Merrill Lynch. The tenth bank is Wachovia, later is acquired by Wells Fargo.

1.3 Research Questions

There are three broad research questions I am looking at in this dissertation: How does government intervention affect (1) bailout banks' cost of equity, (2) idiosyncratic volatility, and (3) institutional ownership and how institutional ownership influences banks' decisions on bailout program exit.

I examine the cost of equity of a group of banks that received financial bailout under the Capital Purchase Program during 2008-2009. I match the sample banks with non-CPP recipient banks that have similar probability of receiving bailout funds. I aim to investigate the bailout effect on the cost of equity of my sampled financial institutions.

In the first essay of my dissertation "Impact of Government Bailout on Banks' Cost of Equity: Evidence from Financial Bailout of 2008-2009", I provide empirical evidence to the cost of equity capital literature in the presence of financial bailouts, especially from the regulated industry-banking sector. The findings show that government intervention, via liquidity-injections to the banking industry, effectively decreases firms' cost of equity. The banks that have not repay the bailout funds as of March 2013 have higher cost of equity relative to banks that repay, regardless of liquidating in one payment or in installments. I contribute to the cost of capital literature with the additional evidence of the moderating effect of institutional investors. Institutional investors are expected to monitor and discipline managers. Higher percentage of institution investor shareholding predicts better corporate governance; therefore, it should lead to lower cost of capital (Collins and Huang, 2011; Shleifer and Vishny, 1997b; Chung and Zhang, 2011). I find consistent evidence from cross-sectional regression analyses. However, institutional investors are not homogeneous. The country where they headquartered at and the monitor role they play in the firms might lead to different incentives and conflict of interests. I find that the firms dominated by foreign institutional investors command higher cost of equity, while "grey" institutional investors dominated firms have lower cost of equity. More interestingly, if the bailout firms have "*Blockholder*", then the negative impact on cost of capital from bailout can be overturn.

My findings from essay one have implications for investors and financial institutions. Investors need unbiased measures of cost of equity to evaluate the intrinsic value of firms. Implied cost of equity measure provides a comprehensive approach in mitigating the dependence on researchers-assumed growth rates and realized historical stock returns, and also correcting possible predictive errors by incorporating additional firm-level information. In particular, the institutional investors could restructure their portfolios based on the cost of equity in response to such unique financial events. Financial institutions estimate cost of equity for their capital budgeting projects and determine how the cost of equity changes depend on receiving government bailout.

The injected capital from CPP program is expected to improve liquidity and capital base for the bailout banks, so as to reduce the perceived risks associated with banks' operations. The existing literature exhibits two competing arguments on the relationship between idiosyncratic risk (IVOL) and stock return. Levy (1978), Merton (1987), Fu (2009), Goyal and Santa-Clara (2003) suggest a positive relationship between risk and return because investors expect higher rates of returns to compensate the risk of holding non-fully diversified portfolios in the presence of market friction and information asymmetry. However, others argue that it is a negative relationship, and provide some evidence of mispricing from conventional asset pricing models (Ang et al., 2006, 2009; Easley et al., 2002; Guo and Savickas, 2008; Guo and Savickas, 2010; Guo and Whitelaw, 2006). The risk-return relationship is a "substantive puzzle" as suggested by Ang et al. (2006). Particularly, there is no consensus in methodology to measure idiosyncratic risk, therefore making the documented evidence on this risk-return relationship more far from conclusive. There is especially scant empirical evidence on the effects of the bailout by the government as a lender of last resort on banks' IVOL. How this relationship evolves in the recent financial bailout event is an ongoing open question. One of the motivations of my second essay of this dissertation "Idiosyncratic Volatility in Banking Industry During 2008-2009 Financial Bailout" is to fill the gap with empirical evidence using a unique sample of financial institutions that received government bailout in the recent financial crisis to test risk-return relationship. In addition, I attempt to examine whether the idiosyncratic volatility changes at the presence of the bailout events and what the determinants of IVOL are.

The findings from essay two using Fama and MacBeth (1973) standard error regression model suggest that only the lagged realized IVOL is positively related to the return. The results are consistent with the observations by Brei and Gadanecz (2012), Black and Hazelwood (2013), and Duchin and Sosyura (2014) that financial bailout does not deter the risk-taking behavior among banks to the fullest, especially for the banks with highest IVOL. Furthermore, I document the important role played by corporate governance and information asymmetry on banks' IVOL. In this essay, I contribute to the existing literature with empirical evidence on risk-return relationship on banking industry in the presence of 2008-2009 financial bailout. In addition, the findings from this paper contribute to the existing literature on the impact of government intervention on financial market operations with findings on the bailout effects on the banking industry specifically. The findings from this paper have important implications to investors, financial institutions and regulators in their portfolio allocations, risk evaluations, and assessment of the bailout program, respectively.

The introduction of TARP and Dodd-Frank Act constitutes significant regulatory regime changes, and provides the necessary framework to explore the effects of the government intervention. Notably, while the institutional ownership has been documented to exert significant impacts on board structure, executive compensation, and financial decisions (dividend policy, mergers and acquisitions etc.), it is unclear whether or to what extent institutional ownership influences banks' decision to exit the bailout program. In the third essay of my dissertation "Institutional Ownership and Capital Purchase Program (CPP) Bailout", I address the following four research questions. First, is there any change in institutional ownership stability and their aggregate shareholding during the recent financial bailout? Second, does institutional ownership pose any impact on banks' decision on CPP exit? Third, does the impact differ between high and low institutional investors stability banks given control of institutional investor shareholding? Last, does the impact differ between high and low institutional investor shareholdings given control for institutional investor stability?

Using two measures of institutional ownership, I examine the relationship between institutional ownership and bailout banks' decision on CPP exit. I document that firms with more institutional ownership stability and high institutional ownership shareholding tend to pay back bailout funds in shorter timeframe. The results are robust with controls for bank size, non-performing loan, efficiency, profitability and capital ratio. On the other hand, banks with lower institutional ownership shareholding and less stable institutional ownership take longer time to repay CPP funds. I also observe that high percentage of aggregate institutional shareholding in a bank is the key determinant to forecast the timing of repaying the CPP funds, regardless of the stability of institutional ownership. The findings from this paper add to the existing literature as evidence of market discipline of corporate governance-institutional ownership on banks' decision on bailout exit.

The remainder of this dissertation is organized as follows. Chapter 2 reviews government bailout programs in the recent financial crisis and explains the sample selection method. Chapter 3 explores the cost of equity capital and determinants of change in the cost of equity capital. Chapter 4 investigates the idiosyncratic risk puzzle and determinants of the change in idiosyncratic risk. Chapter 5 examines how institutional ownership stability and aggregate shareholding affect banks' decision on bailout exit during the recent financial bailout 2008-2009 and concludes the dissertation.

CHAPTER II

CAPITAL PURCHASE PROGRAM (CPP) AND SAMPLE SELECTION

2.1 Capital Purchase Program (CPP)

To ease the liquidity crisis and possible contagion effects, Congress allocated $700 billion to the financial sector with the Emergency Economic Stabilization Act of 2008 (EESA). EESA authorized the U.S. Department of the Treasury to establish the Troubled Asset Relief Program (TARP) to bail out the financial industry. In July 2010, the financial regulation overhaul reduced TARP to $475 billion. Most banks received their money through the Capital Purchase Program (CPP, or health bank program), the largest one among thirteen programs created under TARP. About $204.9 billion (or 43.93 percent of TARP) were actually invested into 707 banks from October 2008 through November 2009, as shown in Table 2.1.

[Insert Table 2.1 about here]

As for the terms of CPP, the Treasury purchases preferred shares in the banks with a five percent annual dividend or nine percent after five years. The Treasury also receives warrants to purchase stocks at pre-determined strike prices. The CPP places restrictions on banks' activities (e.g. hiring in foreign workers, dividend payments, repurchases, related party transactions, and executive compensation) but not on banks' off-balance activities. It has been argued that banks have taken advantages of the government's "funding for lending" initiatives to buy back billions of dollars in senior debts with cheap funds and to re-issue lower interest bonds with the intention of maximizing their net interest margin by cutting interest expenses.

As of October 2012, there were $191.9 billion out of the $204.9 billion actually injected through preferred stocks purchase or stock warrants (U.S. Department of The Treasury, October, 2012) (U.S. Department of Treasury, 2010). Citigroup, JP Morgan Chase, and Wells Fargo received the largest investment ($25 billion) among CPP recipients, and The Freeport State Bank (Harper, KS) received the smallest investment of $301,000. The government has received a cumulative revenue of $11.9 billion from dividends, interests, and fees.

As for the remaining unpaid CPP investment, the government offers banks alternative options to repay it. The government can exchange its preferred stock for mandatorily convertible preferred stock (MCP) with capitalized dividends, or convert its preferred stocks into common stocks, or force the issuers to repurchase the stocks back. According to the most recent Treasury Monthly Report in March 2013, CPP recipients have repaid $199.79 billion out of the $204.89 billion in one lump-sum payment or 2-4 installments through self-generated capital, or refinanced capital through the Small Business Lending Fund (SBLF, a new funding program but not a TARP program), or capital repayment (i.e. Citigroup converts preferred shares to common stock in Sept. 2009), or share repurchase (i.e. Citizens First Corporation and Valley Financial Corporation).

2.2 Sample Selection

2.2.1 Sample Banks

The sample period extends from January 2003 to March 2013. There are 959 financial institutions receiving government funding under the Emergency Economic Stabilization Act (2008). In this paper, I only focus on publicly listed banks that received funds through the CPP between October 2008 and November 2009. The initial sample includes 959 CPP recipients listed in the U.S. Treasury financial stability reports[4]. I cross- examine reports from ProcPublica[5], Wall Street Journal[6], CNN[7] and New York Times[8], and I remove two non-TARP recipients, Fannie Mae and Freddie Mac since they received fund through the Preferred Stock Investment program. Then I exclude 125 mortgage service companies under the Making Home Affordable program, 74 community development companies[9] under the Community Development Capital Initiative program, 4 auto companies under the Automotive Industry Financing Program, 2 auto parts suppliers under the Auto Supplier Support Program, 9 public-private investment fund companies, and 19 state house organizations. AIG is also removed since its main business is insurance. Similarly, banks participating in the FHA refinance program fund and SBA are excluded. The Bank of America and Citigroup receive funds from both the Target Investment Program and Capital Purchase Program; I keep them in the sample and consider only

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[4]http://www.treasury.gov/initiatives/financial-stability/reports/pages/default.aspxaccessed during August 2012-March 2013

[5] http://projects.propublica.org/bailout/list/simple accessed during August-October, 2012

[6] http://blogs.wsj.com/deals/2012/07/20/tarp-banks-the-remaining-322-banks-holding-bailout-funds/ accessed during August-October, 2012

[7] http://money.cnn.com/news/specials/storysupplement/bankbailout/ accessed during August-October, 2012

[8] http://www.nytimes.com/packages/html/national/200904_CREDITCRISIS/recipients.html accessed during August-October, 2012

[9] There are 84 recipients under Community Development Capital Initiative, but the data from ProPublica only shows 74 companies.

the funds they received from the CPP for data analysis. After the above screenings, the sample includes 259 banks.

Panel A of Table 2.2 and Figures 2.1-2.3 report the sample distribution by various characteristics. The majority of the sample CPP banks list their stocks on NASDAQ (84.14%). Most publicly-traded bank receiving CPP funds cluster in six states: California, North Carolina, Pennsylvania, Virginia, New York, and Ohio. More than half of the sample CPP banks (63 percent) have repaid the full funding amount to the government, and approximately 18.5 percent of sample CPP banks have repaid with installments as of March 2013.

Based on the "Troubled Asset Relief Progress (TARP) Monthly Report to Congress"[10], the disbursement and repayment amount from the sample CPP banks represent 70.78 percent of the total CPP disbursed funds and 68.64 percent of total CPP repayment, respectively, as shown in Panel B of Table 2.2. The last column of Panel B reports the average repayment days for three CPP subgroups[11]. The full- repayment group repays the CPP funds about half-year earlier (752 days or about 2.06 years) than the partial-repayment group (968 days or about 2.65 years), while the no-repayment group has not repaid any money for more than four years (or 1,510 days) after receiving government bailout.

[Insert Table 2.2 about here]

[Insert Figures 2.1-2.3 about here]

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[10] Repayment and total disbursement source: Troubled Asset Relief Progress (TARP) Monthly Report to Congress - February 2013 at http://www.treasury.gov/initiatives/financial-stability/reports/Documents/February%202013%20Monthly%20Report%20to%20Congress.pdf_(Accessed: March 2013)

[11] Group 1 is the group without any repayment as March 1 2013; Group 2 is the group making repayments through installments; Group 3 is the group paying back the full payments in one time. For comparison purpose, I assume that Group1 repays the loans at the end of February, 2013.

2.2.2 Matching Banks

I use the propensity score matching technique to identify matching banks. The propensity score matching method is widely used in the literature to estimate treatment effects (Heckman et al., 1998; Hirano et al., 2003; Li and Zhao, 2006; Rosenbaum and Rubin, 1983, 1985). Rosenbaum and Rubin (1983) define the propensity score as the conditional probability of an assignment to a particular treatment given a vector of observed covariates. If the conditional probability of an assignment to the treatment is exogenous or non-confounding, then adjustment for the propensity score is sufficient to remove all biases. Traditional matching technique using similar ex-ante characteristics may not yield good matches because it cannot match several characteristics simultaneously on multiple dimensions as in propensity matching score method.

In this paper, matching firms must be publicly listed banks that have never received CPP funding, but have as high probability to participate in the program as sample banks. In order to be qualified for entering the matching pool, potential matching banks s must have data available in Compustat and are in the same banking sector (SIC codes from 6000 to 6399). The choice of appropriate conditioning variables in equation (2.1) is guided by theory and prior research (Li and Zhao, 2006). Using data from the year preceding the bailout year, I calculate a predicted value of *Return on Assets* (*ROA)* (i.e., a propensity score) from the following regression for the CPP banks. *ROA* is computed as net income divided by total assets. *MKTCAP* is logarithm value of market capitalization. *DEBT RATIO (DEBT)* is the ratio of total liabilities to total assets. *MARKET-TO-BOOK (MKBK)* is the ratio of market price to book price. All the variables in equation (2.1) are adjusted by industry-median, ε_i is regression residual.

$$ROA_i = \alpha + \beta_1 MKTCAP_i + \beta_2 DEBT_i + \beta_3 MKBK_i + \varepsilon_i \qquad (2.1)$$

The above regression specification is estimated using all sample banks and matching pool of non-CPP banks in the same year. The final matching banks are the ones that are not CPP recipients and have the propensity scores closest to CPP banks. The final sample size is 227 pairs of CPP-matching banks.

Table 2.3 depicts the characteristics of the sample banks and their matching banks using Compustat data in the year preceding and following the bailout event. *Net Interest Margin* (*NIM*), the ratio of net interest income to total assets, is one of primary measures of bank profitability. A reasonable range for *NIM* is 3% to 5%. The results show that both CPP and matching banks fall short in earnings performance before bailout with mean *NIM* values of 2.3% and 2.5% respectively. The situation improves with bailout as the mean *NIM* values for CPP banks have increased to 2.5%, but are still below reasonable level. *Efficiency Ratio* (*ER)*, the ratio of non-interest expense to total income, is a proxy for the cost structure and operation efficiency. The mean *ER* value for CPP banks in pre-bailout period is 62.9%, which is lower than that of matched banks (63.7%). In later analyses, I find that CPP banks catch up with matched banks in *ER* post bailout.

Return on Average Assets (*ROAA*) represents a total picture of profitability and is computed as the ratio of net income to average total assets. Both CPP banks and matching banks have near-zero mean *ROAA* values in pre-bailout period (0.3%), and profitability further drops upon the bailout implementation (0.2%). Capital is the core measure of financial strength for banks, as high ratio and thus good quality of capital could protect banks from unexpected losses especially in financial crisis. *Tier 1 risk-adjusted capital ratio* (*Tier 1 Capital*) measures the amount of core equity (i.e. common stock, retained earnings, and non-redeemable preferred stock) available as a percentage of total risk-adjusted assets. Both CPP banks and matching banks maintain *Tier 1 Capital* above the existing or proposed requirements by the Federal Reserve (i.e. 4% or 6%), regardless in pre- or post-bailout period. Notably, both groups have significant increases in *Tier 1 Capital* after bailout[12].

Equity to assets (*EOA*) is another measure for capital level. It is the ratio of the total tangible equity (including preferred stock) to the total tangible assets, which indicates the percentage of shareholders' equity a bank holds in proportion to its total assets. CPP banks uphold a steady *EOA* ratio within the range of 6.9% to 7.6%, and matching banks have even stronger positions with mean *EOA* values within the range of 7.4% to 9.6% in pre- and post-bailout periods. *Tobin's Q* is a proxy for firm value. It is measured as sum of book value of assets and market value of common equity minus book value of common equity, divided by book value of assets. Financial bailout imposes a negative impact on firm value for CPP banks, as the decrease in *Tobin's Q* is more pronounced in CPP banks than in matching banks. Tests in mean and median differences are the Satterthwaite method and Wilcoxon signed-rank method assuming variances are unequal.

[Insert Table 2.3 about here]

[12] This is different from the finding in Duchin and Sosyura (2014), in which they find the increase of capitalization level apply for bailout banks only.

Table 2.1-Recent Financial Bailout: Emergency Economic Stabilization Act (2008)

Program	**Promised (in Billion)**	**Percent**	**Actually invested (in Billion)**	**Number of Recipients**	**Memo**
Preferred Stock Investment (Unlimited)	187.5		187.5	2	Fannie Mae and Freddie Mac Bailout
TARP					
Capital Purchase Program	**204.900**	**43.93%**	**204.900**	**707**	**The 'Healthy Bank' Program**
Automotive Industry Financing Program	81.300	17.43%	79.300	4	Loan to the auto industry
Systemically Significant Failing Institutions	69.800	14.96%	67.800	1	Money for AIG
Targeted Investment Program	40.000	8.58%	40.000	2	More money for BofA and Citigroup
Making Home Affordable	29.900	6.41%	3.600	125	The mortgage loan modification plan
Public-Private Investment Program	21.900	4.69%	18.400	9	Public-Private Toxic Asset Purchases
FHA Refinance Program	8.100	1.74%	0.050	1	Refinancing underwater mortgage
Housing Finance Agency Innovation Fund	7.600	1.63%	1.100	19	Money for states hit hardest by crisis
Term Asset-Backed Securities Loan Facility	1.400	0.30%	0.000	0	Fed program to spur lending
Community Development Capital Initiative	0.783	0.17%	0.570	84	Cheap loans for community develop banks
Auto Supplier Support Program	0.413	0.09%	0.413	2	Financing for Auto parts suppliers
Small Business and Community Lending Initiative	0.368	0.08%	0.368	1	Program to ease small biz credit market
Asset Guarantee Program	0.000	0.00%	0.000	2	Limiting losses for Citi and BofA
Subtotal Total	466.464	100.00%	416.501	959	
Grand Total	653.964		604.001		

Source: Department of Treasury/ Troubled Asset Relief Progress (TARP) Monthly Report to Congress-February 2013 at http://www.treasury.gov/initiatives/financialstability/reports/Documents/February%202013%20Monthly%20Report%20to%20Congress.pdf (Accessed: Oct., 2012-March 2013). BofA is Bank of American. Bank of America and Citigroup receive funds from both the Target Investment Program and Capital Purchase Program.

Table 2.2-Sample Distribution

Panel A. by Exchange, Repayment status and State

	N	%	State	N	%	State	N	%
Exchange-NYSE	27	11.894	Alabama	3	1.170	North Carolina	16	6.610
AMEX	9	3.965	Arkansas	3	1.170	New Hampshire	1	0.390
Nasdaq	191	84.141	California	21	9.340	New Jersey	10	4.670
Total	**227**	**100.000**	Colorado	1	0.390	New York	15	5.840
			Connecticut	3	1.560	Ohio	13	5.450
			Delaware	1	1.170	Oklahoma	1	0.390
			Florida	5	1.950	Oregon	1	0.780
			Georgia	5	2.330	Pennsylvania	16	6.610
Subgroup(repayment)			Hawaii	1	0.390	Puerto Rico	2	0.780
1. No repayment	42	18.502	Iowa	3	1.560	Rhode Island	1	0.390
2. Partial Repayment	42	18.502	Illinois	12	5.060	South Carolina	6	2.330
3. Full repayment	143	62.996	Indiana	9	3.500	South Dakota	1	0.390
Total	**227**	**100.000**	Kentucky	4	1.950	Tennessee	5	1.950
			Louisiana	2	1.170	Texas	5	1.950
			Massachusetts	6	3.110	Virginia	13	6.610
			Maryland	10	3.890	Washington	6	3.110
			Maine	2	1.170	Wisconsin	3	1.170
			Michigan	7	3.110	West Virginia	1	0.780
			Minnesota	3	1.170			
			Missouri	7	2.720			
			Mississippi	3	1.170	**Total**	**227**	**100.000**

(Continued)

(Table 2.2-Continued)

Panel B.

			Disbursed (in millions)					Returned (in millions)			Payback (in days)
Subsample	N	%	Amount $	%	Mean Amount $	Maximum $	Minimum $	Amount $	%	Mean Amount $	Mean
No Repayment	42	18.502%	4482.400	2.188%	106.72	967.870	5.800	NA	NA	NA	1510
Partial Repayment	42	18.502%	3574.479	1.744%	85.11	600.000	4.000	3379.6	1.692%	80.467	968
Full Repayment	143	62.996%	136979.531	66.852%	957.90	25000.000	4.227	133745.532	66.943%	935.283	752
Subtotal	**227**	**100.000%**	**145036.410**	**70.784%**	**638.93**	**25000.000**	**4.000**	**137125.132**	**68.635%**	**604.075**	
Total	**707**	**100.000%**	**204900.000**		**289.82**	**25000.000**	**0.301**	**199790**	**100.00%**		

The sample includes 227 publicly listed banks that received funds through Capital Purchase Program (CPP) between October 2008 and November 2009.

Different Repayment groups are categorized based on repayment status: 1. *No Repayment* (the group without any repayment as March 1, 2013); 2. *Partial Repayment* (the group making repayments through installments); 3. *Full Repayment* (the group paying back the full payments). *Total* row reports the results from whole CPP program under the TARP, while *Subtotal* row reports the results from the sample banks in this paper. Payback (in days) is the difference in days between disbursed dates to the first repayment date. For comparison purpose, I assume the repayment date for the group is Feb. 28, 2013. Repayment and total disbursement source: Troubled Asset Relief Progress (TARP) Monthly Report to Congress-February 2013 at http://www.treasury.gov/initiatives/financial-stability/reports/Documents/February%202013%20Monthly%20Report%20to%20Congress.pdf (Accessed: March 2013)

Table 2.3--Sample Descriptive Statistics

Panel A-CPP Banks

	Pre-Bailout Period				Post-Bailout Period				Pre- vs. Post-Bailout			
	N	Mean	Median	Std Dev	N	Mean	Median	Std Dev	Mean Difference	(t-statistics)	Median Difference	(Wilcoxon)
SIZE	1024	8.137	7.910	1.456	735	8.457	8.112	1.529	0.320	4.409***	0.203	4.744***
NIM	1024	0.023	0.020	0.016	735	0.025	0.022	0.018	0.002	2.267**	0.001	1.725*
ER	1024	0.629	0.629	0.087	735	0.640	0.640	0.090	0.011	2.572**	0.011	2.192**
ROAA	1024	0.003	0.002	0.002	735	0.002	0.002	0.002	-0.001	-10.779***	-0.001	-14.180***
Tier 1 Capital	1024	10.510	10.275	1.949	735	12.067	12.010	2.492	1.557	14.118***	1.735	13.512***
EOA	1024	0.069	0.071	0.031	735	0.076	0.082	0.031	0.007	4.820***	0.011	8.311***
Tobin's Q	1024	1.062	1.059	0.046	735	0.993	0.991	0.037	-0.069	-34.764***	-0.068	-26.937***

Panel B-Matching Banks

	Pre-Bailout Period				Post-Bailout Period				Pre- vs. Post-Bailout			
	N	Mean	Median	Std Dev	N	Mean	Median	Std Dev	Mean Difference	(t-statistics)	Median Difference	(Wilcoxon)
SIZE	138	7.622	7.334	0.930	73	7.623	7.376	0.783	0.001	0.005	0.042	0.471
NIM	138	0.025	0.022	0.022	73	0.023	0.019	0.013	-0.003	-1.056	-0.002	-0.331
ER	138	0.637	0.628	0.087	73	0.640	0.642	0.064	0.003	0.274	0.015	0.167
ROAA	138	0.003	0.002	0.003	73	0.002	0.002	0.001	-0.001	-2.780***	0.000	3.649***
Tier 1 Capital	138	11.355	10.500	3.384	73	13.728	13.870	4.359	2.372	4.049***	3.370	3.583***
EOA	138	0.074	0.071	0.038	73	0.096	0.092	0.044	0.022	3.628***	0.020	6.190***
Tobin's Q	138	1.073	1.062	0.060	73	1.008	1.003	0.033	-0.065	-10.107***	-0.059	-7.808***

This table reports sample statistical characteristics of CPP banks (as in Panel A) and matching banks (as in Panel B) seven years around bailout dated (-3, +3) and pre- vs. post-bailout difference. CPP banks are the sample banks that received funds from Capital Purchase Program under the TARP. Matching banks are the non-CPP banks, based on industry-adjusted median *ROA*, *MKTCAP*, *DEBT*, and *MKBK* as shown in equation (2.1). There are 227 pairs of banks are successfully matched. *SIZE* is log value of total assets, where total assets is average total assets from previous five quarters. *NIM* is the ratio of net interest income to total assets. *ER* is the ratio of non-interest expense to total income. *ROAA* is the ratio of net income to average assets. *Tier 1 Capital* is risk-adjusted tier 1 capital ratio which is the ratio of bank's core equity to its total risk-weighted assets. *EOA* is the ratio of tangible equity to tangible assets. *Tobin's Q* is proxy for firm value and it is sum of book value of assets and market value of common equity minus book value of common equity, divided by book value of assets. Tests in mean and median difference are the Satterthwaite method and Wilcoxon signed-rank method assuming variances are unequal. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 2.1-Sample CPP Banks-Exchanges Distribution

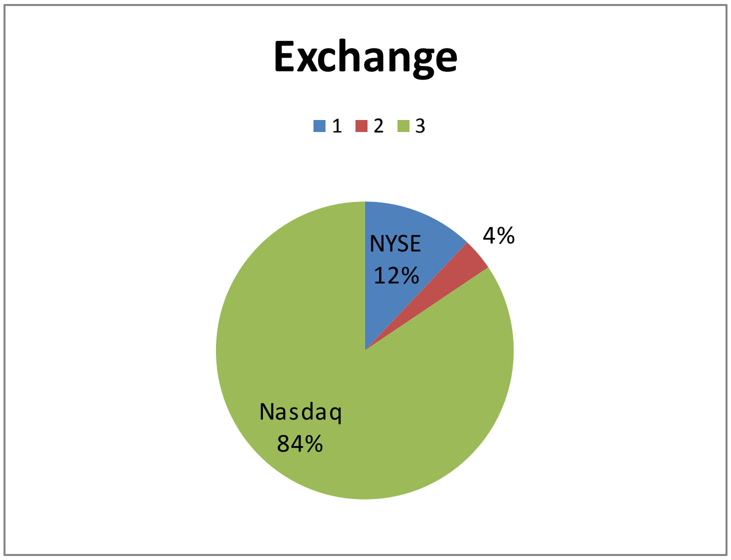


Figure 2.2-Sample CPP Banks-Repayment

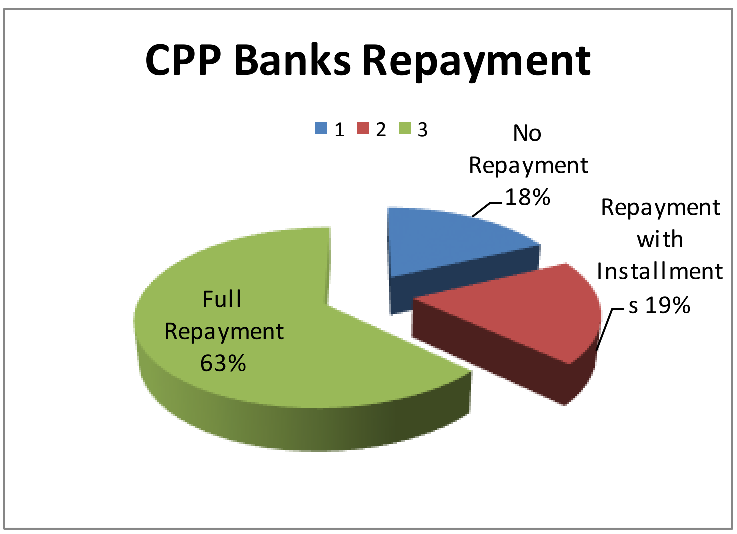
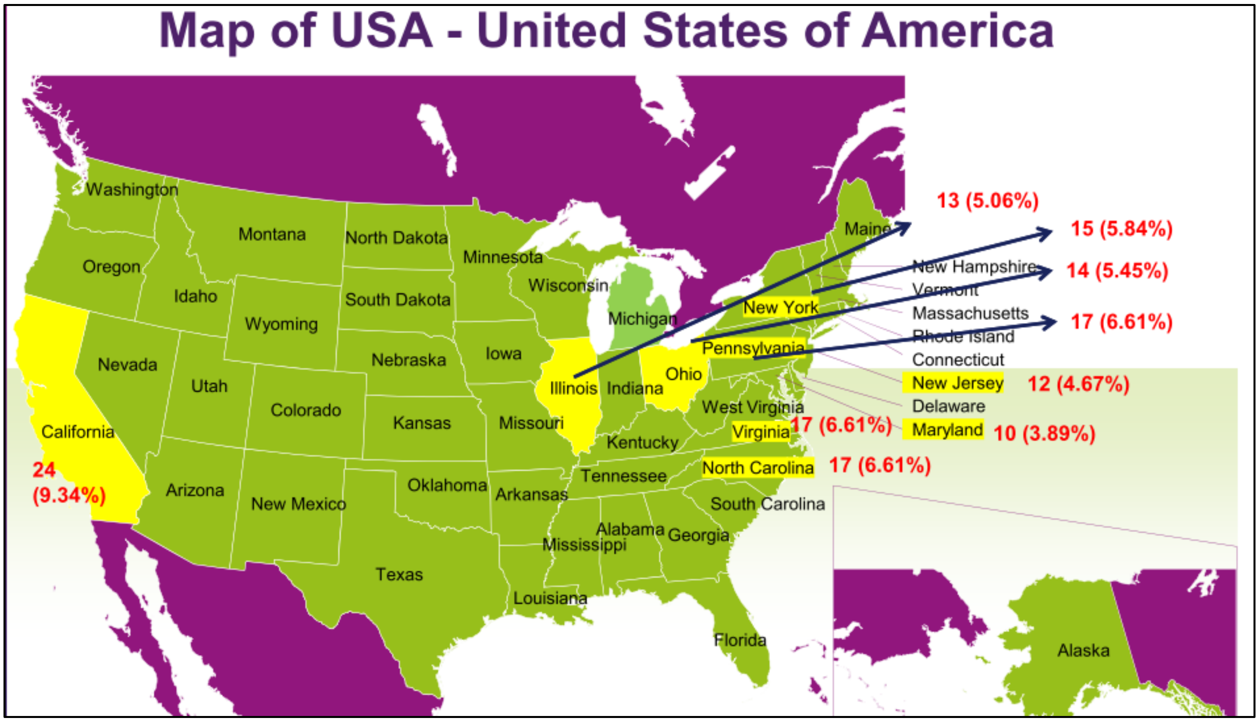


Figure 2.3 Cluster Map for Public-listed Sample CPP Banks



This Figure highlights the clusters of CPP banks in the U.S. (i.e. the number of public-listed CPP banks in that state is more than 10).

CHAPTER III

IMPACT OF GOVERNMENT BAILOUT ON BANKS' COST OF EQUITY: EVIDENCE FROM THE FINANCIAL BAILOUT OF 2008-2009

3.1 Introduction

Following the recent financial crisis and stock market crash of 2008 (and subsequent government stimuli to the economy), a number of academicians have focused their attention to the effect of government bailouts on the recipient banks with regard to the stock market reaction (Fahlenbrach et al., 2012; Fratianni and Marchionne, 2013), market volatility (Huerta et al., 2011), risk-taking behavior (Aebi et al., 2012; Bedendo and Bruno, 2012; Berger et al., 2014; Black and Hazelwood, 2013; Brei and Gadanecz, 2012; Duchin and Sosyura, 2014; Ellul and Yerramilli, 2013; Varotto, 2012), dividend policy (Acharya et al., 2011; Kanas, 2013), and executive compensation (Cornett et al., 2013; Fahlenbrach and Stulz, 2011). However, the impact of the government bailout campaign on the cost of equity (COE)[13] of banks is largely neglected. To fill this gap, I investigate how the government intervention in the recent financial bailout, specifically the Capital Purchase Program (CPP), the largest and the most important program under the Troubled Asset Relief Program (TARP) during 2008-2009, affects the cost of equity of 227 publicly-traded banks in comparison to their matched non-bailout-banks.

[13] Cost of capital (COC) consists of three components: cost of equity (COE), cost of debt, and cost of preferred stock. In this paper, I only focus on COE.

Cost of equity (COE) is the discount rate applied to the expected cash flows to derive the intrinsic value of the firm. Investors require a precise estimate of the COE for equity valuation. While various measurements have commonly been used in the literature, there is no consensus on which one is superior. The first approach to derive the discount rate is referred to as the expected COE, which employs the ex-post stock returns in a capital asset pricing model (CAPM), Fama-French three-factor model or four-factor model frameworks (e.g. Grullon and Michaely (2004) and Baran and Dolly King (2012)). The CFO quarterly survey (from June 2000 to March 2012) shows that about 75 percent of CFOs use the CAPM model to estimate the cost of equity for their capital budgeting activities (Graham and Harvey, 2012). However, Fama and French (1997), Claus and Thomas (2001), Gebhardt et al. (2001) and Dhaliwal et al. (2005) suggest that using historical returns to estimate expected returns may result in imprecise risk estimates given the time-varying nature of risk. Gebhardt et al. (2001), Ohlson and Juettner-Nauroth (2005), and Easton (2004) suggest the second approach to estimate cost of equity which incorporates additional firm-level information such as market value, book value, analysts earnings forecasts, and dividend ratio. This approach is referred to as the implied COE approach.

Using three alternative robust measures of expected and implied COE, I examine the changes in the COE of 227 publicly-traded banks upon their receipt of funds from the CPP, the largest one and the most important program under TARP during the 2008-2009 period. I observe significant decreases in the cost of equity of these banks around the bailout. The findings have important implications for the assessment of government bailout program, and investment management practices such as portfolio allocation. In addition, I document the moderating effect of institutional investors, an important corporate governance mechanism, on the bailout impact on the COE. Consistent with prior literature, I find that higher institutional investor shareholding leads to reduced COE, especially for firms dominated by domestic and grey institutional investors.

This study contributes to the literature in the following ways. First, I provide empirical evidence on the bailout effects by employing sophisticated and comprehensive measures on the COE. The findings show that government intervention, via liquidity-injection to the banking industry, has a significant impact on reducing banks' cost of equity. Second, I provide evidence from the banking industry on the relation between institutional investor ownership and the cost of equity with additional consideration on institutional investor heterogeneity. The findings have important implications for the assessment of government bailout program and for investment management practices such as portfolio allocation.

This essay proceeds as follows. In Section 3.2, I review the extant literature and develop the testable hypotheses. Section 3.3 describes the data and methodology. I present the empirical findings in Section 3.4. I summarize and conclude in Section 3.5.

3.2 Literature Review and Hypotheses Development

3.2.1 Bailout Effects from Government Intervention

There are three possible economic predictions on the impact of government bailout on firm's risk-taking behavior as summarized by Duchin and Sosyura (2014). First, financial bailout could be implicitly interpreted as a government protection from future financial distress, which may encourage banks' risk-taking and promote moral hazard issues. Second, government intervention will increase the value of banks by reducing the refinancing costs and the probability of bankruptcy; therefore, the bailout will reduce the risk-taking behavior of bailout banks. The last prediction asserts that the bailout will have little effect on banks' risk-taking behavior since the costs and benefits will offset each other.

For example, Brei and Gadanecz (2012) assess the soundness of government bailout programs in the G10 and four other developed countries (87 large internationally active banks) in the pre-crisis (2000-2007) and during-crisis (2008-2010) periods. They compare the lending practices (particularly on syndicated loans) between bailout banks and non-bailout banks and document that, after receiving public funds, bailout banks involve more risky lending than non-bailout banks. These findings suggest that government bailout programs do not deter banks from conducting risky lending. However, Brei and Gadanecz do not examine stock-related risk measures.

The conventional wisdom states that the "too-big-to-fail" policy encourages risk-taking behavior in larger banks. Black and Hazelwood (2013) examine the effect of TARP on bank risk-taking activities and find that the average risk of loan origination increases among large TARP-banks, but decreases among small TARP-banks. However, their sample consists only of 37 TARP-banks; therefore, it is difficult to draw a general conclusion about the government intervention effect on bailout banks. Huerta et al. (2011) study the short-term impact of TARP bailout on stock volatility and find that stock market volatility (i.e. a proxy for firm's total risk) is significantly reduced on the bailout-funding date and the day after. Unlike my focus on CPP recipients' COE, they emphasize the market volatility changes for four TARP recipient groups: banking, insurance, finance and automotive industries. Duchin and Sosyura (2014) analyze the effect of government capital infusions on CPP banks and find that recipient banks improve their capitalization level while at the same time increasing their risk-taking behavior in both lending and investment.

Veronesi and Zingales (2010) investigate the costs and benefits of the U.S. government intervention plan to the ten largest banks[14] in the recent financial bailout and find that the value of banks' financial claims increases by $130 billion with a cost for tax payers of about $21 billion. Fratianni and Marchionne (2013) apply an event study methodology to estimate the value creation/destruction for 122 banks following government bailout programs in 19 countries. They identify general announcements as those associated with government intervention plans such as capital injection and asset/debt guarantees program, and specific announcements as the announcements about specific banks to receive government financial support. They find different market reactions across regions and by type of rescue announcements. General announcements tend to bring about positive cumulative abnormal returns (CARs), while specific announcements often generate negative CARs. Interestingly, Fahlenbrach et al. (2012) connect recent financial crisis with previous ones and show that a bank's stock performance during the 1998 crisis can predict its own stock performance and probability of failure in the 2008-2009 financial crisis. These findings suggest that banks' risk culture and business model make its performance sensitive to future crises.

3.2.2 Theories on Factors that Affect Cost of Equity

3.2.2.1 Capital structure theorem and corporate taxes. Classical capital structure irrelevance theorem proposed by Modigliani and Miller (1958) states that under certain assumptions (i.e. in efficient markets and in the absence of taxes, bankruptcy costs, agency costs, asymmetric information), the choice of financial leverage does not affect firm value. The rationale is that the arbitrageurs can substitute homemade leverage for corporate leverage till the

[14] Nine largest banks are Citigroup, Bank of America, JP Morgan Chase, Wells Fargo, Bank of NY Mellon, State Street Corp, Goldman Sachs, Morgan Stanley, and Merrill Lynch. The tenth bank is Wachovia, later is acquired by Wells Fargo.

market values of these two firms (levered vs. unlevered firms) are identical. If this proposition holds, then firm's leverage has no effect on its weighted average cost of capital and the expected return on levered firms will be a linear increasing function of leverage. If the assumption of no taxes is relaxed, the tax benefits of debt increase firm value and decrease the cost of capital (Modigliani and Miller, 1963).

3.2.2.2 Dividend policy and dividend taxes. Miller and Modigliani (1961) propose that firm value is independent of its dividend policy under a similar set of certain assumptions as the capital structure irrelevance theorem. Another implication of this theorem is that stockholders are indifferent as to whether they receive the payment via cash dividend or share repurchase. Dividend is subject to double taxations in the U.S., because it is taxed at the firm level as well as the investor level. Before the Job and Growth Tax Relief Reconciliation Act of 2003, the historical tax rate on capital gains is less than the taxation on cash dividend income. Individual investors prefer share repurchase to cash dividend not only for the lower tax rates, but also for the benefit of deferring the taxes by postponing the sale of capital assets. Conversely, institutional investors prefer cash dividend because they can exempt at least 70 percent of dividend income. Litzenberger and Ramaswamy (1979) test the relationship between dividend and equity returns by using Brennan (1970) model and find that risk-adjusted returns are higher for stocks with higher dividend yields. The implication is that the dividends are undesirable; therefore, high returns are necessary to compensate investors for holding high dividend-yield stocks.

Baker and Wurgler (2004) propose the catering hypothesis, which suggests that firms change their dividend policy to fit their investors' needs in the long run. Desai and Jin (2011) support this hypothesis with evidence on dividend policy difference between high institutional-holding firms and low institutional-holding firms.

3.2.2.3 Information asymmetry hypothesis. Fama (1970) defines efficient market hypothesis (EMH)[15] by stating markets are "informationally efficient", meaning prices at all times reflect public and private information. New information regarding securities comes to market in a random fashion. Profit-maximizing investors cause security prices to adjust rapidly to reflect the effect of new information. Empirical studies have found evidence against the strong-form EMH (Chowdhury et al., 1993; Jaffe, 1974). Notably, Grossman and Stiglitz (1980) find "informed" traders acquire better estimates of future states of nature and take trading position based on the information, while "uninformed" traders invest no resources in collecting information, but they can infer the information of informed traders by observing the price fluctuation. It indicates that the private information affects the equity prices. Wang (1993) and Dow and Gorton (1995) show that informed traders profit from their information relative to the uninformed investors.

The distribution of private information also affects the incentive and investors' required rate of return. Information disclosure by the firms essentially makes private information available to the public. Enhanced disclosure can reduce the adverse selection problem by reducing the transaction costs and information asymmetry, avoid possible government regulation and further improve liquidity (Diamond and Verrecchia, 1991). As suggested by Easley and

[15] Fama (1970) further subcategories the EMH into three sub hypotheses: (1) weak-form hypothesis argues that no investor can earn excess return on historical consequence of prices, rates of return, trading volume data, and other market-generated information; (2) semi-strong form EMH states that no investor can earn excess returns from trading rules based on any publicly available information, and (3) strong-form EMH suggests that no investor can consistently earn excess returns using any information, whether publicly available or not.

O'hara (2005), public information reduces the risk for holding such assets. If there is greater private information related to a firm's stock, it will face a higher cost of capital.

The relationship between disclosure quality and cost of equity has found to be negative in the existing literature (Dhaliwal et al., 2009; Diamond and Verrecchia, 1991; Hail, 2002). El Ghoul et al. (2011) investigate the effect of corporate social responsibility (CSR) on the cost of equity. They find that firms with better CSR scores exhibit cheaper equity financing and attract institutional investors and analyst coverage.

3.2.2.4 Liquidity hypothesis. Becker-Blease and Paul (2006); Gebhardt et al. (2001) suggest a lower cost of capital might be the result of better liquidity. Baran and Dolly King (2012) use three alternative measures of costs of equity to examine the impact of index inclusion and deletion upon cost of equity. They find supporting evidence for the liquidity hypothesis as the COE decreases upon index inclusion and increases after index exclusion.

Existing literature report mixed results on the bailout effect. However, I believe that capital injections through CPP funds can release potential concerns of illiquidity and bankruptcy, further reducing the required rate of return.

3.3 Data and Methodology

3.3.1 Data Sources and Sample Selection

In this paper, I focus on publicly-listed banks that receive bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). In order to address potential endogeneity issues, I use the propensity score matching technique to identify non-CPP matching banks as the control group. Propensity score matching is widely used in the literature to estimate the treatment effect (Heckman et al., 1998; Hirano et al., 2003; Li and Zhao, 2006; Rosenbaum and Rubin, 1983, 1985). Different from traditional matching techniques, propensity score matching method allows matching on several characteristics simultaneously. The selection of matching variables is guided by theory and prior research (Li and Zhao, 2006).

$$ROA_i = \alpha + \beta_1 SIZE_i + \beta_2 DEBT_i + \beta_3 MKBK_i + \varepsilon_i \qquad (3.1)$$

I obtain the predicted value of *ROA* (i.e. a propensity score) from the regression of industry-adjusted *ROA* on three industry median-adjusted regressors (i.e. *SIZE, DEBT and MKBK*[16]) for all sample banks and matching pool of non-CPP recipients as shown in equation (3.1), which are drawn from Compustat dataset within the same banking sector (SIC codes from 6000-6399). I successfully find 227 matching banks for our sample of CPP banks. Please refer to Chapter 2 for the details of sample and matching techniques.

3.3.2 Implied Cost of Equity (Implied COE) Approach

In this section, I estimate the COE using the implied COE approach that has been developed in prior studies[17], which derives the COE from the residual income valuation model. Dividend discount model (DDM) of Williams (1938) is frequently used in fundamental analysis as a tool to identify mispriced equity.

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[16] *ROA* is Net income on Total Assets. *SIZE* is the logarithm value of market capitalization. *DEBT* is the ratio of total liabilities to total assets. *MKBK* is the ratio of market price to book price.

[17] Alternative techniques to estimate cost of equity capital are expected cost of equity capital approach and the portfolio-based method. The former approach uses realizing returns with market model and/or Fama-French model (Grullon and Michaely, 2004; Baran and Dolly King, 2012) .The portfolio-based method (e.g. Dhaliwal et al. (2005)) constructs cost of capital with Easton et al. (2002) model and finds inconsistent results. They suggest that this portfolio-based model lacks efficiency since firm-specific information is lost during the portfolio formation, thus the interpretation on the results demands more caution.

$$p_0 = \frac{d_1}{(1+r)^1} + \frac{d_2}{(1+r)^2} + \frac{d_3}{(1+r)^3} + \cdots + \frac{d_n}{(1+r)^n} \tag{3.2}$$

$$P_0 = \sum_{i=1}^{\infty} \frac{E(d_{t+i})}{(1+r)^i} \tag{3.3}$$

$$p_0 = \frac{d_1}{(r-g)}, \text{ where } r > g \tag{3.4}$$

$$r = \frac{d_1}{p_0} + g \tag{3.5}$$

As in equation (3.2), the equity value p_0 can be estimated as the present values of the expected future cash flows (e.g. dividends) based on all available information. To evaluate a dividend-paying firm, the dividend discount model is commonly used and can be expressed as equation (3.3). Gordon (1959) assumes dividends will grow at a constant rate forever (as shown in equation (3.4)) and suggests that the only relevant variables that determine a stock value are dividends and the discount rate. Conversion of equation (3.4) to equation (3.5) infers that the expected rate of return *r* equals dividend yield $\frac{d_1}{p_0}$ (or dividend payment as a percentage of share prices) plus a perpetual dividend growth rate g. However, dividend growth rate g in Gordon DDM is unobservable; therefore, any hypothetical proxy will leave room for disagreement on stock valuation.

$$p_0 = bv_0 + \frac{ae_1}{(1+r)^1} + \frac{ae_2}{(1+r)^2} + \frac{ae_3}{(1+r)^3} + \frac{ae_4}{(1+r)^4} + \cdots \frac{ae_n}{(1+r)^n} \tag{3.6}$$

To mitigate the impact of the assumed growth rate g, the residual income value model (RIVM) replaces forecasted dividends by current book value of equity (bv_0) plus the stream of future accounting earnings (ae) as shown in equation (3.6). The RIVM is similar to Gordon DDM as both models take future growth opportunity into account. However, DDM assumes that dividend will grow at a constant rate, while the RIVM assumes that estimated future cash flows will grow at differential rate up to a terminal period and remain constant after the respective terminal period. Thus, the right-hand-side of the RIVM can be decomposed into two parts, a finite series of expected future cash flows and a terminal value[18], discounted to the present at the cost of equity. Implied COE in RIVM is the internal rate of return to make the present value of expected future cash flows equals the current market price.

3.3.2.1 GLS model. My measure of implied COE closely follows the RIVM approach by Gebhardt, Lee and Swaminathan (2001) (GLS, henceforth). The GLS model uses actual book value per share and earnings per share to impute future expected residual income for 3-period ahead, and then it assumes that the residual income series from periods 4 to 12 will linearly converge to industry median ROE.

$$g_{GLS} = R\hat{O}E_{t+i} = \frac{\hat{x}_{t+i}}{bv_{t+i-1}} \tag{3.7}$$

$$\hat{x}_{t+\tau} = \hat{x}_{t+\tau-1} * (1 + g_{GLS}) \tag{3.8}$$

$$bv_t = bv_{t-1} + \hat{x}_t - d_t \tag{3.9}$$

$$p_t = bv_t + \sum_{\tau=1}^{T} \frac{(\hat{x}_{t+\tau} - r_{GLS} * bv_{t+\tau-1})}{(1+r_{GLS})^{\tau}} + \frac{(\hat{x}_{t+T+1} - r_{GLS} * bv_{t+T})}{r_{GLS}(1+r_{GLS})^{T}} \tag{3.10}$$

The implementation of the GLS model are as follows. First, I collect actual current book value per share from Compustat and annual median forecasted earnings per share ($FEPS_{t+1}$, $FEPS_{t+2}$) up to two years using Institutional Brokers' Estimate System (I/B/E/S)monthly data. Second, I compute dividend payout ratio d using accounting data from Compustat[19], assuming

[18] Terminal value is an estimated market price of a firm based on cash flows earned after explicit forecasting period (or terminal period).
[19] Dividend payout ratio d is the ratio of total dividend paid to net income.

that dividend payout ratio *d* remains constant. Third, I estimate long-term growth rate g_{GLS} using median industry ROE with 3-year moving average method, where ROE is the ratio of earnings to book value (as in equation (3.7)). Then, I estimate forecast earnings per share for the third year from previous forecasted earnings and growth rate as in equation (3.8). Fourth, I apply accounting clean plus[20] rule and estimate book value per share up to three years ahead as in equation (3.9). The equation (3.9) shows that future book value equals sum of beginning book value and forecasted earnings minus forecasted dividends. Fifth, I derive the residual income series by linearly fading the forecasted accounting ROE for the period of year 4 to 12[21]. From year 12, residual income is assumed to be constant[22]. Last, I solve for the valuation equation (3.10) using an iterative procedure to obtain the cost of equity r_{GLS} . To avoid possible estimation bias, I further remove about 3.91 percent of no-convergence cases[23].

3.3.2.2 OJ model. To ensure the results are not driven by the assumption of a specific estimation method, I also adapt Ohlson and Juettner-Nauroth (2005) (OJ model, henceforth) and Price-earnings growth model (PEG model, henceforth).

$$p_t = \frac{\hat{x}_{t+1}}{r_{OJ}} + \frac{(\hat{x}_{t+2} - \hat{x}_{t+1} - r_{OJ} * \hat{x}_{t+1}) * (1-d)}{r_{OJ} * (r_{OJ} - g_{OJ})} \qquad (3.11)$$

Different from GLS model, OJ model provides a special case of RIVM model without using book value of equity. The short-term earnings growth rate is estimated as the average of between the forecasted percentage change in earning from year $t+1$ to $t+2$, and the long-term

[20] Based on accounting clean plus rule to estimate future book values, it requires that all relevant factors affecting book value be included.
[21] Based on Gebhardt et al,(2001), it is the assumption of mean reversion: the forecasted earnings per share beyond year three will gradually approaching to the median industry ROE by year 12 through simple linear interpolation. This assumption is aiming to capture the long-term erosion of abnormal ROE.
[22] It suggests that there is no incremental economic value after year 12.
[23] Hail and Leuz (2009) also follow GLS model and find about 3 percent of non-convergence cases.

growth rate is the five-year growth forecast provided from I/B/E/S. Following Hail and Leuz (2009) and Chen et al. (2009), I use the annualized median of industry-specific one-year ahead realized monthly inflation rates as the proxy of long-term earnings growth rate g_{OJ} when it is missing in I/B/E/S. I solve for the valuation equation (3.11) using an iterative procedure to obtain the cost of equity r_{OJ}.

3.3.2.3 PEG model. Price-earnings growth model (PEG model, henceforth) is modified from Easton (2004), and represents another special case of RIVM model. It assumes that residual earnings is the difference between one-year ahead and two-year ahead forecast earnings, plus re-invested dividend earnings. PEG model also assumes that the growth in residual earnings persists in perpetuity after initial period. To derive the cost of capital r_{PEG}, I need to solve for the valuation equation (3.12).

$$p_t = \frac{(\hat{x}_{t+2} - \hat{x}_{t+1} + r_{PEG} * \hat{x}_{t+1} * d)}{{r_{PEG}}^2} \tag{3.12}$$

In the above models,

r_{GLS}	Implied cost of equity calculated as the internal rate of return by solving valuation equation (3.10) (Gebhardt et al., 2001)
r_{OJ}	Implied cost of equity calculated as the internal rate of return by solving valuation equation (3.11) (Ohlson and Juettner-Nauroth, 2005)
r_{PEG}	Implied cost of equity calculated as the internal rate of return by solving valuation equation (3.12) (Easton, 2004)
p_t	Market price of a firm at time *t*
p_0	Market price of a firm at time 0
ae_t	Expected abnormal earnings for year *t*
bv_t	Book value per share at time *t*
$bv_{t+\tau-1}$	Expected future book value at time $t+\tau-1$
$\hat{x}_{t+\tau}$	Expected future earnings at time t+τ using either explicit analyst forecasts or future earnings derived from long-term growth rate lgt
d_t	Dividend at time *t*
d	Dividend payout ratio

g_{GLS}	Expected long-term future growth rate in the terminal value in GLS model
g_{OJ}	Expected long-term future growth rate in the terminal value in OJ model

The approach to estimate the implied cost of equity above improves the original Gordon DDM estimation of cost of equity by mitigating the use of assumed growth rates. The approach could be superior to the expected cost of equity approach since it does not depend on realized stock returns, which is often criticized for failing to produce accurate estimates of COE. However, implied COE approach is not immune from methodical limitations. Implied COE approach assumes that short-term and long-term earnings forecasts from analyst forecasts are reliable or reasonable proxies for the expectation of future earnings. Analyst forecasts mainly focus on public firms; therefore, the information asymmetry might be more serious in private or small firms due to less extend of analyst coverage. On the other hand, analyst forecasts might suffer predictive errors because analysts underreact to information in prices with timeliness and punctuality (Gebhardt et al., 2001; Guay et al., 2011; Hail and Leuz, 2009).

To mitigate the impacts from above limitations, I follow the similar procedures as in previous studies by first winsorizing the estimate of r_{GLS} , r_{OJ} , r_{PEG} to the range of 0 to 0.6 (Chen et al., 2009), and then take arithmetic average estimates of three implied COE (Attig et al., 2013; Chen et al., 2009; Hail and Leuz, 2009). It is not my intention to take stand on which approach is the best. My sole focus is to attempt to explore whether government intervention casts impacts on firms' cost of equity during financial crisis.

Table 3.1 reports the descriptive statistics of the implied COE measures over the seven years (-3, +3) around bailout year. Regardless of the model of choice, CPP banks have consistently lower cost of equity than matched banks across all sample period, or pre- and post-bailout period as shown in Panel C of Table 3.1. That CPP banks have lower COE than matching banks before the bailout may be attributed to firm size. Firm size is normally negatively related to COE, and I report CPP banks are relative larger than matching banks in term of size in previous section.

The average COE measure from the 3 models ($r_{ICOC(3)}$) is the major measure I use in the rest of paper. Consistent with my hypothesis, the results from *Average 3 Model* indicate that CPP banks experience a significant reduction in cost of equity at the presence of financial bailout event (-0.8%). The matching banks, which didn't receive government bailout funds, do not seem to experience significant changes in COE during economy downturn.

[Insert Table 3.1 about here]

I am speculating that the financial positions of CPP banks in terms of the capability of repaying bailout funds might related to the cost of equity. Table 3.2 displays the interaction between three repayment groups and COE measures. Group 1 is *No Repayment* (the group without repayment as March 2013) (Panel A); Group 2 is *Partial Repayment* (the group with installments) (Panel B); and Group 3 is *Full Repayment* (the group with full repayment) (Panel C). The results indicate that *No Repayment* group suffers the highest cost of capital (9.6%) relative to the other two groups (about 8.9%).

[Insert Table 3.2 about here]

My main goal is to examine how the cost of equity changes upon financial bailouts. Table 3.3 presents the measures of changes in COE with three basic models and Average 3 Model. Panel A of Table 3.3 shows additional support for the downward pattern in COE around bailout for CPP banks (-0.725%). The results from GLS model do not seem to agree with the other competing models, which confirm my concerns on the possible estimation error and further reinforce the decision to use the average model as the main COE measure for the remaining of the paper. Overall, there is a significant difference between CPP banks and matching banks in terms of shifts in COE across all models.

To control for possible announcement effect, I run the robustness test and examine the bailout effect on the change in COE with a subsample of all years excluding (-1, 0) year as in Panel B of Table 3.3, and find consistent results.

[Insert Table 3.3 about here]

3.3.3 Control Variables

Several factors that might affect the COE have been discussed in the literature section, including too-big-to-fail factor, liquidity, information asymmetry, leverage, corporate governance, agency cost etc.(Alexander and Cohen, 1999; Attig et al., 2013; Collins and Huang, 2011; Dhaliwal et al., 2005; Gebhardt et al., 2001; Lakonishok et al., 1994; Malkiel and Xu, 1997; Modigliani and Miller, 1958, 1963; Shleifer and Vishny, 1997a). In this section, I describe the rationale and the constructs of the control variables based upon previous literature.

3.3.3.1 Institutional ownership. Better corporate governance can reduce COE by lowering the monitoring costs and thus reducing information asymmetry and agency costs. Institutional investors often play vital roles in disciplining managers and improving the quality of corporate governance. With higher percentage of shares held by institutional investors, company can expect lower COE. However, institutional investors are not homogeneous. Brickley et al. (1988) suggest that institutional investors likely face different incentives and conflicts of interest, especially when they have business relationship with the firms they invest. Such business ties might hinder them from having an active role on monitoring. They find that mutual funds, endowments, foundations, and public pension funds are more likely to oppose management than banks, insurance companies, and trusts which frequently derive benefit from lines of business under management control. Based on their findings, they classify institutions investors into two groups: independent and grey. The grey institutions have high cost of monitoring since they have to protect existing relationship with the firm and therefore they are less likely to challenge management decisions. Especially, the grey institutional investors tend to trade frequently to exploit their information advantage (Wermers, 2000). As a consequence, firms dominated by grey institutional investors are better in information quality and price efficiency, which in turn results in a lower level of cost of capital. Similarly, domestic institutional investors are more likely to have business ties with the firms than foreign institutional investors. They are encumbered by ties with incumbent management or by private benefits. Therefore, firms dominated by domestic institutional investors are less concerned of information asymmetry and do not have higher cost of capital. Conversely, firms dominated by foreign institutional investors are expected to have higher cost of capital.

I obtain quarterly institutional ownership data from Thomson Financial Institutional 13F common stock holding and transactions files. All investment managers must file Form 13F to the Security and Exchange Commission if they have an aggregate fair market value of at least $ 100 million in equity holding within 45 days of each quarter. Institutional investors include banks (bank trusts), insurance companies, investment companies (mutual funds) and their managers, independent investment advisor (most of the large brokerage firms), and “all others” (pension funds and endowments) etc. I construct several institutional ownership variables, including:

Shareholding. Following prior studies, I construct *Shareholding* as the percentage of institutional investors holding relative to total shares outstanding for each stock in each quarter (Ferreira and Matos, 2008; Parrino et al., 2003)[24].

High-Shareholding. It is a dummy variable equals to one if the fraction of shares owned by institutions is greater than, sample median; zero otherwise. The higher percentage of institution ownership predicts better corporate governance which in turn leads to reduced cost of capital (Shleifer and Vishny, 1997a).

Shareholding_F* and *Shareholding_D. According to the definition of Croci et al. (2012) and Ferreira and Matos (2008), *Shareholding_F* is the percentage of shares held by institutional investors who domicile in countries other than the U.S to total shares outstanding. *Shareholding_D* is the percentage of shares held by institutional investors incorporated in the U.S. to total shares outstanding.

Shareholding_I* and *Shareholding_G. Following prior studies (Brickley et al., 1988; Chen et al., 2007; Ferreira and Matos, 2008), I distinguish the *Shareholding* variable into two categories based on the monitoring role. Particularly, *Shareholding_I* represent the ratio of shares held by independent institutional investors (i.e. mutual funds and investment advisers), while *Shareholding_G* represent the ratio of shares held by grey institutional investors (i.e. bank trusts, insurance companies, and others). Different types of institutions are subject to distinct investment mandates and regulations.

[24] I also construct alternative shareholding measure as robustness check using market value of shares instead of the number of shares, the results are qualitative similar.

F_dominate. It is a dummy variable equals to one if the average *Shareholding_F* is greater than *Shareholding_D* in a firm in each fiscal year. Firms dominated by foreign institutional investors are expected to have higher costs of capital.

G_dominate. It is a dummy variable equals to one if the average *Shareholding_G* is greater than *Shareholding_I* in a firm in each fiscal year. Firms dominated by grey institutional investors are expected to have lower costs of capital.

Blockholder. Following Chen et al. (2007), it is a dummy variable equals to 1 if *Shareholding* by one single institutional investor is greater than 5 % in a firm; else equals to zero.

3.3.3.2 Size. Banz (1981) and Reinganum (1981) show that small-capitalization firms earn higher average returns. It could be a proxy for information asymmetry because the risk to invest in smaller firms is relative higher due to low information transparency or limited analyst coverage. *Size* can also be a proxy for growth opportunity. Smaller firms normally have more growth potential than larger firms. Additionally, small firms are less liquid than larger firms, so size may also be a proxy for illiquidity. *Size* is computed as natural log of total assets[25], and is expected to have negative impact on cost of capital (Gebhardt et al., 2001).

3.3.3.3 Volatility. *Volatility* quantifies the dispersion of price changes. I measure it as the annualized standard deviation of monthly returns. The higher volatility indicates higher risks to

[25] Log value of total assets is common measurement in banking industry. I use average total assets as total assets, which is total assets from previous five quarters divided by five.

investors and thus a higher cost of capital. I predict a positive relationship between *Volatility* and COE.

3.3.3.4 ROE. *ROE* is the ratio of net income to shareholding equity. *ROE* is a proxy for profitability and it gives information on how much profit a firm generates with the money shareholders have invested. It is expected to negatively relate to COE.

3.3.3.5 Dividend yield. *Dividend Yield* is the amount of cash dividend divided by share price. Since dividends are not desirable, investors have to be compensated with higher rate of return to hold high dividend yield stocks (Litzenberger and Ramaswamy, 1979). Therefore, I predict a positive relationship between *Dividend Yield* and COE.

3.3.3.6 Book to market. *Book to Market* is the ratio of book value of equity to the market value of equity. Based on Lakonishok et al. (1994), value stocks with high book-to-market ratios earn higher return than glamour stocks with low book-to-market ratios due to the tendency of underpricing. Gebhardt et al. (2001) suggest that undervalued stocks should earn a higher risk premium until the mispricing is corrected. I predict a positive relationship between *Book to Market* variable and COE.

3.3.3.7 Leverage. *Leverage* is measured as the ratio of total liability to the net worth. According to the capital structure irrelevance theorem of Modigliani and Miller (1958), firm value is independent of financial leverage; and the expected returns in levered firms will be a linear increasing function of leverage. I predict a positive relationship between *Leverage* and COE.

3.3.3.8 Dispersion. *Dispersion* is distribution of analyst forecasts is computed as the standard deviation of the firm’s estimated EPS for 1-yr ahead by I/B/E/S, scaled by the stock price at the earnings forecast date. The variability of forecast earnings indicates possible information asymmetry between insiders and outsiders, which exposes investors to more risks. Thus, it is expected to have positive relationship with COE (Dhaliwal et al., 2005; Gebhardt et al., 2001).

3.3.3.9 Bid-ask spread. *Bid-Ask Spread* serves as a proxy of liquidity. The higher the *Bid-Ask Spread*, the lower the liquidity is. Liquidity is negatively related to firm size and should have positive relationship with cost of equity as suggested by Gebhardt et al. (2001). I measure bid-ask spread as the absolute value of bid-ask difference deflated by share price[26] and I predict a negative association between bid-ask spread and COE. Appendix B outlines the definitions and data sources for all variables.

3.3.4 Multivariate Analyses

To investigate the determinants of cost of equity and the changes in cost of equity, I employ several cross-sectional regression specifications as following.

$$COE_{it} = \alpha_0 + \alpha_1 CPP_i + \alpha_2 CPP_i * PostBailout_t + \alpha_3 IIi_{it} + \sum_{j=1}^{k} \beta_j x_{it}^{j} + u_t + \varepsilon_{it} \quad (3.13)$$

$$\Delta\, COE_{it} = \alpha_0 + \alpha_1 CPP_i + \alpha_2 IIi_{it} + \sum_{j=1}^{k} \beta_j x_{it}^{j} + u_t + \varepsilon_{it} \quad (3.14)$$

, where x_{it} is a vector of *k* regressors and u_t is year-fixed effect

I regress average measures of COE in the level and first difference on a CPP dummy variable and the interaction term of CPP and Post Bailout dummies, together with institutional investor

[26] Gebhardt et al (2001) use average dollar trading volume as proxy for liquidity. I construct Turnover variable and find the results are qualitative similar to that with Bid-ask spread variable. I later keep only Bid-Ask spread in my cross-sectional tests.

variables (*IIi*) and a set of control variables (x_i) and year fixed effects as in equations (3.13) and (3.14).

I suspect that some coefficients in multivariate analysis might differ by various institutional investor measures due to differences in control influences or monitoring roles. Repayment status might also distinguish groups in cross-sectional regression models. Therefore, I employ seemingly unrelated regressions (SUR) analyses based on Zellner (1962) in order to compare coefficients across regression models separated by institutional investor measures and by repayment status, alternatively, in equations (3.13) to (3.14).

3.4 Results and Discussion

3.4.1 Cost of Equity

In Table 3.4, I report the empirical relationship between explanatory variables and cost of equity using OLS regression models with year-fixed effects. The dependent variable is the average implied cost of capital $r_{Icoc\,(3)}$ in all regression specifications, and the sample period is the (-3, +3) years window around the bailout year (t = 0). In Panel A of Table 3.4, the *CPP* dummy is negatively related to COE as shown in model (1), and the result is robust with additional set of control variables as in model (2). The findings are consistent with the observations from univariate tests, which indicates that the bailout event significantly reduces banks' cost of equity. However, the significance disappears as inclusion of *Size* and *Volatility* variables. Notably, the *CPP x PostBailout* is negatively related to COE in models (2)-(3), which suggests that the decrease in the COE is exclusive to the post-bailout period. I also find *High-Shareholding* leads to reduced cost of capital (Shleifer and Vishny, 1997a) as in model (4). In

Panel B, I include *F-dominate* and *G-dominate* variables to investigate whether the heterogeneity of institutional investors influences the COE. I find the banks dominated by foreign institutional investors tend to suffer from higher COE, while firms dominated by "grey" institutional investors have lower COE.

[Insert Table 3.4 about here]

Table 3.5 reports the results from the SUR analyses. I compare the coefficients of cross-sectional regression models between "*Blockholder*" group and "*non-Blockholder*" group in Panel A of Table 3.5. Interestingly, while the impact of the bailout on the cost of equity is negative for banks without blockholders, it is positive for banks with blockholders. . In Panel B of Table 3.5, I find that repayment status differentiates the CPP banks in post-bailout. Specifically, the No-Repayment group suffers more pronounced negative impact upon the bailout relative to two other groups. This result is consistent with the univariate findings in Table 3.2.

[Insert Table 3.5 about here]

3.4.2 Change in Cost of Equity

In previous univariate tests, I observe a reduction in the cost of equity of CPP banks upon the bailout. In Panel A of Table 3.6, I show that the results hold even with additional *Size* and *Volatility* variables as in the models (2). The *High-Shareholding* variable is positively related to the change in cost of equity, controlling for bailout event and other explanatory variables as in models (5)-(6). In Panel B, the *F-dominate* and *G-dominate* variables can explain 1.0-1.4 % of variance in the dependent variable-change in cost of equity. Overall, bailout event and institutional investor variables can predict the change in cost of equity, but with limited magnitude. *Volatility* and *Leverage* variables are negatively associated with the change in cost of equity across models and different subsamples at 1 % level of significance.

[Insert Table 3.6 about here]

In SUR analysis, I find that the change in cost of equity is positively related to *Shareholding* only in the firms with *Blockholder* as shown in Panel A of Table 3.7. *Blockholder* also plays important role in explaining the negative relation between *Volatility* (and *Leverage*) and change in cost of equity. With respect to repayment status, the positive association between *High-Shareholding* and change in cost of capital is significant only with partial-repayment group.

[Insert Table 3.7 about here]

3.5 Conclusions

I examine the cost of equity of a group of banks that received financial bailout under the Capital Purchase Program during 2008-2009. I match the sample banks with non-CPP recipient banks that have similar probability of receiving bailout funds. I aim to investigate the bailout effect on the cost of equity of our sampled financial institutions.

I provide additional empirical evidence to the cost of equity capital literature in the presence of financial bailouts, especially from the regulated industry-banking sector. The findings show that government intervention, via liquidity-injections to the banking industry, effectively decreases firms' cost of equity. The banks that have not repay the bailout funds as of

March 2013 have higher cost of equity relative to banks that repay, regardless of liquidating in one payment or in installments.

I contribute to the cost of capital literature with the additional evidence of the moderating effect of institutional investors. Institutional investors are expected to monitor and discipline managers. Higher percentage of institution investor shareholding predicts better corporate governance; therefore, it should lead to lower cost of capital (Collins and Huang, 2011; Shleifer and Vishny, 1997b; Chung and Zhang, 2011). I find consistent evidence from cross-sectional regression analyses. However, institutional investors are not homogeneous. The country where they headquartered at and the monitor role they play in the firms might lead to different incentives and conflict of interests. I find that the firms dominated by foreign institutional investors command higher cost of equity, while "grey" institutional investors dominated firms have lower cost of equity. More interestingly, if the bailout firms have "*Blockholder*", then the negative impact on cost of capital from bailout can be overturn.

My findings have implications for investors and financial institutions. Investors need unbiased measures of cost of equity to evaluate the intrinsic value of firms. Implied cost of equity measure provides a comprehensive approach in mitigating the dependence on researchers-assumed growth rates and realized historical stock returns, and also correcting possible predictive errors by incorporating additional firm-level information. In particular, the institutional investors could restructure their portfolios based on the cost of equity in response to such unique financial events. Financial institutions estimate cost of equity for their capital budgeting projects and determine how the cost of equity changes depend on receiving government bailout.

Table 3.1-Measures of Implied Cost of Equity

Model	Period	GLS Model r_{GLS} N	Mean	Median	OJ Model r_{OJ} N	Mean	Median	PEG Model r_{PEG} N	Mean	Median	Average 3 Models $r_{ICOC(3)}$ N	Mean	Median
Panel A-CPP Banks													
Whole Sample Period (-3 yr, +3 yr)	**(1)**	**631**	**7.75%**	**6.41%**	**631**	**9.35%**	**8.77%**	**631**	**9.59%**	**8.76%**	**631**	**8.90%**	**7.93%**
By Bailout													
Pre-Bailout (-3 yr, 0)	(2)	384	6.04%	5.80%	384	10.84%	9.74%	384	10.80%	9.71%	384	9.23%	8.40%
Post-Bailout (0, +3 yr)	(3)	247	10.40%	8.15%	247	7.03%	4.58%	247	7.72%	5.08%	247	8.38%	5.79%
Pre- vs. Post-Bailout													
Mean vs. Median difference	(4)		4.36%	2.35%		-3.81%	-5.16%		-3.09%	-4.63%		-0.84%	-2.61%
(t-statistics and Wilcoxon statistics)			(8.755***)	(13.836***)		(-6.848***)	(-12.294***)		(-5.829***)	(-12.098***)		(-1.651*)	(-9.136***)
Panel B- Matching Banks													
Whole Sample Period (-3 yr, +3 yr)	**(5)**	**278**	**8.93%**	**6.62%**	**278**	**11.54%**	**9.84%**	**278**	**11.66%**	**9.83%**	**278**	**10.71%**	**8.91%**
By Bailout													
Pre-Bailout(-3 yr, 0)	(6)	176	6.48%	5.62%	176	12.49%	11.09%	176	12.43%	11.04%	176	10.47%	9.39%
Post-Bailout (0, +3 yr)	(7)	102	13.16%	9.25%	102	9.89%	6.07%	102	10.33%	7.00%	102	11.13%	7.35%
Pre- vs. Post-Bailout													
Mean vs. Median difference	(8)		6.68%	3.63%		-2.60%	-5.02%		-2.10%	-4.04%		0.66%	-2.04%
(t-statistics and Wilcoxon statistics)			(6.296***)	(8.042***)		(-2.243**)	(-5.246***)		(-1.858*)	(-4.929***)		(0.612)	(-2.318*)
Panel C-CPP vs. Matching Banks													
(1)-(5) Whole Sample Period Difference			-1.19%	-0.21%		-2.19%	-1.07%		-2.06%	-1.07%		-1.81%	-0.98%
(t-statistics and Wilcoxon statistics)			(-2.266**)	(-0.483)		(-3.788***)	(-3.802***)		(-3.670***)	(-3.663***)		(-3.624***)	(-3.791***)
(2)-(6) Pre-bailout Period Difference			-0.44%	0.18%		-1.66%	-1.35%		-1.63%	-1.33%		-1.24%	-0.99%
(t-statistics and Wilcoxon statistics)			(-1.109)	(0.613)		(-2.723***)	(-2.806***)		(-2.690***)	(-2.770***)		(-2.672***)	(-2.529**)
(3)-(7) Post-bailout period Difference			-2.76%	-1.10%		-2.86%	-1.49%		-2.61%	-1.93%		-2.74%	-1.57%
(t-statistics and Wilcoxon statistics)			(-2.507**)	(-2.272**)		(-2.520**)	(-2.782***)		(-2.388**)	(-2.380**)		(-2.509**)	(-2.595***)
(4)-(8) Pre- and Post-bailout Difference			-2.32%	-1.28%		-1.20%	-0.14%		-0.98%	-0.59%		-1.50%	-0.57%
(t-statistics and Wilcoxon statistics)			(-3.641***)	(-3.408***)		(-1.762*)	(-1.801*)		(-2.246**)	(-1.963**)		(-2.666**)	(-1.918*)

The table reports various measures of implied cost of equity for CPP banks (as in panel A) and matching banks (as in Panel B) seven years around bailout year (-3, +3) and pre- vs. post-bailout difference (as in Panel C). Average 3 models $r_{Icoc\,(3)}$ is the arithmetic average of r_{GLS}, r_{OJ}, and r_{PEG}. All variables are defined in Appendix 3.A. Tests in mean and median difference are the Satterthwaite method and Wilcoxon signed-rank method assuming variances are unequal. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3.2-Interaction of Cost of Equity and Repayment Status

Model	GLS Model			OJ Model			PEG Model			Average 3 Models		
	r_{GLS}			r_{OJ}			r_{PEG}			$r_{ICOC(3)}$		
	N	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median
Panel A- No Repayment												
Whole Sample Period (-3 yr, +3 yr)	78	6.32%	5.76%	78	11.30%	10.07%	78	11.28%	10.01%	78	**9.63%**	8.59%
By Bailout												
Pre-Bailout (-3 yr, 0)	65	5.72%	5.60%	65	11.97%	10.44%	65	11.90%	10.38%	65	9.86%	8.99%
Post-Bailout (0, +3 yr)	13	9.31%	7.15%	13	7.96%	5.67%	13	8.16%	5.62%	13	8.48%	5.82%
Pre- vs. Post-Bailout												
Mean vs. Median difference		3.60%	1.55%		-4.01%	-4.76%		-3.74%	-4.75%		-1.38%	-3.17%
(t-statistics and Wilcoxon statistics)		(2.164*)	(2.413**)		(-2.248**)	(-3.298***)		(-2.163**)	(-3.285***)		(-0.821)	(-2.829***)
Panel B-Partial Repayment												
Whole Sample Period (-3 yr, +3 yr)	117	7.87%	6.08%	117	9.22%	8.57%	117	9.48%	8.50%	117	**8.86%**	7.63%
By Bailout												
Pre-Bailout (-3 yr, 0)	71	6.05%	5.72%	71	10.60%	9.49%	71	10.54%	9.45%	71	9.06%	8.16%
Post-Bailout (0, +3 yr)	46	10.69%	8.28%	46	7.11%	4.56%	46	7.84%	4.98%	46	8.55%	5.88%
Pre- vs. Post-Bailout												
Mean vs. Median difference		4.64%	2.56%		-3.49%	-4.94%		-2.70%	-4.47%		-0.52%	-2.28%
(t-statistics and Wilcoxon statistics)		(3.226***)	(6.169***)		(-2.261**)	(-5.644***)		(-1.816*)	(-5.516***)		(-0.353)	(-3.998***)
Panel C-Full Repayment												
Whole Sample Period (-3 yr, +3 yr)	436	7.97%	6.63%	436	9.03%	8.42%	436	9.32%	8.45%	436	**8.78%**	7.82%
By Bailout												
Pre-Bailout (-3 yr, 0)	248	6.12%	5.87%	248	10.61%	9.61%	248	10.59%	9.54%	248	9.11%	8.34%
Post-Bailout (0, +3 yr)	188	10.41%	8.13%	188	6.95%	4.40%	188	7.65%	5.00%	188	8.34%	5.66%
Pre- vs. Post-Bailout												
Mean vs. Median difference		4.28%	2.26%		-3.66%	-5.21%		-2.93%	-4.54%		-0.77%	-2.68%
(t-statistics and Wilcoxon statistics)		(7.808***)	(11.617***)		(-5.874***)	(-9.925***)		(-4.961***)	(-9.751***)		-1.364	(7.327***)

The table reports the interaction between various measures of implied cost of equity for CPP banks and three repayment groups : Group 1 is *No Repayment* (the group without repayment as March 2013) (Panel A); Group 2 is *Partial Repayment* (the group with installments) (Panel B); and Group 3 is *Full Repayment* (the group with full repayment) (Panel C). Average 3 models $r_{Icoc(3)}$ is the arithmetic average of r_{GLS}, r_{OJ}, and r_{PEG}. All variables are defined in Appendix 3.A. Tests in mean and median difference are the Satterthwaite method and Wilcoxon signed-rank method assuming variances are unequal. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3.3-Changes in Cost of Equity around Bailout

Model	GLS Model			OJ Model			PEG Model			Average 3 Models		
	Δ r_{GLS}			Δ r_{OJ}			Δ r_{PEG}			Δ $r_{ICOC(3)}$		
	N	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median
Panel A. All Years												
CPP Banks	456	3.957%	2.694%	456	-3.382%	-3.955%	456	-2.751%	-3.230%	456	**-0.725%**	-1.628%
Matching Banks	141	6.569%	3.801%	141	-1.812%	-3.971%	141	-0.923%	-2.633%	141	1.278%	-1.991%
CPP vs. Matching Banks												
Mean vs. Median difference		-2.612%	-1.107%		-1.570%	0.016%		-1.829%	-0.597%		-2.004%	0.363%
(t-statistics and Wilcoxon statistics)		(-3.641***)	(-3.048**)		(-1.762*)	(1.801*)		(-2.246**)	(-1.963**)		(-2.666***)	(1.918*)
Panel B. Robustness-All Years except (-1,0) Year												
CPP Banks	337	3.842%	2.504%	337	-3.638%	-4.381%	337	-2.971%	-3.311%	337	-0.922%	-1.882%
Matching Banks	106	6.812%	4.712%	106	-1.963%	-3.971%	106	-1.042%	-2.633%	106	1.269%	-1.461%
CPP vs. Matching Banks												
Mean vs. Median difference		-2.970%	-2.208%		-1.675%	-0.410%		-1.929%	-0.678%		-2.191%	-0.421%
(t-statistics and Wilcoxon statistics)		(-3.647***)	(-3.178***)		(-1.592)	(-1.852*)		(-2.014**)	(-1.985**)		(-2.511**)	(-2.088**)

The table compares changes in cost of equity for the CPP banks and matching banks in the window period of seven years around bailout (-3, +3) as in Panel A. Additional robustness tests in Panel B using sample period of all years except (-1, 0) year to control for announcement effect. Average 3 models $r_{Icoc\ (3)}$ is the arithmetic average of r_{GLS}, r_{OJ}, and r_{PEG}. All variables are defined in Appendix 3.A. Tests in mean and median difference are the Satterthwaite method and Wilcoxon signed-rank method assuming variances are unequal. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3.4-Cross-sectional Determinants of Cost of Equity

Panel A-Bailout Effect

Model	(1)	(2)	(3)	(4)	(5)	(6)
CPP	-0.120***	-0.092**	-0.040	-0.054*	-0.071*	-0.027
	(-3.293)	(-2.405)	(-1.107)	(-1.730)	(-1.914)	(-0.761)
CPP x PostBailout	-0.048	-0.204**	-0.254***	-0.104	-0.215***	-0.241***
	(-0.597)	(-2.487)	(-2.992)	(-1.278)	(-2.652)	(-2.864)
High-Shareholding				-0.074**	-0.033	-0.054
				(-2.132)	(-0.958)	(-1.525)
Size			-0.000	0.054*		0.008
			(-0.014)	(1.817)		(0.242)
Volatility			0.088***	0.150***		0.087***
			(2.723)	(4.572)		(2.718)
ROE		-0.069	-0.085*		-0.098*	-0.087*
		(-1.349)	(-1.742)		(-1.824)	(-1.779)
Dividend Yield		0.167***	0.150***		0.159***	0.149***
		(3.506)	(3.025)		(3.290)	(3.043)
Book to Market		0.190**	0.225**		0.231**	0.220**
		(2.092)	(2.077)		(2.158)	(2.011)
Leverage		-0.053	-0.055		-0.022	-0.051
		(-1.510)	(-1.515)		(-0.607)	(-1.408)
Dispersion		0.075	0.032		0.071	0.031
		(1.288)	(0.553)		(1.177)	(0.541)
Bid-Ask Spread			-0.079		-0.104**	-0.096*
			(-1.402)		(-1.970)	(-1.691)
Adjusted R-squared	0.050	0.132	0.141	0.071	0.147	0.142
Year-Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
F-statistics	7.997***	8.023***	6.796***	7.656***	7.385***	6.595***
N	840	812	774	799	804	774

(Table 3.4-Continued)

Panel B- Heterogeneity of Institutional Investor Effect

Model	(1)	(2)	(3)	(4)	(5)	(6)
CPP	0.027	-0.034	0.023	0.012	-0.041	0.012
	(0.799)	(-0.886)	(0.659)	(0.358)	(-1.078)	(0.343)
CPP x PostBailout	-0.097	-0.206**	-0.231***	-0.106	-0.213***	-0.241***
	(-1.212)	(-2.552)	(-2.761)	(-1.313)	(-2.624)	(-2.869)
F-dominate	0.169***	0.111**	0.141***			
	(4.131)	(2.573)	(3.289)			
G-dominate				-0.153***	-0.100**	-0.124***
				(-3.954)	(-2.509)	(-3.105)
Size	0.022		-0.013	0.027		-0.007
	(0.758)		(-0.401)	(0.973)		(-0.223)
Volatility	0.145***		0.082***	0.146***		0.083***
	(4.486)		(2.609)	(4.504)		(2.627)
ROE		-0.100*	-0.086*		-0.099*	-0.086*
		(-1.829)	(-1.752)		(-1.827)	(-1.756)
Dividend Yield		0.155***	0.148***		0.156***	0.148***
		(3.339)	(3.111)		(3.357)	(3.123)
Book to Market		0.230**	0.220**		0.230**	0.219**
		(2.168)	(2.036)		(2.150)	(2.014)
Leverage		0.008	-0.014		0.002	-0.022
		(0.203)	(-0.363)		(0.064)	(-0.584)
Dispersion		0.067	0.026		0.068	0.029
		(1.131)	(0.474)		(1.162)	(0.511)
Bid-Ask Spread		-0.087*	-0.079		-0.088*	-0.079
		(-1.683)	(-1.408)		(-1.717)	(-1.396)
Adjusted R-squared	0.084	0.153	0.151	0.082	0.152	0.150

Year-Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
F-statistics	8.840***	7.793***	7.086***	8.684***	7.866***	7.124***
N	799	804	774	799	804	774

In this table, I report the empirical relationship between explanatory variables and cost of equity using OLS regression models with year-fixed effect. The Dependent Variable is average implied cost of capital $r_{Icoc\,(3)}$ for all specification models, where $r_{Icoc\,(3)}$ is the arithmetic average of r_{GLS}, r_{OJ}, and r_{PEG}. The sample period is a window period of (-3, +3) around the year of bailout (t=0). The key explanatory variables in Panel A are *CPP* dummy, *CPP x PostBailout* interaction term, and *High Shareholding*; *CPP* is a dummy variable equals to one if it is CPP bank, else is zero (i.e. matching bank). *CPP x PostBailout* is interaction term of CPP and PostBailout dummies. *High-Shareholding* is a dummy variable equals to 1 if shareholding is greater than median shareholding; zero equals to Low shareholding. In Panel B, I include two institutional investor variables *F_dominate* and *G_dominate* as main indicators. *F_dominate* is a dummy variable equals to one if Shareholding_F is greater than Shareholding_D, else equals to zero. *G_dominate* is a dummy variable equals to one if Shareholding_G is greater than Shareholding_I, else equals to zero. Other control variables are: *Size* is log value of total assets, where total assets is average total assets from previous five quarters. *Volatility* (or systematic risk) equals to annualized standard deviation of monthly return. *ROE* is return on equity. *Dividend Yield* is measured as the ratio of cash dividend to share price. *Book to Market* is the ratio of net worth to market capitalization. *Leverage* is total liability divided by net worth. *Dispersion* is standard deviation of one-year ahead analyst's earning forecast (FEPS1), deflated by share price. *Bid-Ask Spread* is absolute value of bid-ask difference, deflated by share price. All variables are defined in Appendix 3.A. Numbers presented in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3.5-Seemingly Unrelated Regression Analysis: Determinants of Cost of Equity

	Panel A		Panel B		
	Blockholder vs non-Blockholder		Different Repayment Groups		
	(1)	(2)	(3)	(4)	(5)
	Blockholder	Non-Blockholder	No Repayment	Partial Repayment	Full Repayment
CPP	0.085**	-0.020			
	(1.986)	(-0.147)			
CPP x PostBailout	-0.292***	-0.403*	-0.785***	-0.610***	-0.396***
	(-5.561)	(-1.775)	(-4.076)	(-5.031)	(-6.097)
High-Shareholding			0.122	0.200*	0.105*
			(0.635)	(1.783)	(1.957)
Size	0.049	0.069	0.096	-0.293**	0.056
	(1.006)	(0.491)	(0.356)	(-2.247)	(1.020)
Volatility	0.026	0.073	0.057	0.083	-0.001
	(0.601)	(0.565)	(0.390)	(0.981)	(-0.026)
ROE	-0.208***	-0.190	-0.283	-0.252**	-0.309***
	(-4.218)	(-1.057)	(-1.540)	(-2.361)	(-4.855)
Dividend Yield	0.175***	0.271	-0.043	0.724***	0.199***
	(4.148)	(1.295)	(-0.227)	(5.624)	(4.169)
Book to Market	0.234***	0.448*	1.413**	0.328*	0.299***
	(3.599)	(1.700)	(2.353)	(1.686)	(4.465)
Leverage	0.039	0.179	-0.086	0.057	0.119**
	(0.908)	(1.427)	(-0.565)	(0.539)	(2.401)
Dispersion	0.029	-0.140	-0.786	0.026	-0.027
	(0.610)	(-1.199)	(-1.524)	(0.180)	(-0.563)
Bid-Ask Spread	-0.093*	0.151	-0.083	0.281**	-0.021
	(-1.671)	(1.032)	(-0.296)	(2.626)	(-0.364)
Adjusted R-squared	0.131	0.257	0.227	0.356	0.205
Chi-squared	2569.00***		2661.02***	35635.64***	
F-statistics	9.342***	3.176***	2.671**	6.861***	11.51***
N	552	64	58	107	409

The table reports the results from seemingly unrelated regression (SUR) estimates The Dependent Variable is average implied cost of capital $r_{Icoc\,(3)}$ for all specification models, where $r_{Icoc\,(3)}$ is the arithmetic average of r_{GLS}, r_{OJ}, and r_{PEG}. *Blockholder* (in Panel A) is a dummy variable equals to one if shareholding by one single institution investor is more than 5% in a firm, else equals to zero (i.e. *non-Blockholder*). Different Repayment groups (in Panel B) are categorized based on repayment status: *No Repayment* (the group without any repayment as March 1, 2013); *Partial Repayment* (the group making repayments through installments); *Full Repayment* (the group paying back the full payments). *CPP* is a dummy variable equals to one if it is CPP bank, else is zero (i.e. matching bank). *CPP x PostBailout* is interaction term of CPP and PostBailout dummies. *High-Shareholding* is a dummy variable equals to 1 if shareholding is greater than median shareholding; zero equals to Low shareholding. *Size* is log value of total assets, where total assets is average total assets from previous five quarters. *Volatility* (or systematic risk) equals to annualized standard deviation of monthly return. *ROE* is return on equity. *Dividend Yield* is measured as the ratio of cash dividend to share price. *Book to Market* is the ratio of net worth to market capitalization. *Leverage* is total liability divided by net worth. *Dispersion* is standard deviation of one-year ahead analyst's earning forecast (FEPS1), deflated by share price. *Bid-Ask Spread* is absolute value of bid-ask difference, deflated by share price. All variables are defined in Appendix 3.A. Numbers presented in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3.6-Determinants of Changes in Cost of Equity

Panel A-Bailout Effect

Model	(1)	(2)	(3)	(4)	(5)	(6)
CPP	-0.141***	-0.123**	-0.043		-0.144***	-0.066
	(-2.717)	(-2.368)	(-0.860)		(-2.840)	(-1.364)
High-Shareholding				0.021	0.081**	0.073*
				(0.499)	(2.077)	(1.780)
Size		-0.025	-0.018		-0.048	-0.031
		(-0.749)	(-0.380)		(-1.382)	(-0.679)
Volatility		-0.166***	-0.147***		-0.164***	-0.146***
		(-3.244)	(-2.663)		(-3.223)	(-2.646)
ROE			-0.028			-0.023
			(-0.735)			(-0.612)
Dividend Yield			0.011			0.014
			(0.520)			(0.626)
Book to Market			0.029			0.028
			(0.437)			(0.436)
Leverage			-0.225***			-0.225***
			(-5.266)			(-5.250)
Dispersion			0.012			0.016
			(0.210)			(0.280)
Adjusted R-squared	0.018	0.044	0.082	-0.001	0.047	0.085
F-statistics	7.383***	8.708***	6.660***	0.249	7.869***	6.432***
N	576	574	574	576	574	574

(Continued)

(Table 3.6-Continued)

Panel B- Heterogeneity of Institutional Investor Effect

Model	(1)	(2)	(3)	(4)	(5)	(6)
CPP		-0.070	-0.033		-0.093**	-0.045
		(-1.492)	(-0.708)		(-1.980)	(-0.950)
F-dominate	0.127**	0.084*	0.019			
	(2.340)	(1.648)	(0.381)			
G-dominate				-0.107**	-0.055	0.003
				(-2.138)	(-1.302)	(0.060)
Size		-0.032	-0.019		-0.027	-0.018
		(-0.898)	(-0.405)		(-0.786)	(-0.380)
Volatility		-0.171***	-0.148***		-0.169***	-0.147***
		(-3.373)	(-2.729)		(-3.317)	(-2.694)
ROE			-0.028			-0.027
			(-0.749)			(-0.728)
Dividend Yield			0.011			0.012
			(0.513)			(0.544)
Book to Market			0.028			0.029
			(0.423)			(0.436)
Leverage			-0.221***			-0.226***
			(-5.153)			(-5.227)
Dispersion			0.011			0.012
			(0.195)			(0.210)
Bid-Ask Spread			-0.035			-0.036
			(-0.775)			(-0.787)
Adjusted R-squared	0.014	0.046	0.081	0.010	0.044	0.081
F-statistics	5.477***	7.367***	6.061***	4.573***	7.015***	6.004***
N	576	574	574	576	574	574

(Continued)

(Table 3.6-Continued)

In this table, I report the empirical relationship between explanatory variables and change in cost of equity using OLS regression models with year-fixed effect. The Dependent Variable is average change in implied cost of capital $r_{Icoc\ (3)}$ for all specification models, where $r_{Icoc\ (3)}$ is the arithmetic average of r_{GLS}, r_{OJ}, and r_{PEG}. The sample period is a window period of (-3, +3) around the year of bailout (t=0). The key explanatory variables in Panel A are *CPP* dummy, and *High-Shareholding*; *CPP* is a dummy variable equals to one if it is CPP bank, else is zero (i.e. matching bank). *CPP x PostBailout* is interaction term of CPP and PostBailout dummies. *High-Shareholding* is a dummy variable equals to 1 if shareholding is greater than median shareholding; zero equals to Low shareholding. In Panel B, i include two institutional investor variables *F_dominate* and *G_dominate* as main indicators. *F_dominate* is a dummy variable equals to one if Shareholding_F is greater than Shareholding_D, else equals to zero. *G_dominate* is a dummy variable equals to one if Shareholding_G is greater than Shareholding_I, else equals to zero. Other control variables are: *Size* is log value of total assets, where total assets is average total assets from previous five quarters. *Volatility* (or systematic risk) equals to annualized standard deviation of monthly return. *ROE* is return on equity. *Dividend Yield* is measured as the ratio of cash dividend to share price. *Book to Market* is the ratio of net worth to market capitalization. *Leverage* is total liability divided by net worth. *Dispersion* is standard deviation of one-year ahead analyst's earning forecast (FEPS1), deflated by share price. *Bid-Ask Spread* is absolute value of bid-ask difference, deflated by share price. All variables are defined in Appendix 3.A. Numbers presented in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3.7-Seemingly Unrelated Regression Estimates: Determinants of Changes in Cost of Equity

	Panel A		Panel B		
	Blockholder vs non-Blockholder		Different Repayment Groups		
	(1)	(2)	(3)	(4)	(5)
	Blockholder	Non-Blockholder	No Repayment	Partial Repayment	Full Repayment
CPP	0.024	0.421			
	(0.496)	(1.620)			
Shareholding	0.163***	-0.135			
	(2.755)	(-0.601)			
High-Shareholding			0.527	0.223*	0.068
			(1.147)	(1.743)	(1.082)
Size	-0.058	0.145	-0.576	-0.316**	0.001
	(-0.832)	(0.587)	(-0.926)	(-2.011)	(0.013)
Volatility	-0.164***	0.102	-0.070	-0.179*	-0.152**
	(-3.327)	(0.445)	(-0.198)	(-1.773)	(-2.542)
ROE	0.036	0.549	0.299	-0.011	0.076
	(0.636)	(1.310)	(0.679)	(-0.082)	(0.975)
Dividend Yield	0.005	-0.075	0.122	0.312*	-0.004
	(0.082)	(-0.228)	(0.198)	(1.978)	(-0.059)
Book to Market	0.123*	0.127	0.394	-0.599**	0.117
	(1.668)	(0.325)	(0.253)	(-2.591)	(1.450)
Leverage	-0.154***	-0.208	-0.447	-0.326**	-0.088
	(-3.000)	(-0.810)	(-1.329)	(-2.604)	(-1.412)
Dispersion	0.025	0.240	0.136	0.613***	0.031
	(0.442)	(0.770)	(0.107)	(3.127)	(0.511)
Bid-Ask Spread	-0.038	0.276	0.130	0.157	-0.081
	(-0.571)	(1.038)	(0.216)	(1.283)	(-1.076)
Adjusted R-squared	0.068	-0.096	-0.042	0.322	0.012
Chi-squared	24.27***		144.98***	600.66***	
F-statistics	4.214***	0.745	0.884	5.381***	1.437
N	439	30	27	84	332

The table reports the results from seemingly unrelated regression (SUR) estimates. The Dependent Variable is average change in implied cost of capital for all specification models, where $r_{Icoc(3)}$ is the arithmetic average of r_{GLS}, r_{OJ}, and r_{PEG}. *Blockholder* (in Panel A) is a dummy variable equals to one if shareholding by one single institution investor is more than 5% in a firm, else equals to zero (i.e. non-Blockholder). Different Repayment groups (in Panel B) are categorized based on repayment status: *No Repayment* (the group without any repayment as March 1, 2013); *Partial Repayment* (the group making repayments through installments); *Full Repayment* (the group paying back the full payments). *CPP* is a dummy variable equals to one if it is CPP bank, else is zero (i.e. matching bank). *Shareholding* is the ratio of shares held by institutional investors (II) to total shares outstanding. *High-Shareholding* is a dummy variable equals to 1 if shareholding is greater than median shareholding; zero equals to Low shareholding. *Size* is log value of total assets, where total assets is average total assets from previous five quarters. *Volatility* (or systematic risk) equals to annualized standard deviation of monthly return. *ROE* is return on equity. *Dividend Yield* is measured as the ratio of cash dividend to share price. *Book to Market* is the ratio of net worth to market capitalization. *Leverage* is total liability divided by net worth. *Dispersion* is standard deviation of one-year ahead analyst's earning forecast (FEPS1), deflated by share price. *Bid-Ask Spread* is absolute value of bid-ask difference, deflated by share price. All variables are defined in Appendix 3.A. Numbers presented in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The authors recognized that the numbers of observations in model (2) and (3) are small, the inclusion of more RHS variables makes the models less relevant to interpret. To maintain consistency of analyses, the author didn’t remove any of RHS variables.

CHAPTER IV

IDIOSYNCRATIC VOLATILITY IN BANKING INDUSTRY DURING 2008-2009 FINANCIAL BAILOUT

4.1Introduction

The injected capital from the Capital Purchase Program (CPP) is expected to improve the liquidity and capital base for the bailout banks so as to reduce the perceived risk associated with the bank operation. However, the evidence on the changes in idiosyncratic volatility (IVOL)[27] among public-listed banks upon government bailout events in the recent financial crisis is still unexplored. In this essay, I attempt to contribute to the existing literature by filling this gap.

Modern portfolio theory suggests that the investors hold a portfolio of financial instruments to diversify IVOL. In equilibrium, only systematic risk is priced and IVOL should not be priced since it can be eliminated through diversification. However, in reality, investors may not hold perfectly diversified portfolios (Barber and Odean, 2000; Benartzi and Thaler, 2001). As suggested by Merton (1987), investors should expect higher stock returns given higher IVOL in the presence of incomplete information. In other words, under-diversified investors may demand higher rates of returns as compensation for bearing IVOL. In addition, Goyal and Santa-

[27] Idiosyncratic volatility, alternatively named idiosyncratic risk or idiosyncratic variance, is non-systematic risk.

Clara (2003) argue that the systematic risk cannot fully explain the variance in total stock returns and IVOL plays the most important role for the average stock returns.

The existing literature exhibits two competing arguments on the relationship between risk and stock return. Levy (1978), Merton (1987), Fu (2009), and Goyal and Santa-Clara (2003) suggest a positive relationship because investors should expect higher rates of returns to compensate for the risk of holding non-fully diversified portfolios in the presence of market friction and information asymmetry[28]. Conversely, others argue for a negative relationship, implying some evidence of mispricing from conventional asset pricing models (Ang et al., 2006, 2009; Easley et al., 2002; Guo and Savickas, 2008; Guo and Savickas, 2010; Guo and Whitelaw, 2006). The risk-return relationship is a "substantive puzzle" as suggested by Ang et al. (2006). Particularly, there is no consensus in methodology to measure idiosyncratic risk, therefore making the documented evidence on this risk-return relationship more far from conclusive.

Brown and Kapadia (2007) also summarize few more reasons why it is critical to explore IVOL. First, some investors cannot fully diversify their portfolios (e.g. the participants in employee stock option plans) and must bear IVOL. Second, stock option prices depend on the total volatility of the underlying assets, of which IVOL accounts for a larger portion. Third, the level of IVOL may have important consequences for the amount of information conveyed by stock returns. Furthermore, these inconsistent results on the risk-return relationship warrant further examination.

There is especially scant empirical evidence on the effects of the bailout by the government as a lender of last resort on banks' IVOL. How this relationship evolves in the recent financial bailout event is an ongoing open question. One of motivations of this study is to fill the

[28] The findings from Goyal and Santa-Clara (2003) and Ang et al (2006) suggest that an idiosyncratic risk may be a priced risk factor.

gap with empirical evidence using a unique sample of financial institutions that receive government bailout in the recent financial crisis to test risk-return relationship. In addition, I attempt to examine whether the IVOL changes at the presence of the bailout events and what the determinants of IVOL are.

In this essay, I focus on publicly-listed banks that have received bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). I use the propensity score matching technique to identify non-CPP matching banks (matching banks) as control group. The findings from Fama and MacBeth (1973) standard error regression model suggest that only the lagged realized IVOL is positively related to the return.. The results are consistent with the observations by Brei and Gadanecz (2012), Black and Hazelwood (2013), and Duchin and Sosyura (2014) that financial bailout does not deter the risk-taking behavior among banks to the fullest, especially for the banks with highest IVOL. Furthermore, I document the important role played by corporate governance and information asymmetry on banks' IVOL.

In this essay, I contribute to the existing literature with empirical evidence on risk-return relationship on banking industry in the presence of 2008-2009 financial bailout. In addition, the findings from this paper contribute to the existing literature on the impact of government intervention on financial market operations with findings on the bailout effects on the banking industry specifically. The findings from this paper have important implications to investors, financial institutions and regulators in their portfolio allocations, risk evaluations, and assessment of the bailout program, respectively.

The remainder of this chapter is organized as follows. In Section 4.2, I review the extant literature and develop testable hypotheses. Section 4.3 describes the data and methodology. Section 4.4 presents the results, and Section 4.5 concludes the chapter.

4.2 Literature Review and Hypotheses Development

4.2.1 Risk-Return Puzzle

Total risk includes systematic risk and non-systematic risk. Stock return volatility (or variance) is a common proxy for total risk. Idiosyncratic volatility (idiosyncratic risk/variance) (IVOL) is the non-systematic part of total risk. Modern portfolio theory suggests that the investors hold a portfolio of financial instruments to diversify IVOL. In equilibrium, only systematic risk is priced and IVOL should not be priced since it can be eliminated through diversification. IVOL reflects firm-specific information that is volatile in its nature. Many factors may contribute to the time-varying nature of firm-specific information, such as disclosures of high risk lending information, earnings announcements, dividend payout news or corporate restructuring events.

However, in reality, investors may not hold perfectly diversified portfolios (Barber and Odean, 2000; Benartzi and Thaler, 2001). Goyal and Santa-Clara (2003) argue that systematic risks cannot explain all of the variance in total stock returns after controlling macroeconomic factors. They suggest that IVOL plays the most important role in explaining stock returns. They use equally-weighted average IVOL measure[29] to predict market portfolio returns on NYSE/AMEX/NASDAQ indices. They suggest that investors require higher rates of return given that increased risk as non-traded assets[30] have been included in their portfolios. However, they

[29] They use the term 'average stock variance' in their paper.
[30] Goyal and Santa Clara (2003) mention two examples of non-traded assets: (1) human capital, and (2) private business. The rationale for the increased risk from human capital is because human capital is firm-specific and its

find no statistically significant relationship between the value-weighted portfolio returns and IVOL.

Ang et al. (2006) use value-weighted IVOL measure and find that high IVOL stocks earn lower future returns in comparison to low IVOL stocks, which is opposite to the argument by Merton (1987) and Goyal and Santa-Clara (2003) that IVOL should be priced in the same direction of expected returns as suggested in. The risk-return relationship is a "substantive puzzle" as suggested by Ang et al. (2006). Ang et al. (2009) further demonstrate that this puzzling relation is present in international markets as well. They find confirming evidence for the negative relationship between risk-return in the seven largest (G7) equity markets. Most importantly, they indicate that there is a mispricing by the Fama-French model.

Fu (2009) and Huang et al. (2010) disagree with the "risk-return puzzle" and demonstrate that the negative risk-return relationship is only the artifact of biased value-weighted portfolio measurement and biased estimates induced by return reversals[31]of small stocks that have high IVOL. Fu (2009) shows that the realized IVOL as measured in Ang et al. (2006) is not stationary, and that the negative risk-return is the result of spurious regression. He uses exponential GARCH model (i.e. generalized autoregressive conditional heteroskedastic model) to estimate conditional IVOL and finds a positive relationship between the conditional IVOL and the expected return even after controlling for return reversals.

Peterson and Smedema (2011) address the risk-return puzzle by directly comparing the methodology of Ang et al. (2006;2009) and Fu (2009) with a data series from 1966 to 2008.

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value can affect firm value subject to the quality of the employers they hire. On the other hand, private business is similar to small traded firms. Private equity investment stands for important portion of investor portfolio.

[31] Huang et al. (2010) use "winners minus losers" portfolio as a proxy for return reversals in Fama-French three- and four-factor models.

They find evidence of a negative risk-return relation if a realized IVOL measure (as in Ang et al., 2006; 2009) is applied. But if they control the realized IVOL, then the relationship between return and expected IVOL (as in Fu, 2009) is positive. They link the negative risk-return relation to mispricing[32] and show that the relationship is a manifestation of January seasonality.

The mixed findings about idiosyncratic risk-return relationship indicate that the results are sensitive to methodology[33]. In this essay, I adopt the methodologies of Ang et al. (2006; 2009) and Fu (2009) to estimate the realized IVOL and implied IVOL, respectively, for a unique group of banking sample that receives financial bailout from the government.

4.2.2 Bailout Effects from Government Intervention

There are three possible economic predictions of the impact of government bailout on firm's risk-taking behavior as summarized by Duchin and Sosyura (2014). First, financial bailout could be implicitly interpreted as government protection from future financial distress, which may encourage banks' risk-taking activities and promote moral hazard issues. Second, government intervention might increase bank value by reducing the refinancing costs and the probability of bankruptcy; therefore, the bailout might inhibit the risk-taking behavior of bailout banks. The last prediction asserts that the bailout might have little effects on banks' risk-taking behavior since the costs and benefits will offset each other. For example, Brei and Gadanecz (2012) assess the soundness of government bailout programs in the G10 and four other

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[32] Peterson and Smedema (2011) use two proxies for mispricing: analyst coverage and dispersion of analyst forecasts. They employ two measures for both proxies. Analyst coverage is (1) the natural log of one plus number of analysts following a stock, and (2) a "high coverage" dummy variable equals to 1 if the number of analysts following is equals to or greater than three, 0 otherwise. Dispersion of analyst forecasts is (1) the natural log of one plus standard deviation of earning forecasts, scaled by the absolute value of the mean forecasts, and (2) a "high dispersion" dummy variable equals to 1 if the dispersion is greater than median dispersion, 0 otherwise.

[33] The author acknowledge that recent literature also find the evidence of no relation on return-IVOL using different sample periods, subsamples, data frequency, for example Bali et al. (2005), Bali and Cakici (2008) and Wei and Zhang (2005).

developed countries (87 large internationally active banks) in the pre-crisis (2000-2007) and during-crisis (2008-2010) periods. They compare the lending practices (particularly on syndicated loans) between bailout banks and non-bailout banks and document that bailout banks involve more risky lending than non-bailout banks after receiving public funds. These findings suggest that government bailout programs do not deter banks from conducting risky lending. However, Brei and Gadanecz do not examine stock-related risk measures.

The conventional wisdom states that the "too-big-to-fail" policy encourages risk-taking behavior in larger banks. Black and Hazelwood (2013) examine the effect of TARP on bank risk-taking activities and find that the average risk of loan origination increases among large TARP-banks but decreases among small TARP-banks. However, their sample consists only of 37 TARP-banks; therefore, it is difficult to draw a general conclusion about the government intervention effect on bailout banks. Huerta et al. (2011) study the short-term impact of TARP bailout on stock volatility and find that stock market volatility (i.e. a proxy for firm's total risk) is significantly reduced on the bailout-funding date and afterward. Unlike my focus on CPP recipients and COE, they emphasize on the market volatility changes for four TARP recipient groups: banking, insurance, finance and automotive industries. Duchin and Sosyura (2014) analyze the effect of government capital infusions on CPP banks and find that bailout improves the capitalization level of recipient banks, but induce their risk-taking behavior in both lending and investment.

Veronesi and Zingales (2010) investigate the costs and benefits of the U.S. government intervention plan to the ten largest banks[34] in the recent financial bailout and find that the value

[34] Nine largest banks are Citigroup, Bank of America, JP Morgan Chase, Wells Fargo, Bank of NY Mellon, State Street Corp, Goldman Sachs, Morgan Stanley, and Merrill Lynch. The tenth bank is Wachovia, later is acquired by Wells Fargo.

of banks' financial claims increases by $130 billion with a cost imposed on tax payers of about $21 billion. Fratianni and Marchionne (2013) apply the event study methodology to estimate the value creation/destruction for 122 banks following government bailout programs in 19 countries. They identify general announcements as those associated with government intervention plans such as capital injection and asset/debt guarantees program, and specific announcements as the announcements about specific banks to receive government financial support. They find different market reactions across regions and by types of rescue announcements. General announcements tend to bring about positive cumulative abnormal returns (CARs) while specific announcements often generate negative CARs. Interestingly, Fahlenbrach et al. (2012) connect the recent financial crisis with previous ones and show that banks' stock performance during the 1998 crisis can predict their own stock performance and probability of failure in the 2008-2009 financial crisis. These findings suggest that banks' risk culture and business model make its performance sensitive to future crises.

4.2.3 Theories on Factors that Affect IVOL

Prior studies suggest several factors that might affect IVOL, including firm fundamentals, corporate governance and information asymmetry (Ang et al., 2006; Brandt et al., 2010; Brown and Kapadia, 2007; Diether et al., 2002; Harvey and Siddique, 2004; Wang and Nguyen, 2015).

4.2.3.1 Size. *Size* is one of the market anomies**.** Banz (1981) and Reinganum (1981) show that small-capitalization firms earn higher average returns. Bank size also affects the degree of idiosyncratic risk as suggested by Wang and Nguyen (2015). *Size* can be a proxy for information asymmetry because the risk to invest in smaller firms is relatively higher due to lower transparency in information or limited analyst coverage. Size can also be a proxy for growth opportunity. Smaller firms normally have more growth potential than larger firms. Additionally, small firms are less liquid than larger firms, so size may also be a proxy for illiquidity. *Size* is measured as the log value of average assets from the previous five quarters. I expect IVOL to be higher among small firms as suggested by Brown and Kapadia (2007) , Harvey and Siddique (2004) and Wang and Nguyen (2015). Size should be negatively related to IVOL (small firms are riskier).

4.2.3.2 Corporate governance. *Free cash flow* in a firm can be a proxy for agency costs. Based on Jensen (1986), managers in cash-rich firms have more incentives to go on a spending spree, which leads to increased agency costs. Government bailout in recent financial crisis 2007-2009 is believed to have interfered with market functioning ((Acharya et al., 2009) and Ellul and Yerramilli (2013)), because government provides debt guarantees[35] and increases the level of deposit insurance protection[36]. Debt guarantee program weakens the incentives of debt holders of banks and add protections for the financial institutions from market disciplines (e.g. takeover or shareholder activism). On the other hand, unstable banks usually have to pay a risk premium to its depositors in the form of higher interest rates to compensate for bearing higher default risks. But this default risk for depositors is eliminated by the deposit insurance. Deposit insurance removes the incentive of depositors to demand such a risk premium. Deposit insurance also provides the incentive for banks to engage in riskier activities.

Institutional investors are expected to monitor and discipline managers (Chazi et al., 2011). The higher percentage of institution ownership predicts better corporate governance, and

[35] Government provides three-year guarantee of all new issuance (long-term and short-term) maturing between then and June 2009, with a maximum of 125 percent of face value and with a fee of 0.75%. The guarantee of all new debt issuance is to prevent lending freeze and to encourage lending to the banks.

[36] The 100 percent guarantee of non-interest-bearing accounts in FDIC insured banks increased from $ 100,000 to $ 250,000.

consequently minimal monitoring and exit costs (Chung and Zhang, 2011). In their multi-country study, Aggarwal et al. (2011) find that changes in institutional ownership over time affect subsequent changes in firm-level governance. More importantly, changes in institutional ownership are positively associated with future changes in firm values. Elyasiani and Jia (2008) and Elyasiani et al. (2010) argue that stable institutional investors are better motivated and possess better ability to monitor effectively; thereby, they play an important role in mitigating agency conflicts and information risk in the firm. Consistent with this view, Elyasiani and Jia (2008) find a significant positive relation between institutional ownership stability and bank holding company performance.

However, Booth et al. (2002) find these internal monitoring mechanisms to be significantly less related with regulated firms (banks and utilities). Adams and Meehran (2003) suggest that governance structures are industry-specific. Fewer institutional investors hold shares of BHCs relative to shares of manufacturing firms. Institutional investors look into not only growth opportunities, but also the presence of regulation in the banking industry.

4.2.3.3 Information asymmetry hypothesis. Fama (1970) proposes the efficient market hypothesis (EMH)[37] which suggests that markets are "informationally efficient" and prices at all times reflect all current public and private information. New information regarding securities comes to the market in a random fashion. Trading by profit-maximizing investors cause security prices to adjust rapidly to reflect the effect of new information. Empirical studies have found evidence against the strong-form EMH (Chowdhury et al., 1993; Jaffe, 1974). Notably,

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[37] Fama further subcategories the EMH into three sub hypotheses: (1) weak-form hypothesis argues that no investor can earn excess return on historical consequence of prices, rates of return, trading volume data, and other market-generated information; (2) semi-strong form EMH states that no investor can earn excess returns from trading rules based on any publicly available information, and (3) strong-form EMH suggests that no investor can consistently earn excess returns using any information, whether publicly available or not.

Grossman and Stiglitz (1980) find "informed" traders acquire better estimates of future states of nature and take trading positions based on the information, while "uninformed" traders have limited resources in collecting information, but they can infer the information of informed traders by observing the price fluctuation. It indicates that the private information affects the equity prices. Wang (1993) and Dow and Gorton (1995) show that informed traders profit from their information relative to the uninformed investors.

The distribution of private information also affects the incentive and investors' required rate of return. Information disclosure by the firms essentially makes private information available to the public. Enhanced disclosure can reduce the adverse selection problem by reducing the transaction costs and information asymmetry, and further improve liquidity (Diamond and Verrecchia, 1991). As suggested by Easley and O'hara (2005), public information reduces the risk for holding such assets. Gervais et al. (2001) find a positive relationship between trading volume and stock return. So stocks with high IVOL might be those with low turnover. Harvey and Siddique (2004) find supporting evidence for the negative relationship between IVOL and turnover. Turnover or bid-ask spread is often used as alternative proxies for liquidity.

Based on the findings from reviewed literature, I propose the following hypotheses about the determinants of IVOL.

H1. Firms with better corporate governance have lower IVOL.

H2. Firms with less degree of information asymmetry have lower IVOL.

4.3 Data and Methodology

4.3.1 Data Sources and Sample Selection

In this essay, I focus on publicly-listed banks that receive bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). In order to address potential endogeneity issue, I use the propensity score matching technique to identify non-CPP matching banks as control group. Propensity score matching is widely used in the literature to estimate the treatment effect (Heckman et al., 1998; Hirano et al., 2003; Li and Zhao, 2006; Rosenbaum and Rubin, 1983, 1985). Different from traditional matching techniques, propensity score matching method allows finding matching firms on several characteristics simultaneously. The selection of matching variables is guided by theory and prior research (Li and Zhao, 2006). I calculate a predicted value of *ROA* (i.e. a propensity score) with three industry median-adjusted regressors (i.e. *MKTCAP*, *DEBT and MKBK*[38]) for all sample banks and matching pool of non-CPP recipients, which are drawn from Compustat dataset within the same banking sector (SIC codes from 6000-6399). I successfully find 227 matching banks for our sample of CPP banks. Please refer to Chapter 2 for the details of sample and matching techniques.

4.3.2 Realized Idiosyncratic Volatility (IVOL) Approach

Conventional capital asset pricing model (CAPM) is typically employed to estimate the risk. However, CAPM beta may not be sufficient to capture firm market risk. Fama and French (1992; 1993) find that firm size and book-to-market ratio can improve the predictive power of

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[38] *MKTCAP* is the logarithm value of market capitalization. *DEBT* is the ratio of total liabilities to total assets. *MKBK* is the ratio of market price to book price.

CAPM one-factor model. Following Ang et al. (2006; 2009), IVOL can be measured as the standard deviation of the regression residuals from Fama-French three-factor market model[39].

$$R_{i\tau} - R_{f\tau} = \alpha_{it} + \beta_{it}\left(R_{m\tau} - R_{f\tau}\right) + s_{it}\left(SMB_{\tau}\right) + h_{it}\left(HML_{\tau}\right) + \varepsilon_{i\tau} \tag{4.1}$$

Where τ is the subscript for the day and t is the subscript for the month, $\tau \in t$.

Using similar procedure and model specification in equation (4.1), I obtain monthly *IVOL3* for CPP banks and matching banks from the following procedures. First, I estimate equation (4.1) with daily returns from CRSP and obtain the residuals ε_{it} for each firm each period. Second, I estimate daily IVOL as standard deviation of the residuals based on a rolling 30-day window. Third, I calculate monthly *IVOL3* as the squared root of the product between the daily IVOL and the average number of trading days in a month.

$$R_{i\tau} - R_{f\tau} = \alpha_{it} + \beta_{it}\left(R_{m\tau} - R_{f\tau}\right) + s_{it}\left(SMB_{\tau}\right) + h_{it}\left(HML_{\tau}\right) + u_{it}\left(UMD_{\tau}\right) + \varepsilon_{i\tau} \tag{4.2}$$

Following Brown and Kapadia (2007), I obtain the second measurement IVOL4 from equation (4.2) by including Carhart (1997) momentum factor (UMD)[40]using the same estimation procedure as above.

In the above models,

$R_{i\tau}$	Stock daily returns for firm i at time τ
$R_{f\tau}$	Risk –free rate is one-month U.S. Treasury bill return
$R_{i\tau} - R_{f\tau}$	Excess returns or risk premium for firm i at time τ
α_{it}	Intercept
$\varepsilon_{i\tau}$	Regression residual
β_{it}, s_{it}, h_{it}, u_{it}	Risk factor sensitivities or loading for each risk factor
$\left(R_{m\tau} - R_{f\tau}\right)$	Market risk premium at time τ
(SMB_{τ})	The difference between the daily average return on a portfolio of small and large firms at time τ
(HML_{τ})	The difference between the daily average return on a portfolio of high and low book-to-market stocks at time τ

[39] The daily factor data are downloaded from Kenneth R. French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[40] Momentum factor data is downloaded from Kenneth R. French's website.

(UMD_{τ})	The difference between the daily average return on a portfolio of high and low momentum stocks at time τ

4.3.3 Expected Idiosyncratic Volatility (E(IVOL)) Approach

Ang et al (2006) suggest a negative relationship between monthly returns and one-month lagged $IVOL$. However, the pre-assumption of *IVOL* following a random walk process stirs up the controversy. Fu (2009) replicates the time-series realized IVOL measure and finds opposite result to this assumption, and argues that realized IVOL approach is not appropriate to determine risk-return relation.

Fu (2009) provides an alternative approach to estimate idiosyncratic risk, namely the expected IVOL (*E (IVOL)*), using time-series EGARCH model. Time-series analysis comprises methods for analyzing time-series data in order to extract meaningful statistics or characteristics of the data and to develop models capable of forecasting, or testing hypotheses of interest. Autoregressive moving-average (ARMA) (*p*, *q*) model assumes the variance of the disturbance term to be constant. However, most financial data do not have constant mean and variance. Furthermore, most of time series data exhibit either trends or periods of high or low volatility. Thus, the Autoregressive conditional heteroskedastic (ARCH) model is more appropriate because the variance and the mean processes can be estimated jointly (Engle, 1982). Bollerslev (1986) extends Engle's original work, suggesting ARCH model to allow for both autoregressive (AR) and moving average (MA) components in the heteroskedastic variance. GARCH (*p, q*) is the generalized ARCH model.

The standard GARCH has the drawback of not capturing a well-known phenomenon of asymmetric volatility in stock returns series. The tendency for volatility to decline when the returns rise or vice versa is often called the leverage effect (Enders, 2008). Behavior finance literature suggests that "bad" news has a more pronounced effect on volatility than does "good" news. Nelson (1991) proposes an Exponential-GARCH (EGARCH) model allowing for asymmetry effects in the conditional variance of epsilon. EGARCH has the advantages of handling the asymmetries in the conditional variance, and capturing volatility persistence from residual variances and past squared innovations.

$$R_{i,t} - R_{ft} = \mu_0 + \gamma_1(R_{mt} - R_{ft}) + \gamma_2(SMB_t) + \gamma_3(HML_t) + \sum_{k=1}^{p} \delta_k (R_{i,t-k} - R_{ft-k}) + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_{i,t} \tag{4.3}$$

Where, $\varepsilon_{i,t} \mid (\varepsilon_{i,t-1}, \varepsilon_{i,t-2}, \dots\dots\dots) \sim N(0, \sigma_{i,t}^2)$

$$\log(h_t) = \alpha_0 + \alpha_1(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + \lambda_1 |\varepsilon_{t-1}/\sqrt{h_{t-1}}| + \beta_1 \log(h_{t-1}) + \vartheta_1 \varepsilon_{t-1}^2 \tag{4.4}$$

Where conditional variance h_t is an asymmetric function of lagged disturbance ε_{t-1}

Following Fu (2009), I estimate the Fama-French 3-factor model as in equation (4.3) and estimate the conditional variance $\log(h_t)$ from the EGARCH (*p,q*) model, in which $1 \leq p \leq 3$ and $1 \leq q \leq 3$ as present in equation (4.4), for each CPP bank and matching bank individually. I choose the model with the lowest Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC) as the best fitting model for each firm. Among successfully converged models[41], EGARCH (3,q) model accounts for 66.67 percent and 71.3 percent of best fitting models for CPP banks and matching banks respectively[42].

Table 4.1 reports the descriptive statistics of the IVOL measures over the eleven years (-5, +5) around the bailout year (i.e. year 0). To investigate the risk-return relation, several control variables are constructed based on previous literature (e.g. Fu 2009). *Beta* is the rolling 60-month window beta and serves as the proxy for the systematic risk. *Ln (ME)* is the natural logarithm of market capitalization (or market cap), where market cap is the product of share price and the

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[41] The convergence rate is 92.09 percent and 100 percent for CPP banks and matched banks respectively.
[42] Fu (2009) also finds EGARCH (3,q) generates the most best fitting models (i.e. 40%).

number of shares outstanding. *Ln (BKMK)* is the natural logarithm of book-to-market, where book value is book equity value and market value is market cap. I also include two transaction cost variables, momentum and liquidity. *Ln (Ret (-2,-7)),* a proxy for momentum factor, is natural logarithm of *Ret (-2, -7),* while *Ret (-2,-7)* is compound gross return from t-2 to t-7 period and serves as a proxy for momentum factor, and t=0 is the month of bailout. *Ln (Bidaskspread)* are the proxies for liquidity. *Ln (Bidaskspread)* is the natural logarithm of the absolute difference between adjusted ask price and adjusted bid price.

To avoid the distortion of the results from extreme values due to typos, misreporting, or non-typical firms, I winsorize *IVOL3*, *IVOL4*, and *E (IVOL)* at top and bottom 5 percent. In Panel A of Table 4.1, the mean values of the two realized IVOL and their lagged values are in the range of 12.1 percent to 12.4 percent, which are close to 14.1 percent reported by Fu (2009). The mean and median values of *E (IVOL)* are 60.5 percent and 0.2 percent, which are apparently deviate from the range of 10.29-12.67 percent of Fu (2009). To investigate whether the bailout event affects the returns and IVOL measures, I separate the sample into two periods, pre- and post- bailout as shown in Panel B and Panel C. By comparing the mean values of the three IVOL measures between pre- and post-bailout periods, I observe that *IVOL3* and *IVOL4* significantly increase in the post-bailout period.

[Insert Table 4.1 about here]

4.3.4 Stationarity Tests

To examine the stationarity of the return and IVOL series, I aggregate the monthly data into the context of time series and examine the series in line plots. Figure 4.1 displays the results from the period of October 2003 to December 2012. There is a sudden fluctuation around the

October 2007 financial bailout period on the monthly return (ln (*Ret)*) variable at level and first difference as in Figure 4.1.1. Consistent with the argument of Fu (2009), the realized IVOL measures (i.e. *IVOL3 and IVOL4*) exhibit non-stationary characteristics as shown in Figures 4.1.2-4.1.3. After taking the first difference, the realized IVOL series become stationary. In Figure 4.1.4, the expected IVOL (*E (IVOL*)) exhibits stationarity at both the level and the first difference.

[Insert Figures 4.1 about here]

Granger and Newbold (1974) suggest that unit root tests should be imposed on most time series before any modeling procedures to prevent any misleading interpretation from spurious regression. Especially, inflated R squared statistics and t-statistics often lead to possible Type I errors.

$$\Delta y_t = \propto + \beta y_{t-1} + \delta_t + \vartheta_1 \Delta y_{t-1} + \vartheta_2 \Delta y_{t-2} + \cdots + \vartheta_k \Delta y_{t-k} + \varepsilon_t \quad (4.5)$$

I use the augmented Dickey and Fuller (1979) test (ADF test) with a trend model as shown in equation (4.5) for time-series data. The null hypothesis for ADF test is that the series contains a unit root ($\alpha = 0$), where δ_t is time trend and k is the number of lags specified by the lag ( ) option. ADF tests are performed on the level and the first difference for each variable. If the computed statistic is larger than the MacKinnon critical value, I reject the null and conclude that the data series is stationary.

In order to test risk-return relation in the pooled cross-section data, I also examine the stationarity properties of returns and IVOL variables using ADF Fisher unit root tests for panel data (Choi, 2001). The null hypothesis for ADF Fisher unit root test is that all panels contain a unit root. It needs at least one panel is stationary to reject the null hypothesis. To test Fisher-type unit root tests on each panel, I first subtract the cross-sectional average from the series, and include trend and one lag (to remove higher-order autoregressive components of the series). Fisher-type unit root test is less restrictive and does not require strongly balanced data and the individual series can have gaps.

In Table 4.2, the ADF tests from time-series data suggest that both *IVOL3* and *IVOL4* variables and their lagged values do not evolve as stationary processes at level, which are consistent with the arguments by Fu (2009). However, the non-stationary issues in these two variables do not exist in panel data as shown from ADF-Fisher tests. The findings from unit root tests suggest using reliable measures in return and IVOL so as to test the risk-return relation.

[Insert Table 4.2 about here]

4.3.5 Risk-Return Relationship

4.3.5.1 Bivariate correlation. To have a quick picture of risk-return relation, I plot return and IVOL series over time in Figure 4.2. As the result of the unit root tests, I take the first differences of Ln (Ret) and both *IVOL3* and *IVOL4* so that the series can be stationary. Risk and return tend to move in the same direction as shown in Figures 4.2.1-4.2.2, but not clear when E(IVOL) is employed in Figure 4.2.3.

[Insert Figure 4.2 about here]

In addition to the plots, Table 4.3 provides the Pearson's correlation coefficients which show the relationship between risk and return. Panel A of Table 4.3 reports a positive and significant Ln (*Ret)-IVOL* relationship for all three IVOL measures and lagged values of two realized IVOL. However, the correlation between return and *E (IVOL)* is not significant.

Basically, the positive *Ln (Ret)-IVOL* relationship supports the argument of Fu (2009), except for the *E (IVOL)* measure. The bivariate correlations between *Ln (Ret)* and control variables are also consistent with intuition. In non-tabled results, I find the Ln (Ret)-IVOL relationship is robust even in panel data, or in pre-bailout, or in post-bailout period.

[Insert Table 4.3 about here]

4.3.5.2 Fama-MacBeth cross-sectional regression. Fama and MacBeth (1973) model is extensively used in empirical estimation of risk premium. It essentially includes two steps. First, I estimate the parameters of interest through cross-sectional regression for each time period. Second, I obtain final estimates for the parameters and the standard errors and calculate the mean of the parameters and t-statistics. The advantage of the Fama-MacBeth model is to avoid error-in-variable problem since the regressors are time-varying and directly observable in the context of panel data. Following Fama and French (1992), Fu (2009) and Brandt et al. (2010), I examine risk-return relationship month-by-month using pooled cross-sectional Fama MacBeth (1973) regression model as shown in equation (4.6).

$$Ln\ (Ret)_{it} = \alpha_i + \beta_1 IVOL_{it} + \beta_2 Beta_{it} + \beta_3 Ln\ (ME)_{it} + \beta_4\ Ln\ (BKMK)_{it} + \beta_5\ Ln\ (Ret(-2,-7))_{it} + \beta_6 Ln\ (Bidaskspread)_{it} + \varepsilon_{it} \tag{4.6}$$

Where $IVOL_{it}$ is one of three IVOL measures (i.e., Lagged value of *IVOL3*, lagged value of *IVOL4*, and *E (IVOL)* for firm *i* at time *t*.

4.3.6 Panel Methodology

Time series data analysis has its criticized weakness of ignoring heterogeneity between individual observations. To investigate the bailout effect on IVOL and determinants of IVOL, I employ a series of panel data analysis techniques. Panel data provides the additional benefits to (1) capture the time dynamics (2) control for endogeneity and (3) control for unobservable individual characteristic.

4.3.6.1 OLS, random effect, and fixed effect. The basic regression model to bailout effect on IVOL is shown in equation (4.7).

$$y_{it} = x_{it}\beta + \mu_i + \varepsilon_{it} \tag{4.7}$$

If the error term ε_{it} is uncorrelated with any explanatory variable x_{it}, and μ_i contains only a constant term, ordinary least squared (OLS) provides consistent and efficient estimates of α and β. If the unobserved individual heterogeneity μ_i is uncorrelated with the explanatory variable x_{it}, then I estimates the model with random effects. But if μ_i is unobserved and also correlated with explanatory variable x_{it}, then the OLS estimate of β is biased. Using fixed effects allows for correlation between μ_i and x_{it} estimating group-specific constants in the regression model to capture the differences across firms. Hausman test can help determine whether the fixed effect or the random effect is more appropriate.

4.3.6.2 Multivariate regression model with clustered standard errors. To explore the determinants of IVOL, I employ several regression specifications. When analyzing panel data, the residuals may be correlated over time (King and Segal, 2009; Sarkissian and Schill, 2009). In order to mitigate such error, I correct the standard errors for clustering effects in 2 dimensions (by time and by firm) following Petersen (2009) as shown in equation (4.8).

The specification of Pooled OLS regression models are:

$$IVOL_{it} = \beta_1 CPP_i + \beta_2 PostBailout_t + \beta_3 CPP_i * PostBailout_t + \beta_4 X_{it} + \alpha_i + u_t + \varepsilon_{it} \tag{4.8}$$

Where, α_i is time-invariant firm specific characteristic, u_t is the quarter fixed effect, and ε_{it} is the remainder error term. I also construct a set of control variables (X_{it}) as follows.

Size is computed as the natural log of total assets[43], and is expected to have a negative impact on IVOL as discussed in the literature section. *Debt* is the ratio of total liability to total assets. Higher the debt indicates higher risk. Efficiency Ratio (*ER)*, the ratio of non-interest expense to total income, is a proxy for the cost structure and operation efficiency. A lower ER is generally favorable. *Return on Average Assets* (*ROAA*) is an important measure of profitability and is computed as the ratio of net income to average total assets. Capital is the core measure of financial strength for banks, as high ratio and thus good quality of capital could protect banks from unexpected losses especially in financial crisis. *Tier 1 risk-adjusted capital ratio* (*Tier 1 Capital*) measures the amount of core equity (i.e. common stock, retained earnings, and non-redeemable preferred stock) available as a percentage of total risk-adjusted assets.

4.3.6.3 Seemingly unrelated regression model. To further investigate the corporate governance and information asymmetry effects on IVOL as stated in the hypotheses, I separate the sample (include CPP banks and matching banks) into two sets of group, Good vs. Poor Corporate Governance, and High vs. Low Information Asymmetry. I suspect that some coefficients in multivariate analysis might differ between the two groups; therefore, I employ seemingly unrelated regressions (SUR) analysis based on Zellner (1962) in order to compare coefficients across regression models in equations (4.9). The specifications of the seemingly unrelated regression models are:

[43] Log value of total assets is common measurement in banking industry. We use average total assets as total assets, which is total assets from previous five quarters divided by five.

$$IVOL_{it} = \alpha_0 + \beta_1 CPP_i + \beta_2 CPP_i * PostBailout_t + \beta_3 X_{it} + \ + u_t + \varepsilon_{it} \qquad (4.9)$$

Where, α_0 is a constant, u_t is time-fixed effect, and ε_{it} is an error term. The rationale and the constructions of the Corporate Governance and Information Asymmetry are explained as below.

Corporate Governance. Corporate governance is expected to have positive impacts on the perceived IVOL. I include three variables as proxies for corporate governance. *Free Cash Flow,* a proxy for agency cost, is computed as the difference between income before extraordinary items and total deposit, scaled by total average assets**;** higher free cash flow indicates poor corporate governance since high levels of free cash flow in a firm provide a great opportunity to managers to spend on non-wealth enhancing projects. *Institutional Investor* ***(****Shareholding)* is the percentage of institutional investors holding relative to total shares outstanding for each stock each quarter (Ferreira and Matos, 2008; Parrino et al., 2003)[44]. Higher institutional investor shareholding indicates better corporate governance. *Blockholder* is a dummy variable equals to 1 (or Yes) if *Shareholding* by one single institutional investor is greater than 5 % in a firm and 0 else. Firms with *Blockholde*r are assumed to be well governed.

Information Asymmetry. The degree of information asymmetry is predicted to be positively associated with IVOL. Similarly, three alternative proxies are employed. *Size* could be a proxy for information asymmetry because the risk to invest in smaller firms is relatively high due to low transparency in information or limited analyst coverage. *Ln (Bidaskspread)* is the proxy for liquidity. The higher the *Ln (Bidaskspread),* the lower the liquidity. Low *Liquidity* (or high *Ln (Bidaskspread)* is expected to induce high IVOL. *Dispersion* of analyst forecasts is

[44] We also construct alternative shareholding measure as robustness check using market value of shares instead of the number of shares, the results are qualitative similar.

computed as the standard deviation of the firm's estimated EPS for 1-yr ahead by I/B/E/S, scaled by stock price at the earnings forecast date. The variability of forecast earnings indicates possible information asymmetry between insiders and outsiders, therefore increases the risk for investors.

4.4 Results and Discussions

4.4.1 Risk-Return Puzzle

Table 4.4 reports the results of the Fama-MacBeth regression in the context of panel quarterly data[45]. The dependent variable is *Ln (Ret)*, while the IVOL measure is *Lag (IVOL3)* for models (3)-(4), *Lag (IVOL4)* for models (5)-(6), and *E (IVOL)* for models (7)-(8). Consistent with the findings in bivariate simple correlation, the two realized IVOL measures are positively related to *Ln (Ret)* at one percent level of significance. The results are robust with the inclusion of systematic risk factor *Beta*, size factor *Ln (ME)*, growth factor *Ln (BKMK)*, momentum factor *Ln (Ret (-2,-7)* to control for return reversal, and liquidity factor *Ln (Bidaskspread)* as in models (4) and (6). Interestingly, the risk-return relationship is positive and significant at one percent level when *E (IVOL)* is employed as shown in model (7), but the R-squared is below 1 percent. I include additional control variables in the models (8), the insignificance results remain.

Essentially, the findings from this table are consistent with the observations from bivariate simple correlation tests: The risk-return relationship is positive only when lagged values of two realized IVOL measures are the key indicators. The results are robust as demonstrated in Appendix B in the subsamples of pre-bailout, post-bailout, CPP banks only, or matched banks only.

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[45] In non-tabled results, I compare the random effect and fixed effect models for same model using Hausman test. The fixed effect model prevails.

[Insert Table 4.4 about here]

4.4.2 Bailout Impact on Idiosyncratic Volatility (IVOL)

To examine whether financial bailout causes any significant impact on banking industry (in terms of idiosyncratic risk), I provide univariate analysis in this section. In Panel A of Table 4.5, the mean *IVOL3* values in CPP banks are 11.64 percent and 8.55 percent in whole sample and pre-bailout period, which are significantly lower than those in matching banks (13.31 percent and 9.88 percent). Even the mean value of *IVOL3* for CPP banks increases after the bailout, but it is still lower than for their counterparts. The results are quantitatively similar with *IVOL4* measure as in Panel B[46] .

[Insert Table 4.5 about here]

Table 4.6 provides close examinations on IVOL by relative year, given that t=0 is the year of bailout. CPP banks and matching banks are sorted by *IVOL3* and grouped into four quantiles as shown in Panel A. I notice that there is a sharp increase in the *IVOL3* one year prior to the bailout, notably in the highest quantile for CPP banks (507.10%). After the bailout, the mean value of *IVOL3* decreases significantly, but still relatively higher than the lowest level as in Year -2 and Year -3. In addition, the mean difference between highest and lowest quantile remains statistically significant regardless of the presence of bailout event. The results are consistent with *IVOL4* measure as in Panel B.

The results from this section seems to be consistent with the observations of Brei and Gadanecz (2012), Black and Hazelwood (2013), and Duchin and Sosyura (2014) that financial

[46] Different from realized IVOL measures (i.e. IVOL3 and IVOL4), E(IVOL) is an expected conditional risk measure and it is not appropriate to measure the real impacts of financial bailout.

bailout does not deter the risk-taking behavior among banks to fully extend, especially for the banks with highest IVOL. However, I also notice that risk-taking behavior is less severe in CPP banks than in non-CPP banks since the CPP banks are subject to stringent monitoring from the government under the conditions of bailout. It implies that financial bailout can mitigate the banks' risk-taking activities to certain extent.

[Insert Table 4.6 about here]

In this section, I provide multivariate regression analysis to determine the factors affecting IVOL using Petersen (2009) clustered standard error model in the context of quarterly panel data with firm-fixed effect and time-fixed effect. In Table 4.7, the dependent variable is *IVOL3* in models (1)-(3) and *IVOL4* in models (4)-(6).The main findings from Panel A are consistent with univariate results. First, *CPP* dummy is negatively related to the two IVOL measures significantly at least at the five percent level, which indicates that CPP banks have lower IVOL than non-CPP banks. The results are robust with inclusion of control variables as in model (3) and (6). Secondly, *PostBailout* dummy is positively related to IVOL in model (1) and (4), which suggests that CPP banks have reduced level of IVOL in post-bailout period.

In additions, I find *Size* is negatively related to IVOL, as small-size banks bear higher IVOL. *ER* is positively related to IVOL as expected, since lower *ER* is preferable. Both *ROAA* and *Tier 1 Capital* are negatively associated with IVOL at one percent significant level, which means the banks with high profitability and Tier 1 risk-adjusted core equity deserve lower level of IVOL. In univariate test, I notice that there is huge jump in the level of IVOL for CPP banks and matching banks one year before bailout. Therefore, I re-test the models in subsample (all, exclude year -1) and the findings are pronounced as shown in Panel B.

[Insert Table 4.7 about here]

4.4.3 Determinants of Idiosyncratic Volatility (IVOL)

To investigate whether corporate governance and information asymmetry play important role on IVOL, multivariate regressions with clustered standard errors models are employed in the context of quarterly panel data. The dependent variable is *IVOL3* in models (1)-(3) and *IVOL4* in models (4)-(6) of Table 4.8. I observe that two of three proxies for corporate governance (i.e. *Free Cash Flow*, *Institutional Investor*, and *Blockholder*) are related to IVOL significantly at predicted direction except *Free Cash Flow* as shown in Models (1) and (2), which indicates that the banks with higher *Institutional Investor* Shareholding, and contains *Blockholder* will have decreases in IVOL. The significance in *Free Cash Flow* variable disappears with inclusion of information asymmetry proxies in model (3) and (6).

Furthermore, three proxies for information asymmetry (i.e. *Size*, *LnBidaskspread*, and *Dispersion*) are related to IVOL in the right direction significantly. The results suggest that the banks that are small in size, low in liquidity, and high in analysis forecast dispersion will have increase in IVOL. In summary, the findings from this table essentially support all the hypotheses.

[Insert Table 4.8 about here]

4.4.3.1 Corporate governance on idiosyncratic volatility. To further investigate whether the differences between good and poor-corporate governance banks are statistically significant, SUR estimates are employed in Table 4.9. First, the sample (includes CPP banks and matching banks) are sorted and ranked into two groups, Good vs. Poor Corporate Governance. The decision rule is if the firms have low *Free Cash Flow*, *High Institutional Investor*

Shareholding, and contain *Blockholder*, then they are classified into Good Corporate Governance Group as in models (2), (4), and (6). The remaining firms will be the group of Poor Corporate as in models (1), (3) and (5). The dependent variable is *IVOL3* in Panel A and *IVOL4* in Panel B of Table 4.9. As expected, the corporate governance on IVOL is significantly different across two corporate governance groups in both Panel A and Panel B.

[Insert Table 4.9 about here]

4.4.3.2 Information asymmetry on idiosyncratic volatility. Similarly, to test whether the differences between high and low information asymmetry banks are statistically significant, I sort and rank the sample into two groups, High vs. Low Information Asymmetry. The decision rule is if the firms are larger in S*ize,* and low in *LnBidaskspread* and *Dispersion*, then they are classified into Low Information Asymmetry group as in models (2), (4), and (6). The remaining firms will be the group of High Information Asymmetry as in model (1), (3), and (5). The dependent variable is *IVOL3* in Panel A and *IVOL4* in Panel B of Table 4.10. Unsurprisingly, the information asymmetry on IVOL is significantly different across two information asymmetry groups in both Panel A and Panel B.

[Insert Table 4.10 about here]

4.5 Conclusions

In this essay, I contribute to the existing literature with documented evidence on risk-return relationship using a unique group of bailout banks in the recent financial crisis of 2007-2008. I focus on publicly-listed banks that receive bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act

(2008). I use the propensity score matching technique to identify non-CPP matching banks (matching banks) as control group.

The findings from Fama-MacBeth (1973) standard error regression model suggest that the lagged values of realized IVOL measures are positively related with returns. The results are robust for different subsamples. The positive risk-return findings are consistent with Fu (2009) and Huang et al. (2010) when realized lagged value of IVOL of are utilized.

However, the results do not apply in the case of expected IVOL as suggested by Fu (2009). There are several major differences between this paper and Fu's (2009). First of all, the sample period in Fu's paper is longer (i.e., 44 Years, from 1963 to 2006) relative to this paper (i.e. 11 years). The recent financial bailout casts significant impacts on stock returns, especially in banking industry. Secondly, my sample is a unique group of banks that receive financial bailout funds under TARP during 2008-2009 and their counterpart banks that are not CPP recipients but have same probability to receive financial bailout. The sample in Fu's paper is not industry specific.

The findings from this paper contribute to government intervention literature on the bailout effect on banking industry. The results are consistent with the observations by Brei and Gadanecz (2012), Black and Hazelwood (2013), and Duchin and Sosyura (2014) that financial bailout does not deter the risk-taking behavior among banks to the full extent, especially for the banks with highest IVOL. Furthermore, I document the important role played by corporate governance and information asymmetry on banks' idiosyncratic risk. The results support all hypotheses.

The findings from this paper have important implications for investors, financial institutions, and regulators. Investors should be compensated with higher rates of return if the firm-specific risk (IVOL) is high, given the fact that most investors do not have fully diversified portfolios. Many factors may contribute to the time-varying nature of firm-specific risk, such as firm size, quality of corporate governance, the severity of information asymmetry, or deletion or omission of dividend payout. Financial institutions should study the factors affecting the idiosyncratic risk in order to reduce uncertainty or ongoing concerns from the market. Regulators should assess the effectiveness of financial bailout from the aspects of idiosyncratic risk, since idiosyncratic risk directly affects the stock return and stability of financial markets.

Table 4.1-Variable Descriptive Statistics

Panel A-Whole sample (+/- 5 years around bailout date)

Variable	N	Mean	Median	Std Dev	Q1	Q3	Skewness
Ln(Ret)	26471	5.400	4.945	2.129	3.951	6.387	1.349
IVOL3	26471	0.121	0.085	0.092	0.057	0.147	1.522
Lag(IVOL3)	26470	0.121	0.085	0.092	0.057	0.147	1.522
IVOL4	26471	0.124	0.085	0.100	0.056	0.149	1.609
Lag(IVOL4)	26470	0.124	0.085	0.100	0.056	0.149	1.609
E(IVOL)	26471	0.605	0.002	1.133	0.001	0.003	1.344
Beta	21491	0.711	0.598	0.577	0.308	0.990	1.495
Ln(ME)	26471	12.540	12.198	2.031	11.129	13.635	0.829
Ln(BKMK)	26186	-0.131	-0.181	0.638	-0.581	0.245	0.389
Ln(Ret(-2, -7))	25717	-0.001	0.002	0.089	-0.027	0.030	0.136
Ln(Bidaskspread)	26471	-2.101	-2.268	0.975	-2.744	-1.668	1.108

Panel B-Pre-Bailout (-5 , 0 years)

Variable	N	Mean	Median	Std Dev	Q1	Q3	Skewness
Ln(Ret)	9126	4.761	4.345	1.900	3.530	5.452	1.708
IVOL3	9126	0.090	0.067	0.067	0.049	0.100	2.502
Lag(IVOL3)	9126	0.087	0.066	0.064	0.049	0.097	2.640
IVOL4	9126	0.090	0.066	0.072	0.047	0.100	2.587
Lag(IVOL4)	9126	0.087	0.065	0.069	0.047	0.097	2.727
E(IVOL)	9126	0.630	0.002	1.149	0.001	0.003	1.283
Beta	6988	0.505	0.408	0.429	0.216	0.702	1.183
Ln(ME)	9126	13.177	12.696	2.022	11.683	14.305	0.890
Ln(BKMK)	9117	-0.499	-0.550	0.490	-0.808	-0.220	0.604
Ln(Ret(-2, -7))	8768	0.011	0.006	0.079	-0.021	0.031	2.035
Ln(Bidaskspread)	9126	-2.341	-2.514	0.945	-2.939	-1.994	1.409

Panel C-Post-Bailout (0, +5 years)							
Variable	**N**	**Mean**	**Median**	**Std Dev**	**Q1**	**Q3**	**Skewness**
Ln(Ret)	17345	5.736	5.306	2.165	4.261	6.788	1.252
IVOL3	17345	0.138	0.100	0.098	0.065	0.179	1.210
Lag(IVOL3)	17344	0.139	0.101	0.099	0.066	0.182	1.184
IVOL4	17345	0.142	0.100	0.107	0.064	0.183	1.297
Lag(IVOL4)	17344	0.143	0.101	0.107	0.065	0.186	1.272
E(IVOL)	17345	0.592	0.002	1.124	0.001	0.003	1.377
Beta	14503	0.811	0.708	0.612	0.397	1.099	1.428
Ln(ME)	17345	12.204	11.916	1.954	10.801	13.213	0.852
Ln(BKMK)	17069	0.066	0.023	0.620	-0.340	0.433	0.211
Ln(Ret(-2, -7))	16949	-0.008	-0.001	0.093	-0.029	0.028	-0.415
Ln(Bidaskspread)	17345	-1.975	-2.129	0.967	-2.609	-1.543	1.030

This table reposts descriptive statistics for the sample. I focus on publicly-listed banks that received bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). I use the propensity score matching technique to identify non-CPP matching banks (matching banks) as control group. I successfully find 227 matching banks for my sample of CPP banks. The details of sample and matching techniques please refer to Chapter 2; Sample period is eleven years around the year of bailout out (2008-2009); Ln(*Ret)* is aggregated monthly return, while daily return is natural logarithm of (P_t/P_{t-1}) ; *IVOL3* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach; *IVOL4* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach; *E (IVOL)* is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models for each firm; *Beta* is rolling 60-month betas derived from CAPM; *Ln (ME)* is natural logarithm of market capitalization, where market cap is the product of share price and shares outstanding; *Ln (BKMK)* is natural logarithm of book-to-market, where book value if book equity value and market value is market cap; *Ln (Ret (-2,-7))* is natural logarithm of *Ret (-2, -7)*, while *Ret (-2,-7)* is compound gross return from t-2 to t-7 period and serves as a proxy for momentum factor, and t=0 is the month of bailout*; Ln (Bidaskspread)* is the proxy for *liquidity* and is natural logarithm of absolute difference between adjusted bid price and adjusted ask price.

Figures 4.1–Time Series Line Plots for Return and Idiosyncratic Volatility

Figure 4.1.1- In (Ret) vs. Δ In (Ret)

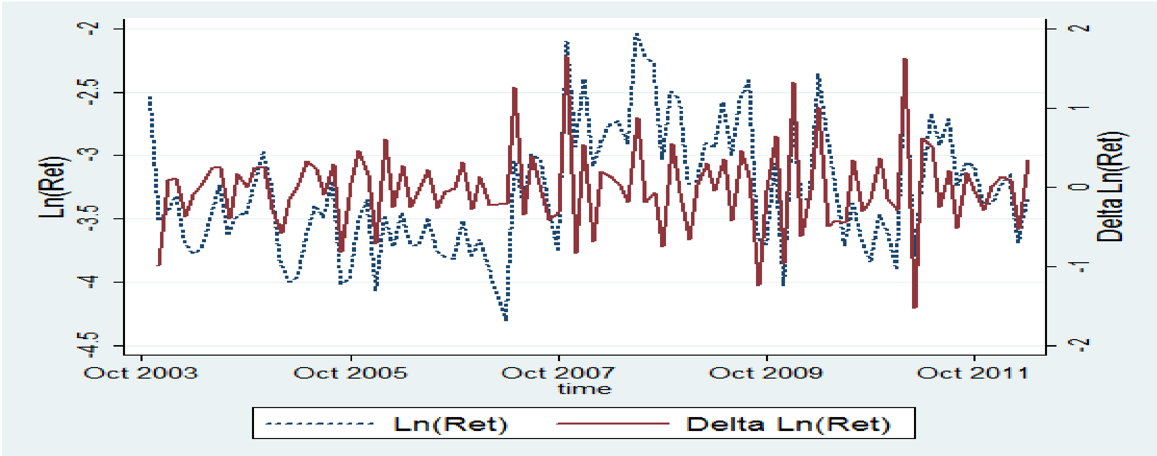


Figure 4.1.2- IVOL3 vs. Δ IVOL3

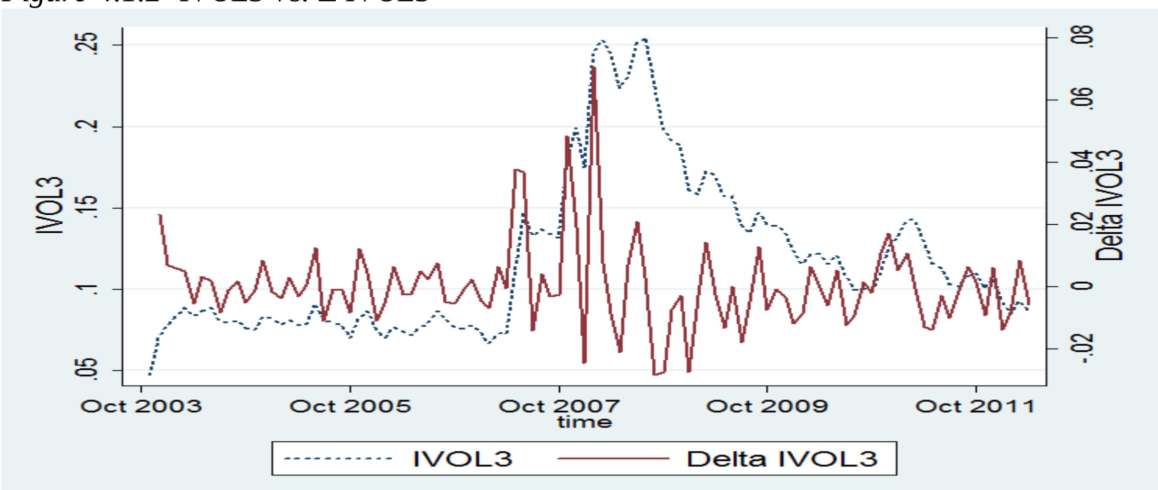


Figure 4.1.3- IVOL4 vs. Δ IVOL4

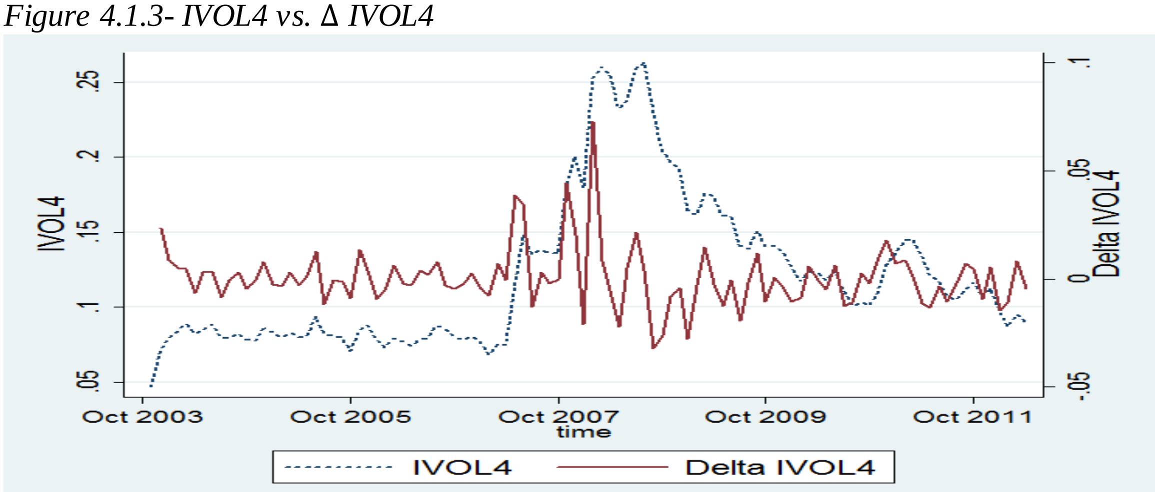
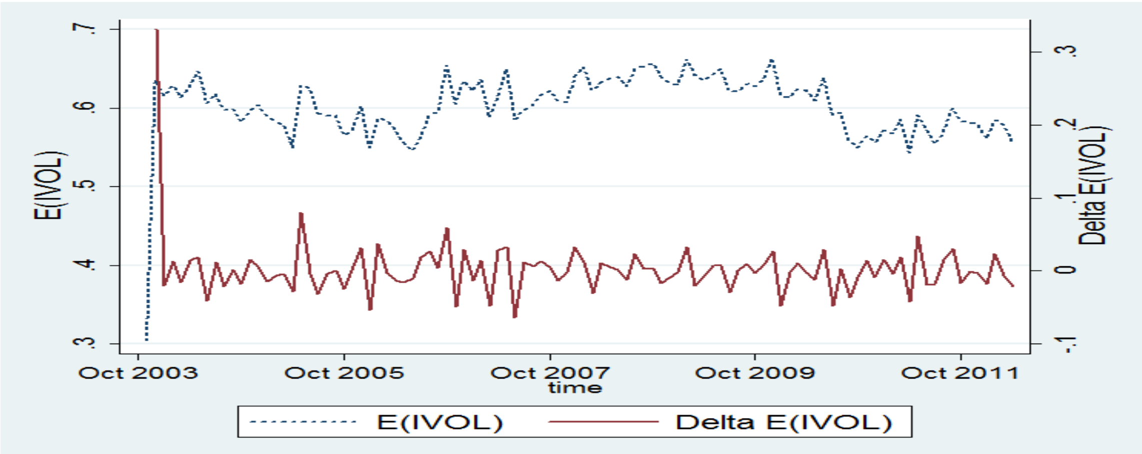


Figure 4.1.4- E (IVOL) vs. Δ E (IVOL)



Figures 4.1 report time-series line plots for return (Ln (Ret)) and idiosyncratic risk (IVOL) at level and at first difference during sample period of Oct 2003-Dec. 2012. Ln(*Ret)* is aggregated monthly return, while daily return is natural logarithm of (P_t/P_{t-1}); *IVOL3* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach; *IVOL4* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach; *E (IVOL)* is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models for each firm. $\Delta\, Ln\ (Ret)$, $\Delta\, IVOL3$, $\Delta\, IVOL4$ and $\Delta\, E(IVOL)$ are the first difference(or delta) of *Ln(Ret)*, *IVOL3*, *IVOL4 and E(IVOL)*.

Table 4.2- Unit Root Tests

	Time Series Data				Panel Data			
	ADF Z-statistics				ADF Fisher Chi-square Statistics			
Series	At Level		At First difference		At Level		At First difference	
Ln(Ret)	-1.595		-7.848	***	86.840	***	367.070	***
IVOL3	-1.078		-7.799	***	71.790	***	326.704	***
Lag(IVOL3)	-1.166		-4.861	***	65.427	***	333.892	***
IVOL4	-1.129		-7.490	***	71.643	***	331.065	***
Lag(IVOL4)	-1.197		-4.845	***	63.137	***	337.099	***
E(IVOL)	-3.353	*	-11.994	***	8.226	***	400.947	***
Beta	-2.323		-8.885	***	5.521	***	200.488	***
Ln(ME)	-2.472		-16.070	***	13.468	***	221.398	***
Ln(BKMK)	-0.930		-6.777	***	11.007	***	218.518	***
Ln(Ret(-2, -7))	-12.463	***	-8.776	***	43.047	***	290.532	***
Ln(Bidaskspread)	-1.706		-9.545	***	129.668	***	393.857	***

In this table, I report the results from unit root tests in the context of timer-series and panel data. In time series, I report ADF-Z statistics. The null hypothesis for ADF unit root test is Ho: There is unit root in the series. In panel, I use ADF-Fisher Chi-square statistics. The null hypothesis for ADF Fisher unit root test is that all panels contain a unit root. It needs at least one panel is stationary to reject the null hypo thesis. Ln(*Ret)* is aggregated monthly return, while daily return is natural logarithm of (P_t/P_{t-1}); *IVOL3* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach; *IVOL4* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach; *E (IVOL)* is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models for each firm; *Beta* is rolling 60-month betas derived from CAPM; *Ln (ME)* is natural logarithm of market capitalization, where market cap is the product of share price and shares outstanding; *Ln (BKMK)* is natural logarithm of book-to-market, where book value if book equity value and market value is market cap; *Ln (Ret (-2,-7))* is natural logarithm of *Ret (-2, -7),* while *Ret (-2,-7)* is compound gross return from t-2 to t-7 period and serves as a proxy for momentum factor, and t=0 is the month of bailout;*; Ln (Bidaskspread)* is the proxy for *liquidity* and is natural logarithm of absolute difference between adjusted bid price and adjusted ask price. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figures 4.2- Time Series Return and Idiosyncratic Volatility Relation

Figure 4.2.1- Δ ln (Ret) and Δ IVOL3

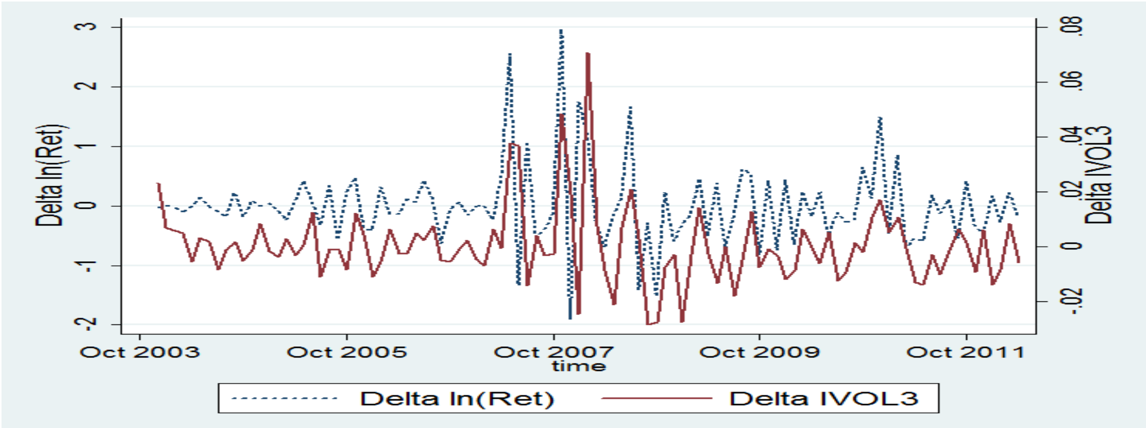


Figure 4.2.2- Δ In (Ret) and Δ IVOL4

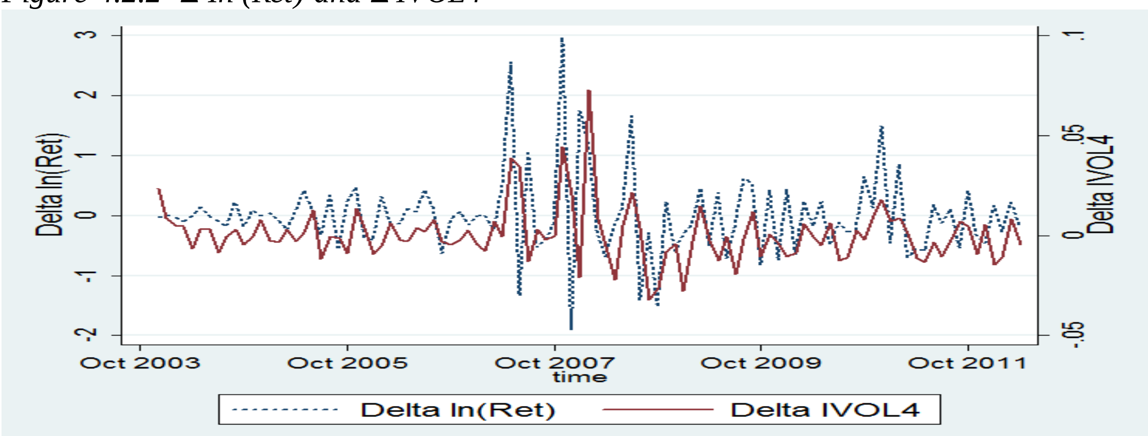
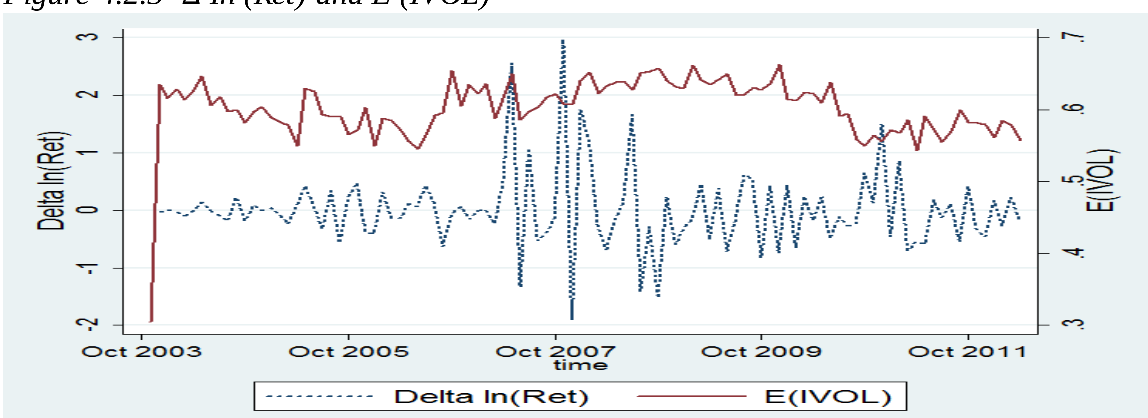


Figure 4.2.3- Δ In (Ret) and E (IVOL)



Figures 4.2 report time-series line plots to examine risk-return relationship (at first difference) during sample period of Oct 2003-Dec. 2012. Ln(*Ret*) is aggregated monthly return, while daily return is natural logarithm of (P_t/P_{t-1}); *IVOL3* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach; *IVOL4* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach; $\Delta\, In(Ret)$, $\Delta\, IVOL3$ and $\Delta\, IVOL4$ are the first difference(or delta) of *Ln(Ret)*, *IVOL3* and *IVOL4*. *E (IVOL)* is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models for each firm.

Table 4.3-Panel Cross-sectional Correlation Tests

Panel A-Return and Idiosyncratic Volatility Variables

	Ln(Ret)	IVOL3	Lag(IVOL3)	IVOL4	Lag(IVOL4)	E(IVOL)
Ln(Ret)	1					
IVOL3	0.574*	1				
Lag(IVOL3)	0.490*	0.898*	1			
IVOL4	0.541*	0.983*	0.889*	1		
Lag(IVOL4)	0.461*	0.888*	0.983*	0.905*	1	
E(IVOL)	0.006	0.025*	0.024*	0.019*	0.018*	1

Panel B-Return and Control Variables

	Ln(Ret)	Beta	Ln(ME)	Ln(BKMK)	Ln(Ret(-2,-7))	Ln(Bidaskspread)
Ln(Ret)	1					
Beta	0.288*	1				
Ln(ME)	-0.138*	0.193*	1			
Ln(BKMK)	0.425*	0.321*	-0.372*	1		
Ln(Ret(-2,-7))	-0.002*	-0.085*	0.080*	0.016*	1	
Ln(Bidaskspread)	0.547*	0.188*	-0.272*	0.383*	-0.028*	1

This table I report simple correlation (Pearson's correlation coefficient r) for indicating the sample relationship between risk and return. Sample period is eleven years around the year of bailout out (2008-2009); Ln(*Ret)* is aggregated monthly return, while daily return is natural logarithm of (P_t/P_{t-1}); *IVOL3* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach; *IVOL4* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach; *E (IVOL)* is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models for each firm; *Beta* is rolling 60-month betas derived from CAPM; *Ln (ME)* is natural logarithm of market capitalization, where market cap is the product of share price and shares outstanding; *Ln (BKMK)* is natural logarithm of book-to-market, where book value if book equity value and market value is market cap; *Ln (Ret (-2,-7))* is natural logarithm of *Ret (-2, -7)*, while *Ret (-2,-7)* is compound gross return from t-2 to t-7 period and serves as a proxy for momentum factor, and t=0 is the month of bailout; *Ln (Bidaskspread)* is the proxy for *liquidity* and is natural logarithm of absolute difference between adjusted bid price and adjusted ask price. * denote significance at the 5% levels.

Table 4.4- Fama-MacBeth Standard Error Regression on Return-Idiosyncratic Volatility Relationship

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(Ivol3)			18.398***	9.864***				
			(33.419)	(6.316)				
lag(Ivol4)					17.873***	8.449***		
					(31.167)	(13.558)		
E(Ivol)							24.654***	4.971
							(6.210)	(0.984)
Beta	0.978*	0.712		2.322		0.704		-1.955
	(1.748)	(1.263)		(1.177)		(1.284)		(-0.798)
Ln(ME)	-14.615	-15.523		-1.528		-1.783		5.660
	(-1.337)	(-1.220)		(-1.050)		(-1.264)		(0.241)
Ln(BKMK)	-12.458	-14.547		-1.512		-1.538		5.452
	(-1.132)	(-1.137)		(-1.084)		(-1.102)		(0.242)
Ln(Ret(-2,-7))		0.564		0.390		0.023		-1,223.924
		(0.225)		(0.160)		(0.009)		(-1.269)
Ln(Bidaskspread)		1.220***		1.124***		1.119***		1.268***
		(22.802)		(22.491)		(22.741)		(16.092)
Constant	165.094	175.367	3.377***	22.151	3.467***	25.465*	-37,575.668***	-8,407.259
	(1.419)	(1.294)	(61.904)	(1.522)	(64.779)	(1.838)	(-6.077)	(-1.022)
R-squared	0.002	0.002	0.240	0.149	0.212	0.084	0.000	0.000
Number of firms	218	214	230	214	230	214	230	214
N	17,494	17,165	20,550	17,164	20,550	17,164	20,551	17,165

In the table, I examine risk-return relationship month-by-month using pooled cross-sectional Fama MacBeth (1973) regression models. The dependent variable is *Ln (Ret)*, while the IVOL measure is *Lag (IVOL3)* for models (3)-(4), *Lag (IVOL4)* for models (5)-(6), and *E (IVOL)* for models (7)-(8). Sample period is eleven years around the year of bailout out (2008-2009); Ln(*Ret)* is aggregated monthly return, while daily return is natural logarithm of (P_t/P_{t-1}); *IVOL3* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach; *IVOL4* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach; *E (IVOL)* is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models for each firm; *Beta* is rolling 60-month betas derived from CAPM; *Ln (ME)* is natural logarithm of market capitalization, where market cap is the product of share price and shares outstanding; *Ln (BKMK)* is natural logarithm of book-to-market, where book value if book equity value and market value is market cap; *Ln (Ret (-2,-7))* is natural logarithm of *Ret (-2, -7)*, while *Ret (-2,-7)* is compound gross return from t-2 to t-7 period and serves as a proxy for momentum factor, and t=0 is the month of bailout; *Ln (Bidaskspread)* is the proxy for *liquidity* and is natural logarithm of absolute difference between adjusted bid price and adjusted ask price. Numbers presented in parentheses are t-statistics; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4.5- Bailout Effects on Idiosyncratic Volatility

Panel A-IVOL3	CPP Banks			Matching Banks			CPP vs. Matching Banks			
							Mean		Median	
	N	Mean	Median	N	Mean	Median	Difference	(t-statistics)	Difference	(Wilcoxon)
Whole Sample Period (-5 yr, +5 yr)	19263	11.64%	8.30%	7208	13.31%	9.16%	-1.66%	-12.36***	-0.86%	-11.65***
By Bailout										
Pre-Bailout (-5yr, 0)	6388	8.55%	6.40%	2738	9.88%	7.46%	-1.33%	-8.21***	-1.05%	-11.27***
Post-Bailout (0, +5 yr)	12875	13.18%	9.59%	4470	15.40%	11.10%	-2.22%	-12.18***	-1.51%	-10.48***
Pre- vs. Post-Bailout										
Mean vs. Median difference		4.62%	3.19%		5.52%	3.64%				
(t-statistics and Wilcoxon statistics)		40.18***	41.10***		25.63***	23.09***				

Panel B-IVOL4	CPP Banks			Matching Banks			CPP vs. Matching Banks			
							Mean		Median	
	N	Mean	Median	N	Mean	Median	Difference	(t-statistics)	Difference	(Wilcoxon)
Whole Sample Period (-5 yr, +5 yr)	19263	11.81%	8.18%	7208	13.95%	9.22%	-2.14%	-14.40***	-1.04%	-13.06***
By Bailout										
Pre-Bailout (-5yr, 0)	6388	8.51%	6.26%	2738	10.11%	7.34%	-1.60%	-9.10***	-1.08%	-12.29***
Post-Bailout (0, +5 yr)	12875	13.45%	9.52%	4470	16.30%	11.35%	-2.85%	-14.07***	-1.83%	-11.82***
Pre- vs. Post-Bailout										
Mean vs. Median difference		4.94%	3.26%		6.18%	4.01%				
(t-statistics and Wilcoxon statistics)		40.35***	42.49***		25.91***	23.58***				

In this table, I provide univariate analysis to examine whether financial bailout causes any significant impact on banking industry in terms of idiosyncratic risk (IVOL). CPP banks are public-listed banks that received bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). Matching banks are non-CPP recipients, but have same probability to receive bailout funds. Sample period is eleven years around the year of bailout out (2008-2009), given t=0 is the year of bailout; The key measure for IVOL is IVOL3 in Panel A and IVOL4 in Panel B. *IVOL3* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach; *IVOL4* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach. Tests in mean and median difference are the Satterthwaite method and Wilcoxon signed-rank method assuming variances are unequal. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4.6-Idiosyncratic Volatility by Relative Year

Panel A - IVOL3		Pre-Bailout			Post-Bailout		
	Quantile	Year -3	Year -2	Year -1	Year +1	Year +2	Year +3
CPP Banks	C1 Low	4.23%	3.23%	9.91%	11.52%	6.73%	5.47%
	C2	5.47%	4.54%	12.98%	15.61%	8.98%	7.60%
	C3	6.59%	6.22%	17.09%	21.55%	12.94%	10.57%
	C4 High	12.04%	99.99%	507.10%	52.86%	65.94%	28.49%
	C4-C1 difference	7.80%	96.77%	497.18%	41.35%	59.21%	23.03%
	(t-statistic)	65.08***	16.94**	33.81***	39.32***	17.37***	95.62***
Matching Banks	C1 Low	4.12%	3.14%	8.90%	10.30%	6.30%	5.08%
	C2	5.42%	4.75%	13.25%	15.12%	9.10%	7.43%
	C3	6.86%	6.29%	16.85%	20.55%	13.33%	10.45%
	C4 High	53.07%	109.42%	380.10%	67.06%	38.57%	23.34%
	C4-C1 difference	48.95%	106.27%	371.20%	56.76%	32.27%	18.26%
	(t-statistic)	15.75***	7.09***	27.99***	19.56***	26.81***	87.31***

Panel B - IVOL4		Pre-Bailout			Post-Bailout		
	Quantile	Year -3	Year -2	Year -1	Year +1	Year +2	Year +3
CPP Banks	C1 Low	3.98%	3.15%	9.67%	11.48%	6.39%	5.36%
	C2	5.36%	4.52%	12.69%	15.57%	8.74%	7.58%
	C3	6.51%	6.22%	16.83%	21.55%	12.77%	10.56%
	C4 High	14.33%	101.25%	515.33%	57.99%	66.69%	30.17%
	C4-C1 difference	10.34%	98.10%	505.66%	46.51%	60.29%	24.81%
	(t-statistic)	47.50***	17.18***	34.04***	38.99***	17.94***	91.35***
Matching Banks	C1 Low	3.82%	3.06%	8.85%	10.41%	6.06%	5.04%
	C2	5.34%	4.67%	13.21%	15.22%	8.92%	7.37%
	C3	6.80%	6.24%	16.89%	20.55%	13.43%	10.55%
	C4 High	56.00%	108.46%	382.30%	69.14%	45.60%	24.33%
	C4-C1 difference	52.18%	105.40%	373.46%	58.73%	39.54%	19.29%
	(t-statistic)	16.22***	7.18***	28.10***	20.48***	29.68***	95.79***

(Table 4.6 Continued)

This table provides close examination on idiosyncratic risk (IVOL) by relative year, given that t=0 (or Year 0) is the year of bailout. CPP banks are publicly-listed banks that received bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). Matching banks are non-CPP recipients, but have same probability to receive bailout funds. CPP banks and matching banks are sorted by IVOL and grouped into four quantiles (C1 to C4). The key IVOL measure is IVOL3 in Panel A and IVOL4 in Panel B. Tests in mean difference are the Satterthwaite method assuming variances are unequal. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4.7-Pooled OLS Regression with Clustered Standard Errors on Bailout Effects

Panel A-Whole Sample

Model	(1)	(2)	(3)	(4)	(5)	(6)
CPP	-0.013**		-0.032**	-0.016**		-0.039***
	(-2.041)		(-2.393)	(-2.120)		(-2.628)
PostBailout	0.054***			0.061***		
	(3.920)			(4.065)		
CPP x PostBailout	-0.001		0.045***	-0.005		0.048***
	(-0.094)		(3.723)	(-0.454)		(3.810)
Size		-0.016***	-0.015***		-0.019***	-0.017***
		(-7.086)	(-5.927)		(-7.372)	(-6.306)
Debt		-0.042*	-0.013		-0.052*	-0.020
		(-1.695)	(-0.527)		(-1.935)	(-0.733)
ER		0.000***	0.000***		0.000***	0.000***
		(7.103)	(7.119)		(8.372)	(7.530)
ROAA		-6.387***	-5.670***		-6.494***	-5.736***
		(-9.738)	(-8.951)		(-9.193)	(-8.512)
Tier 1 Capital		-0.003***	-0.004***		-0.003***	-0.004***
		(-3.028)	(-3.540)		(-3.193)	(-3.637)
Constant	0.097***	0.331***	0.305***	0.100***	0.371***	0.346***
	(10.253)	(8.892)	(8.423)	(9.753)	(9.052)	(8.634)
R-squared	0.081	0.236	0.278	0.082	0.239	0.278
F-statistics	350.469***	239.291***	310.996***	353.134***	270.308***	328.041***
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	9,216	6,444	6,444	9,216	6,444	6,444

(Continued)

(Table 4.7-Continued)
Panel B-Subsample (All, exclude year-1)

	(1)	(2)	(3)	(4)	(5)	(6)
CPP	-0.011*		-0.042***	-0.013*		-0.049***
	(-1.840)		(-3.036)	(-1.929)		(-3.208)
PostBailout	0.066***			0.074***		
	(5.068)			(5.139)		
CPP x PostBailout	-0.002		0.058***	-0.006		0.060***
	(-0.167)		(4.622)	(-0.536)		(4.651)
Size		-0.016***	-0.014***		-0.019***	-0.017***
		(-6.583)	(-5.329)		(-6.889)	(-5.719)
Debt		-0.046	-0.009		-0.056*	-0.016
		(-1.641)	(-0.330)		(-1.865)	(-0.546)
ER		0.000***	0.000***		0.001***	0.001***
		(4.652)	(5.193)		(5.087)	(5.407)
ROAA		-6.531***	-5.438***		-6.635***	-5.500***
		(-9.040)	(-8.126)		(-8.485)	(-7.688)
Tier 1 Capital		-0.002***	-0.004***		-0.003***	-0.004***
		(-2.584)	(-3.196)		(-2.778)	(-3.311)
Constant	0.080***	0.321***	0.289***	0.083***	0.361***	0.328***
	(16.921)	(7.730)	(7.477)	(14.455)	(7.968)	(7.752)
R-squared	0.118	0.238	0.305	0.114	0.239	0.300
F-statistics	598.099***	195.251***	368.762***	564.868***	213.900***	362.440***
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	8,244	5,650	5,650	8,244	5,650	5,650

In this table, I provide multivariate regression analysis to determine the factors affecting IVOL using a two-dimensional Petersen (2009) clustered standard error model in the context of quarterly panel data with firm-fixed effect and time-fixed effect. The dependent variable is *IVOL3* in models (1)-(3) and *IVOL4* in models (4)-(6). In Panel A, I use whole sample, which is eleven years around the year of bailout (Year 0); In Panel B, I use subsample, which is all sample years excluding Year-1; *CPP* is a dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank; *PostBailout* is a dummy variable equals to 1 if it is post-bailout; else is 0 for pre-bailout; *CPP x PostBailout* is Interaction term of *CPP* and *PostBailout* dummies; *Size is* natural logarithm of total Assets, while total assets is average total assets from previous five quarters; *Debt* is the ratio of total liability to total assets; *Efficiency Ratio (ER)* is ratio of non-interest expense to total income; *Return on Average Assets (ROAA)* is ratio of net income to average assets; *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets; Numbers presented in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4.8-Determinants of Idiosyncratic Volatility (IVOL)

Model	(1)	(2)	(3)	(4)	(5)	(6)
CPP	-0.040***	-0.019**	-0.028***	-0.047***	-0.021**	-0.030***
	(-2.646)	(-2.271)	(-2.772)	(-2.831)	(-2.300)	(-2.740)
CPP x PostBailout	0.041***	0.013*	0.016**	0.042***	0.013*	0.015*
	(3.113)	(1.846)	(1.995)	(3.079)	(1.822)	(1.957)
Free Cash Flow	-0.013**		-0.005	-0.016**		-0.005
	(-2.195)		(-1.401)	(-2.445)		(-1.359)
Institutional Investors	-0.015**		-0.015***	-0.018**		-0.016***
	(-2.173)		(-3.666)	(-2.442)		(-3.603)
Blockholder		-0.012**	-0.009*		-0.014**	-0.011*
		(-2.149)	(-1.693)		(-2.236)	(-1.804)
Size	-0.012***	-0.007***	-0.006***	-0.014***	-0.008***	-0.006***
	(-4.557)	(-4.732)	(-3.805)	(-4.935)	(-5.119)	(-4.210)
LnBidaskspread		0.058***	0.057***		0.059***	0.058***
		(7.940)	(7.666)		(7.787)	(7.527)
Dispersion		0.055***	0.062**		0.059***	0.066***
		(3.100)	(2.448)		(3.336)	(2.610)
Constant	0.233***	0.305***	0.302***	0.260***	0.317***	0.315***
	(9.019)	(10.969)	(10.452)	(9.127)	(10.831)	(10.365)
R-squared	0.118	0.489	0.484	0.129	0.480	0.475
F-statistics	183.329***	476.871***	344.416***	198.485***	456.648***	328.901***
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	6,312	6,072	5,685	6,312	6,072	5,685

This table investigates whether corporate governance and information asymmetry play important role on IVOL, multivariate regression with clustered standard errors models (Petersen 2009) are employed in the context of quarterly panel data. Sample period is eleven years around the year of bailout 2008-2009.The dependent variable is *IVOL3* in models (1)-(3) and *IVOL4* in models (4)-(6). *CPP* is a dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank; *CPP x PostBailout* is Interaction term of *CPP* and *PostBailout* dummies; I include three variables as proxies for corporate governance. *Free Cash Flow*, a proxy for agency cost, is computed as difference between income before extraordinary items and total deposit, scaled by total average assets; *Institutional Investor (Shareholding)* is the percentage of institutional investors holding relative to total share outstanding for each stock each quarter. *Blockholder* is a dummy variable equals to 1(or Yes) if *Shareholding* by one single institutional investor is greater than 5 % in a firm; else equals to zero (or No).Similarly, three proxies are employed for information asymmetry. *Size* is a proxy for information asymmetry and is natural logarithm of total Assets. Total assets is average total assets from previous five quarters; *Ln (Bidaskspread)* is the proxy for *liquidity* and is natural logarithm of absolute difference between adjusted bid price and adjusted ask price; *Dispersion* of analyst forecasts is computed as the standard deviation of the firm's estimated EPS for 1-yr ahead by I/B/E/S, scaled by stock price at the earnings forecast date. Numbers presented in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4.9- Corporate Governance on Idiosyncratic Volatility
Panel A-DV=IVOL3

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Free Cash Flow		Institutional Investor		Blockholder	
	High	Low	Low	High	No	Yes
CPP	-0.215***	-0.125***	-0.211***	-0.254***	-0.136***	-0.257***
	(-12.894)	(-5.947)	(-14.553)	(-7.939)	(-5.283)	(-16.275)
CPP x PostBailout	0.234***	0.229***	0.250***	0.075**	0.168***	0.235***
	(13.830)	(10.634)	(16.617)	(2.312)	(6.458)	(14.337)
Debt	0.010	-0.036*	-0.011	0.030	-0.096***	0.025*
	(0.684)	(-1.740)	(-0.709)	(1.304)	(-3.686)	(1.721)
ER	0.057***	0.035**	0.020	0.041*	0.024	0.038***
	(3.989)	(1.977)	(1.475)	(1.833)	(1.032)	(2.745)
ROAA	-0.321***	-0.346***	-0.336***	-0.386***	-0.305***	-0.369***
	(-21.090)	(-18.617)	(-23.370)	(-16.101)	(-12.593)	(-25.216)
Tier 1 Capital	-0.114***	-0.145***	-0.087***	-0.165***	-0.132***	-0.141***
	(-7.402)	(-7.289)	(-5.963)	(-6.734)	(-5.147)	(-9.729)
Adj. R-squared	0.198	0.211	0.224	0.257	0.168	0.250
Chi-squared	47.62***		197.44***		19.00***	
F-statistics	162.9***	112.5***	201.3***	89.63***	53.14***	232.6***
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	3936	2507	4176	1535	1549	4162

(Continued)

(Table 4.9-Continued)
Panel B- DV=IVOL4

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Free Cash Flow		Institutional Investor		Blockholder	
	High	Low	Low	High	No	Yes
CPP	-0.228***	-0.163***	-0.246***	-0.281***	-0.171***	-0.281***
	(-13.569)	(-7.683)	(-16.933)	(-8.776)	(-6.572)	(-17.690)
CPP x PostBailout	0.235***	0.224***	0.242***	0.081**	0.162***	0.227***
	(13.795)	(10.286)	(16.039)	(2.487)	(6.169)	(13.823)
Debt	0.009	-0.033	-0.015	0.025	-0.089***	0.014
	(0.602)	(-1.580)	(-1.008)	(1.077)	(-3.399)	(0.965)
ER	0.054***	0.035*	0.020	0.035	0.023	0.036***
	(3.746)	(1.941)	(1.441)	(1.559)	(0.979)	(2.613)
ROAA	-0.305***	-0.323***	-0.321***	-0.366***	-0.289***	-0.355***
	(-19.897)	(-17.206)	(-22.269)	(-15.214)	(-11.848)	(-24.201)
Tier 1 Capital	-0.112***	-0.149***	-0.090***	-0.165***	-0.135***	-0.143***
	(-7.246)	(-7.407)	(-6.127)	(-6.699)	(-5.251)	(-9.824)
Adj. R-squared	0.188	0.195	0.221	0.252	0.159	0.246
Chi-squared	25.43***		350.97***		19.69***	
F-statistics	153.0***	102.0***	197.9***	87.20***	49.81***	227.7***
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	3936	2507	4176	1535	1549	4162

This table investigates whether the differences between good and poor-corporate governance banks are statistically significant, Seemingly Unrelated Regression (SUR) tests are employed in the context of quarter panel data. Sample period is eleven years around the year of bailout 2008-2009.The dependent variable is *IVOL3* in Panel A and *IVOL4* in Panel B. The sample (includes CPP banks and matching banks) are sorted and ranked into two groups, Good vs. Poor Corporate Governance. The decision rule is if the firms have low *Free Cash Flow*, *High Institutional Investor Shareholding*, and contain *Blockholder* who owns the shares more than 5 percent in the firm, then they are classified into Good Corporate Governance Group as in models (2), (4), and (6). The remaining firms will be the group of Poor Corporate as in models (1), (3) and (5). *CPP* is a dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank; *CPP x PostBailout* is Interaction term of *CPP* and *PostBailout* dummies; *Debt* is the ratio of total liability to total assets; *Efficiency Ratio (ER)* is ratio of non-interest expense to total income; *Return on Average Assets (ROAA)* is ratio of net income to average assets; *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets; The coefficients are standardized beta coefficients and t statistics are in parentheses; F-statistics is test for the null hypothesis of that the coefficients of the regression model are zero. Chi-squared statistics derived from Lagrange multiplier correlation test of Breusch and Pagan is based on the null hypothesis of that the average of the squared pair-wise correlation coefficients of the residuals are all equal; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4.10-Information Asymmetry on Idiosyncratic Volatility
Panel A- DV=IVOL3

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Size		Liquidity		Dispersion	
	Small	Large	Low	High	High	Low
CPP	-0.152***	-0.059**	-0.213***	-0.135***	-0.135***	-0.213***
	(-10.312)	(-2.226)	(-10.887)	(-6.654)	(-6.154)	(-11.393)
CPP x PostBailout	0.221***	0.165***	0.140***	0.161***	0.239***	0.115***
	(14.904)	(4.659)	(7.149)	(7.822)	(10.472)	(6.259)
Debt	-0.021	0.114***	0.054***	0.010	-0.033	0.094***
	(-1.611)	(4.148)	(2.977)	(0.582)	(-1.591)	(5.528)
ER	0.024**	-0.087***	0.009	0.028*	0.041**	0.050***
	(1.975)	(-2.638)	(0.463)	(1.699)	(2.182)	(2.643)
ROAA	-0.310***	-0.582***	-0.163***	-0.271***	-0.322***	-0.237***
	(-23.910)	(-16.927)	(-8.553)	(-15.839)	(-16.123)	(-12.340)
Tier 1 Capital	-0.135***	-0.003	-0.020	-0.165***	-0.159***	-0.005
	(-10.365)	(-0.085)	(-1.101)	(-9.480)	(-7.789)	(-0.302)
Adj. R-squared	0.180	0.332	0.075	0.137	0.201	0.114
Chi-squared	48.01***		26.42***		46.13***	
F-statistics	201.1***	82.67***	43.70***	88.25***	99.22***	71.78***
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	5456	988	3143	3301	2347	3315

(Continued)

(Table 4.10-Continued)
Panel B- DV=IVOL4

Model	(1)	(2)	(3)	(4)	(5)	(6)
	Size		Liquidity		Dispersion	
	Small	Large	Low	High	High	Low
CPP	-0.174***	-0.057**	-0.237***	-0.160***	-0.142***	-0.219***
	(-11.730)	(-2.177)	(-12.147)	(-7.858)	(-6.462)	(-11.715)
CPP x PostBailout	0.217***	0.169***	0.137***	0.165***	0.243***	0.110***
	(14.491)	(4.826)	(7.018)	(7.979)	(10.673)	(5.968)
Debt	-0.024*	0.109***	0.038**	0.012	-0.030	0.084***
	(-1.811)	(3.992)	(2.120)	(0.692)	(-1.455)	(4.907)
ER	0.024**	-0.072**	0.004	0.028*	0.041**	0.050***
	(1.965)	(-2.182)	(0.229)	(1.734)	(2.153)	(2.637)
ROAA	-0.289***	-0.578***	-0.152***	-0.255***	-0.322***	-0.228***
	(-22.109)	(-16.953)	(-7.977)	(-14.818)	(-16.114)	(-11.821)
Tier 1 Capital	-0.140***	0.009	-0.031*	-0.166***	-0.156***	-0.004
	(-10.697)	(0.257)	(-1.722)	(-9.496)	(-7.666)	(-0.241)
Adj. R-squared	0.168	0.342	0.079	0.131	0.201	0.110
Chi-squared	46.85***		23.18***		43.97***	
F-statistics	184.9***	86.50***	45.66***	83.73***	99.40***	69.44***
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	5456	988	3143	3301	2347	3315

This table investigates whether the differences between high and low information asymmetry banks are statistically significant. Seemingly Unrelated Regression (SUR) tests are employed in the context of quarter panel data. Sample period is eleven years around the year of bailout 2008-2009.The dependent variable is *IVOL3* in Panel A and *IVOL4* in Panel B. The sample (includes CPP banks and matching banks) are sorted and ranked into two groups, High vs. Low Information Asymmetry. The decision rule is if the firms are larger in *Size*, and low in *LnBidaskspread* and *Dispersion*, then they are classified into Low Information Asymmetry group as in models (2), (4), and (6). The remaining firms will be the group of High Information Asymmetry as in model (1), (3), and (5). *CPP* is a dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank; *CPP x PostBailout* is Interaction term of *CPP* and *PostBailout* dummies; *Debt* is the ratio of total liability to total assets; *Efficiency Ratio (ER)* is ratio of non-interest expense to total income; *Return on Average Assets (ROAA)* is ratio of net income to average assets; *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets; The coefficients are standardized beta coefficients and t statistics are in parentheses; F-statistics is test for the null hypothesis of that the coefficients of the regression model are zero. Chi-squared statistics derived from Lagrange multiplier correlation test of Breusch and Pagan is based on the null hypothesis of that the average of the squared pair-wise correlation coefficients of the residuals are all equal; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

CHAPTER V

INSTITUTIONAL OWNERSHIP AND CAPITAL PURCHASE PROGRAM (CPP) EXIT

5.1 Introduction

The tremendous growth in institutional ownership for past decades[47] has raised interests in how institutional ownership affects corporate governance and financial decisions. Institutional investors are different from individual investors in the following ways. First, they manage and trade large pools of funds on behalf of others, so they owe fiduciary duties to their investors. Second, they face fewer protective regulations because it is assumed that they are knowledgeable and better to protect themselves. Therefore, they are likely to be informed traders. Third, they are governed by the "prudent-man" rule, so they should invest funds entrusted him/her as would a person of prudent. In other words, they should not put funds into speculative investments to achieve higher rate of return. Fourth, they might be bank trusts, insurance companies, mutual funds, pension funds, hedge funds, investment advisors, and university endowments etc. Last, they are taxed differently. Pension funds, university endowment funds do not pay taxes on their

[47] As noted by Brickley et al. (1998), institutions owned approximately 17.5 percent of U.S. Equities in 1970, and their ownership had increased to over 30 percent by 1986. Chen et al. 2007 report that institutions owned approximately 7% of US equities in 1950 and 51% by the end of 2004.

capital gain or dividends. And some of them can enjoy tax exempt up to at least 70 percent of dividend income.

Elyasiani and Jia (2008) document that institutional investors play a monitor role in banking industry, stabilize BHCs performance, and even substitute government intervention. Institutional investors can exercise shareholder activism to target the firms with poor stock price performance by creating a shareholder advisory committee, changing board of directors member and reducing executive compensation as noted by Smith (1996) in the case of CalPERS. Institutional activism benefits minority shareholders by reducing potential agency costs. It is believed that poor structured incentives will promote executives' risk-taking behavior.

In the wake of the recent financial crisis, the Congress allocated $700 billion for the financial sector in the Emergency Economic Stabilization Act of 2008 (EESA). EESA authorizes the U.S. Department of the Treasury to establish the Troubled Asset Relief Program (TARP) to bail out the financial industry. Most of banks received their money through Capital Purchase Program (CPP, or health bank program), the largest one among thirteen programs created under TARP. There are $204.9 billion (or 43.93 percent of TARP) of tax payers' money promised and actually invested into 707 banks during October 2008 through November 2009 as discussed in Chapter 2. Under EESA section 111(b), there are strict requirements on corporate governance and executive compensation for CPP banks during bailout period[48].

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[48] There are strict requirements on corporate governance and executive compensation under EESA section 111(b), such as (a) limits on compensation that exclude incentives for senior executive officers (SEOs) of financial institutions to take unnecessary and excessive risks that threaten the value of the financial institution; (b) required recovery of any bonus or incentive compensation paid to a SEO based on statements of earnings, gains, or other criteria that are later proven to be materially inaccurate; (c) prohibition on the financial institution from making any golden parachute payment to any SEO; and (d) agreement to limit a claim to a federal income tax deduction for certain executive remuneration.

Lately, the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act), was signed into law on July 21, 2010. Dodd-Frank Act affects almost every aspect of the U.S. financial services industry. The objectives ascribed to the Dodd-Frank Act include restoring public confidence in the financial system, protecting consumers, reining in Wall Street and big bonus, ending bailouts and too-big-to-fail, and preventing another financial crisis etc. The Dodd-Frank Act imposes more restrictions on executive compensation, and provides shareholders with say- on-pay and say-on-golden parachutes on executive compensation[49]. Wilson and Wu (2012) note that the executive pay restriction may have been harder for larger banks, which generally have more highly paid executives, to comply with. They find all measures of 2008 CEO pay are significant predictors of a bank fully or partially exit TARP. Cadman et al. (2012) also find the likelihood of repaying before the end of 2009 is positively related to CEO incentive compensation.

The introduction of TARP and Dodd-Frank Act constitutes significant regulatory regime changes, and provides the necessary framework to explore the effects of the government intervention. Notably, while the institutional ownership has been documented to exert significant impacts on board structure, executive compensation, and financial decisions (dividend policy, mergers and acquisitions etc.), it is unclear whether or to what extent institutional ownership influences banks' decision to exit the bailout program. In this essay, I address the following four research questions. First, is there any change in institutional ownership stability and their aggregate shareholding during recent financial bailout? Second, does institutional ownership

[49] Under the Dodd-Frank Act, the voting records of say-on-pay and say-on-golden parachutes by institutional investors are required to disclose at least annually. Financial institutions are also required to report their incentive-based compensation arrangements to regulators. Basically, the incentive-based compensation of financial institution should not expose financial institutions with inappropriate risk that could lead to potential financial loss.

pose any impact on banks' decision on CPP exit? Third, does the impact differ between high and low institutional investors stability banks given control of institutional investor shareholding? Last, does the impact differ between high and low institutional investor shareholdings given control for institutional investor stability?

Using two measures of institutional ownership, I examine the relationship between institutional ownership and bailout banks' decision on CPP exit. I document that banks with more institutional ownership stability and high institutional ownership shareholding tend to pay back bailout funds in shorter timeframe. The results are robust with controls for bank size, non-performing loan, efficiency, profitability and capital ratio. On the other hand, banks with lower institutional ownership shareholding and less stable institutional ownership take longer time to repay CPP funds. I also observe that high percentage of aggregate institutional shareholding in a bank is the key determinant to forecast the timing of repaying the CPP funds, regardless the stability of institutional ownership. The findings from this paper add to the existing literature as evidence of market discipline of corporate governance-institutional ownership on banks' decision on bailout exit.

The remainder of the essay is organized as follows. Section 5.2 reviews the extant literature. Section 5.3 describes the data and methodology, and provides descriptive statistics. Section 5.4 presents the results, and Section 5.5 concludes the paper.

5.2 Literature Review and Hypotheses Development

5.2.1 Institutional Ownership and Corporate Governance

Government bailout in the recent financial crisis 2007-2009 is believed to remove some functioning of market discipline as suggested by Acharya et al. (2009) and Ellul and Yerramilli

(2013), because government provides debt guarantees[50] and increases the level of deposit insurance protection[51]. Debt guarantee weakens the incentive of debt holders and adds more protection for the financial institutions from market disciplines such as take-over attempts or shareholder activism. On the other hand, unstable banks usually have to pay a risk premium to its depositors in the form of higher interest rates to compensate for bearing higher default risk. But this default risk for depositors is eliminated by the deposit insurance; they cannot demand such a risk premium. Deposit insurance removes the incentive of depositors to exercise market discipline. And also deposit insurance provides an incentive for banks to engage in riskier activities.

Institutional investor are expected to discipline managers (Chazi et al., 2011). The higher percentage of institution ownership predicts better corporate governance through minimizing monitoring and exit costs (Chung and Zhang, 2011); Therefore, it will lead to reduced cost of capital (Collins and Huang, 2011; Shleifer and Vishny, 1997b). Aggarwal et al. (2011) document that governance through institutional ownership travels all over the world. They find that changes in institutional ownership over time affect subsequent changes in firm-level governance. Additionally, the changes in institutional ownership are positively associated with future changes in firm value (Tobin's Q).

Elyasiani and Jia (2008) and Elyasiani et al. (2010) argue that stable institutional investors are better motivated and possess better ability to monitor effectively. As a result, they play an important role in mitigating agency conflicts and reducing information risk in the firm.

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[50] Government provides three-year guarantee of all new issuance (long-term and short-term) maturing between then and June 2009, with a maximum of 125 percent of face value and with a fee of 0.75%. The guarantee of all new debt issuance is to prevent lending freeze and to encourage lending to the banks.

[51] The 100 percent guarantee of non-interest-bearing accounts in FDIC insured banks increased from $ 100,000 to $ 250,000.

Consistent with this view, Elyasiani and Jia (2008) find a significant positive relation between institutional ownership stability and bank holding company performance.

However, Booth et al. (2002) find these internal monitoring mechanisms to be significantly less related with regulated firms (banks and utilities). Adams and Meehran (2003) suggest that governance structures are industry-specific. Fewer institutional investors hold shares of BHCs relative to shares of manufacturing firms. Institutional investors look into not only growth opportunities, but also the presence of regulation in the banking industry**.**

5.2.2 Factors affecting Bailout Exit

Executive pay restrictions are often cited as a reason for early TARP exit, and high levels of CEO pay are associated with banks being significantly more likely to "escape" TARP. For example, Cadman et al. (2012) find that the likelihood of repaying before the end of 2009 is positively related to CEO incentive compensation. Similarly, Wilson and Wu (2012) find all measures of 2008 CEOs' pay are significant predictors of a bank fully or partially exiting TARP. Based on repayment status as the end of 2009 for 250 publicly-traded TARP banks, they also find that banks likely to exit TARP early are those with large size, high return on assets, and strong in capital ratio. Furthermore, they document that banks that can raise private capital tend to exit bailout faster. Cornett et al. (2013) separate CPP banks into over-achievers and under-achievers based on their return on assets, and find over-achievers and larger banks are significantly more likely to repay bailout funds. They suggest that the unexpected high costs of participating in the TARP program and the concerns of losing competitiveness on recruiting banking talents, due to the strict regulation on executive compensation restriction, make larger banks to repay bailout funds faster.

Based on the above arguments, I have the following hypotheses about institutional ownership on banks' decision on CPP exit.

H1: The banks with more stability in institutional ownership tend to exit CPP program faster.

H2: The banks with higher institutional ownership shareholding tend to exit CPP program faster.

5.3 Data and Methodology

5.3.1 Data Sources and Sample Selection

In this paper, I focus on publicly-listed banks that receive bailout funds through the CPP Program, the largest one of the 13 programs under the EESA (2008). In order to address potential endogeneity issues, I use the propensity score matching technique to identify non-CPP matching banks as the control group. Propensity score matching is widely used in the literature to estimate the treatment effect (Heckman et al., 1998; Hirano et al., 2003; Li and Zhao, 2006; Rosenbaum and Rubin, 1983, 1985). Different from traditional matching techniques, propensity score matching method allows matching firms on several characteristics simultaneously. The selection of matching variables is guided by theory and prior research (Li and Zhao, 2006). I calculate a predicted value of *ROA* (i.e. a propensity score) with three industry median-adjusted regressors (i.e. *MKTCAP, DEBT and MKBK*[52]) for all sample banks and matching pool of non-CPP recipients, which are drawn from Compustat dataset within the same banking sector (SIC codes from 6000-6399). I successfully find 227 matching banks for our sample of CPP banks. Please refer to Chapter 2 for the details of sample and matching techniques.

[52] *MKTCAP* is the logarithm value of market capitalization. *DEBT* is the ratio of total liabilities to total assets. *MKBK* is the ratio of market price to book price.

As discussed in Chapter 2, more than half of the sample CPP banks (63 percent) have repaid the full funding amount to the government, and approximately 18.5 percent of sample CPP banks have repaid with installments as of March 2013. The full- repayment group repays the CPP funds about half-year earlier (752 days or about 2.06 years) than the partial-repayment group (968 days or about 2.65 years), while the no-repayment group has not repaid any money for more than four years (or 1,510 days) after receiving government bailout.

5.3.2 Institutional Ownership Variables

I obtain quarterly institutional ownership data from Thomson Financial Institutional 13F common stock holding and transactions file. All investment managers must file Form 13F to the Security and Exchange Commission if they have an aggregate fair market value of at least $100 million in equity holding within 45 days of each quarter. Institutional investors include banks (bank trusts), insurance companies, investment companies (mutual funds) and their managers, independent investment advisor (most of the large brokerage firms), and "all others" (pension funds and endowments) etc.

5.3.2.1 Institutional ownership stability. Following Elyasiani et al. (2010) and Callen and Fang (2013), I construct the proxy $STDI_i$ for Institutional Ownership Stability, which is institutional ownership volatility for a firm, using average standard deviation of institutional shareholding proportions across all investors *j* in the firm *i* over a 5-year period (including the event period). The formula is shown as equation (5.1):

$$STDI_i = \sum_{j=1}^{J_i} STD(p_{i,t}^{j})/J_i \qquad (5.1)$$

where $p_{i,t}^{j}$ is the proportion of firm *i* held by investor *j* at previous quarter *t* (*t*=1,2…20), and J_i is the number of institutional investors in firm *i*. Higher STDI in a firm indicates higher volatility in institutional ownership and lower institutional ownership stability.

5.3.2.2 Institutional ownership shareholding. Following Elyasiani and Jia (2008) and Elyasiani et al. (2010), I construct *PROP, a proxy for Institutional Ownership Shareholding*, as aggregate shareholding proportions of a firm over a 5-year period (including the event period). Higher institutional ownership shareholding in a firm indicates better corporate governance. The formula is shown as equation (5.2):

$$PROP = (\sum_{t=1}^{20} \sum_{j=1}^{j_i} p_{i,t}^{j})/20 \quad (5.2)$$

Table 5.1 presents descriptive statistics and distributions of two institutional ownership measures for the 9,681 firm-quarter observations in my sample. The mean (median) value of *STDI* is 0.126 (0.125), and that in *PROP* is 2.602 (1.575) as shown in Panel A. Panel B shows that *STDI* slightly increases in post 2008-2009 bailout period, while PROP decreases marginally in 2008-2009 from the peak in 2007 and recoup the position right after 2010.

[Insert Table 5.1 about here]

Figure 5.1 shows that the CPP banks experience an upward trend in the *PROP* relative to matching banks, which suggests that CPP banks attract more institutional owners than non-CPP banks. On the other hand, the changes in *STDI* for both groups are not clearly distinguishable in Figures 5.1.1-5.1.2.

[Insert Figures 5.1.1- 5.1.2 about here]

5.3.3 Control Variables

The control variables include the factors discussed in the literature section that can predict bank's decision on repaying CPP funds. *Size* is computed as the natural log of total assets[53], and is expected to have a positive impact on repaying CPP funds. *Non-Performing Assets* (*NPA*) is the ratio of nonperforming assets to total assets. Higher the *NPA* indicates higher risk. *Efficiency Ratio* (*ER)*, the ratio of non-interest expense to total income, is a proxy for the cost structure and operation efficiency. A lower ER is generally favorable. *Return on Average Assets* (*ROAA*) is an important measure of profitability and is computed as the ratio of net income to average total assets. Capital is the core measure of financial strength for banks, as high ratio and thus good quality of capital could protect banks from unexpected losses especially in financial crisis. *Tier 1 risk-adjusted capital ratio* (*Tier 1 Capital*) measures the amount of core equity (i.e. common stock, retained earnings, and non-redeemable preferred stock) available as a percentage of total risk-adjusted assets.

5.3.4 Multivariate Regression Models

5.3.4.1 Bivariate logistic regression models. To explore whether the institutional ownership variables are the factors that affect the likelihood of a bank exits the CPP program, I use pooled logistic regression models. Dependent variable is *Repayment*, it is a dummy variable equals to one if the bank repays the bailout funds by March 1st, 2013; zero otherwise.

The specification of bivariate logistic regression model is:

[53] Log value of total assets is common measurement in banking industry. We use average total assets as total assets, which is total assets from previous five quarters divided by five.

$$Repayment_i = \alpha \quad + \beta_1 CPP_i + \beta_2 STDI_i \ + \beta_3 PROP_i + \beta_4 X_i + \varepsilon_i \qquad (5.3)$$

Where, *Repayment* is bivariate variable for the probability to repay CPP funds, α is a constant, $STDI_i$ is a proxy for Institutional Ownership Stability, $PROP_i$ is a proxy for Institutional Ownership Shareholding, X_i represents a sector of control variables, and ε_i is an error term.

5.3.4.2 Ordinary least square (OLS) regression models. The banks with stable institutional ownership and higher institutional ownership shareholding might not just choose to exit CPP program, but also care about the timing to exit the program. I construct the *Log* (*Pay Back Period)* variable as natural logarithm of the length in days for the banks to make the first repayment to the government[54]. For comparison purpose, the repayment date is assumed to be March 1st, 2013 for those banks that didn't make any installment or repayment before March 1st, 2013. The specification of cross-sectional OLS regression model is:

$$Log(Pay\ Back\ Period_i) = \alpha \quad + \beta_1 CPP_i + \beta_2 STDI_i \ + \beta_3 PROP_i + \beta_4 X_i + u_i \ + \ \varepsilon_i \quad (5.4)$$

Where, u_i is time (quarter) fixed effect.

5.3.4.3 Pooled ordinary least square (OLS) with clustered standard error (Petersen, 2009). To ensure the results are robust, I also run above regression models in panel specifications. In analyzing panel data, the residuals may be correlated over time or across subjects or industries. To address this potential issue, I employ a two-dimensional Petersen (2009) clustered standard errors regression to correct standard errors for time series and cross-sectional correlation in the

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[54] For Full repayment group, the *Pay Back Period* will be the length in days between disbursement date to repayment date. For Installment groups, the *Pay Back Period* will be the length in days between disbursement date to the first installment date.

error term. Clustered effects included in the pooled OLS regressions are time (quarter) and firm effects. The specification of pooled OLS regression model is:

$$Log\ (Pay\ Back\ Period_{it}) = \beta_1 CPP_i + \beta_2 STDI_{it} + \beta_3 PROP_{it} + \beta_4 X_{it} + \alpha_i + u_t + \varepsilon_{it} \quad (5.5)$$

Where, α_i is time-invariant firm specific characteristic, u_t is the quarter fixed effect, and ε_{it} is the remainder error term.

5.3.4.4 Seemingly unrelated regression (SUR). I suspect some coefficients in equation (5.4) might differ by the level of institutional ownership stability or institutional ownership shareholding. Therefore, I employ SUR of Zellner (1962) which assumes that disturbances are uncorrelated across observations but correlated across equations. In order to compare coefficients across equations, I use two sets of institutional ownership groups, Low vs. High PROP, and Low vs. High STDI, as well as three repayment groups.

5.4 Results and Discussions

5.4.1 Bailout Effects

To examine whether financial bailout exerts any significant impact on banking industry in terms of institutional ownership, I perform some univariate analyses in this section. Even though the mean values of *STDI* in CPP banks fluctuate upwardly in the post-bailout period (i.e. from 11.8% to 13.1%), CPP banks have relatively stable institutional ownership with *STDI* measures, in whole sample period, pre-, and post-bailout period compare to matching banks as shown in Panel A of Table 5.2. Similarly, financial bailout brings about increased institutional ownership shareholding (*PROP*) in CPP banks significantly in post-bailout period. On the other hand, matching banks (non-CPP recipients) that have similar probability to receive CPP funds, experience decreases in institutional ownership shareholding upon bailout as revealed in Panel B. In general, the financial bailout differentiates CPP banks and their counterparts with respect to institutional ownership. CPP banks have more stable institutional ownership and higher institutional ownership shareholding, which indicates better corporate governance upon bailout.

[Insert Table 5.2 about here]

The capability to repay bailout funds might affect the incentives of institutional owners to hold the security. Table 5.3 shows that the installment-repaying group that pays back funds with 2-4 installments, has statistically higher *STDI* than the other two groups (i.e. no-repayment and full repayment groups). Given the fact that these installment-repaying banks can only pay back partial amounts, instead of full amount, the institutional investors are intimidated by the uncertainty regarding to banks' future earnings capability and thus the institutional ownership in these banks are more volatile. Conversely, the institutional investors are attracted more to banks, in terms of *PROP*, that are capable to repay bailout funds in one full payment.

[Insert Table 5.3 about here]

5.4.2 Bivariate Correlation Test

Table 5.4 provides the Pearson's correlation coefficients which show the bivariate relationship between the key variables in this paper. As expected, *STDI* is positively related to *Pay Back Period*, while *PROP* is negatively associated with *Pay Back Period*. The results suggest that the banks with higher *STDI* (i.e. less stable in institutional ownership) and lower *PROP* (i.e. poorer corporate governance) will take longer time to repay the CPP funds. The results also show that *Pay Back Period* is negatively related to firm size and *ROAA*, and positively related to *NPA*.

[Insert Table 5.4 about here]

5.4.3 Predicted Probability of CPP Exit

Table 5.5 reports the results from pooled logistic regression model on whether the institutional ownership variables are the factors affecting the likelihood of a bank exiting the CPP program. Model (1) of Panel A shows that the higher the *PROP*, the higher the probability of banks exiting CPP. The results are robustness with STDI and additional control variables as in model (2)-(4). It indicates that banks with higher institutional ownership shareholding have higher probability to repay CPP funds while *STDI* can predict the probability of exiting CPP with limited extent.

How could the volatility of institutional ownership increase the possibility of banks' repaying the bailout funds? I classify banks into three groups based on repayment status and re-test the same specification models for each of the subsamples. In model (1) of Panel B, I first find supporting evidence that the banks with high *PROP* have higher chances to repay the bailout funds using CPP only subsample. Next, I remove full repayment group in model (2) and installment group in model (3). The results indicating that higher *STDI* can predict the probability to repay CPP funds; however, the relationship is only robust in the subsample without installment group. Essentially, the repayment status and institutional ownership can predict banks' CPP exit decision, together with size, NPA, and ROAA variables. The results are qualitative similar when Probit regression models are applied as shown in Appendix 5B.

[Insert Table 5.5 about here]

5.4.4 Time to Exit CPP

TARP and Dodd-Frank Act impose stringent and significant regulatory regime changes on banks' executive compensation and dividend policy. The banks with stable institutional ownership and higher institutional ownership shareholding might not just choose to exit CPP program, but be also concerned about the timing to exit the program. In this section, I explore the factors that determine the length of banks stay within CPP program. The results are consistent with univariate tests that the banks with high *STDI* (i.e. lower institutional ownership stability) and low *PROP* (poor corporate governance) will stay longer in CPP program as shown in Panel A of Table 5.6. These findings suggest that banks with high institutional ownership stability and institutional ownership shareholding can exit CPP program faster, which support all my hypotheses. The results are pronounced with the whole CPP sample as in Panel B, as well as subsample without no-repayment group as shown in Panel C. Notably, the findings in Table 5.6 provide additional support to Wilson and Wu (2012) that the banks are larger in size, with low non-performing loan (i.e. NPA), and high profitability (i.e. ROAA) will pay back CPP funds in shorter period of time.

[Insert Table 5.6 about here]

I also run OLS regression models in the context of panel data using Petersen (2009) two-dimensional firm-fixed effect and time (quarter)-fixed effect in Table 5.7, the results are consistent and robust in whole sample and subsamples, except the significances for *CPP* dummy and *ROAA* disappear.

[Insert Table 5.7 about here]

5.4.5 Seemingly Unrelated Regression (SUR)

I am suspecting that the impact of *STDI* (or *PROP*) on the *Pay Back Period* would evolve differently at different levels of *PROP* (or *STDI*); therefore, I separate the sample into two groups: Low vs High *PROP* and Low vs. High *STDI* as in Panel A of Table 5.8. In model (1), I find banks that are less stable in institutional ownership (i.e. high in *STDI*) and have low institutional ownership shareholding will take longer time to repay the CPP funds. On the other hand, the banks exit CPP program faster if they have high institutional ownership shareholding given unstable institutional ownership as shown in model (2). The results suggest that *PROP* plays a more important role than *STDI* on the timing to exit CPP program. Essentially, the results are consistent as shown in models (3) and (4), but the magnitudes of the coefficients between the two models are not statistically significant.

In Panel B of Table 5.8, I re-run the OLS regression model for the three repayment groups separately. Interestingly, both *STDI* and *PROP* cannot predict the length in days for no-repayment group to exit CP program as shown in model (1). Conversely, the results in models (2) and (3) show that the banks, the installments group and the full repayment group, with stable institutional ownership and high institutional ownership shareholding tend to exit CPP program faster.

[Insert Table 5.8 about here]

5.5 Conclusions

In this essay, I investigate how institutional ownership stability and aggregate shareholding affect banks' decision on bailout exit during the recent financial bailout 2008-2009. I focus on publicly-listed banks that have received bailout funds through the CPP Program, the largest one of thirteen programs under the EESA (2008). I use the propensity score matching technique to identify non-CPP matching banks as the control group. I successfully find 227 matching banks for my sample of CPP banks.

I document that banks with more institutional ownership stability and high institutional ownership shareholding tend to pay back bailout funds in shorter timeframe. The results are robust with control for size, non-performing loan, efficiency, profitability and capital ratio. On the other hand, banks with lower institutional ownership shareholding and less stable institutional ownership take longer time to repay CPP funds.

Prior research suggest that institutional ownership stability plays more vital roles than institutional ownership shareholding on firm's performance (Elyasiani and Jia, 2008). With the findings in this essay, I add to the existing literature with evidence that high percentage of aggregate institutional shareholding in a bank is the key determinant to forecast the timing of repaying the CPP funds, regardless the stability of institutional ownership.

Table 5.1-Sample Descriptive Statistics

Panel A-Mean Statistics for Institutional Ownership

Variable	N	Mean	Median	Std Dev	Q1	Q3	Minimum	Maximum
STDI	9681	0.126	0.125	0.068	0.079	0.161	0.000	0.637
PROP(%)	9681	2.602	1.575	2.572	0.571	4.131	0.001	16.051

Panel B-Institutional Ownership by Year

Year	N	STDI	PROP(%)
2000	591	0.114	2.600
2001	640	0.117	2.568
2002	747	0.119	2.430
2003	817	0.116	2.312
2004	869	0.118	2.276
2005	924	0.125	2.389
2006	968	0.128	2.775
2007	1047	0.128	2.832
2008	1128	0.126	2.805
2009	1139	0.129	2.588
2010	1120	0.134	2.605
2011	989	0.136	2.827
2012	227	0.139	2.738

This table reposts descriptive statistics for the sample. I focus on publicly-listed banks that received bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). I use the propensity score matching technique to identify non-CPP matching banks (matching banks) as control group. I successfully find 227 matching banks for my sample of CPP banks. The details of sample and matching techniques please refer to Chapter 2; Sample period is 2000-2012. *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters).

Figures 5.1 Institutional Ownership

Figure 5.1.1 CPP Banks

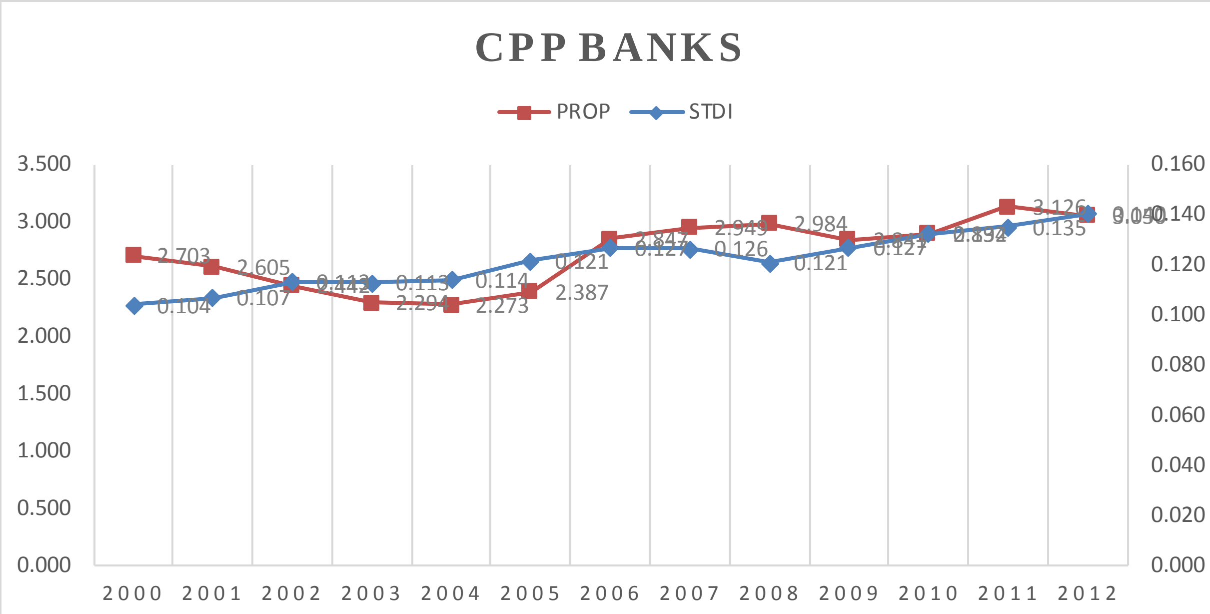
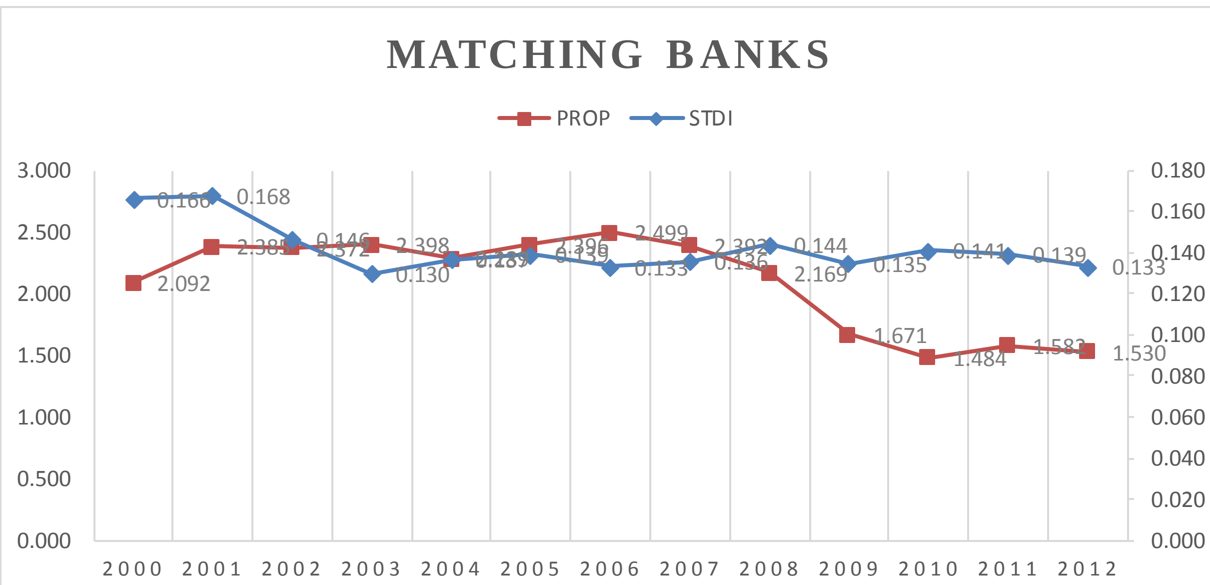


Figure 5.1.2 Matching Banks



Figures 5.1 repost line plots of institutional ownership measures (i.e. *STDI* and *PROP*) for CPP banks and matching banks. I focus on publicly-listed banks that received bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). I use the propensity score matching technique to identify non-CPP matching banks (matching banks) as control group. I successfully find 227 matching banks for my sample of CPP banks. The details of sample and matching techniques please refer to Chapter 2; Sample period is 2000-2012. *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters).

Table 5.2-Bailout Effect on Institutional Ownership

Panel A-STDI	CPP Banks			Matching Banks			CPP vs. Matching Banks			
							Mean		Median	
	N	Mean	Median	N	Mean	Median	Difference	(t-statistics)	Difference	(Wilcoxon)
Whole Sample Period (2000-2012)	7778	0.122	0.124	1903	0.140	0.134	-0.018	-9.05***	-0.010	-7.67***
By Bailout										
Pre-Bailout	5260	0.118	0.115	1254	0.142	0.134	-0.024	-9.14***	-0.018	-8.47***
Post-Bailout	2518	0.131	0.135	649	0.138	0.135	-0.006	-2.10**	0.000	0.66
Pre- vs. Post-Bailout										
Mean vs. Median difference		0.014	0.020		-0.004	0.001				
(t-statistics and Wilcoxon statistics)		9.48***	11.76***		-1.15	-0.01				
Panel B-PROP(%)	CPP Banks			Matching Banks			CPP vs. Matching Banks			
							Mean		Median	
	N	Mean	Median	N	Mean	Median	Difference	(t-statistics)	Difference	(Wilcoxon)
Whole Sample Period (2000-2012)	7778	2.727	1.741	1903	2.094	1.035	0.633	10.30***	0.705	11.16***
By Bailout										
Pre-Bailout	5260	2.599	1.680	1254	2.344	1.294	0.255	3.24***	0.386	4.56***
Post-Bailout	2518	2.994	1.907	649	1.611	0.742	1.383	14.75***	1.165	12.63***
Pre- vs. Post-Bailout										
Mean vs. Median difference		0.395	0.227		-0.733	-0.552				
(t-statistics and Wilcoxon statistics)		6.04***	4.83***		-7.07***	-6.5***				

In this table, I provide univariate analysis to examine whether financial bailout causes any significant impact on banking industry in terms of institutional ownership (I.e. *STDI* in Panel A and *PROP* in Panel B). CPP banks are public-listed banks that received bailout funds through the Capital Purchase Program (CPP), the largest one of 13 programs under the Emergency Economic Stabilization Act (2008). Matching banks are non-CPP recipients, but have same probability to receive bailout funds. Sample period is eleven years around the year of bailout out (2008-2009), given t=0 is the year of bailout; *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters). Tests in mean and median difference are the Satterthwaite method and Wilcoxon signed-rank method assuming variances are unequal. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.3-Interaction between Repayment Status and Institutional Ownership

	N	STDI Mean	STDI Median	PROP Mean	PROP Median
Subsample					
(1) No Repayment	1446	0.121	0.118	1.729	0.906
(2) Installments	1662	0.125	0.121	2.798	1.531
(3) Full Repayment	5831	0.122	0.126	2.946	2.125
Differences					
(1)-(2)		-0.005	-0.004	-1.069	-0.625
t-statistics/Wilcoxon statistics		-1.96**	-1.96**	-11.67***	-11.44***
(1)-(3)		-0.001	-0.008	-1.217	-1.219
t-statistics/Wilcoxon statistics		-0.51	-1.18	-17.61***	-16.06***
(2)-(3)		0.004	-0.004	-0.148	-0.594
t-statistics/Wilcoxon statistics		2.02**	0.82	-1.85*	-2.31**

The table reports the interaction between two measures of institutional ownership among three repayment groups: Group 1 is *No Repayment* (the group without repayment as March 2013); Group 2 is *Installments* (the group with partial repayment); and Group 3 is *Full Repayment* (the group with full repayment). *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters).Tests in mean and median difference are the Satterthwaite method and Wilcoxon signed-rank method assuming variances are unequal. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.4-Cross-sectional Correlation Tests

	Pay Back Period	STDI	PROP	SIZE	NPA	ER	ROAA	Tier 1 Capital
Pay Back Period	1							
STDI	0.128*	1						
PROP	-0.307*	-0.043*	1					
SIZE	-0.331*	-0.322*	0.749*	1				
NPA	0.174*	0.113*	-0.081*	-0.035*	1			
ER	-0.006	-0.013	-0.019*	-0.017	0.002	1		
ROAA	-0.106*	-0.093*	0.085*	0.034*	-0.461*	-0.062*	1	
Tier 1 Capital	0.002	0.015	-0.039*	-0.113*	-0.001	-0.014	0.109*	1

This table reports the simple correlation (Pearson's correlation coefficient r) for indicating the relationship between institutional ownership variables and other control variables. Sample period is 2000-2012. *Pay Back Period* is the length in days for bank to repay CPP funds. *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters). *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters). *Size* is natural logarithm of total Assets. Total assets is average total assets from previous five quarters. *Non-Performing Assets (NPA)* is ratio of nonperforming assets to total assets. *Efficiency Ratio (ER)* is ratio of non-interest expense to total income. *Return on Average Assets (ROAA)* is ratio of net income to average assets. *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets. * denote significance at the 1% levels.

Table 5.5-Pooled Logistic Regression Models

Panel A-Whole Sample

Model	(1)	(2)	(3)	(4)
CPP	0.508***	0.512***	0.539***	0.547***
	(7.809)	(7.798)	(6.506)	(6.591)
STDI		0.028		0.241**
		(0.410)		(2.527)
PROP	1.873***	1.870***	1.968***	1.767***
	(18.233)	(18.196)	(8.719)	(7.490)
SIZE			0.507**	0.680***
			(2.441)	(3.131)
NPA			-0.579***	-0.615***
			(-6.330)	(-6.610)
ER			0.064	0.068
			(0.569)	(0.615)
ROAA			0.256***	0.260***
			(2.780)	(2.829)
Tier 1 Capital			-0.056	-0.036
			(-0.611)	(-0.388)
Pseudo R-squared	0.059	0.059	0.092	0.093
Chi-squared	537.0***	537.2***	567.3***	573.8***
Correctly Classified (%)	82.27	82.27	84.45	84.54
N	9681	9681	7253	7253

(Continued)

(Table 5.5 Continued)

Panel B-Robustness Tests on Subsamples

Model	(1)	(2)	(3)
CPP		0.651***	0.471***
		(6.956)	(5.767)
STDI	0.174	0.092	0.268***
	(1.470)	(0.995)	(2.858)
PROP	1.359***	1.141***	1.565***
	(5.151)	(5.918)	(7.183)
SIZE	0.996***	0.429**	0.682***
	(3.881)	(2.479)	(3.280)
NPA	-1.272***	-0.063	-0.765***
	(-12.223)	(-0.525)	(-8.610)
ER	0.013	-0.256*	0.467
	(0.138)	(-1.923)	(0.529)
ROAA	0.261**	0.591***	0.193**
	(2.422)	(4.108)	(2.071)
Tier 1 Capital	0.591***	0.218**	-0.042
	(4.740)	(2.295)	(-0.471)
Pseudo R-squared	0.105	0.118	0.099
Chi-squared	509.4***	387.0***	569.4***
Correctly Classified (%)	87.33	67.72	81.34
N	6154	2367	5993

In this table, I provide bivariate logistic regression analysis to explore whether the institutional ownership variables are the factors that affect the likelihood of a bank being exit the CPP program. The dependent variable is *Repayment*, it is a dummy variable equals to one if the bank repays the bailout funds by March 1st, 2013; zero otherwise. Sample period is 2000-2012. In Panel A, I test on whole sample, while in Panel B I run additional robustness tests on subsamples. Model (1) of Panel B is CPP banks only subsample; Model (2) I exclude full repayment group; Model (3) I exclude installments group. *CPP* is a dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank; *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters). *Size* is natural logarithm of total Assets. Total assets is average total assets from previous five quarters. *Non-Performing Assets (NPA)* is ratio of nonperforming assets to total assets. *Efficiency Ratio (ER)* is ratio of non-interest expense to total income. *Return on Average Assets (ROAA)* is ratio of net income to average assets. *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets. Numbers presented in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.6- Pooled Cross-sectional OLS Regression Analysis
Panel A- Whole Sample

Model	(1)	(2)	(3)	(4)	(5)	(6)
CPP		-0.064***		-0.056***	-0.061***	-0.061***
		(-6.602)		(-5.715)	(-5.199)	(-5.180)
STDI			0.087***	0.082***		-0.003
			(10.734)	(9.852)		(-0.231)
PROP	-0.346***	-0.339***	-0.341***	-0.335***	-0.210***	-0.209***
	(-33.562)	(-32.246)	(-33.217)	(-32.087)	(-11.524)	(-10.867)
SIZE					-0.150***	-0.152***
					(-9.333)	(-8.477)
NPA					0.164***	0.164***
					(6.424)	(6.366)
ER					-0.018***	-0.018***
					(-5.801)	(-5.771)
ROAA					-0.037***	-0.037***
					(-2.657)	(-2.663)
Tier 1 Capital					-0.022*	-0.022*
					(-1.920)	(-1.937)
Adjusted R-squared	0.116	0.120	0.123	0.126	0.154	0.154
F-statistics	24.07***	25.38***	29.14***	31.07***	26.64***	26.68***
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	9,551	9,551	9,551	9,551	7,158	7,158

(Continued)

(Table 5.6 Continued)

Panel B-CPP Banks Only subsample

Model	(1)	(2)	(3)	(4)
STDI		0.069***		-0.038***
		(7.211)		(-3.290)
PROP	-0.339***	-0.337***	-0.192***	-0.172***
	(-30.432)	(-30.323)	(-9.852)	(-8.514)
SIZE			-0.156***	-0.184***
			(-9.383)	(-10.090)
NPA			0.303***	0.305***
			(12.635)	(12.653)
ER			-0.014	-0.014
			(-1.502)	(-1.563)
ROAA			-0.048***	-0.049***
			(-3.540)	(-3.640)
Tier 1 Capital			-0.086***	-0.089***
			(-6.720)	(-6.954)
Adjusted R-squared	0.110	0.115	0.190	0.191
F-statistics	20.21***	23.14***	37.53***	37.21***
Time Fixed Effect	Yes	Yes	Yes	Yes
N	7,674	7,674	6,062	6,062

(Continued)

(Table 5.6 Continued)

Panel C-Excluded No-repayment group Subsample

Model	(1)	(2)	(3)	(4)	(5)	(6)
CPP		-0.051***		-0.042***	-0.035***	-0.034***
		(-4.471)		(-3.678)	(-2.640)	(-2.592)
STDI			0.102***	0.099***		0.011
			(10.928)	(10.305)		(0.792)
PROP	-0.310***	-0.306***	-0.301***	-0.298***	-0.182***	-0.187***
	(-28.614)	(-27.854)	(-27.617)	(-27.042)	(-9.912)	(-9.588)
SIZE					-0.147***	-0.139***
					(-8.789)	(-7.069)
NPA					0.137***	0.136***
					(4.867)	(4.799)
ER					-0.017***	-0.017***
					(-6.091)	(-5.993)
ROAA					-0.031**	-0.031**
					(-1.994)	(-1.970)
Tier 1 Capital					-0.042***	-0.041***
					(-3.160)	(-3.078)
Adjusted R-squared	0.091	0.093	0.101	0.103	0.116	0.116
F-statistics	17.52***	18.13***	22.19***	23.36***	17.73***	18.29***
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	7,835	7,835	7,835	7,835	6,051	6,051

In this table, I provide multivariate OLS regression analysis to explore whether the institutional ownership variables are the factors that affect the timing for a bank to exit the CPP program. The dependent variable is natural logarithm of *Pay Back Period*, the length in days for bank to repay CPP funds. Panel A is whole sample period during 2000-2012; Panel B is CPP only subsample; I exclude no-repayment group in Panel C; *CPP* is a dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank; *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters). *Size* is natural logarithm of total Assets. Total assets is average total assets from previous five quarters. *Non-Performing Assets (NPA)* is ratio of nonperforming assets to total assets. *Efficiency Ratio (ER)* is ratio of non-interest expense to total income. *Return on Average Assets (ROAA)* is ratio of net income to average assets. *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets. Numbers presented in parentheses are t-statistics. F-statistics is test for the null hypothesis of that the coefficients of the regression model are zero. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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Table 5.7-Robustness Test Using Pooled OLS Regression with Clustered Standard Errors Models
Panel A-Whole Sample

	(1)	(2)	(3)	(4)	(5)	(6)
CPP		-0.127		-0.111	-0.133	-0.133
		(-1.225)		(-1.060)	(-1.096)	(-1.093)
STDI			1.000**	0.935**		-0.053
			(2.486)	(2.263)		(-0.104)
PROP	-0.101***	-0.099***	-0.099***	-0.098***	-0.061**	-0.061**
	(-6.273)	(-6.015)	(-6.253)	(-6.019)	(-2.344)	(-2.242)
SIZE					-0.079*	-0.081*
					(-1.856)	(-1.806)
NPA					4.929***	4.948***
					(3.376)	(3.212)
ER					-0.004***	-0.004***
					(-8.789)	(-8.125)
ROAA					-6.238	-6.265
					(-1.568)	(-1.588)
Tier 1 Capital					-0.010	-0.010
					(-0.936)	(-0.939)
Constant	6.905***	7.001***	6.776***	6.868***	7.548***	7.565***
	(136.397)	(81.366)	(90.028)	(60.395)	(23.857)	(20.892)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.117	0.121	0.125	0.128	0.157	0.157
F-statistics	1110.619***	604.570***	696.175***	509.112***	203.017***	181.566***
N	9,551	9,551	9,551	9,551	7,158	7,158

(Continued)

(Table 5.7 Continued)

Panel B-CPP Banks Only subsample

	(1)	(2)	(3)	(4)
STDI		0.880*		-0.541
		(1.709)		(-0.990)
PROP	-0.096***	-0.095***	-0.056**	-0.050*
	(-5.563)	(-5.586)	(-2.056)	(-1.771)
SIZE			-0.084*	-0.099**
			(-1.911)	(-2.197)
NPA			9.415***	9.634***
			(5.464)	(5.434)
ER			-0.026	-0.027
			(-0.691)	(-0.709)
ROAA			-6.920	-7.283*
			(-1.571)	(-1.658)
Tier 1 Capital			-0.036***	-0.037***
			(-2.877)	(-2.910)
Constant	6.867***	6.758***	7.679***	7.852***
	(114.021)	(77.118)	(22.565)	(21.754)
Firm Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
R-squared	0.110	0.116	0.185	0.187
F-statistics	896.159***	536.651***	332.435***	288.656***
N	7,674	7,674	6,062	6,062

(Continued)

(Table 5.7 Continued)

Panel C-Excluded No-repayment group subsample

	(1)	(2)	(3)	(4)	(5)	(6)
CPP		-0.107		-0.088	-0.082	-0.081
		(-0.852)		(-0.700)	(-0.568)	(-0.559)
STDI			1.192**	1.145**		0.127
			(2.500)	(2.340)		(0.198)
PROP	-0.088***	-0.087***	-0.085***	-0.085***	-0.051*	-0.053*
	(-5.425)	(-5.261)	(-5.291)	(-5.157)	(-1.957)	(-1.945)
SIZE					-0.074*	-0.070
					(-1.712)	(-1.510)
NPA					4.951***	4.902***
					(2.774)	(2.606)
ER					-0.003***	-0.003***
					(-7.792)	(-6.674)
ROAA					-5.678	-5.603
					(-1.176)	(-1.173)
Tier 1 Capital					-0.014	-0.013
					(-1.130)	(-1.111)
Constant	6.744***	6.829***	6.587***	6.663***	7.373***	7.330***
	(114.079)	(62.944)	(74.517)	(47.920)	(21.907)	(18.043)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.093	0.096	0.104	0.106	0.122	0.122
F-statistics	804.928***	428.467***	531.276***	382.713***	133.271***	123.019***
N	7,835	7,835	7,835	7,835	6,051	6,051

In this table, I provide Pooled OLS regression analysis with Petersen (2009) clustered standard error models to explore whether the institutional ownership variables are the factors that affect the timing for a bank to exit the CPP program. The dependent variable is *Log* (*Pay Back Period)*, the length in days for bank to repay CPP funds. Panel A is whole sample period during 2000-2012; Panel B is CPP only subsample; I exclude no-repayment group in Panel C; *CPP* is a dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank; *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters). *Size* is natural logarithm of total Assets. Total assets is average total assets from previous five quarters. *Non-Performing Assets (NPA)* is ratio of nonperforming assets to total assets. *Efficiency Ratio (ER)* is ratio of non-interest expense to total income. *Return on Average Assets (ROAA)* is ratio of net income to average assets. *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets. Numbers presented in parentheses are t-statistics. F-statistics is test for the null hypothesis of that the coefficients of the regression model are zero; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.8- Seemingly Unrelated Regression Analysis
Panel A-Institutional ownership

	(1)	(2)	(3)	(4)
	PROP		STDI	
	Low	High	Low	High
CPP	-0.030*	-0.091***	-0.030*	-0.093***
	(-1.735)	(-5.724)	(-1.903)	(-5.841)
STDI	0.042**	-0.168***		
	(2.503)	(-6.568)		
PROP			-0.202***	-0.204***
			(-7.464)	(-7.551)
SIZE	-0.192***	-0.323***	-0.190***	-0.116***
	(-11.271)	(-12.388)	(-6.813)	(-4.295)
NPA	0.143***	0.183***	0.118***	0.137***
	(7.536)	(9.425)	(6.824)	(7.640)
ER	-0.033**	0.054***	-0.025	-0.005
	(-1.964)	(3.179)	(-1.618)	(-0.304)
ROAA	-0.008	-0.035*	-0.026	-0.046**
	(-0.411)	(-1.874)	(-1.507)	(-2.506)
Tier 1 Capital	-0.025	-0.086***	-0.043***	-0.029*
	(-1.463)	(-5.179)	(-2.714)	(-1.833)
Adj. R-squared	0.058	0.093	0.166	0.142
Chi-squared	1720.80***		2.6	
F-statistics	31.05***	55.54***	104.30***	84.13***
Time-Fixed Effect	Yes	Yes	Yes	Yes
N	3423	3735	3642	3516

(Continued)

(Table 5.8 Continued)

Panel B- Repayment Status

	(1)	(2)	(3)
		Repayment Status	
	No-repayment	Installments	Full repayment
CPP	-0.187***	0.049*	-0.051***
	(-6.208)	(1.844)	(-3.700)
STDI	-0.012	0.057**	0.004
	(-0.417)	(2.016)	(0.249)
PROP	0.051	-0.224***	-0.182***
	(1.137)	(-5.039)	(-8.459)
SIZE	0.324***	-0.132***	-0.140***
	(7.214)	(-2.927)	(-5.871)
NPA	-0.073**	0.271***	0.101***
	(-2.138)	(6.997)	(6.807)
ER	-0.033	0.060**	-0.022
	(-1.074)	(2.119)	(-1.582)
ROAA	0.015	0.036	-0.035**
	(0.424)	(0.976)	(-2.370)
Tier 1 Capital	0.062**	-0.114***	-0.044***
	(2.092)	(-4.155)	(-3.093)
Adj. R-squared	0.147	0.199	0.112
Chi-squared	8417.88***	20.06***	
F-statistics	24.76	38.24	77.66
Time-Fixed Effect	Yes	Yes	Yes
N	1107	1203	4848

This table reports results from seemingly unrelated regression analysis. In order to compare coefficients across equations, I use two sets of institutional ownership groups, Low vs. High PROP (model (1) and (2)), and Low vs. High STDI (Model (3) and (4)) in Panel A. *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters). In additions, in Panel B I compare OLS regression models among three repayment groups: *No-repayment* is the group didn't make any repayment as March 1st, 2013; *Installments* is the group that pays at least one installment to the government by March 1st, 2013; *Full repayment* is the group that repay CPP funds in one full payment by March 1st, 2013. The dependent variable is *Log* (*Pay Back Period)*, the length in days for bank to repay CPP funds *for all models*. *Size* is natural logarithm of total Assets. Total assets is average total assets from previous five quarters. *Non-Performing Assets (NPA)* is ratio of nonperforming assets to total assets. *Efficiency Ratio (ER)* is ratio of non-interest expense to total income. *Return on Average Assets (ROAA)* is ratio of net income to average assets. *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets. Numbers presented in parentheses are t-statistics. F-statistics is test for the null hypothesis of that the coefficients of the regression model are zero. Chi-squared statistics derived from Lagrange multiplier correlation test of Breusch and Pagan is based on the null hypothesis of that the average of the squared pair-wise correlation coefficients of the residuals are all equal; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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APPENDIX

Appendix 3.A- Variables Definitions and Measures

Variable	Definitions and Measures	Data Sources
Panel 1 Cost of Equity Capital Variables		
r_{GLS}	Implied cost of capital for GLS model, derive r from below model $$p_t = bv_t + \sum_{\tau=1}^{T} \frac{(\hat{x}_{t+\tau} - r_{GLS} * bv_{t+\tau-1})}{(1+r_{GLS})^{\tau}} + \frac{(\hat{x}_{t+T+1} - r_{GLS} * bv_{t+T})}{r_{GLS}(1+r_{GLS})^{T}}$$	Compustat; I/B/E/S
r_{OJ}	Implied cost of capital for OJ model, derive r from below model $$p_t = \frac{\hat{x}_{t+1}}{r_{OJ}} + \frac{(\hat{x}_{t+2} - \hat{x}_{t+1} - r_{OJ} * \hat{x}_{t+1}) * (1-d)}{r_{OJ} * (r_{OJ} - g_{lt})}$$	Compustat; I/B/E/S; The Fed
r_{PEG}	Implied cost of capital for PEG model, derive r from below model $$p_t = \frac{(\hat{x}_{t+2} - \hat{x}_{t+1} + r_{PEG} * \hat{x}_{t+1} * d)}{{r_{PEG}}^2}$$	Compustat; I/B/E/S; The Fed
$r_{ICOC(3)}$	Average implied cost of capital = $(r_{GLS} + r_{OJ} + r_{PEG})/3$	
$\Delta\ r_{GLS}$	Change of implied cost of capital for GLS model	
$\Delta\ r_{OJ}$	Change of implied cost of capital for OJ model	
$\Delta\ r_{PEG}$	Change of implied cost of capital for PEG model	
$\Delta\ r_{ICOC(3)}$	Change of $r_{ICOC(3)}$	
Panel 2 CPP Related Variables		
CPP	A dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank	The Treasury; ProPublica

PostBailout	A dummy variable equals to 1 if it is post-bailout period; else is 0 for pre-bailout	The Treasury; ProPublica
CPP x PostBailout	Interaction term of CPP and PostBailout	
Exchange	1: NYSE; 2: AMEX; 3:NASDAQ	The Treasury
Repayment subgroups	1:No Repayment (as March 201)3; 2: Partial Repayment (paying with Installments); 3:Full Repayment	The Treasury
Panel 3 Institutional Investor Variables		
Shareholding	The ratio of shares held by II to total shares outstanding	Thomson Financial Institutional 13 F
Shareholding_F	The ratio of shares held by II who are defined as foreign II to total share outstanding	Thomson Financial Institutional 13 F
Shareholding_D	The ratio of shares held by II who are defined as domestic II to total share outstanding	Thomson Financial Institutional 13 F
Shareholding_I	The ratio of shares held by II who are defined as Independent II to total shares outstanding	Thomson Financial Institutional 13 F
Shareholding_G	The ratio of shares held by II who are defined as Gray II to total shares outstanding	Thomson Financial Institutional 13 F
Blockholder	a dummy variable equals to 1 if Sharesholding by one single II is more than 5 % in a firm; zero equals to non-Blockholder	Thomson Financial Institutional 13 F
F_dominate	A dummy variable equals to 1 if Shareholding_F is greater than Shareholding_D; zero equals to non-F_dominate	Thomson Financial Institutional 13 F
G_dominate	A dummy variable equals to 1 if Shareholding_G is greater than Shareholding_I; zero equals to non-G_dominate	Thomson Financial Institutional 13 F
High-Shareholding	A dummy variable equals to 1 if shareholding is greater than median shareholding; zero equals to Low shareholding	Thomson Financial Institutional 13 F
Panel 4 Control and other Variables		
Size	Log of Total Assets. Total assets is average total assets from previous five quarters	Compustat
ROE	Return on Equity	Compustat
Return on Average Assets (ROAA)	Ratio of net income to average assets	Compustat
Return on Average Equity (ROAE)	Ratio of net income to average shareholder equity	Compustat
Efficiency Ratio (ER)	Ratio of non-interest expense to total income	Compustat
Net Interest Margin (NIM)	Ratio of net interest income to total assets	Compustat

Equity on Assets (EOA)	Ratio of tangible equity to tangible assets	Compustat
Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)	Risk-adjusted Tier 1 capital ratio: ratio of the bank's core equity to its total risk-weighted assets	Compustat
Dividend Yield	Cash dividend deflated by share price	Compustat; CRSP
Book to Market(BKMK)	Proxy for growth; It is ratio of net worth to market capitalization	Compustat; CRSP
Dispersion	Dispersion is standard deviation of one-year ahead analyst's earning forecast (FEPS1), deflated by share price	I/B/E/S; CRSP
Leverage	Total liability divided by Net worth	Compustat
Volatility	Systematic risk (or volatility) equals to annualized standard deviation of monthly return	CRSP
Return	Annualized monthly Stock return	CRSP
Bid-Ask Spread	It is proxy for liquidity. It is absolute value of bid-ask difference, deflated by share price	CRSP
Tobin's Q	Proxy for firm value. It is sum of book value of assets and market value of common equity minus book value of common equity , divided by book value of assets	CRSP, Compustat

Appendix 3.B. Correlation Analysis

Panel 1. Correlation of Cost of Equity Measures

	r_{GLS}	r_{OJ}	r_{PEG}	$r_{ICOC(3)}$
r_{GLS}	1			
r_{OJ}	0.602*	1		
r_{PEG}	0.632*	0.992*	1	
$r_{ICOC(3)}$	0.809*	0.955*	0.965*	1

* denote significance at the 5% levels.

Panel 2. Correlation of Changes in Cost of Equity

	Δr_{GLS}	Δr_{OJ}	Δr_{PEG}	$\Delta r_{ICOC(3)}$
Δr_{GLS}	1			
Δr_{OJ}	0.721*	1		
Δr_{PEG}	0.778*	0.986*	1	
$\Delta r_{ICOC(3)}$	0.872*	0.966*	0.984*	1

* denote significance at the 5% levels.

Appendix 4.A. Variables Definitions and Measures

Variable	Definitions and Measures	Data Sources
Panel 1 Return Variables		
Ln(Ret)	It is aggregated monthly return, while daily return is natural logarithm of (P_t/P_{t-1})	CRSP
Ln(Ret(-2, -7))	It is natural logarithm of Ret(-2, -7); and Ret(-2,-7) is compounded gross return from t-2 to t-7 period and serves as a proxy for momentum factor, while t=0 is the month of bailout	CRSP
Panel 2 Idiosyncratic Volatility Variables		
IVOL3	It is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach	CRSP & Professor French Data library
IVOL4	It is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach	CRSP & Professor French Data library
E(IVOL)	It is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models from each firm	CRSP
Panel 3 CPP Related Variables		
CPP	A dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank	The Treasury
PostBailout	A dummy variable equals to 1 if it is post-bailout; else is 0 for pre-bailout	The Treasury
CPP x PostBailout	Interaction term of CPP and PostBailout dummies	
Panel 4 Control and other Variables		
Beta	Rolling 60-month betas derived from CAPM	CRSP
Ln(ME)	It is natural logarithm of market capitalization, where market cap is the product of share price and shares outstanding	CRSP
Ln(BKMK)	It is natural logarithm of book-to-market, where book value if book equity value and market value is market cap	Compustat; CRSP
In(Bidaskspread)	It is natural logarithm of absolute difference between adjusted bid price and adjusted ask price	CRSP
Size	It is natural logarithm of total Assets. Total assets is average total assets from previous five quarters	Compustat

Debt	It is the ratio of total liability to total assets	
Return on Average Assets (ROAA)	Ratio of net income to average assets	Compustat
Efficiency Ratio (ER)	Ratio of non-interest expense to total income	Compustat
Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)	Ratio of the bank's core equity to its total risk-weighted assets	Compustat
Free Cash Flow	Free cash flow, a proxy for agency cost, is computed as difference between income before extraordinary items and total deposit, scaled by total average assets	Compustat
Dispersion	*Dispersion* of analyst forecasts is computed as the standard deviation of the firm's estimated EPS for 1-yr ahead by I/B/E/S, scaled by stock price at the earnings forecast date	I/B/E/S; CRSP
Institutional Investor (Shareholding)	The ratio of shares held by institutional investor to total share outstanding	Thomson Financial Institutional 13 F
Blockholder	a dummy variable "Blockholder" equals to 1 (Yes)if shares holding by one single institutional investor more than 5 % in a firm; else equals to 0 (or No)	Thomson Financial Institutional 13 F

Appendix 4.B- Robustness Tests for Return-Idiosyncratic Volatility Relationship

Panel A.1-Fama-MacBeth Regression (Panel)-Pre-bailout Subsample

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(Ivol3)			22.439***	6.978***				
			(20.450)	(5.149)				
lag(Ivol4)					22.475***	7.377***		
					(18.860)	(5.333)		
E(Ivol)							38.431***	15.453
							(4.068)	(0.925)
Beta	-1.068***	-1.105**		-1.124**		-1.097**		-1.340**
	(-2.708)	(-2.419)		(-2.452)		(-2.403)		(-2.172)
Ln(ME)	2.428	3.607		2.144		2.316		5.120
	(0.713)	(1.476)		(0.824)		(0.887)		(1.471)
Ln(BKMK)	5.533*	5.012**		2.793		2.944		6.461**
	(1.684)	(2.253)		(1.163)		(1.225)		(2.022)
Ln(Ret(-2,-7))		1.684		-0.151		-0.168		-70.005
		(0.480)		(-0.043)		(-0.048)		(-1.443)
Ln(Bidaskspread)		1.057***		0.980***		0.986***		0.985***
		(12.082)		(10.504)		(10.515)		(10.422)
Constant	-22.053	-36.667	3.047***	-20.596	3.089***	-22.642	-60,518.383***	-7,525.355
	(-0.548)	(-1.230)	(34.769)	(-0.653)	(34.003)	(-0.714)	(-4.240)	(-0.350)
R-squared	0.005	0.004	0.206	0.021	0.176	0.018	0.001	0.001
Number of firms	141	138	164	138	164	138	164	138
N	5,998	5,813	7,504	5,813	7,504	5,813	7,504	5,813

(Continued)

Appendix 4.B-Continued

Panel A.2-Fama-MacBeth Regression (Panel)-Post-Bailout Subsample

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(Ivol3)			16.108***	8.859***				
			(22.943)	(5.519)				
lag(Ivol4)					15.596***	7.484***		
					(24.717)	(10.917)		
E(Ivol)							26.360***	6.201
							(3.631)	(1.062)
Beta	0.836	0.757		2.472		0.828		-1.987
	(1.318)	(1.240)		(1.247)		(1.418)		(-0.808)
Ln(ME)	-17.291	-16.513		-2.388		-2.622*		4.348
	(-1.571)	(-1.297)		(-1.609)		(-1.819)		(0.185)
Ln(BKMK)	-15.669	-15.744		-2.391*		-2.412*		3.847
	(-1.412)	(-1.231)		(-1.682)		(-1.696)		(0.171)
Ln(Ret(-2,-7))		6.175		4.530		4.178		-1,318.243*
		(0.891)		(0.848)		(0.776)		(-1.856)
Ln(Bidaskspread)		1.217***		1.149***		1.144***		1.277***
		(21.338)		(20.234)		(20.994)		(15.832)
Constant	202.219*	189.753	3.899***	33.727**	4.024***	36.801**	-39,302.312***	-12,788.521
	(1.724)	(1.399)	(22.295)	(2.251)	(33.909)	(2.573)	(-3.836)	(-1.242)
R-squared	0.000	0.000	0.220	0.055	0.192	0.027	0.001	0.000
Number of firms	217	214	229	214	229	214	229	214
N	12,040	11,896	14,140	11,895	14,140	11,895	14,141	11,896

(Continued)

Appendix 4.B-Continued

Panel B1-Fama-MacBeth Regression (Panel)-CPP Banks Subsample

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(Ivol3)			18.984***	7.801***				
			(34.318)	(3.800)				
lag(Ivol4)					18.593***	6.471***		
					(32.360)	(5.514)		
E(Ivol)							25.070***	5.744
							(6.033)	(0.853)
Beta	-1.314	-0.659		-2.047		-3.080		-3.254
	(-0.704)	(-0.537)		(-0.446)		(-0.895)		(-1.178)
Ln(ME)	-14.910	-16.334		-3.068		-2.972		6.463
	(-1.293)	(-1.208)		(-1.081)		(-1.184)		(0.260)
Ln(Ret(-2,-7))		0.000		0.000		0.000		0.000
		(.)		(.)		(.)		(.)
Ln(Bidaskspread)		1.192***		0.987***		1.008***		1.243***
		(16.749)		(6.112)		(7.382)		(13.248)
Constant	169.609	189.330	3.359***	54.745	3.427***	51.589	-36,785.863***	-9,741.089
	(1.380)	(1.308)	(52.527)	(1.212)	(53.860)	(1.337)	(-6.203)	(-0.866)
R-squared	0.001	0.002	0.262	0.007	0.238	0.005	0.000	0.000
Number of firms	207	202	220	202	220	202	220	202
N	15,984	15,749	19,006	15,749	19,006	15,749	19,006	15,749

(Continued)

Appendix 4.B-Continued

Panel B2-Fama-MacBeth Regression (Panel)-Matched Banks Subsample

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(Ivol3)			15.377***	7.626***				
			(16.733)	(6.286)				
lag(Ivol4)					14.898***	7.793***		
					(16.655)	(6.332)		
E(Ivol)							66.499***	37.020*
							(3.625)	(1.877)
Beta	-13.601	-0.551		-0.224		-0.366		-0.453
	(-0.959)	(-0.460)		(-0.187)		(-0.296)		(-0.393)
Ln(ME)	-0.149	16.890		17.071		17.220		15.591
	(-0.085)	(1.010)		(1.052)		(1.047)		(1.012)
Ln(Ret(-2,-7))		0.000		0.000		0.000		0.000
		(.)		(.)		(.)		(.)
Ln(Bidaskspread)		1.468***		1.382***		1.385***		1.447***
		(5.011)		(4.742)		(4.746)		(5.111)
Constant	18.970	-152.663	3.440***	-158.370	3.400***	-159.835	-100,020.111***	-51,961.156**
	(1.184)	(-0.948)	(23.718)	(-1.014)	(19.025)	(-1.010)	(-3.998)	(-2.316)
R-squared	0.146	0.000	0.247	0.000	0.206	0.000	0.000	0.000
Number of firms	76	72	92	72	92	72	92	72
N	4,673	4,539	6,566	4,538	6,566	4,538	6,567	4,539

In the table, I examine risk-return relationship month-by-month using pooled cross-sectional Fama MacBeth (1973) regression models in different subsamples as robustness tests. The dependent variable is *Ln (Ret)*, while the IVOL measure is *Lag (IVOL3)* for models (3)-(4), *Lag (IVOL4)* for models (5)-(6), and *E (IVOL)* for models (7)-(8). Subsample for Panel A1 is Pre-bailout period, Panel A2 is Post-bailout period, Panel B1 is CPP banks only, and Panel B2 is Matched banks only subsample. Ln(*Ret)* is aggregated monthly return, while daily return is natural logarithm of (P_t/P_{t-1}) ; *IVOL3* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 3-factor regression residual using rolling 30-day window approach; *IVOL4* is realized Idiosyncratic Volatility, and computed as standard deviation of Fama-French 4-factor regression residual using rolling 30-day window approach; *E (IVOL)* is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models for each firm; *Beta* is rolling 60-month betas derived from CAPM; *Ln (ME)* is natural logarithm of market capitalization, where market cap is the product of share price and shares outstanding; *Ln (BKMK)* is natural logarithm of book-to-market, where book value if book equity value and market value is market cap; *Ln (Ret (-2,-7))* is natural logarithm of *Ret (-2, -7)*, while *Ret (-2,-7)* is compound gross return from t-2 to t-7 period and serves as a proxy for momentum factor, and t=0 is the month of bailout;*; Ln (Bidaskspread)* is the proxy for *liquidity* and is natural logarithm of absolute difference between adjusted bid price and adjusted ask price. Numbers presented in parentheses are t-statistics; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix 5.A-Variables Definitions and Measures

Variable	Definitions and Measures	Data Sources
Panel 1 Institutional Ownership Variable		
STDI	It is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters)	Thomson Financial Institutional 13 F
PROP	It is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters)	Thomson Financial Institutional 13 F
Panel 2 CPP Related Variables		
CPP	A dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank	The Treasury
Panel 3 Repayment Related Variables		
Repayment	A dummy variable equals to 1 if bank paid back CPP funds before March 1, 2013; else is 0	Treasury monthly report to Congress
Pay Back Period	It is the length in days for bank to repay CPP funds	Treasury monthly report to Congress
Panel 4 Control and other Variables		
Size	It is natural logarithm of total Assets. Total assets is average total assets from previous five quarters	Compustat
Non-performing Assets (NPA)	Ratio of nonperforming assets to total assets	Compustat
Efficiency Ratio (ER)	Ratio of non-interest expense to total income	Compustat
Return on Average Assets (ROAA)	Ratio of net income to average assets	Compustat
Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)	Ratio of the bank's core equity to its total risk-weighted assets	Compustat

Appendix 5B-Probit regressions examining the probabilities of CPP exit

Panel A-Whole sample

Model	(1)	(2)	(3)	(4)
CPP	0.283***	0.284***	0.305***	0.308***
	(7.425)	(7.403)	(6.394)	(6.442)
STDI		0.011		0.159***
		(0.271)		(2.964)
PROP	0.950***	0.949***	0.852***	0.747***
	(18.987)	(18.960)	(8.268)	(6.916)
SIZE			0.381***	0.488***
			(3.620)	(4.409)
NPA			-0.338***	-0.357***
			(-6.579)	(-6.896)
ER			0.035	0.037
			(0.569)	(0.615)
ROAA			0.139***	0.143***
			(2.620)	(2.685)
Tier 1 Capital			-0.006	0.005
			(-0.114)	(0.101)
Pseudo R-squared	0.057	0.057	0.090	0.091
N	9681	9681	7253	7253

Panel B-Subsamples

Model	(1)	(2)	(3)
CPP		0.379***	0.272***
		(6.763)	(5.701)
STDI	0.117*	0.063	0.177***
	(1.782)	(1.126)	(3.302)
PROP	0.583***	0.596***	0.677***
	(4.777)	(5.910)	(6.612)
SIZE	0.630***	0.337***	0.496***
	(4.887)	(3.447)	(4.579)
NPA	-0.738***	-0.033	-0.444***
	(-12.067)	(-0.469)	(-8.807)
ER	0.016	-0.126**	0.287
	(0.301)	(-2.159)	(0.565)
ROAA	0.143**	0.315***	0.114**
	(2.230)	(4.058)	(2.069)
Tier 1 Capital	0.345***	0.126**	-0.003
	(5.100)	(2.167)	(-0.068)

Pseudo R-squared	0.104	0.116	0.098
N	6154	2367	5993

In this table, I provide robustness tests for Table 5.5 using probit regression models to explore whether the institutional ownership variables are the factors that affect the likelihood of a bank being exit the CPP program. The dependent variable is *Repayment*, it is a dummy variable equals to one if the bank repays the bailout funds by March 1st, 2013; zero otherwise. Sample period is 2000-2012. In Panel A, I test on whole sample, while in Panel B I run additional robustness tests on subsamples. Model (1) of Panel B is CPP banks only subsample; Model (2) I exclude full repayment group; Model (3) I exclude installments group. *CPP* is a dummy variable equals to 1 if it is CPP bank; else is 0 for matching bank; *STDI* is proxy for institutional ownership stability. It is average standard deviation of institutional shareholding proportions across all investors in the firm over a 5-year period (i.e. previous 20 quarters); *PROP* is aggregate shareholding proportion of a firm over a 5-year period (i.e. previous 20 quarters). *Size* is natural logarithm of total Assets. Total assets is average total assets from previous five quarters. *Non-Performing Assets (NPA)* is ratio of nonperforming assets to total assets. *Efficiency Ratio (ER)* is ratio of non-interest expense to total income. *Return on Average Assets (ROAA)* is ratio of net income to average assets. *Tier 1 Risk-adjusted Capital Ratio (Tier 1 Capital)* is ratio of the bank's core equity to its total risk-weighted assets. Numbers presented in parentheses are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

BIOGRAPHICAL SKETCH

Daphne Shu Nu Wang earned her Bachelor of Arts in Sociology from National Taiwan University. She received her Master of Business Administration in 2010 from the University of Texas at Brownsville. In 2010 she joined the doctoral program at the University of Texas-Pan American. Her research interests are in the area of Corporate Finance, Foreign Direct Investment, Mergers and Acquisitions, Credit Ratings, Financial Crisis, American Depository Receipts, Financial Markets and Institution, Financial Risk Management, Emerging Markets, and Insider Trades. Her publications have appeared in a variety of journals including: *Applied Economics*, *Global Business and Finance Review*, *Research in International Business and Finance*, *International Research Journal of Applied Finance*, and *Journal of Immigrant and Minority Health*. In addition, her work have been presented at major finance conferences including Eastern Finance Association, Southern Finance Association, Southwestern Finance Association, Academy of Economics and Finance, and Association for Global Business. She has inactive real estate license and has more than ten years of industry experience as corporate executive in the U.S. and Taiwan.

Ms. Wang may be contacted at Jacksonville University, Davis College of Business, Department of Accounting and Finance, 2800 University Blvd. N. Jacksonville, FL 32211 or via email: daphnewang99@gmail.com.