IDIOSYNCRATIC VOLATILITY IN BANKING INDUSTRY DURING 2008-2009 FINANCIAL BAILOUT

Abstract

In this paper, we 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 in the recent financial crisis during 2007-2009. 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, we document the important role of corporate governance and information asymmetry on banks' IVOL.

Keywords: Financial Crisis, Idiosyncratic Volatility, Corporate Governance, EGARCH

JEL Classification: G01, G21, G30

I. Introduction

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 injected capital from the Capital Purchase Program (CPP), the largest and most important program among thirteen Troubled Asset Relief Programs (TARP) under EESA, 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. Intuitively, government intervention might increase bank value by reducing the refinancing costs and the probability of bankruptcy. Veronesi and Zingales (2010) investigate the costs and benefits of the U.S. government intervention plan to the ten largest banks[1] in the recent financial bailout and find that the value of banks' financial claims increases by $130 billion with a cost imposed on tax payers of about $21 billion. However, 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. Researchers find that the government bailout programs do not deter banks from conducting risky lending (Black and Hazelwood, 2013; Brei and Gadanecz, 2012; Duchin and Sosyura, 2013). Particularly, the evidence on the changes in idiosyncratic volatility (IVOL)[2] among public-listed banks upon government bailout events in the recent financial crisis is still unexplored. In this essay, we 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

[1] 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.

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

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-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[3]. Conversely, others argue for a negative relationship, implying some evidence of mispricing from conventional asset pricing models (Ang et al., 2006; Ang et al., 2009; Easley et al., 2002; Guo and Savickas, 2008, 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

[3] The findings from Goyal, A., Santa-Clara, P., 2003. Idiosyncratic risk matters! The Journal of Finance 58, 975-1008. and Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Ibid. 61, 259-299. suggest that an idiosyncratic risk may be a priced risk factor.

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 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, we attempt to examine whether the IVOL changes at the presence of the bailout events and what the determinants of IVOL are.

In this paper, we focus on publicly-listed banks that have received bailout funds through the CPP. We 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 (2013) that financial bailout does not deter the risk-taking behavior among banks to the fullest, especially for the banks with highest IVOL. Furthermore, we document the important role played by corporate governance and information asymmetry on banks' IVOL.

In this paper, we 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 II, we review the extant literature and develop testable hypotheses. Section III describes the data and methodology. Section IV presents the results, and Section V concludes the chapter.

II. Literature Review

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[4] 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[5] have been included in their portfolios. However, they 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[6]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

[4] They use the term 'average stock variance' in their paper.
[5] 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 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.
[6] Huang et al. (2010) use "winners minus losers" portfolio as a proxy for return reversals in Fama-French three- and four-factor models.

exponential GARCH 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. 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[7] 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[8]. In this paper, we 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.

2. *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, 2013).

2.1 Size

[7] 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.

[8] 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).

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 (2013). *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. We expect IVOL to be higher among small firms as suggested by Brown and Kapadia (2007) , Harvey and Siddique (2004) and Wang and Nguyen (2013). Size should be negatively related to IVOL (small firms are riskier).

2.2 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[9] and increases the level of deposit insurance protection[10]. 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

[9] 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.
[10] The 100 percent guarantee of non-interest-bearing accounts in FDIC insured banks increased from $ 100,000 to $ 250,000.

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 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.

2.3 Information Asymmetry Hypothesis

Malkiel and Fama (1970) propose the efficient market hypothesis (EMH)[11] 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, 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.

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[11] 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.

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 review literature, we 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.

III. Data and Methodology

1. Data Sources and Sample Selection

In this paper, we 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, we 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). We calculate a predicted value of *ROA* (i.e. a propensity score) with three industry median-adjusted regressors (i.e. *MKTCAP, DEBT RATIO and MARKET-TO-BOOK*[12]) for all sample banks and matching pool of non-CPP recipients,

[12] *MKTCAP* is the logarithm value of market capitalization. *DEBT RATIO* is the ratio of total liabilities to total assets. *MARKET-TO-BOOK* is the ratio of market price to book price.

which are drawn from Compustat dataset within the same banking sector (SIC codes from 6000-6399). We successfully find 227 matching banks for our sample of CPP banks.

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 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[13]. Using similar procedure and model specification in equation (1), we obtain monthly *IVOL3* for CPP banks and matching banks from the following procedures. First, we estimate equation (1) with daily returns from CRSP and obtain the residuals ε_{it} for each firm each period. Second, we estimate daily IVOL as standard deviation of the residuals based on a rolling 30-day window. Third, we calculate monthly *IVOL3* as the squared root of the product between the daily IVOL and the average number of trading days in a month.

$$R_{it} - R_{ft} = \alpha_i + \beta_{it}\left(R_{mt} - R_{ft}\right) + s_{it}\,(SMB_t) + h_{it}\,(HML_t) + \varepsilon_{it} \qquad (1)$$

Following Brown and Kapadia (2007), we obtain the second measurement IVOL4 from equation (2) by including Carhart (1997) momentum factor (UMD)[14]using the same estimation procedure as above.

$$R_{it} - R_{ft} = \alpha_i + \beta_{it}\left(R_{mt} - R_{ft}\right) + s_{it}\,(SMB_t) + h_{it}\,(HML_t) + u_{it}\,(UMD_t) + \varepsilon_{it} \qquad (2)$$

In the above models,

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

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

R_{it}	Stock daily returns for firm i at time t
R_{ft}	Risk –free rate is one-month U.S. Treasury bill return
$Rit - R_{ft}$	Excess returns or risk premium for firm *i* at time *t*
α_i	Intercept
ε_{it}	Regression residual
β_{it} , s_{it} , h_{it}	Risk factor sensitivities or loading for each risk factor
$(R_{mt} - R_{ft})$	Market risk premium at time *t*
(SMB_t)	The difference between the daily average return on a portfolio of small and large firms at time *t*
(HML_t)	The difference between the daily average return on a portfolio of high and low book-to-market stocks at time *t*
(UMD_t)	The difference between the daily average return on a portfolio of high and low momentum stocks at time *t*

2. *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. 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 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 an autoregressive conditional heteroskedastic (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 asymmetries in the effect of ε_{it}. EGARCH has the advantages of handling the asymmetries in the conditional variance, and capturing volatility persistence from residual variances and past squared innovations.

Following Fu (2009), we estimate the Fama-French 3-factor model as in equation (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), for each CPP bank and matching bank individually. We 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[15], EGARCH (3,q) model accounts for 66.67 percent and 71.3 percent of best fitting models for CPP banks and matching banks respectively[16].

$$R_{i,t} - R_{ft} = \mu_0 + \gamma_1 (R_{mt} - R_{ft}) + \gamma_2 (SMB_t) + \gamma_3 (HML_t) + \sum_{k=1}^{p} \delta_k (R_{i,t-k} - R_{ft-k}) + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_{i,t} \tag{3}$$

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

$$\log(h_t) = \alpha_0 + \alpha_1 (\varepsilon_{t-1}/\sqrt{h_{t-1}}) + \lambda_1 | \varepsilon_{t-1}/\sqrt{h_{t-1}} | + \beta_1 \log(h_{t-1}) + \vartheta_1 \varepsilon_{t-1}^2 \tag{4}$$

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

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

Table 1 reports the descriptive statistics of the IVOL measures over the eleven years (-5, +5) around the bailout year (e.g. 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 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. We 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 due to extreme values, we winsorize *IVOL3*, *IVOL4*, and *E (IVOL)* at top and bottom 5 percent. In Panel A of Table 1, the mean values of 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, we separate sample into two periods, pre- and post- bailout as shown in Panel B and Panel C. By comparing the mean values of three IVOL measures between pre- and post-bailout periods, we observe that *IVOL3* and *IVOL4* significantly increase in the post-bailout period.

[Insert Table 1 about here]

3. Stationarity Tests

To examine the stationarity of the return and IVOL series, we aggregate the monthly data into the context of time series and examine the series in line plots. Figure 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 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 1.2-1.3. After taking the first difference, the realized IVOL series become stationary. In Figure 1.4, the expected IVOL (*E (IVOL*)) exhibits stationarity at both the level and the first difference.

[Insert Figures 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. We use the augmented Dickey and Fuller (1979) test (ADF test) with a trend model as shown in equation (5) for time-series data. The null hypothesis for ADF test is that the series contains a unit root (α = 0), where u_t is an i.i.d. zero-mean error term. 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, we reject the null and conclude that the data series is stationary.

$$y_t = \propto + y_{t-1} + u_t \tag{5}$$

In order to test risk-return relation in the pooled cross-section data, we also examine the stationarity properties of returns and IVOL variables using ADF Fisher unit root tests for panel data (Choi, 2001). For ADF unit root tests on each panel, we 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 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 2 about here]

4. Risk-Return Relationship

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, we 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 2.1-2.2, but not clear when E (IVOL) is employed in Figure 2.3.

[Insert Figure 2 about here]

In addition to the plots, Table 3 provides the Pearson’s correlation coefficients which show the relationship between risk and return. Panel A of Table 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 correlation between *Ln (Ret)* and control variables are also consistent with intuition. In non-tabled results, we find the Ln (Ret)-IVOL relationship are robustness even in panel data, or in pre-bailout, or in post-bailout period.

[Insert Table 3 about here]

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, we estimate the parameters of interest through cross-sectional regression for each time period. Second, we 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), we examine risk-return relationship month-by-month using pooled cross-sectional Fama MacBeth (1973) regression model as shown in equation (6).

$$Ln\ (Ret)_{it} = \alpha_i + \beta_1 IVOL_{it} + \beta_2 Beta_{it} + \beta_3 Ln\ (ME)_{it} + \beta_4\ Ln\ (BKMK)_{it} + \beta_5\ Ln\ (Ret(-2,-7))_{it} + \beta_6 Ln\ (Bidaskspread)_{it} + \varepsilon_{it} \quad (6)$$

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*.

5. *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, we 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.

6.1 Multivariate Regression Model with Clustered Standard Errors

To explore the determinants of IVOL, we 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, we correct the standard errors for clustering effects in 2 dimensions (by time and by firm) following Petersen (2009) as shown in equation (8).

The specification of Pooled OLS regression models are:

$$IVOL_{it} = \alpha_i + \beta_1 CPP_i + \beta_2 PostBailout_t + \beta_3 CPP_i * PostBailout_t + \beta_4 X_{it} + u + \varepsilon_{it} \qquad (8)$$

Where, α_i is a constant, u is firm fixed effect and time-fixed (quarter) effect, and ε_{it} is an error term. We also construct a set of control variables (x_i) as follows.

Size is computed as the natural log of total assets[17], and is expected to have a negative impact on IVOL as discussed in the literature session. *Debt* is the ratio of total liability to total assets. Higher the debt indicates higher risk. Efficiency Ratio (*ER)*, the ratio of non-interest

[17] 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.

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.

6.2 Seemingly Unrelated Regression Model

To further investigate the corporate governance and information asymmetry effects on IVOL as stated in the hypotheses, we 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. We suspect that some coefficients in multivariate analysis might differ between two groups; therefore, we employ seemingly unrelated regressions (SUR) analysis based on Zellner (1962) in order to compare coefficients across regression models in equations (9). The specifications of the seemingly unrelated regression models are:

$$IVOL_{it} = \alpha_i + \beta_1 CPP_i + \beta_{2_3} CPP_i * PostBailout_t + \beta_3 X_{it} + u + \varepsilon_{it} \qquad (9)$$

Where, α_i is a constant, u 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. We 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)[18]. 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 relative 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 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.

[18] 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.

IV Results and Discussions

1. Risk-Return Puzzle

Table 4 reports the results of the Fama-MacBeth regression in the context of panel quarterly data[19]. 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, 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. We 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.

[Insert Table 4 about here]

2. Bailout Impact on Idiosyncratic Volatility (IVOL)

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

To examine whether financial bailout causes any significant impact on banking industry (in terms of idiosyncratic risk), we provide univariate analysis in this section. In Panel A of Table 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 their counterparts. To save space, the non-tabled results are quantitatively similar with *IVOL4* measure[20].

[Insert Table 5 about here]

Table 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. We 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 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 (2013) that financial bailout does not deter the risk-taking behavior among banks to fully extend, especially for the banks with highest IVOL. However, we 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

[20] 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.

the government under the conditions of bailout. It implies that financial bailout can mitigate the banks' risk-taking activities to certain extend.

[Insert Table 6 about here]

In this section, we 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 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 two IVOL measures significantly at least 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, we 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, we notice that there is huge jump in the level of IVOL for CPP banks and matching bank one year before bailout. Therefore we re-test the models in subsample (all, exclude year -1) and the findings are pronounced as shown in Panel B.

[Insert Table 7 about here]

3. Determinants of Idiosyncratic Volatility (IVOL)

To investigate whether corporate governance and information asymmetry play important role on IVOL, multivariate regression 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 8. We 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 at right direction significantly. The results suggest that the banks are small in size, high in liquidity and analysis forecast dispersion will have increase in IVOL. In summary, the findings from this table essentially support all the hypotheses.

[Insert Table 8 about here]

4. Corporate Governance on Idiosyncratic Volatility (IVOL)

To further investigate whether the differences between good and poor-corporate governance banks are statistically significant, SUR tests are employed in Table 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 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 9 about here]

5. Information Asymmetry on Idiosyncratic Volatility (IVOL)

Similarly, to test whether the differences between high and low information asymmetry banks are statistically significant, we 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 10. Unsurprisingly, the information asymmetry on IVOL is significantly different across two information asymmetry groups in both Panel A and Panel B.

[Insert Table 10 about here]

V. Conclusions

In this paper, we 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. We 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). We 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, our 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 (2013) that financial bailout does not deter the risk-taking behavior among banks to the full extent, especially for the banks with highest IVOL. Furthermore, we 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.

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Table 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. We 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). We use the propensity score matching technique to identify non-CPP matching banks (matching banks) as control group. We successfully find 227 matching banks for my sample of CPP banks; 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 (BKM K) 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.

Figure 1–Time Series Line Plots for Return and Idiosyncratic Volatility

Figure 1.1- In (Ret) vs. D. In (Ret)

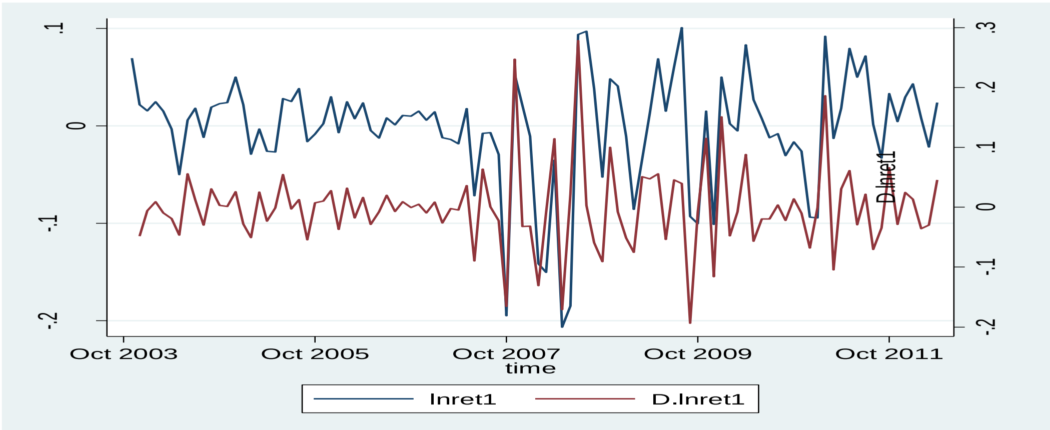


Figure 1.2- IVOL3 vs. D. IVOL3

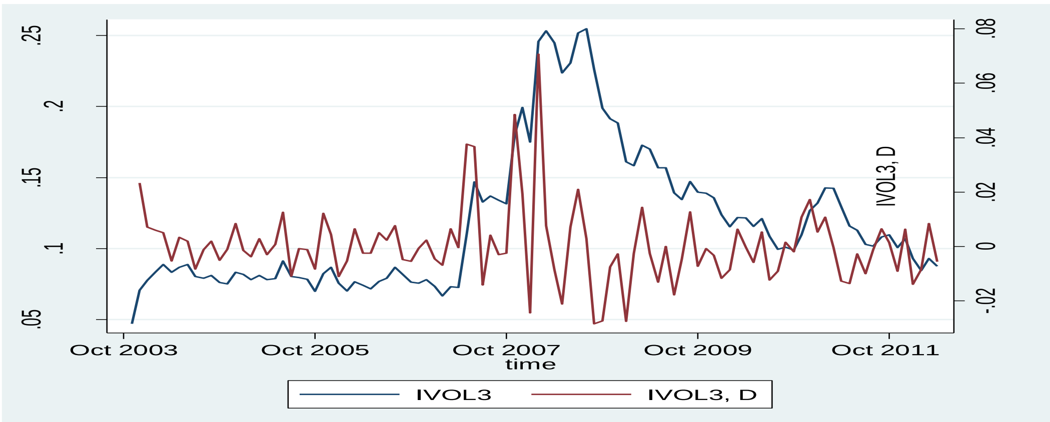


Figure 1.3- IVOL4 vs. D. IVOL4

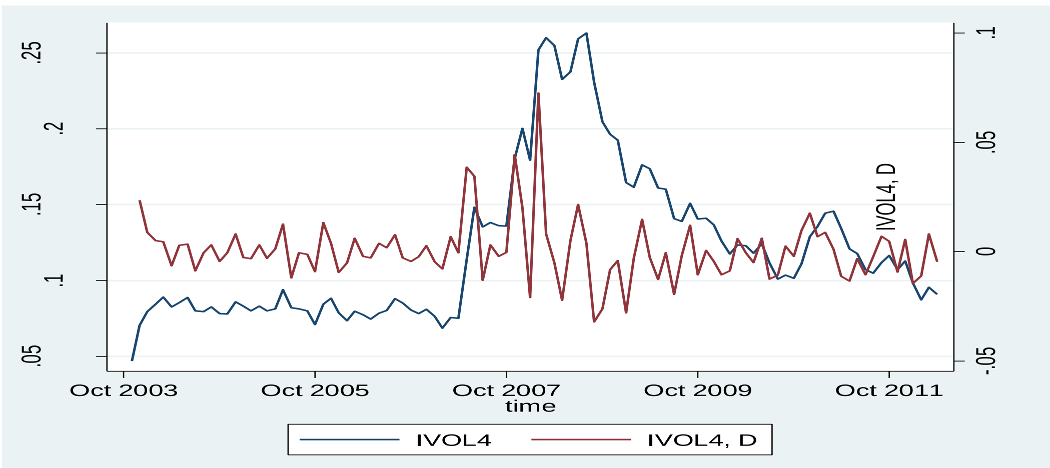
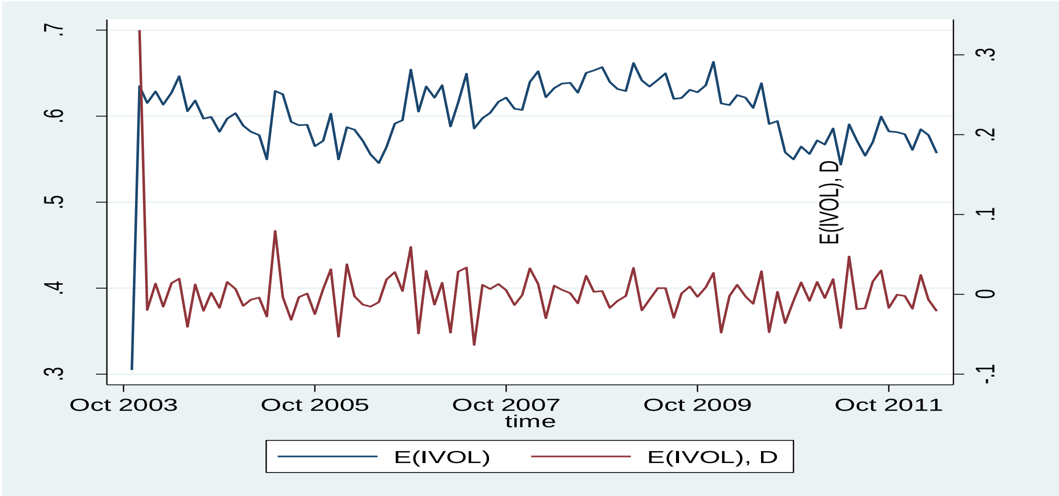


Figure 1.4- E (IVOL) vs. D. E(IVOL)



This Figure reports 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.

Table 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, we report the results from unit root tests in the context of timer-series and panel data. In time series, we report ADF-Z statistics; and in panel, we use ADR-Fisher Chi-square statistics. The null hypothesis for unit root test is Ho: There is unit root in the series. 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.

Figure 2- Time Series Return and Idiosyncratic Volatility Relation

Figure 2.1- D. ln (Ret) and D. IVOL3

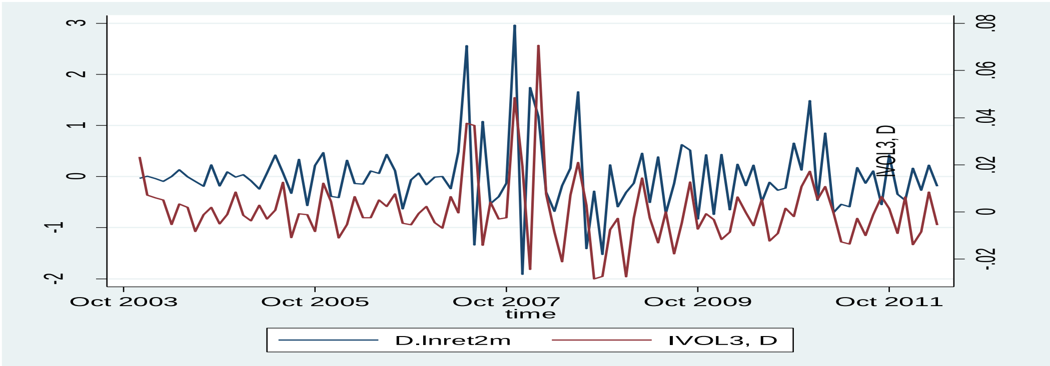


Figure 2.2- D. In (Ret) and IVOL4

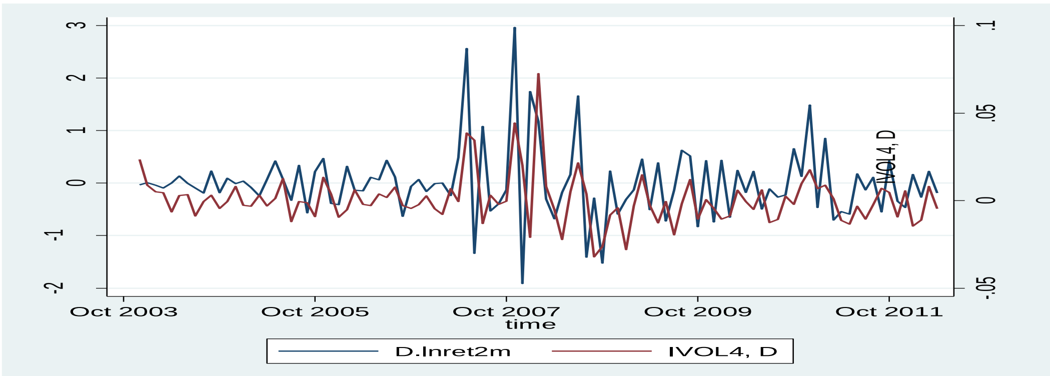
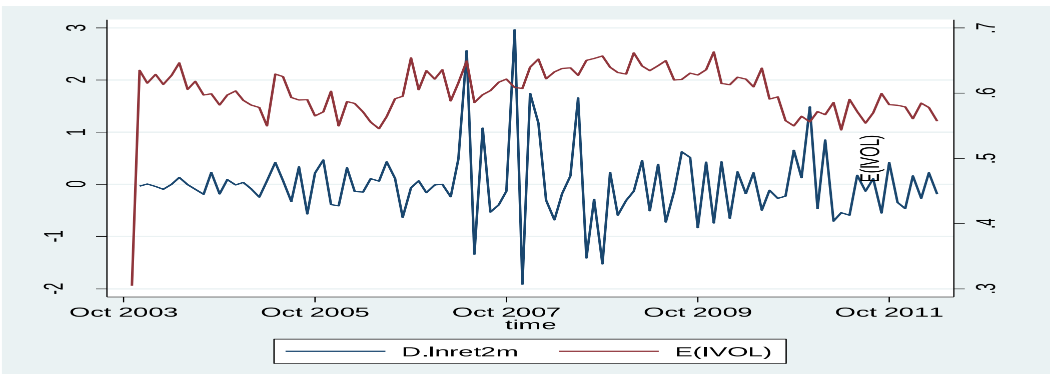


Figure 2.3- D. In (Ret) and E (IVOL)



This Figure reports 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; *E (IVOL)* is expected Idiosyncratic Volatility and derived from conditional variance predicted from E-GARCH models for each firm.

Table 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 we report simple correlation (Pearson's correlation coefficient *r*) for indicating the 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- 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 groups	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, we 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 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)	19,263	11.64%	8.30%	7,208	13.31%	9.16%	-1.66%	-12.36***	-0.86%	-11.65***
By Bailout										
Pre-Bailout (-5yr, 0)	6,388	8.55%	6.40%	2,738	9.88%	7.46%	-1.33%	-8.21***	-1.05%	-11.27***
Post-Bailout (0, +5 yr)	12,875	13.18%	9.59%	4,470	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)	19,263	11.81%	8.18%	7,208	13.95%	9.22%	-2.14%	-14.40***	-1.04%	-13.06***
By Bailout										
Pre-Bailout (-5yr, 0)	6,388	8.51%	6.26%	2,738	10.11%	7.34%	-1.60%	-9.10***	-1.08%	-12.29***
Post-Bailout (0, +5 yr)	12,875	13.45%	9.52%	4,470	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, we 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 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 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 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 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, we 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, we use whole sample, which is eleven years around the year of bailout (Year 0); In Panel B, we 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 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; We 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 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 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; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 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 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; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix 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