TWO ESSAYS IN BANKS' RISK-TAKING BEHAVIOR

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Two Essays in Banks' Risk-taking Behavior

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

This thesis consists of two essays. The commonality of the essays is that I study the banks' earnings volatility in terms assessing bank' risk-taking behaviour. In first essay, "Banks' Earnings Volatility and Earnings Predictability," uses the setting of banks to investigate Dichev and Tang's (2009) hypothesis that volatility of earnings has a negative effect on the predictability of earnings. Consistent with their hypothesis, I find that banks' earnings predictability is lower when they have higher earnings volatility.

The findings suggest that there is a trade-off between banks' earnings stability and their risk-taking, and provide important implications for banks' risk-taking behavior. First, assuming that the purpose of corporate risk-taking is to assure a high level of future earnings, then the worst position for a bank is to have low earnings and high earnings volatility, which indicate that the bank took too much risk with a poor result. To improve its position and to avoid insolvency, the bank should reduce risk-taking. While the literature on corporate risk-taking suggests that firms with low earnings have higher incentives to take more risk, the first implication notes that banks with low earnings should decrease their risk-taking if they face high earnings volatility. Second, for banks with high earnings and high earnings volatility, their earnings are likely not persistent. To assure a high level of future earnings, they should also reduce risk-taking to lower their earnings volatility. Third, for banks with low earnings and low volatility, their future earnings are likely to be low. They should increase risk-taking to improve their future earnings. Fourth, the best position for banks is to have high earnings and low earnings volatility because they can assure a high level of future earnings. Since all banks would try to maintain or get into this best position, competition is likely to increase. How to protect their position becomes the top priority.

The second essay of my thesis, "Is there an Optimal Risk-Taking in Banks?," examines how banks manage their risk-taking, in terms of high earnings volatility. Specifically, I address the following questions: First, is there an optimal risk in banks? Second, if there is an optimal risk then how quickly bank adjust towards the optimal? How the risk adjustment mechanism differs in short term and long term? Finally, I test the asymmetric effects in the risk adjustment mechanism, which one is costly for banks: over risk-taking or under risk-taking, and how banks manage their risk-taking during high earnings volatility.

To address these questions, I propose an empirical model with two partial-adjustment mechanisms for bank risk-taking behavior, where the risk-adjustment occurs in the cross-section and the time-series variations of bank setting. The model is sufficiently rich for examining whether there is an optimal risk in banks and if so, what is the speed of adjustment with which banks move toward the optimum level of risk. Using the US banks data, I find that banks tend to follow an optimal risk target, and typical banks converge toward their target level at a rate of 23.78% per year. Furthermore, due to banking stability and regulatory concerns, there is an asymmetry effect in the speed of risk adjustment. That is, when there is excess volatility (risk), banks adjust back to the optimum level much faster. In sum, my second essay provides new evidence in the literature of bank risk-taking and contributes to the literature by developing a partial risk adjustment model to estimate banks' optimal risk-taking.

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Chapter 1

Banks' Earnings Volatility and Earnings Predictability

Abstract

This study uses the setting of banks to investigate Dichev and Tang's (2009) hypothesis that volatility of earnings has a negative effect on the predictability of earnings. Consistent with their hypothesis, I find that banks' earnings predictability is lower when they have higher earnings volatility. The findings suggest that there is a trade-off between banks' earnings stability and their risk-taking, and provide important implications for banks' risk-taking behavior. First, assuming that the purpose of corporate risk-taking is to assure a high level of future earnings, then the worst position for a bank is to have low earnings and high earnings volatility, which indicate that the bank took too much risk with a poor result. To improve its position and to avoid insolvency, the bank should reduce risk-taking. While the literature on corporate risk-taking suggests that firms with low earnings have higher incentives to take more risk, the first implication notes that banks with low earnings should decrease their risk-taking if they face high earnings volatility. Second, for banks with high earnings and high earnings volatility, their earnings are likely not persistent. To assure a high level of future earnings, they should also reduce risk-taking to lower their earnings volatility. Third, for banks with low earnings and low volatility, their future earnings are likely to be low. They should increase risk-taking to improve their future earnings. Fourth, the best position for banks is to have high earnings and low earnings volatility because they can assure a high level of future earnings. Since all banks would try to maintain or get into this best position, competition is likely to increase and how to protect their position becomes the top priority for banks.

Keywords: Bank earnings persistence, earnings volatility, earnings predictability.

1.1 Introduction

The accounting and corporate finance literature document the importance of earnings volatility in earnings forecasting. Graham et al. (2005) provide survey evidence on executives' beliefs that earnings volatility is negatively related to earnings predictability. Following this survey and U.S. industry data, Dichev and Tang (2009) provide strong empirical evidence for the negative relationship between earnings volatility and earnings predictability. They argue that their empirical evidence is consistent with survey evidence provided by Graham et al. (2005) and propose that future research could consolidate and extend their study using different samples and variable descriptions. In response to Dichev and Tang (2009), Frankel and Litov (2009) use ex-ante annual earnings volatility to conduct stock market tests and argue that investors often contemplate the effects of earnings volatility to predict earnings. However, most of the literature focuses only on the industrial sector.

Given the findings of Dichev and Tang (2009), this study contributes to two main aspects of the literature. First, I investigate the effect of banks' earnings volatility on their earnings predictability and highlight the negative relationship between earnings volatility and predictability also holds for banking institutions. I examine whether banks' past earnings can predict their future earnings and whether this predictability depends on earnings volatility. Second, I explore the implications of Dichev and Tang's (2009) study for banks' risk-taking strategies. I use their analytical framework to analyze the impact of earnings volatility on the estimation of prediction models and forecasted earnings.

It is important to identify why banks are a well-suited setting to test the Dichev and Tang's (2009) hypothesis on the relationship between earnings volatility and predictability relative to industry firms. The key difference between banks and industry firm is that banks' investments are related to financial assets (easier to dispose of risk) and industry investments are related to real assets (difficult to dispose of risk from plant and production). In addition to that banks are subject to stringent capital regulations (risk-adjusted capital ratio) and have high leverage which affect bank risk-taking (Gonzalez; 2005). Extant risk-based capital regulation focuses on risk in lending and investment that banks are exposed to in determining capital adequacy and capital adequacy then affect risk-taking. Though earnings volatility may be related to lending and investment, they are not completely the same as economic risk-taking. Moreover, it is interesting to see whether banks' assets risk (EV) plays a role in determining capital regulation and the regulators should also factor banks' earnings volatility in capital adequacy regulation.

As financial intermediaries, banks play a key role in the economic development of a country, and economic soundness depends on banking stability. To measure a bank's financial health, I use earnings as a primary indicator, which in several cases functions as an initial indicator of weakness. Bank regulators are usually concerned about operating performance (Cohen et al., 2012). Negative or declining earnings for banks can often be the result of improvident risks taken to increase earnings, which may further facilitate the decline in their financial position. Therefore, it is important to detect volatile earnings (weaknesses) in time, to allow bank managers and regulators to take adequate measures before the financial health of the bank is threatened (Couto, 2002). However, there is no empirical study on the association between banks' present earnings volatility to measure their future performance and the theory of accounting and corporate finance come up with this motivation as to know why does earnings volatility matter for banks.

Following Dichev and Tang (2009), I predict that in the banking industry, the association between earnings volatility and predictability is negative; such negative relationship arises for two reasons: the volatility of economic shocks and the expected volatility of the error in determining accounting income, both of which reduce the predictability of earnings. On the one hand, due to economic shocks, firms face a scarcity of internal funds and relinquish new investment opportunities, as external financing is costly (Stiglitz & Weiss, 1981; Myers & Majluf, 1984). On the other hand, excess funds motivate managers to finance beyond the optimal level. Managers are either overenthusiastic about returns from new profitable opportunities (Malmendier & Tate, 2005a and 2005b; Heaton, 2002; and Roll, 1986), capitalize on favorable market sentiment (Polk & Sapienza, 2009; Dong, Hirshleifer & Teoh, 2007; Gilchrist, Himmelberg & Huberman, 2005; Jensen, 2005; Stein, 1996;), or prioritize their own interests over shareholder interests (Morellec, 2004; Stulz, 1990; Jensen, 1986). Moreover, earnings volatility expands the probability of excess or lack of internal funds and accordingly increases the probability of overinvestment and underinvestment (Morellec & Smith, 2002; and Froot, Scharfstein & Stein, 1993). Such investments distortions lower profitability, indicating that volatility of earnings can be negatively associated to predictability of future earnings.

The accounting literature demonstrates that persistence of earnings is less if the volatility of earnings is high (Dichev & Tang, 2009; Dechow & Dichev, 2002). This indicates that firms' mean-reverting process is faster as their earnings are either far above or below their target earnings, which is a result of the noise factor of volatility (Petrovic et al., 2009). The noise factor of volatility arises from uncertainty in firm performance, complications in accounting estimation of accruals, and inconsistency between income and expenses. Due to the highly volatile and less persistent association, the negative relationship between earnings volatility and predicted earnings is more pronounced for organizations with high returns than for those with low returns. The study conducted by Milton, Schrand, and Walther (2002) was the first to provide evidence for the role of volatility in predicting future cash flows. Using a U.S. non-financial sample, they show a statistically and economically significant negative association between volatility and forecasted operating income and cash flows. Similarly, Dichev and Tang (2009) show that in the five-year predictive horizon, firms with the lowest earnings volatility quintile have higher persistence from t+1 to t+5 (around 0.934 to 0.805) compare to the firm's persistence with the highest volatility of earnings quintile (0.507 to 0.177). Banking studies also show that managers smooth income to increase the differential predictive informativeness of future earnings. For example, Beatty and Harris (1998) document that public banks are more engaged in smoothing earnings than private banks to reduce agency problems and information asymmetry. They re-examine this issue following Warfield, Wild, and Wild (1995). Moreover, it is well documented that past performance is a crucial indicator of future performance (Couto, 2002; Bromiley 1998).

Following this, I investigate the negative association between earnings volatility and earnings predictability, as predicted by the accounting and corporate finance literature. I follow empirical specifications of Dichev and Tang (2009) to evaluate the association among earnings volatility and predictability for the period of short and long run. To categorize the data into portfolio quintiles of volatility I use historical estimates of earnings volatility. Then I use historical earnings to predict future earnings for each earnings volatility quintile. Using U.S. Compustat bank fundamental annual data over the 1983–2020 period, I find that in short-term predictability over one-year period across the quintiles, the persistence of low volatility earnings is much higher (0.94) than that of high volatility earnings (0.45). In the long term, the evidence shows that in the future up to 5 years the earnings volatility has considerable predictive power. During the whole predictive horizon, the R^2 value and the persistence are notably higher for low volatile earnings. However, high volatile earnings demonstrate little reliable predictability and revert to the mean faster, which is consistent with the findings of Freeman et al. (1982). They hypothesize that due to the extreme attributes of volatile earnings, it tends to revert to the mean faster. Moreover, my findings are robust to alternative measures of volatility and earnings.

I conduct a series of additional sub-sample analyses to provide further corroborating evidence to evaluate the relationship between banks' earnings volatility and earnings predictability. I try to observe whether the relation between earnings volatility and predictability does vary based on after the SOX enactment in the aftermath of the 2008 financial crisis and the capital adequacy ratio. I find that the results still hold in sub-sample analysis. The implications of the results remain same; however, the coefficients are less predictable in the sub-sample analysis.

For robustness check, I test the impact of past earnings persistence on recognized earnings for example earnings persistence based on quintiles of residual volatility. Results indicate the sizeable impact of historical persistence on the documented results. To validate the incremental explanatory power of earnings volatility of banks, I further test the earnings persistence regression based on the other risk-taking measures of banks', for instance, quintiles of equity to assets ratio (EAR), quintiles of z-score, and quintiles of return on equity (ROE) volatility. I find that in comparison to the earnings persistence coefficients based on the quintiles of earnings volatility, the coefficients of other measures are lower. Hence, it provides evidence of the incremental explanatory power of earnings volatility as a measure of banks' risk-taking.

The findings of this study suggest that there is a trade-off between banks' earnings stability and their risk-taking, and provide important implications for banks' risk-taking behavior. First, assuming that the purpose of corporate risk-taking is to assure a high level of future earnings, then the worst position for a bank is to have low earnings and high earnings volatility, which indicate that the bank took too much risk with a poor result. To improve its position and to avoid insolvency, the bank should reduce risk-taking. While the literature on corporate risk-taking suggests that firms with low earnings have higher incentives to take more risk, the first implication notes that banks with low earnings should decrease their risk-taking if they face high earnings volatility. Second, for banks with high earnings and high earnings volatility, their earnings are likely not persistent. To assure a high level of future earnings, they should also reduce risk-taking to lower their earnings volatility. Third, for banks with low earnings and low volatility, their future earnings are likely to be low. They should increase risk-taking to improve their future earnings. Fourth, the best position for banks is to have high earnings and low earnings volatility because they can assure a high level of future earnings. Since all banks would try to maintain or get into this best position, competition is likely to increase and how to protect their position becomes the top priority for banks.

The contributions of this study are as follows. First, I fill the gap in the banking literature and provide important implications for banks' risk-taking behavior. Given the lack of studies on banks, this paper is the first to explore the importance of earnings volatility in estimating future earnings in the banking context. The intuition for this research is based on two aspects of the literature: accounting and corporate finance. I demonstrate that the findings of a negative relationship between earnings volatility and predictability hinge on previous earnings research conducted in non-banking settings. My findings are also statistically and economically significant and are consistent with the findings of Dichev and Tang (2009), who show that earnings with low volatility are highly persistent compare to high volatile earnings which are less persistent. Second, by showing that earnings volatility affects earnings forecasting, this study contributes to the immense literature on fundamental analysis research that identifies a set of variables to improve valuation[1]. Valuation research uses earnings predictability and practice to evaluate firm value.

The remainder of the paper is organized as follows. First, I review the relevant literature on earnings volatility and persistence, in particular the studies of Dichev and Tang (2009) and Frankel and Litov (2009), to introduce the background for my research. Next, I present the research design, data, and sample. Following this, I discuss the main empirical results, other specifications, and robustness checks. Finally, I conclude the study in the last section.

1.2 Background and Literature Review

The theories of corporate finance that are based on the agency cost of equity, information asymmetry, and behavioral explanations such as overvalued equity and managerial overconfidence all propose that volatility of earnings may result in investment distortions. However, the accounting literature evident that the relation between volatility of earnings and persistence of earnings is inverse. Giving due consideration to these two aspects of the literature, I assume that in the banking industry, earnings volatility is negatively associated to earnings predictability, especially with high levels of current earnings (Petrovic et al., 2009). Several accounting studies, such as Ball and Shivakumar (2006), Dechow et al. (1998), and Dechow (1994) show that for evaluating firm performance, earnings are a better proxy than the cash flow from operations (CFO). However, a few studies for example Lev et al. (2005) disagree with this notion. Moreover, the starting point for any valuation analysis is forecasting the

[1] Stock prices (Collins et al., 1987; Shroff, 1999), disaggregated earnings (Fairfield et al., 1996), and accruals (Sloan, 1996).

earnings, irrespective of the model used. Demirakos et al. (2004) reveal that financial analysts would rather choose to predict earnings than cash flows. However, they also propose that for valuation models, financial analysts depend more on cash flow-based analysis than on earnings-based analysis.

Variations in documented earnings are an outcome of uncertainty in operations and accounting choices. For example, large, stable firms with predictable and steady demand may have less volatile earnings than small, growing firms with recurring changes in demand; the latter may be less predictable but may still have high volatility earnings. From an accounting perspective, Dechow and Dichev (2002) find a strong correlation between earnings volatility and accrual quality. They measure accrual quality as the level of precision when historical, current, and future earnings are recorded for current accruals. Moreover, Dichev and Tang (2009) propose that expenses that correspond poorly to sales intensify volatility. They show that earnings volatility is negatively associated with earnings persistence (see also Nissim, 2002), with earnings predictability measured by R^2. Earnings persistence estimates how rapidly earnings revert towards the mean or, instead, how much of the available cash flow surprises can be converted into series of permanent earnings (Schipper & Vincent, 2003). Moreover, they also incorporate a noise element into earnings volatility. These findings are consistent with those of Dechow and Dichev (2002), who also show a negative association between accrual quality and earnings persistence.

Petrovic et al. (2009) argue that, when earnings levels are low, it (earnings) reverts towards the mean faster and the rise in the magnitude of earnings is higher as volatility rises. Conversely, at high levels of earnings more volatile earnings become less persistent and eventually decline more rapidly over the next period (Petrovic et al., 2009). This indicate that the relationship between earnings volatility and future earnings is negative when the levels of earnings are high and more volatile.

The empirical study conducted by Dichev and Tang (2009) is more relevant to my study. They argue that our knowledge of predictability, particularly long-term earnings forecasts, is limited and that there is little evidence of how earnings volatility affects earnings predictability. The authors were motivated by a survey conducted by Graham et al. (2005) to test the rationality of these theories. This survey of 401 managers shows that 97% of the respondents prefer smooth earnings and have a pronounced aversion to earnings volatility; 80% of these responses arise because managers dislike volatility, as it is thought to decrease earnings projections. To increase knowledge of the subject, Dichev and Tang test whether volatility is negatively associated to predictability and provide empirical evidence for widely held managerial beliefs.

Given the above evidence, Frankel and Litov (2009) believe that the study of Dichev and Tang (2009) address a stimulating question for which that has hitherto been little evidence. Therefore, they re-examine the results to provide evidence in support of the existence of a negative association between earnings volatility and earnings persistence. Moreover, Frankel and Litov (2009) examine whether investors completely understand the effects of earnings volatility. They conclude that with additional controls, empirical tests remain robust and that investors do not undervalue the effects of earnings volatility.

The long-term viability of banks depends on their ability to generate sufficient earnings to increase and protect their capital and reward their shareholders (Cohen et al., 2012). Past performance is an important indicator of future performance. High earnings volatility and losses may reduce the capital and liquidity of banks and corrode stakeholders’ confidence in these institutions. The accumulation of volatility may hinder the ability of banks to continue operations, thus increasing the probability of the devastating consequences of bank failure. The present study focuses on the earnings volatility of U.S. banks. I focus on banks' earnings volatility because more volatile earnings may result in capital ambiguity and can deteriorate the soundness of banks (Couto, 2002). For example, Abbertazzi and Gamacorta (2009) suggest that high volatility in bank earnings can lead to unstable capital structures. Motivated by the above discussion, I examine how banks' current earnings can predict their future earnings. Following the literature, I expect the relationship between banks' earnings volatility and predictability to be negative.

1.3 Research Design

1.3.1 Sample Selection and Variable Description

The sample comprises U.S. banks. The data are obtained from Compustat's annual bank fundamentals for the 1984–2020 period. Following Dichev and Tang (2009), I begin my sample in 1984 and use the 1984–1988 period to estimate earnings volatility. Moreover, I use statements of cash flow data, which are available on a broad scale from 1988 onward, to accurately estimate accruals and cash flows (Collins & Hribar, 2002). The following variables are scaled by average total assets and used for my empirical analysis: earnings, CFO, and accruals. Earnings are income before extraordinary items, CFO is cash flow from operating activities, and accruals represent the deviation between earnings and CFO. Earnings volatility and CFO volatility are estimated using the standard deviation of deflated earnings and cash flow in the past 5 years. I truncate the bottom and top 1% of cash flow, accruals and earnings, to circumvent the effects of extreme observations. I impose two more sample selection criteria. First, I restrict my sample to economic and substantially large firms with assets ≥ US$100 million. Due to this criterion, small firms are likely to be economically nonsignificant but statistically influential. Second, to simplify the empirical analysis and interpretation of the results, I restrict the data to the 12/31 fiscal year-end observations. After applying all of the sample selection criteria, my final sample consists of 4,153 bank years over the 1988–2020 period. Details of the sample selection criteria are provided in Table 1, Panel A.

1.3.2 Model and Framework

Following the simple framework described by Dichev and Tang (2009), I use an autoregressive regression model of future earnings on current earnings and assess the relationship among earnings volatility and earnings predictability.

$$\text{ROA}_{t+1} = \alpha + \beta\ \text{ROA}_{t} + \varepsilon \quad (1)$$

Take the variance on both sides,

$$\text{Variance}\ (\text{ROA}_{t+1}) = \beta^2\ \text{Variance}\ (\text{ROA}_{t}) + \text{Variance}\ (\varepsilon) \quad (2)$$

Assume that over time the earnings dispersion is static, by rearranging, I obtain

$$\text{Variance}\ (\varepsilon) = \text{Variance}\ (\text{ROA})\ (1- \beta^2) \quad (3)$$

The above equation (3) provides an important framework of my study explaining the relationships and main variables. Earnings volatility is proxied by *Var(ROA)*. Earnings predictability is proxied by $Var(\varepsilon)$ as an inverse proxy, because after incorporating the autoregressive effect of the beta coefficient (β), the error term variance $Var(\varepsilon)$ denotes the discrepancy in remaining earnings. Equation (3) indicates that when earnings persistence is held constant, earnings volatility is inversely associated to earnings predictability. Therefore, the inverse relationship is more robust due to the impact of persistence coefficients because β is inversely related to earnings volatility. For instance, noise in earnings increases earnings volatility and decreases earnings persistence.

To thoroughly investigate this relationship, Dichev and Tang (2009) take the total derivative of the deviation in disturbance with reference to earnings volatility

$$d[Var(\varepsilon)]/ d[Var(ROA)] =(1- \beta^2)-2Var(ROA)(\delta\beta/\delta Var(ROA)) \qquad (4)$$

Equation (4) provides the propositions made in my study on the basis of two terms. The first term in Equation (4) proposes that the association among volatility and predictability of earnings is determined by the persistence of earnings because higher persistence level indicates the higher predictability of earnings. The second term (Equation 4) denotes the hypothesized inverse effect on earnings persistence due to earnings volatility.

It is important to note that the predictability concept captured by the error term variance (*Var(ε))* is ‘absolute’ predictability and is not adjusted for earnings volatility environments. By taking the natural scalar of *Var(ROA)* for *Var(ε)*, one can determine relative predictability. Dividing Equation (3) by *Var(ROA)* and rearranging the terms, I obtain

$$\beta^2 = 1- Var(\varepsilon)]/ Var(ROA) \qquad (5)$$

From Equation (5), I can see that R^2 is relative predictability, which is equivalent to the coefficient of the squared value of persistence. Therefore, examining the association between volatility and persistence of earnings is crucial to the determination of both relative and absolute predictability of earnings.

From the above framework I use the intuitions in two aspects for the empirical test. First, I formulate the significance of the projected negative association among volatility of earnings and long- and short-term persistence of earnings. Second, I examine in what way the volatility of earnings evidence results in substantial improvements in predictability of future earnings.

1.3.3 Descriptive Statistics

The descriptive statistics for the full sample used in my study are provided in Table 1, Panel B. The mean and median of deflated earnings and CFO are positive. The mean and median of accruals are negative, which is consistent with previous study (Dichev and Tang, 2009) because, on average, accruals reflect bad news. The mean of the bank-specific volatility of deflated earnings is 0.48% and the standard deviation is 0.57%. The variable volatility of earnings is nonlinear; for more robust estimation, I use portfolio quintiles derived from conditioning variables. Most of the analysis is based on portfolio quintiles, which offer a strong interpretation of the economic significance of the results.

[Insert Table 1]

Table 1, Panel C shows the Pearson correlation matrix of the variables. The contemporaneous correlation matrix shows that earnings are positively and significantly related to accruals and CFO.

1.4 Empirical Results

1.4.1 Short-Term Predictive Horizon Results

Table 2 presents the regression results of short-term future earnings (t+1 year) on current earnings (t), with R^2 values and the coefficients of persistence. The results provide proof of the statistical and economic implication of the conjectured negative link between volatility and persistence of earnings. Although the R^2 values and coefficients of persistence are evidently associated, they vary due to the methodical discrepancy between the variability of future and current earnings. Panel A provides the baseline results for the full sample, with an R^2 of 0.38 and a persistence coefficient of 0.58, which are in line with extant results for this identification.

[Insert Table 2]

Panel B shows the results of the quintiles derived from the conditioning variable, earnings volatility. Panel B reveals that the association among volatility and persistence of earnings is strong and monotonic. The coefficients of persistence consistently decrease from quintile 1 (0.94) to quintile 5 (0.45). The values of adjusted R^2 also decrease from quintile 1 (0.55) to quintile 5 (0.29). My results are consistent with the findings of Dichev and Tang (2009). These monotonically declining results are large on an absolute scale and indicate that my conditioning on volatility of earnings is economically significant. Table 2, Panel B also presents an analysis of the statistical significance of these changes across quintiles 1 to 5, more precisely the variances of R^2 and the persistence coefficients. Using a simple t-test, which associates the observations in quintiles 1 and 5, I evaluate changes in persistence such as slope variables and dummy intercepts for the observations in quintile 5.

The analysis for the variation in R^2 is more difficult because it requires contrasting R^2 values between two different regressions. Therefore, I use a bootstrap test instead of traditional Vuong test. Moreover, the dependent variable appears similar (future earnings) and in such cases, the Vuong test is not suitable. The reason is the modification of the dependent variable differs significantly over the earnings volatility quintiles. In the bootstrap test constructed by replicating the observed distributions of the test measures, I assume that the null hypothesis is true (Noreen, 1989). As a result, I present the null hypothesis as, there is no relation among the volatility and predictability of earnings; the measure used in the test is the variation in adjusted R^2 across quintiles 1 and 5 of earnings volatility. Under the null hypothesis, I simulate the observed distributions into pseudo-quintiles of earnings volatility from full sample. Following this, I run the regression for earnings persistence and obtain the variation in R^2 between quintiles 1 and 5. The formal statistical analysis is performed by comparing the variation between actual and simulated R^2 values. Overall, the statistical analysis of Panel B shows that the variation in R^2 and persistence between the highest (quintile 1) and lowest (quintile 5) quintiles of earnings volatility are extremely significant, with p-values < 0.001 (both).

Panels C and D provide evidence of earnings persistence conditional on accruals and earnings levels. This result satisfies two aims. First, the results of earnings volatility offer a standard of economic magnitude. Second, these results are proof of the projecting effect of volatility of earnings being incremental to the prevailing effects, as earnings volatility is expected to be correlated with the levels of earnings and accruals. The variable absolute accruals level is derived from Sloan (1996), who confirms that this variable is an important determinant of the persistence of future performance (earnings). The earnings level is also an important element of earnings persistence, as established by Freeman et al. (1982). They show that extreme earnings incline to mean-revert faster. I designate the variables in quintile 1 as having the highest earnings persistence and quintile 5 as having the lowest earnings persistence. The results are thus comparable over panels.

Following Sloan (1996), extreme accruals are less persistent. Therefore, I expect in quintile 1 the persistence of earnings to be high and in quintile 5 to be low. Indeed, Panel C shows that earnings persistence in quintile 5 is 0.48, which is much lower than that of the remaining accrual quintiles (0.91–0.62). The R^2 of the lowest quintile is also lower than that of the highest quintile, with both R^2 and earnings persistence in the lowest quintile being statistically significant. Comparing the quintile results across panels, I find that in Panel B, the persistence drops across earnings volatility quintiles is 0.49, which is moderately higher compare to the persistence drop across accruals level quintiles (0.14) in Panel C. I observe the same pattern of results in the differences in R^2 across Panel B (0.26) and C (0.04). Overall, the findings of this study show that the differences in persistence and R^2 across quintiles of earnings volatility are much larger than the deterioration in the level of accruals. To verify the statistical significance of the results over quintiles and the variation over panels, I conduct a bootstrap test. Specifically, following Dichev and Tang (2009), I construct pseudo-earnings volatility quintiles, to run the regression among quintiles, and find the differences in the values of R^2 and persistence over quintiles. Overall, the results show that in Panels B and C the variation in persistence is 0.49 and 0.14, respectively, and the variation in R^2 is 0.26 and 0.04 in Panels B and C, respectively, both with p-values < 0.001. Summarizing the results of Panels B and C propose that the predictive power of earnings volatility is very strong and supersedes the predictive power of the level of accruals. Results are consistent with the findings of Dichev and Tang (2009).

Panel D shows the conditioning test on quintiles constructed based on the level (decile) of earnings. I first sort earnings based on deciles 1–10, after which I convert the deciles to quintiles. For instance, I form quintile 5 by combining decile 1 and decile10, quintile 4 by combining decile 2 and decile 9, quintile 1 by combining deciles 5 and 6, and so on. I expect quintile 1 to have the highest earnings persistence and quintile 5 to have the lowest earnings persistence, as quintile 5 represents the most extreme level of earnings. Consistent with my expectations, Panel D shows that earnings persistence declines across quintiles, except in quintile 1 having a persistence of 0.34. However, from quintile 2 (1.27) to quintile 5 (0.37) earnings persistence declines simultaneously. The differences are statistically significant, as shown by the bootstrap analysis, with a p-value < 0.001. Therefore, the results in Panels B and D suggest that when predicting future earnings, the effect of earnings volatility cannot be subsumed by the effect of the level of earnings. In the following section of long-term earnings predictability specification, I show further explicit evidence of the incremental effects of these variables (earnings volatility and earnings level). Similar to Panels B and C, R^2 decreases from 0.11 in quintile 1 to 0.048 in quintile 5.

Panel E presents the results of last conditioning variable, cash flow volatility as an indicator for economic volatility. Considering the outcomes in Panel B, which suggest that the benefits of using earnings volatility lies in predicting future earnings, earnings volatility consolidates the explanatory power of both accounting-problems based and economic volatility. If this is true, I assume that in predicting future earnings, the explanatory power of earnings volatility is much higher than that of cash flow volatility. The analysis in Panel E shows that cash flow volatility provides a virtuous estimate for forecasting earnings, through an R^2 of 0.03 and a persistence coefficient of 0.18. Nevertheless, the R^2 values and persistence coefficients for earnings volatility shown in Panel B are much higher compare to the estimates in Panel E and the differences across panels are significant. Therefore, the estimates in Panel E indicate that when predicting future earnings, volatility of earnings (Panel B) supersedes cash flow volatility (Panel E), even though the magnitude of cash flow volatility is similar to that of earnings volatility. The results of this test imply that because of the accounting process, earnings volatility is crucial when determining the future earnings.

1.4.2 Long-Term Predictive Horizon Results

Table 3 presents the long-term (t+5 year) predictive horizon of earnings, conditional on volatility of earnings. The full sample baseline results are shown in Panel A, which presents the result of the unconditional regression of future earnings data over 5 years on current earnings. This result suggests that the analytical power of earnings rapidly declines over time, as do earnings persistence coefficients and R^2 values, which is consistent with existing outcome.

In year t+1, the earnings persistence coefficient is 0.58 and in year t+5, 0.17. Over 5 years, the persistence coefficients decrease monotonically. The R^2 value declines from year t+1 (values 0.38) to year t+5 (values 0.09), which is also a monotonic decrease.

[Insert Table 3]

To examine the impact of earnings volatility, I analyze extreme quintiles, such as the highest and lowest earnings volatility quintiles. Panels B and C of Table 3 present the results of the highest and lowest earnings volatility quintiles, respectively, for firm-years. Surprisingly, an investigation of these two panels reveals substantial variation in the prediction of long-term earnings features for the underlying sample. Panel B illustrates a rapid drop in R^2 (from 0.29 to 0.05) and persistence coefficients (from 0.45 to 0.09) across the 5-year predictive period for high volatility banks, showing that for all future periods, the R^2 values and persistence coefficients in Panel B are lesser compare to the values in Panel A. Compare to that, the results in Panel C show that the forecasting power of banks in the lowest quintile of earnings volatility is robust over the entire 5-year period. The R^2 value declines slightly from year t+1 to year t+5 with a value of 0.55 to 0.37 respectively. The persistence coefficient for the lowest earnings volatility quintile is much higher than that for highest earnings volatility quintile, as shown in Panel B. The drop in persistence coefficients from year t+1 (0.95) to year t+5 (0.73) is quite dramatic, but relative to their absolute magnitude, I am reasonably confident in the predictability of earnings even for year t+5. The magnitude of these results suggests that predicting earnings for low volatility banks in the long term (5 years ahead) is much easier than predicting earnings for high volatility banks, or even all banks, in the short term (1 year ahead). Overall, the results in Panel B and Panel C indicate that when predicting earnings in the long term, earnings volatility has extraordinary distinguishing power.

The graphical representation of the results of Table 3, Panels A–C are presented in Figure 1(a–c), respectively. In Figure 1(a), the diagrams use a constant scale conditional on portfolio quintiles, derived by ranking current earnings to display the evolution of median earnings over the next 5 years for the full sample. The highest and lowest earnings volatility quintile shows in Figure 1(b) and Figure 1(c) accordingly. The first (Figure 1.a) graph shows the baseline results with the predictable mean reversion; by the end of the 5-year horizon the portfolio profitability of current earnings of 0.016 diminishes to 0.012. This is a consistent finding with the implications of the finding of Table 3. However, the second (Figure 1.b) graph illustrates a much faster reversion to the mean for the high quintile of earnings volatility, with the median profitability series decreasing from year *t* to year *t*+5 with a values of 0.017 to 0.009 respectively. Unlike graphs a and b in Figure 1, there is no clear change in mean reversion in graph c. Median earnings are about 0.013 and remain almost unchanged by the end of year *t*+5. Moreover, all quintile lines appear straight and never intersect; the distances between the quintiles also never decrease. To the best of my knowledge, this is the first illustration of a banking structure revealing such clear and long-lasting earnings deviations. This figure also demonstrates the confounding effects of the association between volatility and levels of earnings discussed earlier. As with industry (non-financial), I find that banks with high quintile of volatility of earnings have greater divergence in their current earnings level. As a result, they are also projected to revert faster to the mean. Thus, it is important to control for the current earrings level when adjusting the association between earnings volatility and predictability.

I control for the current earnings level by following Dichev and Tang (2009), who use a two-pass sorting procedure. I first sort each observation into 20 portfolios constructed on the magnitude of the level of current earnings. Next, observations are further sorted into five quintiles of earnings volatility, within each of these 20 portfolios. After that, I form quintile 1 (low earnings level) by merging the high quintiles of earnings volatility from portfolios 1–4; for quintile 2, I merge the high quintiles of earnings volatility from portfolios 4–8, and so on, for the high earnings volatility subsample. I repeat this process to generate the low earnings volatility quintiles subsample. This two-pass sorting results are shown in Figure 2. Figure 2, graph (a) represents the full sample baseline results, which are the same as in Figure 1 but have a different scale. The second (b) and third graphs (c) in Figure 2 present the subsamples of high and low earnings volatility, respectively, along with the dispersion of present earnings. When I compare subsample graphs (b) and (c) with full sample graph (a), it is clear that the two-pass procedure can successfully control the dispersion of present earnings. In the second (b) and third (c) graphs, controlling current earnings is less successful in quintile 1 but seems satisfactory. However, in quintiles 2–5, median current earnings are similar nearly across graphs, where high volatile banks appearing to revert faster to the mean. The range of median profitability of current earnings is reduced from year t+1 (0.016) to year t+5 (0.010) for the full sample; for the high volatility subsample, the corresponding numbers are 0.016 and 0.006, respectively, and for the low volatility subsample, 0.016 and 0.013, respectively. I show the regression analysis after controlling for the dispersion of present levels of earnings both in Panels D and E of Table 3.

The findings of Panels D and E support the corresponding findings of Panels B and C, implying that in the long term, high volatility banks have significantly lower power in predicting earnings than low volatility banks. In reality, in the regression, controlling for the current level of earnings appears to have a marginal effect on the estimates of overall results. Therefore, it is evident from the above analysis that in predicting earnings, the effect of earnings volatility is extremely incremental to the effect of the level of earnings.

1.4.3 Other Specifications for Earnings Volatility

For further empirical analysis and more robust long-term results, Table 4 presents another specification used to test the association between volatility of earnings with long-term predictability of earnings. This table presents the summation of earnings for the next 5 years regressed on the current earnings level. R^2 is an aggregate measure to describe interpretive power across the 5-year period, and the persistence coefficients of the explanatory variable can be interpreted as the sum of 5 years of earnings persistence coefficients. The empirical analysis of Table 4 is equivalent to the analysis shown in Table 2 (1-year measure) and includes the analytical differences in persistence as measured by the t-test and in R^2 as measured by the bootstrap test. Moreover, the results in Table 4 imply that both the magnitude and tenor of the tests are similar to those in Table 3. It is essential to note that the estimates in Table 4, Panels A–C are equivalent to those in Table 3, Panels A–C. For the full sample, the R^2 value and persistence coefficient in Panel A are considerably higher (0.26 and 1.34, respectively) than those for the high volatility sample (0.20 and 0.92, respectively). Moreover, the R^2 value and persistence coefficient of the low volatility earnings quintile (0.53 and 4.21, respectively) are much higher than those for the high volatility of earnings quintile (0.20 and 0.92, respectively). The differences in R^2 and persistence coefficients among the low and high volatility quintile of earnings are significant at the 1% level and confirm that after controlling for current levels of earnings, all of the results hold, as similar to the results of Table 3, Panels D and E.

[Insert Table 4]

I describe a group specification in Figure 3, which provides an instinctive implication of the economic importance for the results of long-term earnings volatility. Figure 3 represents median future earnings over 5 years, constructed with two portfolios to control for current levels of profitability (earnings) and based on earnings volatility information, upsurge future earnings differences. Specifically, based on their current earnings level the baseline full sample of bank-years is first sorted into 20 portfolios, which are then further sorted into volatility of earnings quintiles. Following this, I construct the portfolio with the highest current earnings in the lowest volatility of earnings quintile (high earnings–low volatility) by combining four sub-portfolios, and compare it with the portfolio with the highest current earnings in the highest volatility of earnings quintile (high earnings–high volatility) by combining another four sub-portfolios. I combine these portfolios because the high earnings portfolio is expected to revert to the mean faster and stronger. However, the reversion of mean might be low for the portfolio of low earnings volatility and high for the portfolio of high earnings volatility, which could reveal variations in future earnings.

Figure 3 only shows high earnings banks, as Dichev and Tang (2009) focus on a setting that proposes a keen direction for forecasted earnings. Following their study, I exclude medium earnings banks since their earnings are anticipated to largely remain identical. I also eliminate banks with low earnings due to the contradiction between my results and those of Minton et al. (2002) and because the range of low earnings probably cancel each other out. According to my results, banks with high volatility and low current earnings should revert to the mean faster, implying that they should have higher future earnings. However, Minton et al. (2002) posit that high volatility firms should have low future earnings due to high cost of external capital. Alternatively, in the range of high earnings, these two effects may support each other. Therefore, I anticipate a considerable deterioration in the forecasted earnings of banks with high earnings and high volatility, particularly because high volatility banks have low forecasted earnings and, in general, high volatile earnings are seem to be less persistent. A closer look at Figure 3 discloses that the two-pass method controls for present earnings almost perfectly. As a result, all of the difference in forecasted earnings can be explained by the benefit of using information of earnings volatility.

Figure 3 shows a sharp and immediate decline in future earnings, starting from year t+1 and continuing up to year t+5. According to my prediction, the graph also reveals that the forecasted earnings of portfolios with high earnings and low volatility decline only slightly, whereas the future earnings of other portfolios decline dramatically from their current levels. The resulting differences persist over the 5-year period, with the magnitude of the differences being 0.06–0.2%. The portfolio differences shown in Figure 3 in my banking setting are smaller than in the industry settings used by Dichev and Tang (2009) and Penman and Zhang (2002), the magnitudes of which are 3% and 1.5–2%, respectively. However, the setting used by Penman and Zhang (2002) is different from that used by Dichev and Tang (2009) in terms of motivation, sample selection, portfolio selection, and variable definitions. Penman and Zhang (2002) show that over a 5-year horizon, the conservatism effect of "hidden reserves" produces differences in earnings. Overall, the combined inference from the results is that accounting for earnings volatility can significantly improve long-term earnings forecasts.

1.4.5 Additional Specifications

I conduct a series of additional sub-sample analyses to provide further corroborating evidence to evaluate the relationship between banks' earnings volatility and earnings predictability. I try to observe whether the relation between earnings volatility and predictability does vary based on after the SOX enactment in the aftermath of the 2008 financial crisis and the capital adequacy ratio. I predict that the results still hold in sub-sample analysis.

1.4.5.1 The relation between EV and EP after the Financial crisis

To further investigate the relation between earnings volatility and earnings predictability, I test the sub-sample analysis of tables 2 and 3 based on before and after the financial crisis and clustering for standard error. I expect that the results are still robust after clustering for standard error by bank and year. Tables 5 and 6 represent the analysis of Tables 2 and 3 based on before and after the financial crisis respectively.

[Insert Table 5]

Table 5, Panel A shows the full sample results for the earnings persistence regression, where all the specifications show statistically and economically significant results even after clustering for standard errors by bank and year. The full sample results are significant with a coefficient of 0.5827. However, consistent with my expectation, the sub-sample analysis shows a decline in the persistence of coefficients after the financial crisis of 2008. Thus, it suggests that after the financial crisis, the relation between earnings volatility and earnings predictability is less predictable (persistence coefficients of 0.5434) compare to the results before the financial crisis of 2008 (persistence coefficients of 0.6273).

Panel B of Table 5 presents the sub-sample results based on quintiles of earnings volatility. Consistent with the results of Table 2 panel B, it shows a monotonically decrease in the persistence of coefficients. However, I report only the results based on after the 2008 financial crisis. Because the results for before the 2008 financial crisis are insignificant in some of the quintiles, instead of its high persistence of coefficients. Following that Panels C, D, and E represent the sub-sample analysis based on quintiles of the absolute amount of accruals, earnings levels, and cash flow volatility. All the panels' results are consistent with the results in Table 2. After comparing all the panels, I find that the results based on quintiles of earnings volatility show a monotonically decrease in persistence compare to accruals, earnings level, and cash flow volatility.

[Insert Table 6]

Next, I analyze the implications of earnings volatility for long-term earnings (Table 3) based on the sub-sample analysis. Regression results for the full sample infer in Table 6, Panel A in terms of clustering standard error, before and after the 2008 financial crisis. The results imply that after clustering the standard error by bank and year the results still hold. Moreover, the results before and after the SOX enactment also illustrate significant results economically and statistically. All the results of panel A show a monotonically decrease in coefficients of current earnings on future earnings from year t+1 to t+5. However, similar to Table 5, the results of Table 6 after the 2008 financial crisis are less predictable compared to those before the financial crisis.

Consequently, Panel B of Table 6 reports the sub-sample results based on the highest earnings volatility quintiles. Consistent with the results of Table 3 panel B, it shows a monotonically decrease in the persistence of coefficients from year t+1 to t+5. A quick deterioration of persistence coefficients from 0.4224 to 0.0917 and R^2 of 0.276 to 0.041. However, I report only the results based on after the 2008 financial crisis. Because the results for before the 2008 financial crisis are insignificant in some of the years, instead of its high persistence of coefficients. The results of Panels C represent the sub-sample analysis based on the lowest earnings volatility quintiles and it also shows a monotonically decrease in the persistence of coefficients from year t+1 to t+5. Remarkably, the coefficients of Panel C are larger than the coefficients of Panel B which is similar to the results of Table 3. In contrast, the low volatility banks' results in Panel C infer a robust predictive power over the whole 5-year period. The persistence of coefficients is high in year t+1 (0.9319) and declines modestly to year t+5 (0.8572); similarly, the R^2 of 0.0.564 in year t+1 decline to 0.328 in year t+5. The collective of these results suggests that earnings volatility has notable predictive power in the long-term prediction of earnings.

Panel D and E of Table 6 represent the results of the highest and lowest earnings volatility quintile controlling for the current earnings level accordingly. Even after controlling for the current level of earnings, the results of Panel D and E correspond to the results of Panel B and C, Table 6. Overall, all the results in Table 6 are consistent with the results in Table 3. After comparing all the panels, the results suggest that banks with high volatility have a substantially low predictive power of long-term future earnings. The results of this sub-sample analysis after the 2008 financial crisis correspond to the main results of Table 3.

1.4.5.2 The relation between EV and EP according to the Capital adequacy ratio (CAR)

I also test the sub-sample analysis of tables 2 and 3 based on the capital adequacy ratio. Based on the capital adequacy ratio, Tables 7 and 8 represent the sub-sample analysis of Tables 2 and 3 respectively. I divide the sample based on the median capital adequacy ratio (high CAR>median and low CAR<median). I predict that in the sub-sample analysis based on the capital adequacy ratio, the result between EV and EP would not vary that much. I expect that the results are still robust after clustering for standard error by bank and year. However, the low CAR result may be less predictable compared to high CAR results. Because it's another level of volatility that makes it less predictable.

[Insert Table 7]

Table 7, Panel A shows the full sample results for the earnings persistence regression, where all the specifications show statistically and economically significant results even after clustering for standard errors by bank and year. The full sample results are significant with a coefficient of 0.5827 after clustering for standard error. However, consistent with my expectation, the sub-sample analysis shows a decline in the persistence of coefficients with Low CAR. Thus, it suggests that the relationship between banks' earnings volatility and earnings predictability is less predictable with Low CAR (persistence coefficients of 0.5768) compared to the results with High CAR (persistence coefficients of 0.5847).

Panel B of Table 7 presents the sub-sample results based on quintiles of earnings volatility. Consistent with the results of Table 2 panel B, it shows a monotonically decrease in the persistence of coefficients. However, the persistence coefficients with High CAR (1.0291 to 0.4096) are larger than the coefficients of Low CAR (0.8039 to 0.4690). Thus, the results propose that the Low CAR results are less predictable. Following that Panels C, D, and E represent the sub-sample analysis based on quintiles of the absolute amount of accruals, earnings levels, and cash flow volatility. All the panels' results are consistent with the results in Table 2. After comparing all the panels, I find that the results based on quintiles of earnings volatility show a monotonically decrease in persistence. Although the results of persistence coefficients in quintiles of accruals, earnings level, and cash flow volatility are decreased but not monotonically.

[Insert Table 8]

After that following Table 3, I examine the implications of earnings volatility for long-term earnings based on the sub-sample analysis of the capital adequacy ratio. Regression results for the full sample infer in Table 8, Panel A in terms of High CAR and Low CAR. The results imply that after clustering the standard error by bank and year the results still hold both is High and Low CAR. Moreover, the results are significant economically and statistically. All the results of panel A show a monotonically decrease in coefficients of current earnings on future earnings from year t+1 to t+5. However, the results of Table 8 with the Low CAR (0.5768 to 0.1525) are less predictable compared to those with High CAR (0.5847 to 0.1807) which is similar to the results of Table 7.

Consequently, Panel B of Table 8 reports the sub-sample results based on the highest earnings volatility quintiles. Consistent with the results of Table 3 panel B, it shows a monotonically decrease in the persistence of coefficients from year t+1 to t+5. A quick deterioration of persistence coefficients from 0.4096 to 0.0620 and R^2 of 0.226 to 0.022 in High CAR. Similarly, the results with Low CAR also report a quick decline in coefficients (0.4690 to 0.0950) and R^2 (0.299 to 0.033). The results of Panels C represent the sub-sample analysis based on the lowest earnings volatility quintiles and it also shows a monotonically decrease in the persistence of coefficients from year t+1 to t+5. Remarkably, the coefficients of Panel C are larger than the coefficients of Panel B which is similar to the results of Table 3. In contrast, the low volatility banks' results in Panel C infer a robust predictive power over the whole 5-year period. The persistence of coefficients with High CAR is high in year t+1 (1.0291) and declines modestly to year t+5 (0.8657); similarly, the R^2 of 0.641 in year t+1 declines to 0.503 in year t+5. The results with Low CAR also infer similar results with High CAR. However, Low CAR results are less predictable as the persistence coefficients (0.8039 in t+1 and 0.7197 in t+5) and R^2 (0.399 in year t+1 to 0.154 in year t+5) is lower. The collective of these results suggests that earnings volatility has notable predictive power in the long-term prediction of earnings.

Panel D and E of Table 8 represent the results of the highest and lowest earnings volatility quintile controlling for the current earnings level accordingly. Even after controlling for the current level of earnings, the results of Panel D and E correspond to the results of Panel B and C, Table 8. Overall, all the results in Table 8 are consistent with the results in Table 3. After comparing all the panels, the results suggest that banks with high volatility have a substantially low predictive power of long-term future earnings. Overall, the results of this sub-sample analysis of the High and Low capital adequacy ratio (CAR) correspond to the main results of Table 3.

1.4.6 Robustness Checks

1.4.6.1 Earnings Persistence Regression by Quintiles of Residual Volatility

This study is also motivated by instances of accounting and economic noise which are captured in the residual more naturally due to past persistence. I formulate some propositions on the comparative roles of accounting and economic factors. Table 9 presents two measures and the impact of past earnings persistence on recognized earnings. Panel A shows the first measure, which is calculated by sorting the residual variance of the autoregressive model over the past 5 years in lieu of the raw earnings variance of equal time. Based on this structure, this residual detects the differences in earnings after the persistence effect is removed. An analysis of this measure shows that the difference in extreme quintile persistence coefficients is 0.72 and the difference in R^2 is 0.84, both of which are statistically significant at the 1% level. Table 9, Panel A corresponds to the baseline results of Table 2, Panel B where results of Table 9, Panel A are lower than Table 2, Panel B. The second measure is illustrated in Table 9, Panel B; this measure directly evaluates historical persistence and determines whether the historical volatility effect is incremental to the historical persistence effect after 5 × 5 sorting. The results of this panel show that after controlling for earnings volatility, historical persistence has very little effect on future persistence after 5 × 5 sorting. Moreover, after controlling for historical persistence, the spread of future persistence across earnings volatility quintiles is large. In general, the two measures in Table 9 indicate the sizeable impact of historical persistence on the documented results.

1.4.6.2 Incremental Explanatory Power of Earnings Volatility

To demonstrate the incremental explanatory power of earnings volatility of banks, I further test the earnings persistence regression based on the other risk-taking measures of banks', for instance, quintiles of equity to assets ratio (EAR), quintiles of z-score, and quintiles of return on equity (ROE) volatility. Table 10, Panel A represents the earnings persistence regression based on the model by quintiles of equity to assets ratio. Similar to the quintiles' earnings volatility all the quintiles show a monotonically decrease in earnings persistence coefficients from quintiles 1 to 5. However, compared to the coefficients of earnings persistence regression based on quintiles of earnings volatility (Table 2, Panel B), the Panel A of Table 10 shows comparatively low coefficients from 0.5603 in quintile 1 to 0.5121 in quintile 5. Panel B of Table 10 presents the earnings persistence regression based on quintiles of z-score (probability of default). The results of this panel are opposite compared to the quintiles of earnings volatility coefficients. In Panel C, I test the model of earnings persistence regression based on the banks' risk-taking measure of return on equity volatility quintiles. This panel also shows a decrease in persistence coefficients from quintile 1 (0.8925) to quintile 5 (0.2621). Finally, I show the comparison between the coefficients of earnings persistence regression based on quintiles of earnings volatility measures with other alternative measures of banks' risk-taking. In figure 4, it is clear that earnings volatility shows monotonically decreasing persistence coefficients compared to other specifications and the coefficients take the control over other measures. Overall, the results suggest that in comparison to the earnings persistence coefficients based on the quintiles of earnings volatility, the other measures coefficients are lower. Hence, it provides evidence of the incremental explanatory power of earnings volatility as a measure of banks' risk-taking.

1.5 Conclusion

This study investigates the proposed hypothesis of Dichev and Tang (2009), which states that earnings volatility has a negative effect on earnings predictability. An industry sample can be used to empirically show that conditioning on the volatility of earnings significantly diminishes the predictability of earnings. However, there is no previous research that directly examines the sensibility of this relationship in terms of banks' risk-taking behavior. In general, I find that banks' earnings volatility has a negative relationship with earnings predictability.

The findings of this study provide important implications for Dichev and Tang's (2009) hypothesis on the dynamics of banks' risk-taking behavior. First, assuming that the purpose of corporate risk-taking is to assure a high level of future earnings, then the worst position for a bank is to have low earnings and high earnings volatility, which indicates that the bank took too much risk with a poor result. To improve its position and avoid insolvency, the bank should reduce risk-taking. While the literature on corporate risk-taking suggests that firms with low earnings have higher incentives to take more risks, the first implication notes that banks with low earnings should decrease their risk-taking if they face high earnings volatility. Second, for banks with high earnings and high earnings volatility, their earnings are likely not persistent. To assure a high level of future earnings, they should also reduce risk-taking to lower their earnings volatility. Third, for banks with low earnings and low volatility, their future earnings are likely to be low. They should increase risk-taking to improve their future earnings. Fourth, the best position for banks is to have high earnings and low earnings volatility because they can assure a high level of future earnings. Since all banks would try to maintain or get into this best position, competition is likely to increase and how to protect their position becomes the top priority.

The findings of this study demonstrate that banks' historical earnings volatility can predict the sensibility of their forecasted earnings. The findings imply that regulators should also factor banks' earnings volatility in capital adequacy regulations. These findings are most consistent with the overinvestment and persistence explanations. My results open several avenues for future research. One potential direction is the extent to which earnings volatility affects banks' risk-taking decisions. For instance, the next essay of my thesis tests whether there is an optimal risk-taking behavior in banks, which could prove costly for them. I also examine cases of over risk-taking and under risk-taking, and how banks manage risk-taking in the face of high earnings volatility.

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Table 1. 1: Sample selection and Descriptive statistics

Panel A: Sample Derivation

1. Compustat bank -years over 1983-2020 with fiscal year end 31/12 and available earnings, total assets, and cash flow from operation	9825
2. Bank- years with available deflated earnings, accruals and cash flows	8706
3. Bank- years assets with greater than or equal to $100 million	8680
4. Bank-years with available data on earnings volatility and cash flow volatility (based on the most recent 5 years)	4282
5. Bank-years remaining after truncating the top and bottom 1% on all variables	4153
6. Bank-years in the final sample	4153

Panel B: Descriptive Statistics

Variables	N	Mean	Median	SD	P25	P75	Min	Max
Earnings	4153	0.0063	0.0081	0.0085	0.0045	0.0108	-0.0389	0.0245
Accruals	4153	-0.0065	-0.005	0.0129	-0.0101	-0.0017	-0.0742	0.066
|Accruals|	4153	0.0098	0.006	0.0107	0.0032	0.0118	0.0001	0.0742
CFOs	4153	0.0128	0.0133	0.0113	0.0093	0.0173	-0.0614	0.0704
Vol (Earnings)	4153	0.0048	0.0024	0.0057	0.0014	0.0056	0.0003	0.0326
Vol (CFOs)	4153	0.0083	0.0048	0.0103	0.0029	0.009	0.0004	0.0877

Panel C: Correlation Matrix

Variables	Earnings	Accruals	|Accruals|	CFOs	Vol (Earnings)	Vol (CFOs)
Earnings	**1**					
Accruals	0.512***	**1**				
|Accruals|	-0.535***	-0.455***	**1**			
CFOs	0.169***	-0.760***	0.118***	**1**		
Vol (Earnings)	-0.511***	-0.316***	0.381***	-0.025	**1**	
Vol (CFOs)	-0.037**	0.069***	0.383***	-0.107***	0.093***	**1**

Earnings is defined as earnings before extraordinary item deflated by average total assets. CFOs is defined as the cash flow from operating activities deflated by average total assets. Accruals is calculated as the difference between Earnings and CFOs. |Accruals| is the absolute amounts of Accruals. Vol (Earnings) is defined as the firm-specific volatility of earnings, which is calculated as the standard deviation of Earnings over the most recent 5 years. Vol (CFOs) is defined as the firm-specific volatility of cash flows from operations, which is calculated as the standard deviation of CFOs over the most recent 5 years.

Table 1. 2: Results for the earnings persistence regression: $Earnings_{t+1}=\alpha+\beta Earnings_{t}+\varepsilon$

Panel A: Regression result for the full sample

	$Earnings_{t+1}$
$Earnings_{t}$	0.5806***
	(47.33)
_cons	0.0034***
	(26.30)
N	3620
adj. R^2	0.382

Panel B: Regression results by quintiles of earnings volatility- Quintiles by Volatility of Earnings

	(Quintile 1) $Earnings_{t+1}$	(Quintile 2) $Earnings_{t+1}$	(Quintile 3) $Earnings_{t+1}$	(Quintile 4) $Earnings_{t+1}$	(Quintile 5) $Earnings_{t+1}$
$Earnings_{t}$	0.9433***	0.9512***	0.8866***	0.7828***	0.4471***
	(30.45)	(22.18)	(25.84)	(19.00)	(16.87)
_cons	0.0007**	0.0003	0.0009***	0.0010***	0.0031***
	(2.26)	(0.62)	(2.78)	(2.84)	(8.58)
Differences in Q1 to Q5 Persistence	0.49				
Differences in R^2 Q1 to Q5	0.26				
p-value on differences	<0.001				
N	754	706	714	750	696
adj. R^2	0.552	0.411	0.483	0.325	0.290

Panel C: Regression results by quintiles of absolute amount of accruals

	(Quintile 1) $Earnings_{t+1}$	(Quintile 2) $Earnings_{t+1}$	(Quintile 3) $Earnings_{t+1}$	(Quintile 4) $Earnings_{t+1}$	(Quintile 5) $Earnings_{t+1}$
$Earnings_{t}$	0.6159***	0.9082***	0.9131***	0.7356***	0.4779***
	(20.79)	(22.33)	(22.52)	(17.52)	(19.79)
_cons	0.0036***	0.0006	0.0007*	0.0016***	0.0033***
	(12.25)	(1.48)	(1.74)	(4.49)	(10.01)
Differences in Q1 to Q5 Persistence	0.14				
Differences in R^2 Q1 to Q5	0.04				
p-value on differences	<0.001				
N	669	721	756	753	721
adj. R^2	0.392	0.409	0.401	0.289	0.352

Panel D: Regression results by quintiles of earnings level

	(Quintile 1) Earnings$_{t+1}$	(Quintile 2) Earnings$_{t+1}$	(Quintile 3) Earnings$_{t+1}$	(Quintile 4) Earnings$_{t+1}$	(Quintile 5) Earnings$_{t+1}$
Earnings $_t$	0.3365***	1.2707***	0.9957***	0.7864***	0.3710***
	(9.26)	(6.28)	(5.12)	(5.45)	(5.89)
_cons	0.0008*	-0.0014	0.0004	0.0020	0.0074***
	(1.73)	(-1.30)	(0.27)	(1.37)	(8.21)
Differences in Q1 to Q5					
Persistence	-0.03				
Differences in R^2 Q1 to Q5	0.059				
p-value on differences	<0.001				
N	708	751	760	738	663
adj. R^2	0.107	0.049	0.032	0.037	0.048

Panel E: Regressions results by quintiles of cash flow volatility

	(Quintile 1) Earnings$_{t+1}$	(Quintile 2) Earnings$_{t+1}$	(Quintile 3) Earnings$_{t+1}$	(Quintile 4) Earnings$_{t+1}$	(Quintile 5) Earnings$_{t+1}$
Earnings $_t$	0.7040***	0.5338***	0.5384***	0.6386***	0.5311***
	(18.96)	(16.73)	(23.08)	(25.70)	(18.85)
_cons	0.0024***	0.0038***	0.0037***	0.0030***	0.0034***
	(6.62)	(12.15)	(14.87)	(11.08)	(11.50)
Differences in Q1 to Q5					
Persistence	0.18				
Differences in R^2 Q1 to Q5	0.03				
p-value on differences	<0.001				
N	676	712	756	747	729
adj. R^2	0.347	0.282	0.413	0.469	0.327

The table reports the result of earnings persistence regression for the full sample (panel A), quintiles of earnings volatility (panel B), quintiles of absolute accruals (panel C), quintiles of earnings level (panel D), and quintiles of cash flow volatility (panel D). All beta coefficients (persistence) are significant at the 0.001 level. The p-value for the difference in persistence coefficients across quintiles is derived from a t-test. The p-value for the difference in the Adj. R^2 across quintiles is derived from a bootstrap test. Earnings$_t$ is defined as earnings before extraordinary item deflated by the average total assets. |Accruals| is the absolute amount of Accruals. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. CFOs is defined as the cash flow from operating activities deflated by average total assets. Vol (CFOs) is defined as the firm-specific standard deviation of CFOs over the most recent 5 years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

Table 1. 3: The implications of earnings volatility for long-term earnings

Panel A: Regression results for the full sample

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.5806***	0.4290***	0.2715***	0.2197***	0.1707***
	(47.33)	(35.49)	(22.46)	(18.67)	(14.64)
_cons	0.0034***	0.0053***	0.0069***	0.0077***	0.0083***
	(26.30)	(42.68)	(56.03)	(64.43)	(68.98)
N	3620	3155	2733	2323	1946
adj. R^2	0.382	0.285	0.156	0.130	0.099

Panel B: Regression results for the highest earnings volatility quintile

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.4471***	0.3223***	0.1571***	0.1014***	0.0926***
	(16.87)	(12.47)	(7.32)	(4.72)	(4.67)
_cons	0.0031***	0.0055***	0.0074***	0.0081***	0.0090***
	(8.58)	(15.42)	(25.43)	(27.92)	(32.69)
N	696	637	570	497	438
adj. R^2	0.290	0.195	0.085	0.041	0.045

Panel C: Regression results for the lowest earnings volatility quintile

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.9433***	0.8807***	0.8850***	0.8095***	0.7291***
	(30.45)	(24.90)	(17.56)	(16.90)	(13.19)
_cons	0.0007**	0.0017***	0.0016***	0.0024***	0.0030***
	(2.26)	(5.12)	(3.28)	(5.22)	(5.44)
N	754	658	527	408	291
adj. R^2	0.552	0.485	0.369	0.411	0.373

Panel D: Regression results for the highest earnings volatility quintile, controlling for the level of current earnings

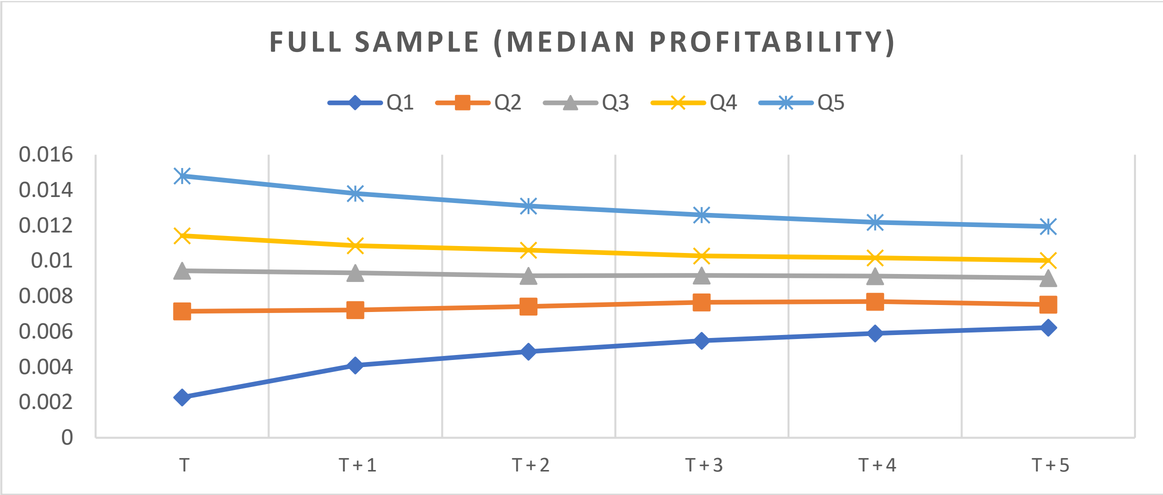
	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.4424***	0.2865***	0.1081***	0.0425	0.0130
	(11.78)	(7.65)	(3.44)	(1.34)	(0.44)
_cons	0.0037***	0.0051***	0.0067***	0.0070***	0.0073***
	(5.04)	(6.80)	(10.85)	(11.41)	(12.33)
N	696	637	570	497	438
adj. R^2	0.314	0.207	0.104	0.055	0.070

Panel E: Regression results for the lowest earnings volatility quintile, controlling for the level of current earnings

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.9428***	0.8536***	0.8611***	0.7831***	0.7425***
	(28.31)	(22.52)	(16.03)	(15.47)	(12.95)
_cons	0.0005	0.0009*	0.0005	0.0011	0.0026***
	(1.31)	(1.87)	(0.70)	(1.58)	(2.68)
N	754	658	527	408	291
adj. R^2	0.552	0.492	0.378	0.422	0.394

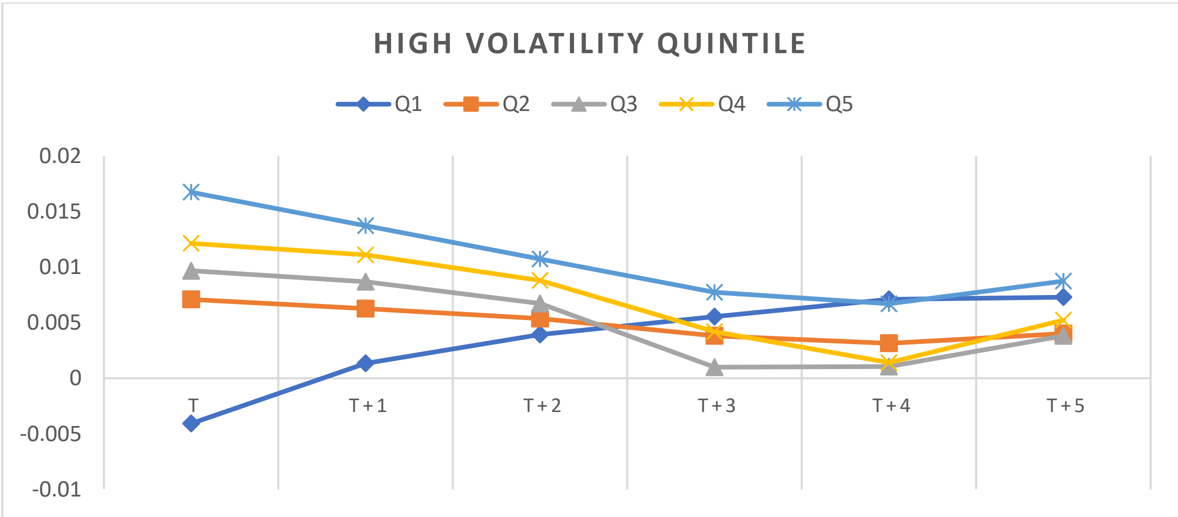
The table reports the effect of earnings volatility for long-term earnings for the full sample (panel A), quintiles of highest earnings volatility (panel B), quintiles of lowest earnings volatility (panel C), and quintiles of highest earnings volatility by controlling for current earnings level (panel D) and quintiles of lowest earnings volatility by controlling for current earnings level (panel D). All beta coefficients are statistically significant at the 0.001 level. $Earnings_t$ is defined as earnings before extraordinary item deflated by the average total assets. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. Earnings t is current year Earnings, Earnings t+1 is the one-year ahead Earnings, Earnings t+2 is the two-year ahead Earnings, Earnings t+3 is the three-year ahead Earnings, Earnings t+4 is the four-year ahead Earnings, Earnings t+5 is the five-year ahead Earnings. The t-statistics have shown in the parentheses and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

a.



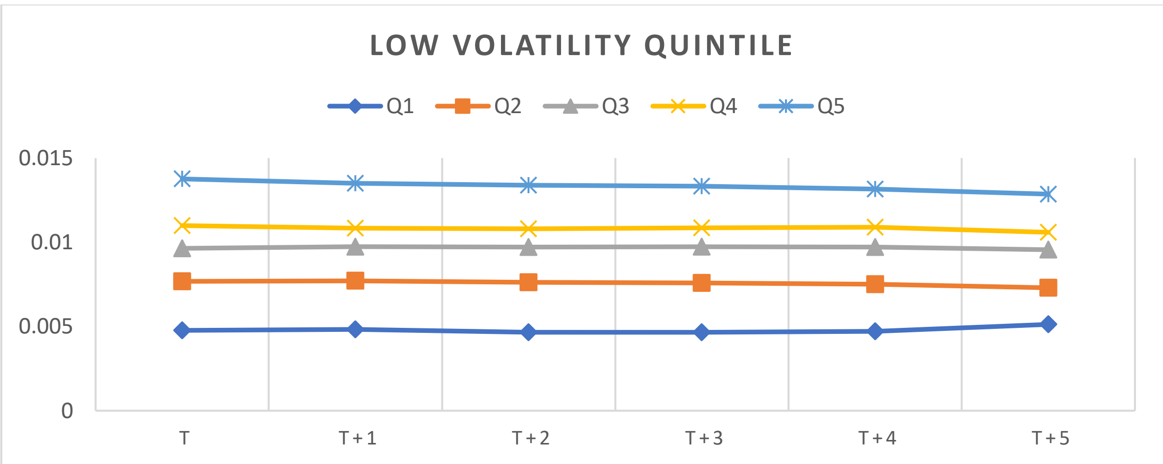
FULL SAMPLE (MEDIAN PROFITABILITY)
Q1
Q2
Q3
Q4
Q5
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
T
T+1
T+2
T+3
T+4
T+5

b.



HIGH VOLATILITY QUINTILE
Q1
Q2
Q3
Q4
Q5
0.02
0.015
0.01
0.005
0
-0.005
-0.01
T
T+1
T+2
T+3
T+4
T+5

c.

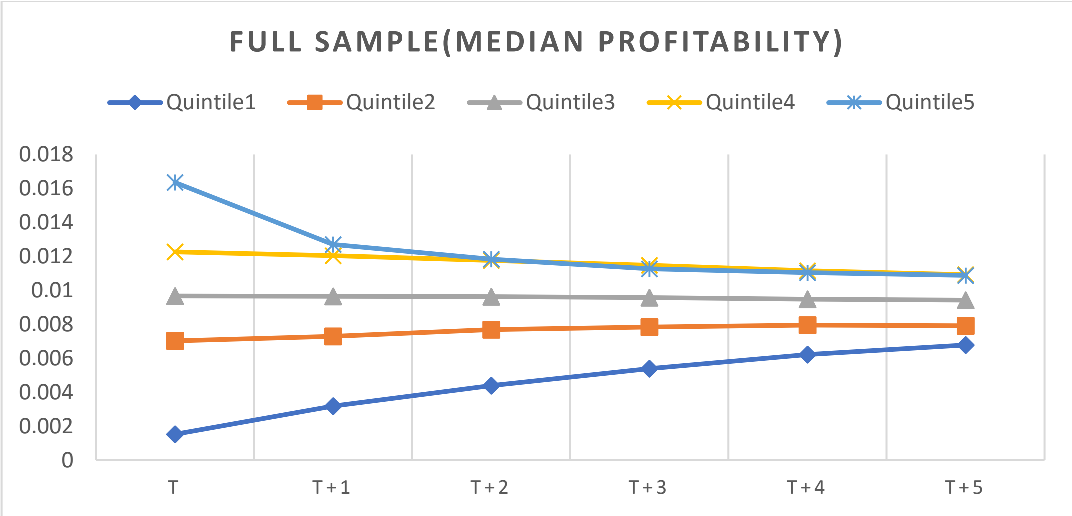


LOW VOLATILITY QUINTILE
Q1
Q2
Q3
Q4
Q5
0.015
0.01
0.005
0
T
T+1
T+2
T+3
T+4
T+5

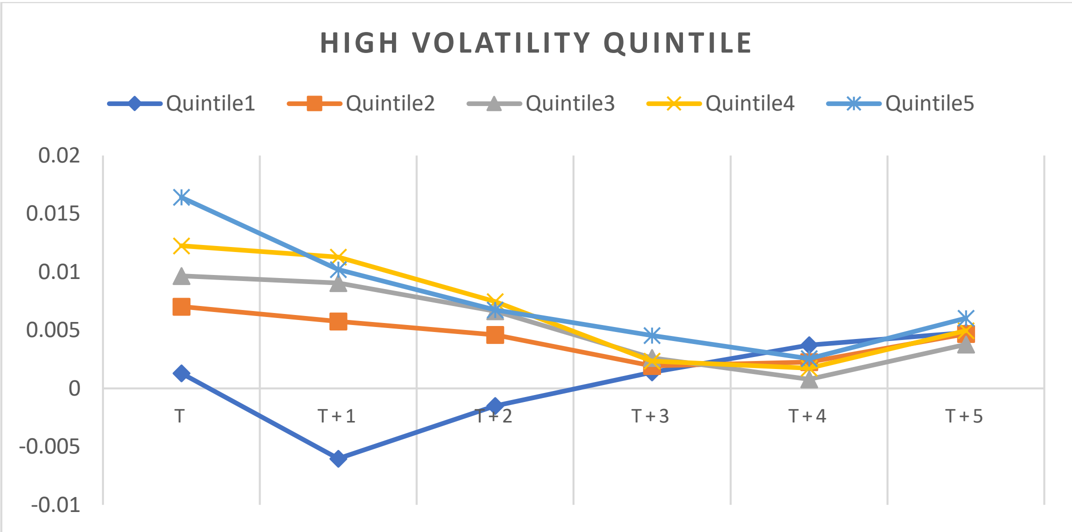
Figure 1. 1: Mean Reversion on 5 years earnings conditional on current earnings volatility.

Figure 1 reports the mean reversion of 5-year future earnings conditional on earnings volatility. In Figure 1a, the full sample is sorted into five quintiles by the level of current earnings. The graph for the full sample plots the median current earnings and future earnings for each quintile. In Figures 1b and c, the full sample is first sorted into five quintiles by the level of earnings volatility. Then the observations within the highest (lowest) earnings volatility quintile are sorted into five quintiles by the level of current earnings. The graph for highest (lowest) earnings volatility plots the median current earnings and future earnings for each quintile. Current earnings is defined as the earnings before extraordinary item deflated by the average total assets. Future earnings is future earnings over the next 5 years: (a) full sample, (b) highest earnings volatility sample and (c) lowest earnings volatility sample.

a.


FULL SAMPLE(MEDIAN PROFITABILITY)
Quintile1 Quintile2 Quintile3 Quintile4 Quintile5
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
T T+1 T+2 T+3 T+4 T+5

b.


HIGH VOLATILITY QUINTILE
Quintile1 Quintile2 Quintile3 Quintile4 Quintile5
0.02
0.015
0.01
0.005
0
-0.005
-0.01
T T+1 T+2 T+3 T+4 T+5

c.

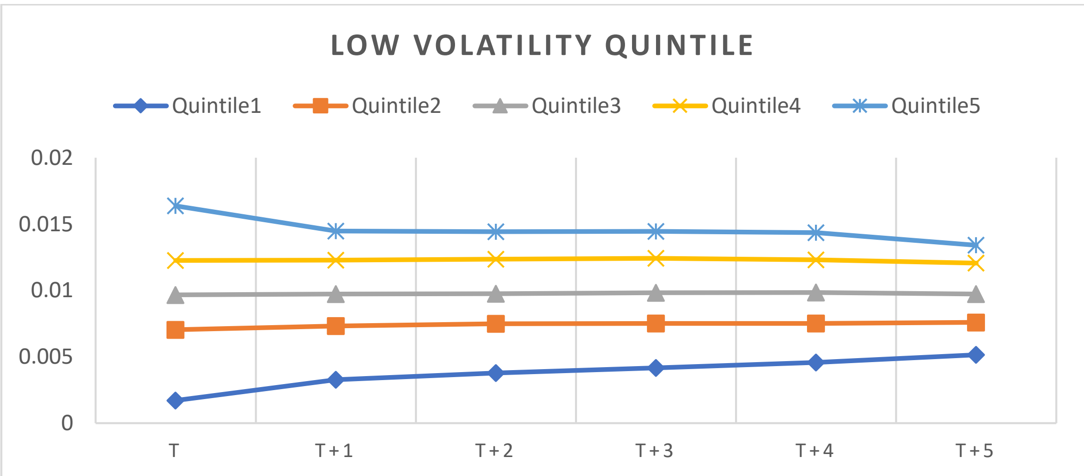

LOW VOLATILITY QUINTILE
Quintile1 Quintile2 Quintile3 Quintile4 Quintile5
0.02
0.015
0.01
0.005
0
T T+1 T+2 T+3 T+4 T+5

Figure 1. 2: Mean reversion of 5 year forecasted earnings conditional on current earnings volatility and controlling for the dispersion of current earnings.

Figure 2 demonstrates the mean reversion of 5-year future earnings conditional on earnings volatility and controlling for the dispersion of current earnings. In Fig. 2a, the full sample is sorted into five quintiles by the level of current earnings. The graph for the full sample plots the median current earnings and future earnings for each quintile. The following steps are involved to produce the graph for the highest (lowest) earnings volatility sample in Fig. 2b and c. First, the full sample is sorted into 20 portfolios by the level of current earnings. Five earnings volatility quintiles are formed within each 20 current earnings portfolio. Combining each of the highest (lowest) earnings volatility quintiles from the 20 current earnings portfolios together forms the highest (lowest) earnings volatility sample. Then the observations in the highest (lowest) earnings volatility sample are sorted into five quintiles by the level of current earnings. The graph for the highest (lowest) earnings volatility plots the median current earnings and future earnings for each quintile. Current earnings are defined as the earnings before extraordinary items are deflated by the average total assets. Future earnings are future earnings over the next 5-years: (a) full sample, (b) highest earnings volatility sample, and (c) lowest earnings volatility sample.

Table 1. 4: The implications of earnings volatility for the sum of earnings over the next 5 years

Panel A: Regression results for the full sample

Dependent Variable	
	Earnings $_{t+1 \text{ to } t+5}$
Earnings_t	1.3405***
	(25.94)
_cons	0.0332***
	(62.09)
N	1938
adj. R^2	0.258

Panel B: Regression results for the highest earnings volatility quintile

Dependent Variable	
	$\text{Earnings}_{+1 \text{ to } t+5}$
Earnings_t	0.9173***
	(10.59)
_cons	0.0370***
	(30.70)
N	439
adj. R^2	0.202

Panel B: Regression results for the lowest earnings volatility quintile

Dependent Variable	
	$\text{Earnings}_{t+1 \text{ to } t+5}$
Earnings_t	4.2180***
	(18.20)
_cons	0.0067***
	(2.92)
N	291
adj. R^2	0.532

The table reports the effect of earnings volatility on the sum of earnings across the future 5 years where panel A shows the results for the full sample, panel B reports the results for the highest earnings volatility, and panel C reports the results for the lowest earnings volatility. All beta coefficients are statistically significant at the 0.001 level. Earnings_t is defined as earnings before extraordinary item deflated by the average total assets. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. Earnings t is current year Earnings, Earnings t+1 is the one-year ahead Earnings, Earnings t+2 is the two-year ahead Earnings, Earnings t+3 is the three-year ahead Earnings, Earnings t+4 is the four-year ahead Earnings, Earnings t+5 is the five-year ahead Earnings. The p-value for the difference in persistence coefficients and Adj. R^2 across panels is derived from a bootstrap test. The t-statistics have shown in the parentheses and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

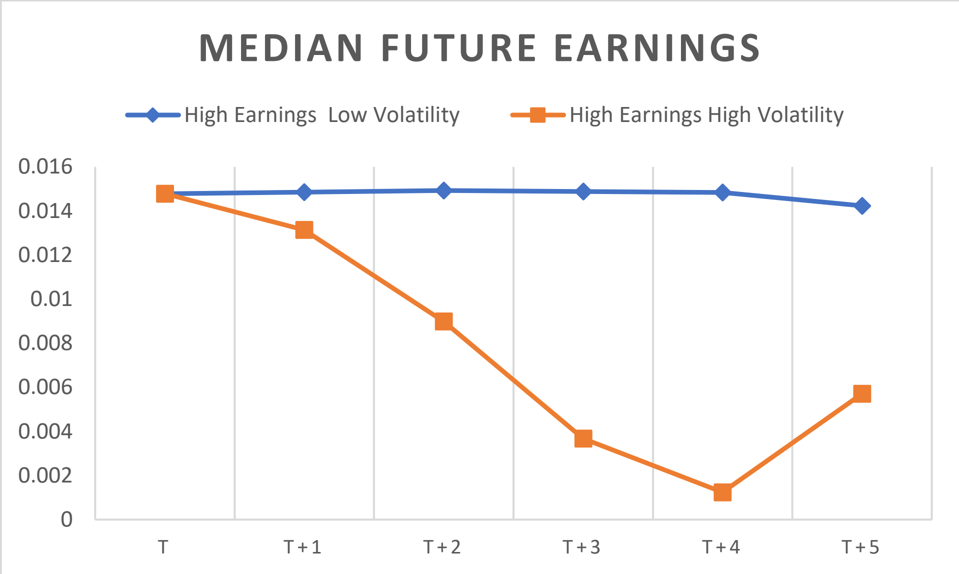


Figure 1. 3: 5-year future earnings for portfolios constructed to control for current earnings.

The figure exhibits the Five-year future earnings for portfolios constructed to control for current earnings. The two portfolios are constructed in the following way. First, the full sample is sorted into 20 portfolios on the level of current earnings. Within each earnings portfolio, quintiles of earnings volatility are formed. The high earnings high-volatility sub-sample includes observations from the intersection of the highest earnings volatility quintile and earnings level portfolios 17–20. The high earnings low-volatility sub-sample includes observations from the intersection of the lowest earnings volatility quintile and earnings level portfolios 17–20. Portfolio1includes the high earnings high-volatility sub-sample. Portfolio 2 includes the high earnings low-volatility sub-sample. Current earnings are defined as the earnings before extraordinary items deflated by the average total assets. Future earnings are future earnings over the next 5 years.

Table 1.5: Results for the earnings persistence regression: $Earnings_{t+1}=\alpha+\beta Earnings_{t}+\varepsilon$, after the 2008 financial crisis and clustering for standard error

Panel A: Regression result for the full sample

	(1) Earnings $_{t+1}$ (1983-2020)	(2) Earnings $_{t+1}$ (before 2008)	(3) Earnings $_{t+1}$ (after 2008)
Earnings $_{t}$	0.5827***	0.6273***	0.5434***
	(49.37)	(10.05)	(50.15)
_cons	0.0033***	-0.0025***	0.0040***
	(26.35)	(-3.78)	(35.19)
N	3907	298	3609
SE Clustered by bank & year	Yes	Yes	Yes
adj. R^2	0.384	0.252	0.411

Panel B - Quintiles of Earnings Volatility (After 2008)

	(Q1) Earnings $_{t+1}$	(Q2) Earnings $_{t+1}$	(Q3) Earnings $_{t+1}$	(Q4) Earnings $_{t+1}$	(Q5) Earnings $_{t+1}$
Earnings $_{t}$	0.9319***	0.8849***	0.7255***	0.6471***	0.4224***
	(32.20)	(12.33)	(10.50)	(18.32)	(10.71)
_cons	0.0008	0.0010	0.0027***	0.0028***	0.0035***
	(1.51)	(1.39)	(4.84)	(7.80)	(5.81)
Difference in persistence between (Q1-Q5)	0.5095				
p-value on difference (Q1-Q5)	<0.001				
Difference in R^2 (Q1-Q5)	0.288				
N	789	723	696	696	705
SE Clustered by bank & year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.564	0.469	0.596	0.385	0.276

Panel C: Regression results by quintiles of absolute amount of accruals- After financial crisis (year>2008)

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+1}$	(3) $Earnings_{t+1}$	(4) $Earnings_{t+1}$	(5) $Earnings_{t+1}$
Earnings $_{t}$	0.5950***	0.7740***	0.8453***	0.6236***	0.4500***
	(6.91)	(20.42)	(17.37)	(14.15)	(12.71)
_cons	0.0037***	0.0020***	0.0015**	0.0032***	0.0038***
	(4.67)	(7.12)	(2.36)	(6.48)	(9.38)
Difference in persistence between (Q1-Q5)	0.145				
p-value on difference (Q1-Q5)	<0.001				
Difference in R^2 (Q1-Q5)	0.029				
N	711	727	759	733	679
SE Clustered by bank & year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.380	0.420	0.467	0.354	0.351

Panel D: Regression results by quintiles of earnings level - After the 2008 financial crisis and clustering SE

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+1}$	(3) $Earnings_{t+1}$	(4) $Earnings_{t+1}$	(5) $Earnings_{t+1}$
$Earnings_t$	0.3328^{***}	1.1002^{***}	0.8117^{***}	0.5338^{**}	0.3237^{*}
	(4.85)	(6.35)	(5.33)	(2.75)	(2.06)
_cons	0.0019^{***}	0.0002	0.0021	0.0045^{**}	0.0080^{***}
	(4.77)	(0.13)	(1.71)	(2.53)	(3.73)
Difference in persistence between (Q1-Q5)	0.0091				
p-value on difference (Q1-Q5)	<0.001				
Difference in R^2 (Q1-Q5)	0.087				
N	640	706	747	749	767
SE Clustered by bank & year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.132	0.057	0.031	0.013	0.045

Panel E: Regressions results by quintiles of cash flow volatility - After the 2008 financial crisis and Clustering SE

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+1}$	(3) $Earnings_{t+1}$	(4) $Earnings_{t+1}$	(5) $Earnings_{t+1}$
$Earnings_t$	0.5752^{***}	0.4946^{***}	0.5017^{***}	0.6006^{***}	0.5124^{***}
	(4.66)	(5.56)	(13.63)	(5.78)	(10.04)
_cons	0.0040^{***}	0.0047^{***}	0.0043^{***}	0.0036^{***}	0.0037^{***}
	(3.43)	(5.55)	(10.13)	(4.00)	(8.54)
N	688	696	760	743	722
SE Clustered by bank & year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.441	0.364	0.431	0.472	0.320

The table reports the sub-sample (before and after the 2008 financial crisis) result of earnings persistence regression for the full sample (panel A), quintiles of earnings volatility (panel B), quintiles of absolute accruals (panel C), quintiles of earnings level (panel D), and quintiles of cash flow volatility (panel D). All beta coefficients (persistence) are significant at the 0.001 level. The p-value for the difference in persistence coefficients across quintiles is derived from a t-test. The p-value for the difference in the Adj. R^2 across quintiles is derived from a bootstrap test. $Earnings_t$ is defined as earnings before extraordinary item deflated by the average total assets. |Accruals| is the absolute amount of Accruals. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. CFOs is defined as the cash flow from operating activities deflated by average total assets. Vol (CFOs) is defined as the firm-specific standard deviation of CFOs over the most recent 5 years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

Table 1.6: The implications of earnings volatility for long-term earnings - after the 2008 financial crisis and clustered for standard error

Panel A: Regression results for the full sample - Clustered SE

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.5827***	0.4270***	0.2776***	0.2257***	0.1783***
	(12.70)	(6.75)	(6.63)	(4.73)	(3.89)
_cons	0.0033***	0.0052***	0.0068***	0.0076***	0.0081***
	(4.43)	(6.86)	(16.03)	(17.01)	(17.43)
N	3907	3423	2982	2568	2189
SE cluster by bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.384	0.276	0.151	0.125	0.093

Before 2008

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.6273***	0.6278**	0.2226***	0.2818***	0.1144***
	(327.66)	(40.63)	(109.46)	(244.95)	(168.78)
_cons	-0.0025**	0.0009	0.0045***	0.0060***	0.0076***
	(-55.92)	(5.96)	(112.38)	(135.73)	(210.59)
N	298	292	285	272	257
SE cluster by bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.252	0.363	0.063	0.134	0.039

After 2008

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.5434***	0.3651***	0.2702***	0.2068***	0.1856**
	(18.07)	(13.42)	(6.21)	(4.34)	(3.40)
_cons	0.0040***	0.0059***	0.0072***	0.0079***	0.0082***
	(12.66)	(18.29)	(21.29)	(19.42)	(14.62)
N	3609	3131	2697	2296	1932
SE cluster by bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.411	0.241	0.161	0.114	0.099

Panel B: Regression results for the Highest Earnings Volatility Quintile - After 2008 financial crisis & clustered SE

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.4224***	0.2439***	0.1435***	0.0781***	0.0917**
	(10.71)	(8.16)	(5.13)	(3.57)	(2.69)
_cons	0.0035***	0.0061***	0.0075***	0.0082***	0.0088***
	(5.81)	(12.16)	(19.63)	(19.92)	(14.62)
N	705	644	581	516	460
SE cluster by bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.276	0.142	0.070	0.026	0.041

Panel C: Regression results for the Lowest Earnings Volatility Quintile - After 2008 and SE clustered

	(1) Earnings$_{t+1}$	(2) Earnings$_{t+2}$	(3) Earnings$_{t+3}$	(4) Earnings$_{t+4}$	(5) Earnings$_{t+5}$
Earnings $_t$	0.9319***	0.8897***	0.8801***	0.8817***	0.8572***
	(32.20)	(17.90)	(13.04)	(11.54)	(9.46)
_cons	0.0008	0.0015**	0.0017**	0.0017	0.0016
	(1.51)	(2.71)	(2.60)	(1.83)	(1.49)
N	789	699	611	471	354
SE cluster by bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.564	0.471	0.378	0.381	0.328

Panel D: Regression results for the Highest earnings volatility quintile, controlling for the level of current earnings - After 2008 and SE Clustered

	(1) Earnings$_{t+1}$	(2) Earnings$_{t+2}$	(3) Earnings$_{t+3}$	(4) Earnings$_{t+4}$	(5) Earnings$_{t+5}$
Earnings $_t$	0.4200***	0.2089***	0.0847	0.0089	0.0116
	(7.13)	(3.41)	(1.59)	(0.21)	(0.49)
_cons	0.0042***	0.0059***	0.0066***	0.0070***	0.0070***
	(5.46)	(5.15)	(6.66)	(8.49)	(8.52)
N	705	644	581	516	460
SE cluster by bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.303	0.164	0.093	0.049	0.068

Panel E: Regression results for the lowest earnings volatility quintile, controlling for the level of current earnings - After 2008 and SE clustered

	(1) Earnings$_{t+1}$	(2) Earnings$_{t+2}$	(3) Earnings$_{t+3}$	(4) Earnings$_{t+4}$	(5) Earnings$_{t+5}$
Earnings $_t$	0.9236***	0.8651***	0.8760***	0.8685***	0.8758***
	(32.95)	(20.05)	(11.38)	(9.83)	(8.43)
_cons	0.0007	0.0010	0.0012	0.0010	0.0018*
	(1.58)	(1.24)	(1.03)	(1.37)	(2.18)
N	789	699	611	471	354
SE cluster by bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.566	0.477	0.382	0.381	0.334

The table reports the sub-sample analysis (the financial crisis 2008) of the effect of earnings volatility for long-term earnings for the full sample (panel A), quintiles of highest earnings volatility (panel B), quintiles of lowest earnings volatility (panel C), and quintiles of highest earnings volatility by controlling for current earnings level (panel D) and quintiles of lowest earnings volatility by controlling for current earnings level (panel D). All beta coefficients are statistically significant at the 0.001 level. Earnings$_t$ is defined as earnings before extraordinary item deflated by the average total assets. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. Earnings t is current year Earnings, Earnings t+1 is the one-year ahead Earnings, Earnings t+2 is the two-year ahead Earnings, Earnings t+3 is the three-year ahead Earnings, Earnings t+4 is the four-year ahead Earnings, Earnings t+5 is the five-year ahead Earnings. The t-statistics have shown in the parentheses and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

Table 1.7: Based on Capital Adequacy Ratio - Results for the earnings persistence regression: $Earnings_{t+1}=\alpha+\beta Earnings_{t} + \varepsilon$

Panel A: Full sample

	(Full sample) $Earnings_{t+1}$	(SE Clustered) $Earnings_{t+1}$	(High CAR) $Earnings_{t+1}$	(Low CAR) $Earnings_{t+1}$
$Earnings_t$	0.5809***	0.5809***	0.5847***	0.5768***
	(48.76)	(12.73)	(9.73)	(11.68)
_cons	0.0032***	0.0032***	0.0033***	0.0032***
	(26.19)	(4.40)	(4.31)	(3.90)
N	3846	3846	1957	1889
adj. R^2	0.382	0.382	0.345	0.400

Panel B: Quintiles of Earnings Volatility –

High CAR= (CAR>median)

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+1}$	(3) $Earnings_{t+1}$	(4) $Earnings_{t+1}$	(5) $Earnings_{t+1}$
$Earnings_t$	1.0291***	0.9198***	0.8131***	0.7862***	0.4096***
	(29.74)	(12.24)	(9.24)	(5.75)	(7.32)
_cons	-0.0004	0.0004	0.0016	0.0006	0.0039***
	(-0.57)	(0.59)	(1.36)	(0.32)	(6.90)
N	438	378	381	395	365
adj. R^2	0.641	0.523	0.404	0.358	0.226

Low CAR = (CAR<=median)

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+1}$	(3) $Earnings_{t+1}$	(4) $Earnings_{t+1}$	(5) $Earnings_{t+1}$
$Earnings_t$	0.8039***	0.8890***	0.7736***	0.7883***	0.4690***
	(13.06)	(9.96)	(4.61)	(4.77)	(8.40)
_cons	0.0019**	0.0005	0.0015	0.0010	0.0024**
	(2.89)	(0.44)	(0.87)	(0.49)	(3.05)
N	381	392	358	374	384
adj. R^2	0.399	0.303	0.403	0.305	0.299

Panel C: Regression results by quintiles of absolute amount of accruals – High CAR

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+1}$	(3) $Earnings_{t+1}$	(4) $Earnings_{t+1}$	(5) $Earnings_{t+1}$
$Earnings_t$	0.6261***	0.9607***	0.9815***	0.6875***	0.4171***
	(5.99)	(13.48)	(5.45)	(7.54)	(7.98)
_cons	0.0034***	-0.0003	-0.0001	0.0020	0.0036***
	(3.21)	(-0.30)	(-0.07)	(1.66)	(6.51)
N	390	402	403	427	335
adj. R^2	0.380	0.459	0.385	0.293	0.271

Low CAR (CAR<=median)

	(1) Earnings$_{t+1}$	(2) Earnings$_{t+1}$	(3) Earnings$_{t+1}$	(4) Earnings$_{t+1}$	(5) Earnings$_{t+1}$
Earnings$_t$	0.5900***	0.7666***	0.8464***	0.7809***	0.4788***
	(8.03)	(7.17)	(13.82)	(5.50)	(8.24)
_cons	0.0035***	0.0018	0.0013*	0.0012	0.0026**
	(5.65)	(1.38)	(1.88)	(0.62)	(3.04)
N	362	374	393	380	380
adj. R^2	0.386	0.316	0.438	0.289	0.346

Panel D: Regression results by quintiles of earnings level - High CAR

	(1) Earnings$_{t+1}$	(2) Earnings$_{t+1}$	(3) Earnings$_{t+1}$	(4) Earnings$_{t+1}$	(5) Earnings$_{t+1}$
Earnings$_t$	0.2628***	0.9115***	1.0039***	0.7489***	0.2781
	(4.85)	(5.12)	(4.71)	(3.21)	(1.39)
_cons	0.0012	0.0004	0.0003	0.0022	0.0085***
	(1.15)	(0.32)	(0.18)	(0.91)	(3.22)
N	333	392	381	415	436
adj. R^2	0.055	0.029	0.032	0.020	0.028

Low CAR (CAR<=median)

	(1) Earnings$_{t+1}$	(2) Earnings$_{t+1}$	(3) Earnings$_{t+1}$	(4) Earnings$_{t+1}$	(5) Earnings$_{t+1}$
Earnings$_t$	0.3734***	1.4423***	0.7357**	0.3834	0.0903
	(5.08)	(3.88)	(2.83)	(1.19)	(0.34)
_cons	0.0004	-0.0025	0.0026	0.0060*	0.0107**
	(0.33)	(-0.87)	(1.22)	(1.94)	(3.08)
N	409	386	397	370	327
adj. R^2	0.133	0.050	0.017	0.006	0.000

Panel E: Regressions results by quintiles of cash flow volatility – High CAR

	(1) Earnings$_{t+1}$	(2) Earnings$_{t+1}$	(3) Earnings$_{t+1}$	(4) Earnings$_{t+1}$	(5) Earnings$_{t+1}$
Earnings$_t$	0.6663**	0.4657***	0.4620***	0.6724***	0.5874***
	(2.97)	(4.51)	(11.38)	(5.02)	(10.51)
_cons	0.0026	0.0048***	0.0045***	0.0027*	0.0024***
	(1.09)	(4.71)	(12.81)	(1.94)	(4.02)
N	406	402	397	397	355
adj. R^2	0.333	0.244	0.359	0.411	0.317

Low CAR (<=median)

	(1) Earnings$_{t+1}$	(2) Earnings$_{t+1}$	(3) Earnings$_{t+1}$	(4) Earnings$_{t+1}$	(5) Earnings$_{t+1}$
Earnings$_t$	0.7286***	0.6071***	0.5585***	0.6326***	0.4664***
	(5.25)	(4.59)	(8.67)	(6.73)	(7.80)
_cons	0.0018	0.0028	0.0033***	0.0031***	0.0037***
	(1.08)	(1.75)	(3.71)	(3.47)	(5.99)
N	357	359	411	391	371
adj. R^2	0.351	0.315	0.434	0.499	0.293

The table reports the result of the sub-sample analysis based on the capital adequacy ratio (CAR) for earnings persistence regression of the full sample (panel A), quintiles of earnings volatility (panel B), quintiles of absolute accruals (panel C), quintiles of earnings level (panel D), and quintiles of cash flow volatility (panel D). High CAR is the CAR greater than the median value of CAR, and Low CAR is lower than the median value of CAR. All beta coefficients (persistence) are significant at the 0.001 level. The p-value for the difference in persistence coefficients across quintiles is derived from a t-test. The p-value for the difference in the Adj. R^2 across quintiles is derived from a bootstrap test. Earnings$_t$ is defined as earnings before extraordinary item deflated by the average total assets. |Accruals| is the absolute amount of Accruals. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. CFOs is defined as the cash flow from operating activities deflated by average total assets. Vol (CFOs) is defined as the firm-specific standard deviation of CFOs over the most recent 5 years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

Table 1.8: Based on Capital Adequacy Ratio - The implications of earnings volatility for long-term earnings

Panel A- Regression results for the full sample - High CAR

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.5847***	0.4822***	0.3094***	0.2558***	0.1807**
	(9.73)	(5.57)	(4.86)	(4.60)	(3.06)
_cons	0.0033***	0.0047***	0.0066***	0.0074***	0.0082***
	(4.31)	(5.21)	(11.00)	(14.89)	(15.46)
N	1957	1744	1535	1335	1148
adj. R^2	0.345	0.291	0.175	0.140	0.092

Low CAR (<=median)

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.5768***	0.3901***	0.2349***	0.1920***	0.1525**
	(11.68)	(6.97)	(5.94)	(3.80)	(3.17)
_cons	0.0032***	0.0054***	0.0070***	0.0077***	0.0081***
	(3.90)	(7.12)	(14.56)	(15.69)	(16.42)
N	1889	1622	1398	1186	996
adj. R^2	0.400	0.261	0.115	0.103	0.075

Panel B: Regression results for the Highest Earnings Volatility Quintile - High CAR

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.4096***	0.3775***	0.1857***	0.1151**	0.0620**
	(7.32)	(3.31)	(4.37)	(2.59)	(2.43)
_cons	0.0039***	0.0055***	0.0076***	0.0079***	0.0089***
	(6.90)	(6.21)	(18.15)	(16.65)	(15.11)
N	365	351	330	297	263
adj. R^2	0.226	0.246	0.119	0.042	0.022

Low CAR (<=median)

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.4690***	0.2799***	0.1168**	0.1047**	0.0950*
	(8.40)	(5.24)	(2.64)	(2.48)	(2.18)
_cons	0.0024**	0.0048***	0.0065***	0.0078***	0.0083***
	(3.05)	(4.95)	(9.94)	(15.50)	(10.63)
N	384	344	302	261	232
adj. R^2	0.299	0.143	0.037	0.039	0.033

Panel C: Regression results for the Lowest Earnings Volatility Quintile - High CAR

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	1.0291***	0.9805***	0.9530***	0.9409***	0.8657***
	(29.74)	(14.87)	(11.74)	(10.02)	(8.02)
_cons	-0.0004	0.0005	0.0008	0.0009	0.0017
	(-0.57)	(0.57)	(0.97)	(0.92)	(1.67)
N	438	397	353	280	216
adj. R^2	0.641	0.536	0.460	0.492	0.503

Low CAR (<=median)

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.8039***	0.6900***	0.7703***	0.7100***	0.7197***
	(13.06)	(7.66)	(9.70)	(6.46)	(7.29)
_cons	0.0019**	0.0034***	0.0025***	0.0031**	0.0025**
	(2.89)	(4.49)	(3.26)	(2.92)	(2.51)
N	381	332	290	224	170
adj. R^2	0.399	0.334	0.182	0.189	0.154

Panel D: Regression results for the Highest earnings volatility quintile, controlling for the level of current earnings - High CAR

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.3818***	0.3240**	0.1084	0.0582	0.0010
	(5.66)	(2.31)	(1.73)	(0.85)	(0.03)
_cons	0.0038***	0.0047***	0.0061***	0.0069***	0.0080***
	(4.00)	(6.00)	(8.72)	(10.94)	(7.83)
N	365	351	330	297	263
adj. R^2	0.232	0.246	0.126	0.044	0.050

Low CAR (<=median)

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.4840***	0.2715***	0.0835	0.0437	0.0023
	(7.79)	(4.66)	(1.32)	(0.78)	(0.06)
_cons	0.0035***	0.0051***	0.0063***	0.0066***	0.0062***
	(3.37)	(3.19)	(5.29)	(5.81)	(5.57)
N	384	344	302	261	232
adj. R^2	0.339	0.157	0.080	0.056	0.059

Panel E: Regression results for the lowest earnings volatility quintile, controlling for the level of current earnings - High CAR

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	1.0213***	0.9472***	0.9439***	0.9364***	0.8914***
	(31.26)	(16.10)	(10.44)	(8.86)	(8.16)
_cons	-0.0005	-0.0001	0.0004	0.0006	0.0019*
	(-0.85)	(-0.14)	(0.31)	(0.67)	(2.11)
N	438	397	353	280	216
adj. R^2	0.640	0.539	0.458	0.490	0.502

Low CAR (<=median)

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+2}$	(3) $Earnings_{t+3}$	(4) $Earnings_{t+4}$	(5) $Earnings_{t+5}$
$Earnings_t$	0.8281***	0.6946***	0.8044***	0.7176***	0.7513***
	(13.09)	(7.78)	(8.68)	(6.24)	(6.49)
_cons	0.0022***	0.0035***	0.0029**	0.0021	0.0011**
	(3.87)	(4.66)	(2.57)	(1.79)	(2.92)
N	381	332	290	224	170
adj. R^2	0.404	0.343	0.184	0.181	0.157

The table reports the results of sub-sample analysis based on the capital adequacy ratio for the effect of earnings volatility for long-term earnings for the full sample (panel A), quintiles of highest earnings volatility (panel B), quintiles of lowest earnings volatility (panel C), and quintiles of highest earnings volatility by controlling for current earnings level (panel D) and quintiles of lowest earnings volatility by controlling for current earnings level (panel D). High CAR is the CAR greater than the median value of CAR, and Low CAR is lower than the median value of CAR. All beta coefficients are statistically significant at the 0.001 level. $Earnings_t$ is defined as earnings before extraordinary item deflated by the average total assets. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. Earnings t is current year Earnings, Earnings t+1 is the one-year ahead Earnings, Earnings t+2 is the two-year ahead Earnings, Earnings t+3 is the three-year ahead Earnings, Earnings t+4 is the four-year ahead Earnings, Earnings t+5 is the five-year ahead Earnings. The t-statistics have shown in the parentheses and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

Table 1. 9: Robustness checks on the influence of past earnings persistence on the documented results

Panel A: Regression results from the model: Earnings $_{t+1}$=α+βEarnings $_t$ +ε by quintiles of AR (1) residual volatility

	(Quintile 1) Earnings$_{t+1}$	(Quintile 2) Earnings$_{t+1}$	(Quintile 3) Earnings$_{t+1}$	(Quintile 4) Earnings$_{t+1}$	(Quintile 5) Earnings$_{t+1}$
Earnings$_t$	0.9737***	0.8906***	0.8839***	0.7266***	0.2448***
	(61.35)	(39.94)	(27.63)	(19.05)	(5.56)
_cons	0.0003*	0.0013***	0.0016***	0.0033***	0.0057***
	(1.74)	(5.80)	(4.83)	(8.34)	(12.69)
Differences in Persistence	0.72				
Differences in R^2	0.84				
N	345	345	344	345	344
adj. R^2	0.916	0.823	0.690	0.513	0.080

Panel B: Earnings persistence using independent sorting on past persistence of Quintile 1 and past volatility of earnings (Quintile 1-5)

Dependent Variable	(Quintile1) Vol (Earn)	(Quintile 2) Vol (Earn)	(Quintile 3) Vol (Earn)	(Quintile 4) Vol (Earn)	(Quintile 5) Vol (Earn)
L.persistence_Q1	0.9728***	0.8716***	0.7453***	0.5673***	0.2164**
	(28.62)	(16.03)	(15.13)	(6.56)	(2.54)
_cons	0.0004	0.0016***	0.0037***	0.0038***	0.0055***
	(1.40)	(2.97)	(7.18)	(4.50)	(5.57)
Differences in Persistence	0.76				
Differences in R^2	0.83				
N	96	121	127	93	81
adj. R^2	0.896	0.681	0.644	0.314	0.064

Panel C: Earnings persistence using independent sorting on past persistence of Quintile 2 and past volatility of earnings (Quintile 1-5)

	(Quintile1) Vol (Earn)	(Quintile 2) Vol (Earn)	(Quintile 3) Vol (Earn)	(Quintile 4) Vol (Earn)	(Quintile 5) Vol (Earn)
L.persistence_Q2	0.8804***	0.8458***	0.9367***	0.5547***	0.2397***
	(32.62)	(19.21)	(14.57)	(6.03)	(2.76)
_cons	0.0012***	0.0018***	0.0012*	0.0042***	0.0041***
	(4.78)	(4.16)	(1.95)	(5.31)	(4.40)
Differences in Persistence	0.64				
Differences in R^2	0.85				
N	114	111	111	77	105
adj. R^2	0.904	0.770	0.658	0.318	0.060

Panel D: Earnings persistence using independent sorting on past persistence of Quintile 3 and past volatility of earnings (Quintile 1-5)

	(Quintile1) Vol (Earn)	(Quintile 2) Vol (Earn)	(Quintile 3) Vol (Earn)	(Quintile 4) Vol (Earn)	(Quintile 5) Vol (Earn)
L.persistence_Q3	0.9159***	0.8751***	0.8298***	0.9123***	0.3478***
	(31.67)	(15.43)	(11.75)	(9.01)	(3.77)
_cons	0.0008***	0.0016***	0.0020***	0.0021**	0.0033***
	(3.26)	(2.84)	(2.98)	(2.49)	(3.54)
Differences in Persistence	0.57				
Differences in R^2	0.76				
N	125	117	93	95	88
adj. R^2	0.890	0.672	0.598	0.461	0.132

Panel E: Earnings persistence using independent sorting on past persistence Quintile 4 and past volatility of earnings (Quintile 1-5)

	(Quintile1) Vol (Earn)	(Quintile 2) Vol (Earn)	(Quintile 3) Vol (Earn)	(Quintile 4) Vol (Earn)	(Quintile 5) Vol (Earn)
L.persistence_Q4	0.9668***	0.8286***	0.8181***	0.7880***	0.4450***
	(34.14)	(19.17)	(13.08)	(13.41)	(5.43)
_cons	0.0003	0.0019***	0.0027***	0.0028***	0.0040***
	(1.05)	(4.73)	(4.36)	(4.87)	(3.66)
Differences in Persistence	0.51				
Differences in R^2	0.53				
N	147	140	110	67	54
adj. R^2	0.889	0.725	0.610	0.731	0.349

Panel F: Earnings persistence using independent sorting on past persistence of Quintile 5 and past volatility of earnings (Quintile 1-5)

	(Quintile1) Vol (Earn)	(Quintile 2) Vol (Earn)	(Quintile 3) Vol (Earn)	(Quintile 4) Vol (Earn)	(Quintile 5) Vol (Earn)
L.persistence_Q5	0.8652***	0.7713***	0.8015***	0.6861***	0.2609***
	(26.16)	(15.39)	(14.49)	(12.32)	(2.98)
_cons	0.0012***	0.0026***	0.0021***	0.0038***	0.0024
	(3.76)	(5.33)	(3.60)	(6.34)	(1.56)
Differences in Persistence	0.61				
Differences in R^2	0.67				
N	127	141	129	79	41
adj. R^2	0.844	0.627	0.620	0.659	0.164

The table reports the effect of earnings volatility on the sum of earnings across the future 5 years where panel A shows the results for the full sample, panel B reports the results for the highest earnings volatility, and panel C reports the results for the lowest earnings volatility. All beta coefficients are statistically significant at the 0.001 level. $Earnings_t$ is defined as earnings before extraordinary item deflated by the average total assets. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. The p-value for the difference in persistence coefficients across quintiles is derived from a t-test. The p-value for the difference in the Adj. R^2 across quintiles is derived from a bootstrap test. Past persistence is the persistent coefficients from the model $Earnings_{t+1}=\alpha+\beta Earnings_t$ using the most recent 5 years. Vol (Residual) is defined as the firm-specific standard deviation of the residuals from the above model. The t-statistics have shown in the parentheses and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

Table 1.10: Incremental Explanatory Power of Earnings Volatility, $Earnings_{t+1} = \alpha_0 + \beta_1 Earnings_t + \varepsilon_{t+1}$

Panel A: Earnings Persistence Regression based on Quintiles of EAR

	(Q1) Earnings $_{t+1}$	(Q2) Earnings $_{t+1}$	(Q3) Earnings $_{t+1}$	(Q4) Earnings $_{t+1}$	(Q5) Earnings $_{t+1}$
Earnings $_t$	0.5603***	0.5573***	0.5371***	0.5232***	0.5121***
	(20.88)	(20.73)	(18.26)	(19.58)	(15.29)
_cons	0.0019***	0.0034***	0.0038***	0.0042***	0.0046***
	(6.37)	(13.00)	(12.93)	(15.24)	(12.55)
N	773	780	777	790	787
adj. R^2	0.360	0.355	0.300	0.326	0.229

Panel B: Earnings Persistence Regression based on Quintiles of z-score

	(Q1) Earnings $_{t+1}$	(Q2) Earnings $_{t+1}$	(Q3) Earnings $_{t+1}$	(Q4) Earnings $_{t+1}$	(Q5) Earnings $_{t+1}$
Earnings $_t$	0.4546***	0.7829***	0.8788***	0.7740***	0.9312***
	(17.26)	(20.74)	(21.69)	(20.60)	(27.48)
_cons	0.0028***	0.0010***	0.0007*	0.0018***	0.0007*
	(8.07)	(3.01)	(1.85)	(4.64)	(1.96)
N	759	797	751	774	822
adj. R^2	0.282	0.350	0.385	0.354	0.479

Panel C: Earnings Persistence Regression based on Quintiles of ROE Volatility

	(1) $Earnings_{t+1}$	(2) $Earnings_{t+1}$	(3) $Earnings_{t+1}$	(4) $Earnings_{t+1}$	(5) $Earnings_{t+1}$
Earnings $_t$	0.8925***	0.8422***	0.6815***	0.7406***	0.2621***
	(22.96)	(18.59)	(18.32)	(20.08)	(6.80)
_cons	0.0011***	0.0015***	0.0031***	0.0025***	0.0051***
	(2.86)	(3.23)	(7.89)	(6.46)	(13.79)
N	417	387	385	366	392
adj. R^2	0.559	0.472	0.466	0.524	0.104

The table reports the result of the earnings persistence regression of the quintiles of equity to assets ratio (panel A), quintiles of z-score (panel B), and quintiles of return on equity volatility (panel C). EAR is defined as the banks' equity to assets ratio. Z-score is defined as (ROA+EAR)/SD of ROA (use the logarithm of z-score). ROE is defined as a banks' return on equity. All beta coefficients (persistence) are significant at the 0.001 level. The p-value for the difference in persistence coefficients across quintiles is derived from a t-test. The p-value for the difference in the Adj. R^2 across quintiles is derived from a bootstrap test. $Earnings_t$ is defined as earnings before extraordinary item deflated by the average total assets. |Accruals| is the absolute amount of Accruals. Vol (Earnings) is defined as the firm-specific standard deviation of Earnings over the most recent 5 years. CFOs is defined as the cash flow from operating activities deflated by average total assets. Vol (CFOs) is defined as the firm-specific standard deviation of CFOs over the most recent 5 years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

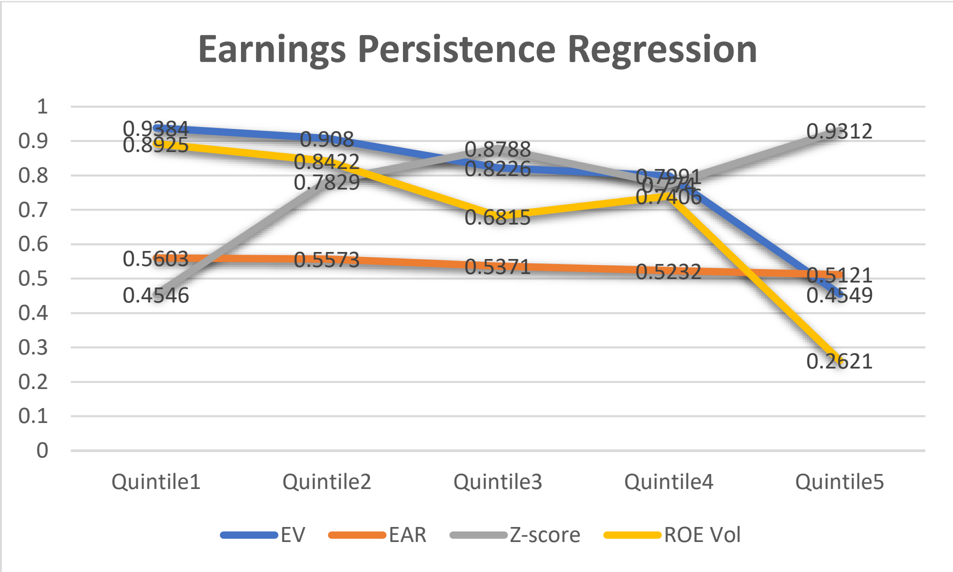


Figure 1.4 Incremental Explanatory Power of Earnings Volatility

Figure 4 reports the coefficients of earnings persistence regression based on the model ($Earnings_{t+1} = \alpha_0 + \beta_1 Earnings_t + \varepsilon_{t+1}$) by quintiles of earnings volatility, quintiles of equity to assets ratio, quintiles of z-score, and quintiles of return on equity volatility. The graph plots the comparison among all the specifications where it is evident that the persistence coefficients of quintiles of earnings volatility plot larger value and a monotonically decrease in coefficients compared to the other measures. Thus, it proves that earnings volatility possesses an incremental explanatory power compared to other measures of banks' risk-taking behavior.

Chapter 2

Is there an Optimal Risk-Taking in Banks?

Abstract

This study examines how banks manage their risk-taking behavior in the face of high earnings volatility. Specifically, I address the question of whether, given high earnings volatility, is there an optimal risk-taking in banks? I propose two partial risk adjustment mechanisms, one with a cross-section and the other with a time series in a banking setting. I find strong evidence that banks have an optimal risk level. Next, I investigate if there is an optimal risk then how quickly banks adjust toward the optimal level. I find banks converge toward the optimal risk level with the speed of 23.78% per year. After that, I show how the risk adjustment differ in terms of short- and long-term. In the short run λ_2 equal to λ_1 and in the long run λ_2 and λ_1 equal to 1 because bank adjust to the target risk level fully. Finally, I test the presence of an asymmetric effect in banks' risk adjustment mechanisms. I test whether over risk-taking or under risk-taking is costly for banks and how bank manage their risk-taking during high earnings volatility.

Keywords: Bank risk-taking, Earnings volatility, Partial risk adjustment.

2.1 Introduction

The global financial crisis (2007–2008) highlighted the importance of banks' risk-taking behavior for regulators, academics, and public media. After the failure of Lehman Brothers in 2008,[2] regulators and researchers focused on implementing steep requirements to be met by banks to stabilize the banking system. The financial crisis thus highlighted the instability resulting from banks' excessive risk-taking behavior, and public policymakers worldwide have questioned whether risk-taking by financial institutions is appropriate. The risk management of banks is subject to regular monitoring. Banking supervisors impose several regulations (capital and liquidity) to increase the resilience of the banking sector. For example, in response to the financial crisis, the Basel Committee on Banking Supervision (2008) implemented the Basel III Accord, which includes measures to strengthen the regulation, supervision, and risk management of banks. Studies also suggest that a high capital ratio can mitigate the excessive risk-taking behavior of banks[3] and Hao and Zheng (2021) show that low-capital banks significantly reduce their loan risk.

Thus, given the importance of banking institutions in modern market-based economies, banks' risk-taking behavior should be examined. Financial market participants can benefit from a better understanding of bank risk. For example, regulators and market supervisors are responsible for maintaining financial stability in the economy and therefore have a strong interest in bank risk. Borrowers, who depend solely on bank health for credit, are also affected, and shareholders and bondholders typically monitor systemic and total bank risk, respectively

[2] The largest bankruptcy filing in U.S. history was around US$600 billion in assets.

[3] See Bernanke and Blinder (1989) for theoretical evidence; Chava and Purnanandam (2011).

(Haq & Heaney, 2012). Thus, banking institutions and their economic stability affect the various financial market participants in terms of bank default risk. Therefore, banks are likely to ensure they have optimized the level of risk when faced with strong regulatory pressure, to maintain their stability.

Many empirical studies examine banks' risk-taking behavior.[4] However, none of these studies investigate the optimal risk-taking behavior of banks. In this study, I take a dynamic approach to exploring banks' optimal risk-taking behavior and the effects of earnings volatility on their decisions concerning risk. I regard banks' earnings volatility as a measure of risk-taking, as more volatile earnings may lead to uncertainty about the level of equity capital and thus deteriorate banks' soundness (Couto, 2002). Albertazzi and Gambacorta (2009) suggest that excess volatility in bank earnings can disrupt the stability of capital structures.[5] Froot et al. (1993) and Froot and Stein (1998) present a rigorous theoretical analysis of how financial market frictions affect non-financial firms' investments and banks' lending and risk-taking decisions. Their model suggests that active risk management can allow banks to hold less capital and invest more aggressively in risky and illiquid loans, which can reduce the volatility of their earnings. Although the current practice of bank risk management largely focuses on assessing and dealing with potential losses, while I suggest a dynamic approach in which the

[4] For example, Saunders et al. (1990); Demsetz and Strahan (1997); Froot and Stein (1998); Bauer and Ryser (2004); Leaven and Levin (2009); Ellul and Yerramilli (2013); Frame et al. (2020).

[5] These empirical studies are consistent with the theoretical study conducted by Froot and Stein (1998), who propose that banks' risk management strategies are developed from the perspective of capital budgeting and capital structure policy.

objective of bank risk management is to achieve an optimum level of risk-taking to ensure a desired level of future earnings.

The present study is motivated by the research of Dichev and Tang (2009), who outline several implications for banks' risk-taking behavior[6]. They propose that a firm's earnings predictability depends on earnings volatility. If earnings volatility is high, future earnings will be less predictable. Based on this proposition, in my second essay I examine how banks manage their risk-taking behavior when faced with high earnings volatility. I address the following questions. First, given high earnings volatility in banks, is there an optimal level of risk in banks? Second, if there is an optimal risk level, how quickly do they adjust to this optimal level of risk? Third, how does the risk adjustment mechanism differ in the short and long term? Finally, I test the asymmetric effects of banks' risk adjustment mechanisms.

The irrelevance theory of leverage (Modigliani and Miller, or MM, 1958) states that in a world of perfect markets, a firm's financial decisions are not relevant to its value. Such decisions do not change the value of shareholders' wealth, so the capital structure and risk management choices of a firm do not affect its wealth maximization decisions (Bauer and Ryser, 2004). Stulz (2014) suggests that for the MM theory (1958) to hold, markets must be frictionless and without any transaction costs. Modern banking research, however, states that under such conditions of irrelevance, banks would become redundant institutions and would not exist (Freixas and Rochet, 1998). Therefore, whether banks are financed by equity or debt does not affect their assets because the asset value remains the same regardless of their risk of

[6] The implications of Dichev and Tang's (2009) study on Bank's risk-taking behaviour are explained in Chapter 1.

distress or default.[7] Consequently, when the MM theorem does not apply, the most debated issue in managing bank risk is that the adverse effect may lead to bankruptcy, which is costly for banks (Smith & Stulz, 1985).[8] On the one hand, an increase in risk may allow a bank to invest in risky assets and valuable projects. On the other hand, such investments may lead to a loss of bank value due to the adverse impact of the risk of financial distress (bankruptcy cost) and the ability to generate value through its deposit (liabilities). Therefore, from the perspective of shareholders, there is an optimal amount of risk in banks which suggest them to process their risk from a level that ensures that they do not deviate from their targets (Stulz, 2014).

Regulatory reforms and the dynamic nature of banks' risk-taking should therefore lead them to optimize their risk-taking behavior. I propose two partial risk adjustment mechanisms for banks' optimal risk-taking behavior, in which risk adjustment occurs in the cross-sectional and time-series variations of a bank setting. The empirical models of this study rationalize the hypothetically dynamic nature of banks' risk-taking behavior. These models are broad enough to examine the presence of optimal risk-taking in banks (if any). After confirming the presence of optimal risk-taking in banks, these comprehensive models can help determine the speed of adjustment toward an optimal level of risk.

I begin the analysis using U.S. bank data, from which I find evidence to support my predictions. I find that banks follow optimal risk-taking behavior, with typical banks converging to their optimal level of risk at a rate of 23.78% per year. Model 1, which measures

[7] Stulz (2003); a bank does not need to manage its risk of distress or default if the MM theorem applies.

[8] Bauer and Ryser (2004) find that the neoclassical MM theorem is logically inconsistent in analyzing the optimal hedging and capital structure decisions of banks. They state that the key to understanding banks' role and financial decisions are information asymmetry and transaction costs.

partial risk adjustment, provides evidence for the mechanism of optimum risk adjustment. I hypothesize that proxies of the optimal risk adjustment mechanism α_1 ($\lambda_1 - \lambda_2$) represent the adjustment differences towards the cross-sectional average in a given time period and α_2 (λ_2) is the risk adjustment mechanism, is negative (α_2<0). The results are consistent with this hypothesis. From Model 1, I can infer the optimum risk adjustment mechanism with speed of adjustment. I find that λ_1 and λ_2 are the same and the speed of risk adjustment is measured by λ_2 and λ_1. I then conclude that the rate (speed) of adjustment is 23.78% in one year. The effect can then be demonstrated over the long term (five years), and the risk will adjust fully to the optimum level in this timeframe.

Model 2 measures the partial risk adjustment and reveals the time series (*DTS*) and cross-sectional (*DCS*) risk adjustment mechanism, in which I assume that optimum risk is the time series mean of the cross-sectional mean. Thus, the cross-sectional and time series risk adjustment mechanisms reflect adjustments in bank risk-taking across the whole sector. In the short term, most of the risk adjustment appears to be through the cross-sectional mechanism but in the long term both cross-sectional and time series adjustments are prominent and significant. The evidence shows that cross-sectional risk adjustment (*DCS*) estimate is about 23.78% and the time series risk adjustment speed (*DTS*) estimate is around 0.78%, which indicates that due to cross-sectional variations across firms, individual firms adjust back to their optimal risk level more quickly than the industry as a whole. Moreover, banks adjust their risk-taking towards cross-sectional means is due to learning channel. Eventually, banks would learn whether the cross-sectional mean is too targeted or not. Thus, a greater cross-sectional deviation from the time-series mean will lead to a greater adjustment in risk-taking, which represents the combination of the two mechanisms in risk-taking.

I use alternative estimation methods in equation (1) to support the partial risk adjustment mechanisms.[9] To model optimal risk-taking, I incorporate a set of bank characteristics ($X_{i,t}$) that are commonly used in the literature (e.g., Fang et al., 2012; Shrives & Dahl 1992; Aebi et al., 2012; Bromiley, 1991). I investigate the determinants of banks' risk-taking behavior and measure the effects of current earnings volatility on future earnings volatility from year t+1 to year t+5. The coefficients of lagged earnings volatility ($EV_{i,t}$) indicate that the speed of adjustment is 23.38% (1 - λ = 1 - 0.7662), which is close to the *DCS* estimates of 23.78%. The result suggests that banks close 23.38% of the gap between their actual and target risk levels within a year.

Next, I assess the dynamic nature of banks' risk-taking behavior when considering my main research question of whether optimal risk-taking is evident in the banking industry and that banks tend to converge toward an optimal risk level. In this approach, current earnings levels and earnings volatility play definite roles in banks' risk-taking strategies because these two factors play important roles in predicting banks' future earnings. This implies that low (high) earnings volatility and a high (low) level of earnings will then represent the best (worst) risk management strategy for banks (see Figure 1). To examine the dynamics of banks' average risk-taking (Figure 2), I use the standard deviation of earnings over the next five years, and thus a clean test with little correlation can be conducted. I identify changes in the pattern of bank risk (earnings volatility) over time without any induced correlation and the general tendency of high-risk banks to revert to the optimal mean. Figure 2 shows that after a specific

[9] I model banks' risk-taking behavior using the following partial risk adjustment model:

$$\Delta EV_{i,\,t+1} = \lambda_1 (EV^* - EV_{i,\,t}) + \varepsilon_{t+1}$$

time period (t+3 or 15 years), all of the portfolios converge to meet the objectives of bank risk management. Notably, the dynamics of banks' risk-taking exhibit significant convergence over time. Those with relatively low (high) risk tend to move toward an optimal level of risk after a certain amount of time, thus proving that banks follow optimal risk-taking behavior.

I then assess how the risk adjustment differs in the short-term and long-terms. In Model 2, I test whether the coefficients of λ_1 and λ_2 are equal. I offer a null hypothesis as the coefficients of λ_1 are equal to λ_2. I assess the parameters of Model 2 using the Wald test. Consistent with my assumption, the Wald test of post estimation shows that the parameters are equal to each other. Thus, the null hypothesis (H0: $\lambda_2 = \lambda_1$) is confirmed with a p-value of 0.6817. However, in the short term (t+1), I obtain no significant result (0.0078) in the whole sector adjustments (DTS) due to the noisy data. In the long term (t+5), the adjustments are more visible with a co-efficient of 1.1644 and a 1% significance level.

I also expect that in the long run (t+5), banks should adjust back to the target risk level fully (100%). The speed of adjustment is 23.78% per year, so after five (5) years they will adjust fully (23.78*5 = 118.9% equivalent to 100%). The null hypothesis is, λ_2 and λ_1 are equal to 1 or ($\lambda_2 - \lambda_1 = 0$). The evidence confirms that banks fully adjust back to the target risk level. The co-efficient of *DTS* and *DCS* in Model 2 are 1.1644 and 1.1163 respectively, and thus λ_1 and λ_2 are very close to each other. The p-value of the Wald test result is 0.1142 which indicates that the null hypothesis is accepted (H0: $\lambda_2 =1$; $\lambda_1 =1$). However, due to the sampling error in the observations, the deviation between λ_2 and λ_1 may not be exactly equal to 0 ($\lambda_2 - \lambda_1 \neq 0$).

I then demonstrate an asymmetry effect in the speed of risk adjustment, due to banking stability and regulatory reforms. Using cross-sectional data, I examine how banks adjust to their optimal level of risk when there is excess volatility (risk). Due to the importance of risk management in banks, managers and owners must manage their risk carefully. Therefore, I propose that the cost of excessive risk-taking is higher than that of low risk-taking. Consequently, the risk adjustment asymmetry between excessive or low risk-taking should be relative to the optimal level of risk. Consistent with this hypothesis, I find that the coefficients of low risk-taking ($DCS^{positive}$) are lower (0.0680, 0.980) than those of excessive risk-taking ($DCS^{negative}$) (0.269, 1.149), both in the short and long term. These results suggest that for the banking industry, over risk-taking is much costlier than under risk-taking. Banks aim to evade the possible cost of financial distress associated with excessive risk-taking beyond the optimal level of risk, which is consistent with the dynamic nature of banks' risk-taking behavior.

Finally, to check the robustness of the asymmetric effect in the speed of risk adjustment, I examine the interaction effect between *DCS* and bank earnings (*ROA*) and investigate the role of earnings, whether excess or low risk-taking increases earnings. I predict that in the short term, low risk-taking increases bank earnings and excessive risk-taking decreases earnings. However, in the long term, low risk-taking decreases bank earnings and excessive risk-taking increases earnings. The findings are consistent with my predictions. The results suggest that banks experience larger reductions in earnings if they take excessive risk as the coefficient of the interaction term ($DCS^{(negative)} \times ROA$) is positive. Banks thus experience greater reductions in earnings if they take more risks. The results generally suggest that banks incur greater costs through high risk-taking and that the speed of adjustment may depend on the level of banks' earnings.

To further confirm the asymmetry in the speed of adjustment, I include the interaction effects between the *DCS* and other bank-specific variables (e.g., *LLP*, *Leverage*) and assess whether the effect of earnings changes. I estimate the interaction terms between the low and excessive risk adjustment proxies and other bank-specific variables. I regress the cross-sectional risk adjustment proxy (DCS) and other bank-specific variables on changes in earnings volatility from year t+1 and year t+5. I find that the sign of the interaction term between the risk adjustment proxy and earnings remains the same. Next, I incorporate the interaction between loan loss provisions (*LLP*) and risk adjustment and find that banks with excessive risk-taking record more loan loss provisions (LLPs), as they expect more loan defaults by their customers. I also add the interaction effect of risk adjustment and leverage, which indicates that the costs of low risk-taking and excessive risk-taking are negatively related to leverage. This implies that at any level of risk-taking reduces banks' leverage. Overall, the results suggest that for the banking industry, the cost of excessive risk-taking is higher than that of low risk-taking relative to the optimal level of risk. Thus, due to asymmetry, high (excess) levels of risk cost relatively more, and the reduction in banks' earnings leads them to increase their LLPs.

I conduct a number of robustness checks. First, I use several alternatives measure of banks' risk-taking. I use the market-based measure of banks' risk-taking for example, stock return volatility, z-score and equity capital ratio. The stock return volatility (SRV) and z-score measures of banks risk-taking suggest that banks also adjust toward the target risk. However, the resulting adjustment is quicker than that measured by earnings volatility (EV). The speed of risk adjustment (SOA) in SRV and z-score is much quicker around 77.86% and 38.76% respectively (SOA is 23% in EV measure). The coefficients of the long-term measure of time-series (DTS) and cross-sectional (DCS) proxy are very similar. This suggest that in the long-term, the speed of adjustment is 100% that means the risk will be fully adjusted. However, in the measure of equity capital ratio (ECR), the results of Model 1 indicate an adjustment toward the target (SOA is quicker around 35.51%) and more adjustment occur in the cross-section proxy. However, in the Model 2, no optimal capital ratio may be presented, as the coefficients of time-series and cross-sectional proxies are different in the long-term. Because ECR is more dynamic and ECR may have a different target for different types of firms depending on the firm's requirements. Thus, the results of ECR measure imply that it has different effects.

Next, to interpret the effects of control variables on earnings volatility correctly, I use control variables of time t-5 as a robustness check. I use the control variables before the start of the rolling period, which is time *t-5*. I find not much change in the results. The results hold for the alternative measure of control variables and with these variables I find that banks close 21.78 % of the gap between their actual and target risk level within 1 year which is very close to the baseline result of 23.38%.

This study contributes to the vast literature on banks' risk-taking behavior. Studies focus on optimal risk-taking strategies through hedging (Froot & Stein, 1998; Bauer & Ryser, 2004), the effects of economic shocks or variables on banks' risk-taking behavior, or increases or decreases in banks' risk-taking. For example, Saunders et al. (1990) study the effect of ownership structure and deregulation on the risk-taking behavior of banks. Using an international sample, Laeven and Levin (2009) demonstrate the effects of governance and regulation on banks' risk-taking behavior. Frame et al. (2020) also provide evidence that foreign investment and regulatory arbitrage change banks' risk-taking behavior. Hao and Zhang (2021) show that the equity capital ratio influences the association between competition and banks' risk-taking behavior. They estimate the effect of competition on banks' risk-taking and argue that this will be influenced by their average equity capital ratio.

I provide new evidence that banks follow optimal risk-taking behavior and contribute to the literature by developing partial risk adjustment models to estimate the optimal level of risk for banks. My proposed mechanisms are consistent and efficiently estimate the heterogeneous adjustment speeds of banks' risk-taking. I demonstrate that bank-level characteristics determine the speed of adjustment and thus identify an asymmetry in the mechanism. My study is related to the study conducted by Flannery and Rangan (2009), which is based on the target capital structure. My findings also contribute to the literature that applies bank risk adjustment models, such as this studies conducted by Shrives and Dahl (1992), Dahl and Shrives (1990), Wall and Peterson (1988), Marcus (1983), and Peltzman (1970), all of whom apply the partial adjustment framework to model bank risk and capital decisions. Unlike those that consider firm-level (bank-level) characteristics to capture the target level of risk, in my proposed model I consider cross-sectional and time series risk adjustment models to observe how the industry and individual banks adjust to optimal levels of risk. Moreover, the short- and long-term models I apply also consider the heterogeneous asymmetry of bank adjustment speed, both in terms of rates (short-term asymmetry) and target risk levels (long-term asymmetry).

Finally, this study contributes to the literature by identifying the importance of bank earnings. I regard earnings as a primary indicator of a bank's financial health, but they can additionally indicate weakness. Banking supervisors are often concerned about banks' operating performance (Cohen et al., 2012). I also note that the implications of earnings volatility in estimating banks' optimal level of risk. I consider the dynamics of banks' average earnings volatility and show that after a specific time period (t+3), high- and low-risk banks converge to an optimal level, due to regulatory pressure from banking supervisors.

The remainder of the paper is organized as follows. Section 2 reviews the literature and provides the background for my research, followed by the development of my hypotheses. In Section 3, I introduce the sample, data, and research design, after which I discuss the empirical results in Section 4. Finally, I conclude the study in the last section.

2.2 Background and Model Specifications

2.2.1 Risk Adjustment and Earnings

The risk management decisions of banks are determined by the extent of their role in the economy and the potential consequences of their failure. Banking regulators therefore enforce restrictions on banks, which can lead them to take excessive risks through the imposition of minimum capital requirements. Thus, the systemic risk of banks is reduced, as their levels of risk-taking are determined by the restrictions. However, these restrictions do not alter the bottom line, which indicates the presence of an optimal risk level in the banking industry (Stulz, 2014). This level differs across banks based on the nature of their business and their characteristics. Therefore, the risk adjustment decisions in banking sector differ due to cross-sectional variations.

The theoretical mean-variance framework of utility maximization suggests that a bank with a preference for low risk will choose risky assets, and vice versa. Option pricing theory proposes that maximizing shareholder value involves increasing risk by maximizing the option value of deposit insurance, as a flat-rate pricing method incentivizes bankers to take risks. In terms of option pricing, the incentive to take risks depends on the level of risk. Banks can issue additional debt (deposit) claims without paying a default risk premium; the marginal benefit of doing so increases assets' risk level. Thus, variations in banks' risk-taking behavior are in part exogenously estimated by changes in their environment, with banks responding (more or less) continuously to the changing marginal incentive by adjusting their risk levels.

If the option pricing framework is valid, Shrives and Dahl (1992) question why banks do not exhibit infinite levels of risk-taking and leverage. They conclude that the risk-levels are finite due to the costs of high risk-taking and leverage, as the degree to which risk and leverage can increase when exploiting the advantage of deposit insurance subsidies is limited. The factors that affect the internal optimal level of risk, marginal costs of risk, and benefits of risk are the same. Thus, the rationale for risk adjustment of banks is based on the substantial risk-related costs such as regulatory costs, minimum capital standards, bankruptcy cost avoidance, and managerial risk aversion.

Dichev and Tang (2009) document the incremental explanatory power of earnings and shows how past earnings volatility has strong predictive power for future earnings persistence. Earnings persistence can be used to forecast returns (Sloan, 1996) and current earnings have a significant role in valuation (Frankel and Litov, 2009). In addition, the literature suggests that considering earnings persistence and earnings volatility can offer insights into the risk-taking behavior of the banking industry. Low earnings volatility leads to low earnings persistence, and to increase their earnings banks must take more risks. Thus, forecasting the earnings levels of firms is important for banks in terms of providing estimates of their equity value and their risk levels. I therefore consider earnings persistence and estimate the risk-taking behavior of banks using changes in earnings volatility to estimate my partial risk adjustment models.

I use a regression specification to assess the dynamic nature of banks' risk-taking behavior. This allows each bank's optimum level of risk to diverge over time and ensures that deviations from the optimal level of risk are not necessarily quickly offset. Both requirements should be satisfied in a model with partial (incomplete) adjustment toward optimal risk-taking conditional on banks' characteristics.

2.2.2 Partial Risk Adjustment Framework

The literature on firms' target capital structure, banks' target capital, and risk levels is well established. For example, Flannery and Rangan (2006) propose a standard partial adjustment model for U.S. firms. They assess whether firms have a long-term target capital structure and how fast they converge to their target levels of risk. In addition, extensive research addresses the behavior of banks using a partial adjustment framework.[10] Following Shrives and Dahl (1992), I model banks' risk-taking behavior using the following partial adjustment model:

$$\Delta EV_{i,\,t+1} = \lambda_1 (EV^* - EV_{i,\,t}) + \varepsilon_{i,t+1} \tag{1}$$

where ΔEV_{t+1} is bank i's earnings volatility in year t+1. Earnings volatility in year t is the change in bank i's risk in year t+1, EV^* is the target risk level, and λ_1 represents the speed of adjustment. EV^* can vary cross-sectionally and cannot be directly observed, making it difficult to estimate. Therefore, I must infer EV^* by regressing it on bank-specific variables. From the above model, I can examine how adjustments are made at industry and individual bank levels. I first transform Equation (1) into Equation (2) to observe how the industry and individual banks adjust to their optimal levels of risk. Thus, I propose the following equations

$$\Delta EV_{i,\,t+1} = \lambda_1 (EV^* - \mu_t + \mu_t - EV_{i,\,t}) + \varepsilon_{i,\,t+1} \tag{2}$$

$$= \lambda_1 (EV^* - \mu_t) + \lambda_1 (\mu_t - EV_{i,\,t}) + \varepsilon_{i,\,t+1} \tag{3}$$

$$= \lambda_1 EV^* - \lambda_1 \mu_t + \lambda_2\, \mu_t - \lambda_2\, EV_{i,\,t} + \varepsilon_{i,\,t+1} \tag{4}$$

Here, the cross-sectional mean of risk is denoted by μ_t, which should be canceled out. However, if I assume that banks have different speeds of adjustment, I can write the above equations as

$$\Delta EV_{i,\,t+1} = \lambda_1 EV^* - (\lambda_1 - \lambda_2)\, \mu_t - \lambda_2\, EV_{i,\,t} + \varepsilon_{i,\,t+1} \tag{5}$$

From Equation (4), I propose the partial risk adjustment Model 1 for banks' risk-taking behavior. Thus, I can rewrite Model 1 as

$$\Delta EV_{i,\,t+1} = \alpha_0 + \alpha_1 * \mu_t + \alpha_2 * EV_t + \varepsilon_{i,t+1} \tag{6}$$

$$\alpha_1 = -\,(\lambda_1 - \lambda_2)$$

[10] See Shrives and Dahl (1992), Dahl and Shrives (1990), Wall and Peterson (1988), Marcus (1983), and Peltzman (1970), who apply the partial adjustment framework to model banks' risk and capital decisions.

$$\alpha_2 = - \lambda_2$$

In the next step, I assume that EV^* is the time series mean of risk level (μ^{-}). Thus, I propose the partial risk adjustment Model 2 and rewrite Equation (2) as

$$\Delta EV_{i,\, t+1} = \lambda_1 (\mu^{-} - \mu_t) + \lambda_2 (\mu_t - EV_{i,\, t}) + \varepsilon_{i,\, t+1} \qquad (7)$$

In Equation (6), I propose a parsimonious model that has a sufficient number of predictors to adequately explain Model 2, and thus has optimal parsimony. To simplify the variable names, I rewrite Model 2 as

$$\Delta EV_{\,i,t+1} = \lambda_1 DTS_t + \lambda_2 DCS_t + \varepsilon_{t+1} \qquad (8)$$

where $DTS = (\mu^{-} - \mu_t)$ and $DCS = (\mu_t - EV_t)$

μ_t = Cross-sectional mean of earnings volatility in year t

μ^{-} = Time series mean of μ_t

Here, *DTS* represents the difference between μ^{-} and μ_t at time t; it is used as a proxy for risk adjustment at the industry level. *DCS* represents the difference between μ_t and EV_t at time t, which is also used as a proxy for cross-sectional risk adjustment. λ_1 and λ_2 are the vectors of coefficients to be estimated and represent banks' speed of adjustment to their optimal risk levels. The observed changes in the level of risk at time t+1 are a fraction of λ_1 and λ_2 of the expected change for that period. If either λ_1 or λ_2 is equal to 1, the actual level of risk will be equal to the expected level of risk, i.e., adjustment to the optimal level will be prompt. In contrast, if either λ_1 or λ_2 is equal to 0, no risk adjustment occurs because the actual level of risk at time t+1 is equal to the observed level of risk at time t. Naturally, the estimates of λ_1 or λ_2 will then lie between 0 and 1 because adjustment to the optimal level of risk will likely be partial. Here, I rewrite the model as

$$EV_{t+1} - EV_t = \lambda_1 (\mu_t - EV_t) + \lambda_2 (\mu^{-} - \mu_t) + \varepsilon_{t+1} \qquad (9)$$

After replacing μ_t by μ^{-}, I get

$$EV_{t+1} - EV_t = \lambda_1 \mu_t - \lambda_1 EV_t + \lambda_2 \mu^{-} - \lambda_2 \mu_t + \varepsilon_{t+1} \quad (10)$$

$$= (\lambda_1 - \lambda_2) \mu_t - \lambda_1 EV_t + \lambda_2 \mu^{-} \quad (11)$$

Thus, my model adopts partial instead of complete simultaneous adjustment, assuming that immediate adjustment to the optimal level of risk is either costly or infeasible. Here, the constant is $\lambda_2 \mu^{-}$. Hence, I propose the time series risk adjustment Model 2 as

$$\Delta EV_{t+1} = \beta_1 *(\mu^{-} - \mu_t) + \beta_2 *(\mu_t - EV_t) + \varepsilon_{t+1} \quad (12)$$

From the regression of Model 2, I find that the coefficients of λ_1 and λ_2 are very similar in value. Thus, if I add the intercept in Model 2, it will become redundant. Therefore, I exclude the intercept from Model 2 as the constant is $\lambda_2 \mu^{-}$. Overall, Model 1 allows for broader inferences from Model 2, specifically for *DCS*. In addition, I also use unobserved effects (fixed effects) to capture constant but unobserved bank-specific effects of each bank's risk-taking behavior over time. I thus exclude the intercept from Model 1 to reduce redundancy. I find that the unobserved effects explain a large proportion of the cross-sectional variation in banks' risk-taking behavior.

I propose two risk adjustment mechanisms, based on the discussed framework, for banks' risk management and earnings. I state my first hypothesis as follows:

H1: From risk adjustment Model 1, the proxies for the optimum risk adjustment mechanism are negative.

$$\Delta EV_{i,\,t+1} = \lambda_1 EV^{*} - (\lambda_1 - \lambda_2) \mu_t - \lambda_2 EV_{i,\,t} + \varepsilon_{i,\,t+1} \quad (5)$$

$$\Delta EV_{i,\,t+1} = \alpha_0 + \alpha_1 {*} \mu_t + \alpha_2 {*} EV_t + \varepsilon_{i,t+1} \quad (6)$$

I expect that, $\alpha_1 = -(\lambda_1 - \lambda_2)$ and $\alpha_2 = -\lambda_2$, That means the difference between λ_1 and λ_2 and λ_2 at time t (α_2) will be negative.

I then assess how risk adjustment differs in the short and long terms. According to the propose partial risk adjustment mechanism (Equation 2), I propose the null hypothesis as, H0: $\lambda_2 = \lambda_1$ in the short term. Following Equation 4, banks fully adjust to the target risk level (100%) in the long term, and thus H0: $\lambda_2 = 1$; $\lambda_1=1$ or ($\lambda_2 - \lambda_1=0$). Therefore, I propose my second hypothesis as follows:

H2: From risk adjustment Model 2, in the short term, the null hypothesis is β_2 equal to β_1 and in the long run the deviations between β_2 and β_1 equal to 0.

$$\Delta EV_{i,\,t+1} = \lambda_1 (\bar{\mu} - \mu_t) + \lambda_2 (\mu_t - EV_{i,\,t}) + \varepsilon_{i,\,t+1} \qquad (7)$$

$$\Delta EV_{t+1} = \beta_1 *(\bar{\mu} - \mu_t) + \beta_2 *(\mu_t - EV_t) + \varepsilon_{t+1} \qquad (12)$$

I expect that in the short term, H0: $\beta_2 = \beta_1$ and in the long term, H0: ($\beta_2 - \beta_1 = 0$)

The global financial crisis has led to increased concerns about banking stability. Together with regulatory reforms, this has an asymmetrical effect on the speed of risk adjustment when considered in the partial risk adjustment framework. This can help determine whether banks with high or low levels risk are more likely to quickly adjust to optimal risk levels. This also implies that taking excessive or little risk is costly. Regulatory requirements, which have been extensively investigated, are a likely reason for banks to not to engage in as much risk as they possibly can (e.g., Kahane, 1977; Buser et al., 1981; Cambell et al., 1992; Bhattacharya &

Thakor, 1993; Gjerde & Semmen, 1995; Besanko & Kanatas, 1996).[11] Bauer and Ryser (2004) model banks banks' risk-taking behavior as restricted by a regulator. They show that bank managers face conflicting incentives for risk management. On the one hand, regulatory restrictions and liquidation costs limit the risk-taking behavior of banks; on the other hand, the limited liabilities of banks create incentive for risk-taking. I therefore predict that regulatory restrictions force high-risk banks to adjust their optimal risk levels faster. Hence, I state my third hypothesis as follows:

H3: Banks with over risk-taking adjust their optimal risk levels faster than banks with under risk-taking.

2.3 Data

2.3.1 Sample Selection and Variable Description

In my sample design, I use U.S. bank data collected from Compustat's Bank Fundamentals Annual North America Database. I use all available annual bank data as I focus on their short- and long-term risk adjustment mechanisms. However, most banking studies, such as Beatty and Liao (2011) and Bushman and Williams (2012, 2015), use quarterly observations. Following Dichev and Tang (2009), I begin my sample in 1984 and use earnings data over the 1984–1988 period to estimate earnings volatility as a measure of banks' risk-taking behavior. I truncate the bottom and top 1% of earnings data and other variables to ensure that extreme observations do not skew the results. I impose one additional sample selection criterion. To

[11] Kahane (1977) was the first to model how regulations restrict capital ratios and asset portfolios. See Bhattacharya and Thakor (1993) for an extensive review of the literature.

simplify the empirical analysis and interpretation of the results, I restrict the data to 12/31 fiscal year-end observations. After incorporating all of the sample selection criteria, my final sample consists of 20,600 bank-years for the 1988–2020 period.

As I focus on banks' earnings volatility, I use changes in earnings volatility to estimate a proxy for banks' risk-taking (the dependent variable) using a partial risk adjustment model.[12] I regard earnings as income before extraordinary items, as defined by Compustat and scale them by average total assets. I use the standard deviation of deflated earnings over the previous five years to measure volatility. I estimate changes in earnings volatility at time t+1 (ΔEV_{t+1}) by taking the difference in earnings volatility between time t+1 and time t. Similarly, to estimate changes in earnings volatility at time t+5 (ΔEV_{t+5}), I take the difference in earnings volatility between time t+5 and time t. I propose two risk adjustment measures to estimate my explanatory variable. First, $\mu_t - EV$ in year t gives the cross-sectional proxy that contains bank-specific information, and second, the difference between $\bar{\mu}$ - μ_t in year t., which is a time series proxy that contains industry-level information. Details of these risk adjustment measures are discussed in the Framework Section (2.2).

2.3.2 Bank-Specific Variables

In the empirical analysis of partial risk adjustment, I use several bank-specific variables, which are discussed below. First, a bank's current performance may have a negative effect on its future risk-taking behavior, and those with poor performance are likely to take more risks in the future to increase their earnings (*ROA*), while those with good performance will take

[12] Such as Shrives and Dahl (1992) and Jokipii and Milne (2011).

fewer risks in the future to reduce their earnings volatility (risk). Thus, I include *ROA.* Next, I use the ratio of current loan loss provisions (*LLP*) because a bank's loan losses affect its future risk-taking behavior. Banks with high *LLP* tend to have high earnings volatility (risk) in the future. To alleviate the risk of potential expected losses, banks will take more risk in the future to increase their earnings; the worst scenario for banks is to have high volatility and low earnings. Thus, I assume a positive relationship between *LLP* and future earnings volatility.

I control for other variables in addition to those mentioned above in a further analysis of risk-taking. In the accounting and finance literature, firm size is a general control variable commonly used in the literature. I control for bank size ($SIZE_{i,t}$) because it plays a role in estimating banks' risk appetite as it affects their investments, diversification opportunities, and access to equity capital (Haan & Poghosyan, 2012). Large banks are more financially stable than small banks. Boyd and Runkle (1993) state that regulatory treatment is asymmetric, as it is based on bank size. Large banks can thus take more risk because they have more government protection than small banks. I also control for the risk-adjusted capital ratio (Aebi et al., 2012) and the deposit and loan ratios (Fang et al., 2014). The loan ratio ($Ln\ Loan\ ratio_{i,t}$) influences a bank's risk because it is possible for the bank to face more risk if it extends credit to financially unhealthy clients with an expectation of higher future earnings. Banks change their risk-taking behavior based on their equity and deposits, and thus I include the risk-adjusted capital ratio ($Tier\ 1\ capital\ ratio_{i,t}$) and the deposit ratio. Bauer and Ryser (2004) also suggest that a bank's optimal risk management strategy is financed by its equity and deposit position, and they state that a bank's motivation for risk management comes from its deposit, which also enable its effective operations. Therefore, I assume that the risk-adjusted capital ratio enables banks to reduce their future risk-taking and also enables banks with a high deposit ratio at time *t* to reduce risk-taking at time *t*+1. I use the market-to-book ratio (*MTB*) as a proxy for a bank's charter value. A high value provides more incentives for a bank to reduce its risk-taking. This helps banks maintain their capital cushion and reduces the likelihood of falling below the minimum regulatory capital level. Thus, banks attempt to maintain a high charter value by reducing risk-taking, leading to the assumption of a negative relationship between risk-taking and *MTB*. Finally, to measure the effect of loan quality on banks' risk-taking, I control for non-performing loans (*NPL*) (Shrieves & Dahl, 1992).

I define the above-mentioned variables in the appendix and winsorize all of the continuous variables at the 1st and 99th percentiles to remove the effects of extreme observations. In addition to these reasons for optimal risk-taking, I add bank-specific fixed effects in partial risk adjustment analysis and alleviate omitted variable bias through time-invariant factors. I cluster all standard errors at the bank and year levels (two-way clustering) in the regressions (Peterson 2009; Gow et al., 2010).

2.3.3 Descriptive Statistics

Table 1, Panel A presents the descriptive statistics of the variables for the full sample. I find that $EV_{i,t}$ has a mean of 0.0036 and a median of 0.0019, demonstrating that, on average, earnings volatility is 0.36%. Panel B presents the Pearson correlation coefficients for these regression variables. The results show that ΔEV_{t+1} and ΔEV_{t+5} and $CSmeanEV_t$ $(\alpha 1)$ and EV_t $(\alpha 2)$ in Model 1 are negatively associated. The positive associations both in the short and long term are consistent with my main hypothesis. I find a positive association between DTS_t and DCS_t in Model 2. I also find that ΔEV_{t+1} is negatively correlated with *ROA*, *Deposit ratio*, and Tier 1 capital ratio (*CAPR1*). However, ΔEV_{t+1} is positively correlated with $LLP_{i,t}$, *Loan ratio*, and *NPL*. The above correlations serve as my primary evidence for partial risk adjustment by banks.

2.4 Empirical Results

To test my main hypothesis and examine whether there is an optimal risk-taking in banks, I first propose two risk adjustment mechanisms: cross-sectional risk adjustment (bank-specific) and industry (industry-wide) risk adjustment. My comprehensive empirical models enable the dynamic nature of banks' risk-taking to be theoretically elucidated. I then test the dynamics of banks' average earnings volatility over a 25-year event window by comparing that of individual banks and in the entire industry. Finally, I assess any asymmetry in banks' risk adjustment mechanisms and discuss the reasons for this.

2.4.1 Partial Risk Adjustment Mechanisms

The risk appetite of banks is derived from assessing how increased risk-taking affects the opportunities that banks can capitalize on. This assessment may change with banks' opportunities. Stulz (2014) states that a bank's risk appetite should be flexible and thus not affected by any small shift in opportunities. The risk-taking behavior of regulated banks depends on the use of optimal levels of capital and asset portfolio ratios (Park, 1997). However, the optimal levels of these two variables depend on banks' investment opportunities, charter value, and the regulatory framework that affects banks' risk adjustment decisions. In H1, I propose that EV_t and $CSmeanEV_t$ are negatively associated with ΔEV_{t+1}. Thus, I test my baseline Model 1 in short-and long-term cross-sections of a banking context.

[Insert Table 2]

Table 2 presents the results of Model 1 (Equation 5) for both short- (t+1) and long-term risk adjustment (t+5). I regress $CSEV_t\_mean$ and EV_t on ΔEV_{t+1} with the intercept. In the short term, I find that $CSEV_t\_mean$ is positively and significantly correlated with ΔEV_{t+1} with a coefficient of 0.23. This indicates that there is an optimal level of risk in the cross-section of a banking context which is statistically and economically significant at the 5% level. However, in the long term (for ΔEV_{t+5}), the coefficients are negative because the coefficients of λ_1 and λ_2 in Model 2 are very similar in value. This result is significant at the 5% level. However, the association between EV_t and ΔEV_{t+1} is negative and significant at the 1% level, for both short- and long-term risk adjustment, with coefficients of 0.2378 and 1.11363, respectively. Overall, the negative coefficients in Model 1 suggest that there is an optimal level of risk for banks, which is consistent with H1.

[Insert Table 3]

Table 3 reports the results of Model 2 (Equation 11) for both short- (t+1) and long-term risk adjustment (t+5). The main difference between Models 1 and 2 is that in Model 2, I include industry-wide information, whereas in Model 1, I only include information at time t. Therefore, Model 2 is parsimonious and has the correct number of predictors. I regress *DTS* and *DCS* on ΔEV_{t+1} without intercept. I find that the coefficients of *DTS* and *DCS* are positive and significant at the 1% level, except in year t+1 for *DTS*. To demonstrate the economic significance of these results, I calculate the effect of a one standard deviation change in *DTS* (*DCS*). Based on the coefficient of *DTS* (*DCS*) and the distribution of *DTS* (*DCS*) and ΔEV, I find that both in the short and long term, the economic significance of partial risk adjustment is higher for *DCS*, with values of 3.56% and 25.11%, respectively. This result suggests that more risk adjustment occurs in the cross-section of a banking setting both in the short and long term. Moreover, the *DCS* speed estimate is about 23.78% and the *DTS* estimate is around 0.78%, suggesting that due to cross-sectional variations across banks, individual banks adjust to their optimal level of risk more quickly than the entire industry.

2.4.2 Determinants of Bank Risk

Several studies investigate the determinants of banks' risk-taking behavior.[13] To support my partial risk adjustment mechanisms, I use alternative estimation methods for Equation (1). To model optimal risk-taking by banks, I incorporate a set of bank characteristics ($X_{i,t}$) that are often used in the literature (e.g., Fang et al., 2012; Shrieves & Dahl 1992; Aebi et al., 2012; Bromiley, 1991). I investigate the determinants of bank risk and measure the effect of current earnings volatility on future earnings volatility from year t+1 to year t+5. Given the importance of the banking system and the role it plays in modern market-based economies, it is necessary to determine bank risk factors. The global financial crisis highlights the importance of understanding the factors affecting bank risk, particularly in the U.S. banking industry, which is supported by federal deposit insurance and the theory of moral hazard associated with a government guarantee. Deposit insurance is designed to protect depositors, but it also reduces the incentive of depositors to monitor banks and claim interest payments that reflect bank risk. Earnings are essential for firms to survive in the market. Therefore, I believe that earnings volatility is a good measure of bank risk. Thus, earnings volatility is likely to be a satisfactory measure of bank risk.

[Insert Table 4]

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[13] Banks formulate their risk management strategies by considering various factors such as ownership structure and deregulation (Saunders et al., 1990), size (Demsetz & Strahan, 1997; De Nicole, 2000; Stiroh, 2006; Haan & Poghosyan 2012), agency problems (Demsetz et al. 1998), capital budgeting and structure (Froot & Stein, 1998; Cebonayan & Strahan 2004; Krishanan et al. 2005; Hilscher & Raviv, 2014; DeAngelo & Stulz, 2015; Bekkum, 2016), governance and regulation (Leaven & Levin, 2009), strong risk management (Ellul & Yerramilli, 2013), institutional reforms (Fang et al., 2014), and regulation and supervision (Frame et al., 2020).

$$EV_{i,\, t+1\ to\ t+5} = \alpha + \beta_1\, EV_{i,\, t} + \beta_2\, Size_{\, i,\, t} + \beta_3\, Ln\ Deposit\ ratio_{\, i,\, t} + \beta_4\, Ln\ Loan\ ratio_{\, i,\, t} + \beta_5\, Ln\ LLP\ ratio_{\, i,\, t} + \beta_6\, NPL_{i,\, t} + \beta_7\, CAPR1_{i,\, t} + \beta_8\, MTB_{\, i,\, t} + \beta_9\, ROA_{\, i,\, t} + \varepsilon_{\, i,\, t+1} \quad (12)$$

Table 4 reports the results of a pooled ordinary least squares regression and presents the determinants of earnings volatility as a measure of bank risk. I use earnings volatility as a proxy for bank risk, which is measured using the standard deviation of earnings over the past 5 years. The main independent variable is current earnings volatility *(EV_t)* and the dependent variable is future earnings volatility *($EV_{t+1\ and\ t+5}$)* of year t+1 and year t+5. I regress future earnings volatility on current earnings volatility. I obtain estimates using the bank fixed effects panel estimator, which is superior to the estimator of random effects based on the Hausman test. In my fixed effects model, I use Newey and West's (1987) heteroskedasticity and autocorrelation robust standard errors clustered by firm and year. Columns (1)-(5) refer to earnings volatility from year t+1 to year t+5, respectively. Although I calculate earnings volatility over a 5-year rolling window, the number of observations declines gradually from year 1 to year 5 because more observations are required to estimate the standard deviation of earnings over 5 years than over 1 year.

My findings are as follows. Column (1) in Table 4 presents the coefficients of $EV_{i,t}$ and show that the speed of adjustment is 23.38% ($1 - \lambda = 1 - 0.7662$), which is equivalent to the *DCS* estimate of 23.78% in Model 2. This result suggests that banks close 23.38% of the gap between their actual and target risk level within 1 year. The other lagged variables have the expected sign and describe banks' optimal risk-taking behavior. First, current earnings volatility is positively correlated with future earnings volatility from year t+1 to year t+3, after which it is negatively correlated (year t+4 and year t+5). Both the short- and long-term effects are significant in years 1, 2, and 5 at the 1% level and in years 3 and 4 at the 10% level. This implies that banks will increase their future risk-taking up to 3 years, after which it will decline. *Bank Size* is positively correlated with earnings volatility both in the short and long term. Thus, as expected, large banks will increase their risk-taking behavior, as they have have more capital and better financial stability, enabling them to take more risk. My results are consistent with the study conducted by De Nicolo (2000), who finds that large banks take more risk and that banks' return volatility increases with size. However, they also find that U.S. Bank Holding Company's return volatility is convex in shape.

Following Fang et al. (2014), I use the logarithm of *Deposit ratio*, *Loan ratio*, and *LLP ratio* to determine bank risk. They use a z-score (probability of default) as a measure of bank risk, while I examine whether these variables affect banks' earnings volatility. My findings are consistent with their study. For instance, *Loan ratio* is positively and significantly correlated with banks' risk-taking. However, *LLP ratio*, which is a proxy of ex ante credit risk, is positively correlated with banks' earnings volatility. *Deposit ratio* is negatively associated with bank risk both in the short and long term. The coefficient of *NPL* is positive and significant at the 1% level, which suggests that if a bank has a high proportion of non-performing assets, it will take more risk in the future to generate earnings because banks need more earnings to protect themselves from *NPL* risk.

The coefficient of *CAPR1* is negative and significant, which suggests that the risk-adjusted capital ratio enables banks to reduce future risk-taking. However, this result is inconsistent with the study by Aebi et al. (2012). The coefficient of *MTB* is negative but not significant. Following Bromiley (1991), I use *ROA* and, consistent with their study, I find that *ROA* in year t is positively associated with future earnings volatility from year t+1 to year t+5. To provide more evidence for my hypotheses that the banking industry exhibits optimal risk-taking behavior, and their tendency to converge to an optimal level of risk, I next use several alternative measures of bank's risk-taking to check the robustness of my test.

2.4.3 Robustness Check

I conduct a number of robustness checks. First, I use several alternatives measure of banks' risk-taking. To show the actual effects of control variables on banks' earnings volatility, I use additional bank level-control variables at time t-5. I measure earnings volatility using past 5 years rolling window period time t-4 to t. Table 4 shows the effect of control variables of time t on earnings volatility. This may it difficult to interpret the effects of control variables on earnings volatility, so I use control variables of time t-5 as a robustness check.

Panel A, B, and C Table 5 presents the result of alternative banks' risk-taking measures. In the baseline analysis (Table 2 and 3), I use the earnings volatility which is an accounting-based measure of bank's risk-taking behaviour, and I test it's effect on the predictability of banks' future earnings. More volatile earnings may lead to uncertainty about the level of equity capital and thus deteriorate banks' soundness (Couto, 2002). Furthermore, Albertazzi and Gambacorta (2009) suggest that excess volatility in bank earnings can disrupt the stability of capital structures. So, it is important to assess how banks manage their risk with high earnings volatility.

[Insert Table 5]

In this analysis, I use the market-based measure of banks' risk-taking. Panel A, Table 5 shows the results of using stock return volatility measure. Similar to the baseline regression in Tables 2 and 3, the stock return volatility (SRV) measures of banks risk-taking suggest that banks also adjust toward the target risk. However, the resulting adjustment is quicker than that measured by earnings volatility (EV). The speed of risk adjustment (SOA) is much quicker around 77.86% (SOA is 23% in EV measure). The coefficients of the long-term measure of time-series (DTS) and cross-sectional (DCS) proxy are very similar. This suggest that in the long-term, the speed of adjustment is 100% that means the risk will be fully adjusted.

Panel B, Table 5 reports the results of using z-score which represents the banks probability of default. I measure the banks' probability of default using the logarithm of z-score, which defined as (ROA+EAR)/SD of ROA. Consistent to the results of baseline regression in Table 2 and 3, the results of panel B also suggest that banks adjust toward the target risk. However, the adjustment speed is quicker in panel B, as in panel A. The speed of risk adjustment (SOA) is around 38.76% (SOA is 23% in EV measure). In addition, the coefficients of the long-term measures of time-series (DTS) and cross-sectional (DCS) proxies are very similar. Thus, the results suggest that in the short-term risk adjustment is partial and in the long-term the risk will be fully adjusted.

In Panel C, I use the change in Equity Capital Ratio (ECR) as the dependent variable for year t+1 and t+5, where, ECR is defined as log of total stock holder's equity to total assets ratio. The results of Model 1 indicate an adjustment toward the target (SOA is quicker around 35.51%) and more adjustment occur in the cross-section proxy. However, in the Model 2, no optimal capital ratio may be presented, as the coefficients of time-series and cross-sectional proxies are different in the long-term. Because ECR is more dynamic and ECR may have a different target for different types of firms depending on the firm's requirements. Thus, the results of ECR measure imply that it has different effects.

[Insert Table 6]

Next, I test for the robustness using bank-level control variables before the start of the rolling window. In Table 4, I analyse the determinants of risk-taking behavior of earnings volatility (EV) of years *t+1* to *t+5*, where EV has measured using SD of earnings using past five years rolling basis (years *t-4* to *t*) and the control variables measured in time *t*. This result may present some difficulties in interpreting the effects of control variables of time *t* in EV of time *t+1* to *t+5*. Thus, in Table 6, I use the control variables before the start of the rolling period, which is time *t-5*. The results suggest that there is not much change. The coefficients of EV of time *t* on EV of time *t+1* is around 0.7822 which is significant at 1% level. The SOA is around 21.78% (1-0.7822) and that is very close to the baseline result of 23.38% (Table 4). Overall, the results hold for the alternative measure of control variables and with these variables I find that banks close 21.78 % of the gap between their actual and target risk level within 1 year.

2.4.4 Post-estimation hypothesis

In my second hypothesis (H2), I propose that the risk adjustment in the short and long terms differs. The dynamic framework of banks' risk-taking behavior suggests that the coefficients of λ_1 are equal to λ_2. In Model 2, I test the post-estimation hypothesis of equality and find that the coefficients of λ_1 and λ_2 are equal, which is consistent with my hypothesis. I use the Wald test to show the parameters of Model 2, and Table 7 indicates that the findings are consistent with my assumption. The test reveals that in the Wald test of post estimation, the parameters are equal. Thus, the null hypothesis (H0: $\lambda_2 = \lambda_1$) is accepted with a p-value of 0.6817 and degrees of freedom is 0.17. The significance level of the test is 6.82%, so we cannot reject the null hypothesis, at a 5% level. However, in the short-term (*t+1*), I find no significant result (0.0078) in the whole sector adjustments (DTS) due to the noisy data. The adjustments are more visible in the long run with a co-efficient of 1.1644 and significant at 1% level.

I also propose that banks should fully adjust to the target risk level (100%) in the long run (t+5). The speed of adjustment is 23.78% per year, so by 5 years it should fully adjust back to the target risk level (23.78*5 = 118.9% ≈ 100%). The null hypothesis proposes that λ_2 and λ_1 are equal to 1 or the deviations between the two parameters is 0 ($\lambda_2 - \lambda_1 = 0$). The evidence confirms that banks fully adjust back to the target risk level. The co-efficient of *DTS* and *DCS* in Model 2 are 1.1644 and 1.1163 respectively, and thus λ_1 and λ_2 are very close to each other. The p-value of the Wald test statistics is 0.1142, including that the null hypothesis is accepted (H0: $\lambda_2 = 1$; $\lambda_1 = 1$). Thus, the null hypothesis cannot be rejected, or at least we cannot reject it at any significance level below 11.42%. However, due to the sampling error in the observations, the deviations between λ_2 and λ_1 may not be exactly equal to 0 ($\lambda_2 - \lambda_1 \neq 0$). Model 1 confirms that the long-run coefficients are negative but not exactly equal to 0.

2.4.5 Dynamics of Banks' Risk-Taking Behavior

The dynamic approach to risk suggests that current earnings and earnings volatility are central to banks' risk-taking strategies, because to a large extent they can predict future earnings. In my first essay, I investigate the relationship between earnings volatility and earnings predictability using U.S. bank data from Compustat for the 1988–2020 period. The results show that banks' earnings volatility reduces earnings predictability, which is consistent with the results of Dichev and Tang (2009) who provides several implications for banks' risk-taking strategies. First, assuming that the purpose of corporate risk-taking is to ensure a high level of future earnings, then the worst position for a bank is to have low earnings and high earnings volatility, as this indicates that the bank's risk is excessive and the outcomes are poor.

To improve its position and to avoid insolvency, the bank should reduce its level of risk-taking. While the literature on corporate risk-taking suggests that firms with low earnings have higher incentives to take more risk, the first implication notes that banks with low earnings should decrease their risk-taking if they face high earnings volatility. Second, for banks with high earnings and high earnings volatility, their earnings are likely not persistent. To assure a high level of future earnings, they should also reduce risk-taking to lower their earnings volatility. Third, for banks with low earnings and low volatility, their future earnings are likely to be low. They should increase risk-taking to improve their future earnings. Fourth, the best position for banks is to have high earnings and low earnings volatility because they can assure a high level of future earnings. Since all banks would try to maintain or get into this best position, competition is likely to increase and how to protect their position becomes the top priority. Based on the implications of their study, I therefore test the dynamic approach to banks' risk-taking which complements my main research questions of whether there is any optimal risk-taking in banks. I expect that risk management is too loose if banks are in the group of low earnings and high earnings volatility. Therefore, these banks should take less risk because of less certainty about future earnings. This suggests that faced with high earnings volatility, banks need to reduce their risk-taking. Alternatively, I expect that if banks are in the group of low earnings and low volatility, then the risk management is too restricted and there is room to take more risk to improve future earnings.

Addressing my main research question, I primarily examine the dynamics of banks' average earnings volatility. I take a dynamic approach to bank risk-taking due to the implications of earnings and earnings volatility suggested by the hypothesis of Dichev and Tang (2009). Figure 1 illustrates these implications of earnings and earnings volatility on bank risk-taking behavior. The best risk management strategy for banks is to have low earnings volatility and high earnings level, and the worst strategy is to have high earnings volatility and low earnings level (Figure 1). Thus, I investigate the dynamics of banks' average risk-taking (Figure 2), using the standard deviation of earnings over the next 5 years, which enables to conduct a clean test with less correlation. Some studies (Dichev and Tang, 2009) use rolling years to determine the standard deviation of earnings, but then the issue arises that previous years are repeated to generate earnings volatility. For example, Lemmon et al. (2008) use previous rolling years to estimate variations in book and market leverage ratios. In contrast, in this study I use the next five years of earnings to estimate variations in earnings volatility. As a result, I do not induce correlations in changes in earnings volatility, which allows us to conduct a clean test. Figure 2 shows how bank risk (earnings volatility) changes over time without any induced correlation and the general tendency of that high-risk banks to revert to the optimal mean.

Figure 2 presents the dynamics of the average earnings volatility of four portfolios in "event time." I follow Lemmon et al. (2008) and construct Figure 2 in the following manner. For each calendar year, I sort firms into quartiles (i.e., four portfolios) based on their earnings volatility: very high, high, medium, and low. The portfolio formation year is denoted event year 0. I then compute the average earnings volatility of each portfolio in each of the following 25 years, holding the portfolio composition constant. I repeat these two steps for every year of the sample period. This process generates 38 sets of event-time averages, one for each calendar year in my sample. I then compute the average earnings volatility of each portfolio across the 38 sets in each event year. I find a remarkable convergence between the averages of the four portfolios over time. The most noticeable convergence is after 20 years. Average earnings volatility declines from 1.2% to 0.5% for the 'very high' portfolio, which indicates that banks high volatility reduces their risk in the future to ensure future cash flows. For the 'low' portfolio, average earnings volatility increases from 0.1% to 0.4%, which indicates that banks with low earnings their risk in the future to increase their future cash flows. Thus, my preliminary examination of the dynamics of average earnings volatility indicates that banks with high earnings volatility reduce their risk-taking behavior, whereas banks with low earnings volatility and low earnings increase their risk-taking behavior to ensure future cash flows. However, this result is only partially consistent with Bromiley (1991) in terms of banks' risk-taking. Figure 2 shows that after a certain amount of time (15 years), all of the portfolios converge to achieve the objectives of risk management. An important aim of bank risk management is bank survival, which implies that banks with high earnings volatility and low earnings (worst situation) can encounter greater problems and will therefore reduce risk. The Global Risk Academy states that a fundamental concept of bank risk management is to manage and not completely eliminate risk, thus allowing for the growth of the financial market.

2.4.6 Comparison of Banking firm and Industry (Non-Banking) firm Risk Dynamics

The corporate risk-taking strategies suggest that the risk dynamics at banking and industry (non-banking) levels differ. I highlight the differences between bank and industry risk dynamics in Figure 3. Figure 2 suggests that banks' earnings volatility converges irrespective of the portfolio (very high, high, medium, and low) after 20 years. This result enables us to determine whether industry earnings volatility converges in the same way as that of banks. Figure 3, Panel A depicts the dynamics of bank risk over 20 years, as described by Lemmon et al. (2008). The benefits of the financial market lead to a convergence of banks' risk-taking dynamics (increase or decrease), and thus earnings volatility evolves over this period (20 years). This convergence of portfolios makes it easier for banks to increase or decrease their risk

Panel B of Figure 3 shows the four portfolio types of non-banking industry risk dynamics. As expected, firms (non-banking industry) also take more risk to ensure future earnings, much like investors who invest in risky securities to earn higher returns. Thus, the dynamic approach to industry risk-taking predicts that firms with high earnings volatility reduce risk-taking, whereas firms with low earnings volatility and low earnings increase risk-taking. The current earnings level and earnings volatility of non-banking industry firms are the fundamental instruments used to predict future earnings. Therefore, the dynamics of average earnings volatility suggest that firms with high (low) earnings volatility reduce (increase) risk-taking to ensure future cash flows. However, unlike banks, the portfolio volatility of non-banking industry firms does not converge over time, but rather diverge from one other. Unlike banks, regular firms thus find it difficult to converge to achieve optimum risk, because of the differences between them. In addition, banks differ from industry firms because their failure can have a systemic effect on the economy, which puts them under pressure to converge risk (Stulz, 2014). The dynamics of banks' risk-taking (Panel A) suggest that banks follow optimal risk-taking behavior and that my partial risk adjustment models account for asymmetric effects. I therefore investigate the asymmetric effects of risk adjustment in banks.

2.4.7 Asymmetry in Risk-Adjustment Speeds

Theories of corporate finance generally consider potential conflicts of interest between firms and individuals due to information asymmetry. These theories suggest that the standard motives can be economically justified, such as how institutions can be important corporate governance mechanisms, as exemplified by debt financing or ownership concentration (Shelifer and Vishny, 1997), the problem of overhand debt (Myers, 1977), or the free cash flow problem (Jensen, 1986). The literature concludes leverage can serves as a disciplinary mechanism for managers and owners, the cost of having too little debt is likely to be higher than the cost of excess debt (Elsas & Florysiak, 2011). As for banks, managers and owners of other types of firms must manage their risk-taking behavior. The cost of excessive risk-taking in the financial market is assumed to be higher than that of low risk-taking. My findings from the dynamic nature of banks' risk-taking (Figure 2), suggest that low-risk banks adjust more quickly than very high-risk banks, and thus the risk adjustment between high or low levels of risk-taking relative to the optimal level is likely to be asymmetric.

These economic motives lead to cross-sectional heterogeneity in risk adjustment speeds, which might depend on banks' earnings levels. The basic intuition is that banks' survival in the market depends on their performance (earnings level). If banks' have low earnings and high volatility (worst situation, Figure 1), they will try to increase their earnings by increasing their risk level. However, high earnings and volatility (the best situation, Figure 1), will lead them to reduce their risk because high volatility means future earnings are less predictable. This opportunity to adjust risk should thus increase the speed of adjustment. Banks are also under pressure from regulatory authorities to maintain market stability, which also reduces risk. Banks excessive risk-taking became a particular concern after the global financial crisis of 2007–2008, and stabilizing the banking system a priority. For example, banks must now have a higher capital ratio, which helps mitigate their excessive risk-taking behavior. Thus, my third hypothesis (H3) states that there should be an asymmetry effect in risk adjustment speeds. Using cross-sectional data, I examine whether banks adjust back to the optimal risk level more quickly when there is excessive (over) volatility or low (under) volatility. I investigate banks' earnings unconditionally and conditionally depending on over or under risk-taking to test for asymmetry in the pattern of risk adjustment.

[Insert Table 8]

Table 8 illustrates the results of the asymmetry effect in the partial risk adjustment model, both in the short-term for year $t+1$ and the long-term for year $t+5$. The dependent variables are

EV_{t+1} and ΔEV_{t+5}. The independent variable *DCS* is calculated as the difference between EV_t and earnings volatility ($CS\mu_t$) in year *t* ($CS\mu_t - EV_t$), with $DCS^{(positive)}$ representing the cost of under (low) risk-taking and which is equal to ($\mu_t - EV_t$) if *DCS* is ≥ 0, and 0 otherwise; $DCS^{(negative)}$ represents the cost of over (high) risk-taking and is equal to ($\mu_t - EV_t$) if *DCS* is < 0, and 0 otherwise. μ_t is as previously defined. I find that the proxies for cross-sectional risk adjustment *(DCS),* excessive (high), and low risk-taking are positively and significantly correlated with changes in bank risk at the 1% level, both in the short and long-term. However, in year *t*+1, low risk-taking is positively correlated but not significant so. I add bank and year fixed effects to test the asymmetry of risk adjustment speeds. I exclude the constant term from my model as the fixed effects model absorbs unobserved effects. The coefficients of $DCS^{positive}$ are lower (0.0680, 0.980) than those of $DCS^{negative}$ both in the short and long term, respectively. However, the coefficients of $DCS^{negative}$ are higher (0.269, 1.149) than $DCS^{positive}$ both in the short and long terms. Thus, this finding suggests that for the banking industry, excessive (over) risk-taking is costlier than low (under) risk-taking. To further confirm my third hypothesis, I show the interaction effects between the cross-sectional risk adjustment proxy and bank earnings.

2.4.8 Risk Adjustment Speed Conditional on Bank Earnings

The literature shows that a firms' survival in the market is primarily based on its earnings. The survey conducted by Graham et al. (2005) and the study of Dichev and Tang (2009) clearly show that high earnings volatility decreases its future earnings predictability in a firm. Moreover, Frankel and Litov (2009) show the importance of earnings persistence. Following these studies, I document in my first essay (banks' earnings volatility and earnings predictability) that high earnings volatility in banks also reduces their future earnings predictability. In Table 3 of my first essay, I show that earnings persistence gradually decreases from year t+1 to year t+5 based on high and low earnings volatility quintiles. I also find that conditional on current earnings, the results are similar in that earnings persistence is higher in year t+1 and lower in year t+5. This suggests that earnings play an important role in determining the asymmetry of banks' partial risk adjustment mechanisms. I investigate the role of earnings by testing the interaction effects of earnings with my risk adjustment tools (i.e., I test whether excessive or low risk-taking increases earnings). I predict that in the short term, under (low) risk-taking increases bank earnings and over (high) risk-taking decreases earnings. However, in the long term, under risk-taking decreases bank earnings and over risk-taking increases earnings.

[Insert Table 9]

The results in Table 9 are consistent with my predictions. In this test, the variable of interest is the interaction between $DCS^{(positive)} \times ROA$ and $DCS^{(negative)} \times ROA$, i.e., $\beta 4$ and $\beta 5$. I regress my proxy for risk adjustment earnings on changes in banks' risk-taking (earnings volatility). As expected, the coefficients of the under and over risk adjustment proxies are positive and significant. In contrast, the coefficient of *ROA* is negative and significant at the 1% level, both in the short and long term. This result suggests that as like as in non-banking industry, risk-taking reduces bank earnings both in the short and long term. In the short term, the positive coefficients of interaction between $DCS^{(positive)} \times ROA$ indicate that under risk-taking increases bank earnings, although the coefficients are not significant. However, in the long term, the negative coefficients of interaction between $DCS^{(positive)} \times ROA$ indicate that under risk-taking reduces bank earnings, although the coefficients are not significant. The coefficient of $DCS^{(negative)} \times ROA$ is negative (-2.4708) and significant at the 5% level in the short term. This suggests that banks face larger reductions in earnings (*ROA*) if they take over risk. In the long term, the coefficient of $DCS^{(negative)} \times ROA$ is positive but not significant. Thus, this suggests that for banks, over risk-taking is costlier than under risk-taking. The speed of adjustment may therefore depend on banks' earnings level. I then include the interaction effect between the risk adjustment proxy and other bank-specific variables (e.g., *LLP*, *Leverage*) to examine whether the effect of earnings changes.

[Insert Table 10]

The results of Table 10 show the estimates of the interaction terms between $DCS^{(positive)}$ and $DCS^{(negative)}$ and other bank-specific variables. I regress these variables on ΔEV_{t+1} and ΔEV_{t+5}. As in Tables 4 and 5, $DCS^{(positive)}$ and $DCS^{(negative)}$ are positive and significantly correlated with ΔEV_{t+1} and ΔEV_{t+5}. Consistent with the literature, *ROA* is negatively related to bank risk and *LLP* is positively related to bank risk.[14] This suggests that high-risk banks face drop-in earnings and an increase in loan loss provisions. These bank-specific characteristics have statistically significant but also economically significant effects on risk-taking. The relationship between leverage and bank risk is negative but not significant, unlike previous studies.[15] This finding indicates that if a bank has high leverage at time *t*, it will reduce its future risk-taking behavior at time *t*+1 because it faces regulatory pressure from the government to manage risk. Table 7 shows that the sign of the interaction term between the risk-adjustment proxy and earnings

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[14] For example, Bromiley (1991) uses performance (*ROA*) and an industry performance estimator to show that *ROA* in year *t* is negatively correlated with future earnings volatility from year *t*+1 to year *t*+5. Fang et al. (2014) also find a positive association between a bank's earnings volatility and loan loss provisions. However, they document a negative relationship between a bank's z-score and loan loss provisions. In addition, Laeven and Levin (2009) report a negative relationship between bank risk and loan loss provisions.

[15] For instance, Haan and Phogoshyan document a positive relationship between banks' current earnings volatility and leverage.

remains the same. This implies that the cost of over risk-taking is high, which reduces earnings, and the cost of under risk-taking is low, which increases earnings in the short term. In the short term, $DCS^{(positive)} \times ROA$ and $DCS^{(negative)} \times ROA$ are not significant, but in the long term, they are statistically and economically significant at the 5% level.

Consistently, $DCS^{(positive)} \times LLP$ is significantly negative both in the short and long term, which suggests that banks that take low risks experience larger reductions in their loan loss provisions. In contrast, $DCS^{(negative)} \times LLP$ is positive but not significant both in the short and long term. This suggests that banks with excessive risk-taking may record more loan loss provisions with an expectation of more loan defaults by their customers. Finally, I add $DCS^{(positive)} \times Leverage$ and $DCS^{(negative)} \times Leverage$ to the model. I find the costs of low and excessive risk-taking are negatively related to leverage. This implies that risk-taking reduces bank leverage and is similar for banks with low or excessive risk-taking. Overall, these results suggest that for the banking industry, the cost of over risk-taking is higher than that of under risk-taking relative to the optimal level of risk. Table 8 shows that banks pay more for taking over risk as it is very costly and, in turn, reduces their earnings and increases their loan loss provisions.

2.4.9 Cost and Benefits of Risk Adjustment by Banks

Tables 8 and 9 indicates the asymmetry in banks' risk adjustment speeds. The results show that due to the high cost of excessive risk-taking, banks with excess volatility adjust their risk much faster than those with less volatility. Hao and Zheng (2021) show that banks reduce their risk for several reasons, such as a loss of market share when faced with increased competition. They may also aim to reallocate assets to different groups without changing their risk preference or may reduce risk according to their levels of regulated capital. Shrives and Dahl

(1992) examine why risk in the banking industry is finite and find that the cost of excessive risk-taking, such as regulatory costs, minimum capital standards, bankruptcy cost avoidance, and managerial risk aversion, determine their risk adjustment.

I offer several reasons (cost and benefits) for risk adjustment by banks. The first reason is banking regulations. Bank regulators play a vital role in monitoring and governing banking conditions to ensure stability in the financial markets that drive the economy, in which banks are major participants. Park (1997) develops a model demonstrating that regulators detect banks with high volatility through their asset and capital ratios and prevent these risky banks from obtaining positive option values. Thus, tighter regulations prevent banks from taking excessive risk. Moreover, Beltratti and Stulz (2012) document that in countries with strict banking regulations, large banks performed better and reduced loans less during the credit crisis.

Second, the capital requirements, a key modern banking regulation tool, can prevent *ex ante* excessive risk-taking in times of economic crisis (see Rochet, 1992; Dewatripont & Tirole, 1994). Capital requirement regulations (Basel I, II) are often modified by the Bank for International Settlements (BIS). Risk-sensitive capital adequacy requirements can discourage banks from taking excess risk. Using data from U.S. Bank Holding Companies and commercial banks, Jokipii and Milne (2011) suggest that the two-way relationship between banks' short-term capital buffers and portfolio risk adjustment is positive. Moreover, they document that such adjustment management strategies depend on the bank capitalization ratio.

Third, financial stability of banks is of major importance to society and the global economy. Any crisis in banking will affect the economy as a whole. Individuals and businesses rely on the banking system to meet their financial needs and settle transactions. So, banking stability is essential, as any complications in the financial industry can have widespread social and economic effects.

Thus, regulators require banks to satisfy minimum capital requirements. They place restrictions on a bank's ability to take risks in terms of assets, which reduces systemic risk. Accordingly, the risks taken by banks are subject to limitations. However, as these do not change banks' bottom line in terms of profits or losses, there is an optimal level of risk that a bank can take, as determined by its business characteristics (Stulz, 2014). Thus, the optimal level of risk is bank-specific and the costs to shareholders of the restrictions imposed by regulators also differ. For example, Boyson, Fahlenbrach, and Stulz (2014) show that banks select low-risk strategies if they have the advantage of high franchise value, so these banks are unlikely to be constrained by capital requirements.

Changes in banks' risk-taking are affected by their risk conditions and earnings. In my first essay of banks' earnings volatility and earnings predictability, I show that high earnings volatility reduces banks' future earnings predictability. Similarly, the assumption concerning bank earnings is that banks with lower earnings and lower volatility will take more risks, while banks with lower earnings and higher volatility will take less risks. My findings on banks' risk adjustment are relevant to this earnings assumption. As a result, banks with excess volatility adjust their risk much faster than banks with low volatility.

2.5 Conclusion

The dynamic nature of banks' risk-taking behavior implies that banks follow an optimal risk-taking behavior, and I find robust evidence. Following the literature, I propose a new empirical approach to test this prediction, involving two partial risk adjustment mechanisms. I use a bank fixed effects model to estimate banks' optimal risk-taking behavior, with risk adjustment occurring both in the cross-sectional and time-series variations of a banking context. My proposed framework shows how the industry and individual banks adjust to their optimal levels of risk. I adopt partial adjustment models instead of complete simultaneous adjustment because immediate adjustment to the optimal risk level is costly or infeasible.

I find that banks typically converge to their optimal level of risk at a rate of 23.78% per year. The results of partial risk adjustment Model 1 provide evidence of the cross-sectional risk adjustment mechanism, which is negatively related to changes in banks' risk-taking. Moreover, I show that in my partial risk adjustment Model 2, the time series and cross-sectional risk adjustment proxies are positively related to changes in future risk-taking. Thus, both in the short term and long term, more risk adjustment occurs in the cross-section of a banking setting. This indicates that due to cross-sectional variations across banks, individual banks (adjustment speed of 23.78%) adjust to the optimal level of risk more quickly than the entire industry as a whole (adjustment speed of 0.78%).

My partial risk adjustment models also provide evidence of an asymmetry effect in terms of the optimal level of risk. Using cross-sectional data, I test whether banks adjust to the optimal level of risk more quickly when there is excess or low volatility (risk). Due to the importance of risk management in banks, managers and owners must manage their risk-taking behavior. Therefore, I propose that the cost of over risk-taking is higher than that of under risk-taking. Consequently, I expect to find an asymmetry effect in banks' risk adjustment between over or under risk-taking relative to the optimal level of risk. The results suggest that banks with over risk-taking adjust to their optimal level of risk faster than those with under risk-taking. This suggests that for the banking industry, over risk-taking is costlier than under risk-taking. Banks aim to avoid the potential cost of financial distress associated with over risk-taking beyond the optimal level, which is consistent with the dynamic nature of banks' risk-taking behavior. To test the robustness of my findings concerning the asymmetry effect in the speed of risk adjustment, I identify the interaction effects between cross-sectional risk adjustment proxies and bank-level variables (e.g., ROA, LLP etc.). I find consistent results, and thus my predictions are supported. My study therefore provides new empirical evidence concerning banks' risk-taking behavior and reveals that they bank's follow optimal risk-taking behavior.

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Table 2.1: Summary Statistics

Panel A: Descriptive Statistics

Variables	Mean	SD	p25	p50	p75	Min	Max
ΔEV_{t+1}	0.0003	0.0027	-0.0003	0	0.0004	-0.0283	0.0316
ΔEV_{t+5}	0.0002	0.0028	-0.0004	0	0.0004	-0.0283	0.0306
DTS	0	0.0016	-0.0006	0.0009	0.0011	-0.0044	0.0017
DCS	0	0.0045	-0.0004	0.0012	0.0021	-0.0305	0.0078
CS mean EV_t	0.0036	0.0016	0.0026	0.0028	0.0043	0.002	0.008
EV_t	0.0036	0.0046	0.0011	0.0019	0.0038	0.0002	0.0257
SIZE	7.527	1.869	6.212	7.136	8.474	4.41	13.62
Deposit Ratio	-0.274	0.161	-0.333	-0.233	-0.168	-1.03	-0.082
Loan Ratio	-0.47	0.233	-0.561	-0.425	-0.315	-1.451	-0.129
LLP Ratio	-6.156	1.178	-6.828	-6.133	-5.44	-9.658	-3.326
NPL	0.0117	0.0156	0.003	0.0062	0.0132	0	0.0914
CAPR1	12.19	3.719	9.8	11.74	13.9	5.43	26.9
MTB	1.003	0.0203	1	1	1	1	1.177
ROA	0.0077	0.0086	0.0057	0.0091	0.012	-0.0378	0.0249

Panel B: Pearson Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) ΔEV_{t+1}	1						
(2) ΔEV_{t+5}	-0.011	1					
(3) DTS	0.012	0.176*	1				
(4) DCS	0.202*	0.154*	0	1			
(5) CS mean EV_t	-0.012	-0.176*	-1	0	1		
(6) EV_t	-0.194*	-0.219*	-0.338*	-0.938*	0.338*	1	
(7) Bank Size	-0.009	-0.020*	-0.053*	0.051*	0.053*	-0.032*	1
(8) Deposit ratio	-0.013	-0.01	-0.050*	-0.027*	0.050*	0.036*	-0.460*
(9) Loan ratio	0.054*	0.044*	0.018*	0.008	-0.018*	-0.013	-0.243*
(10) LLP ratio	0.106*	-0.130*	-0.343*	-0.242*	0.343*	0.362*	0.161*
(11) NPL	0.085*	-0.156*	-0.499*	-0.349*	0.499*	0.515*	-0.030*
(12) CAPR1	-0.063*	-0.031*	-0.033*	0.063*	0.033*	-0.044*	-0.156*
(13) MTB	0.013	-0.035*	-0.089*	-0.089*	0.089*	0.117*	0.014
(14) ROA	-0.065*	0.250*	0.337*	0.427*	-0.337*	-0.523*	0.057*
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
(8) Deposit ratio	1						
(9) Loan ratio	0.266*	1					
(10) LLP ratio	0.01	0.080*	1				
(11) NPL	0.064*	0.036*	0.501*	1			
(12) CAPR1	0.066*	-0.201*	-0.153*	-0.104*	1		
(13) MTB	0.015*	-0.020*	0.094*	0.128*	-0.068*	1	
(14) ROA	-0.018*	-0.018*	-0.402*	-0.560*	0.139*	-0.121*	1

Panel A presents the mean, standard deviation (S.D.), 25th percentile (25%), median and 75th percentile (75%) of the variables for the sample period from 1983 to 2020. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are summarized in Appendix A. Panel B presents the Pearson correlation for each pair of variables. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are summarized in Appendix A. ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 2.2: Baseline Regression- Partial Risk Adjustment Model 1

Table 2 presents the results of my baseline regressions using partial risk adjustment model 1 for analysing the dynamics of risk-taking behavior in Banks, where year t+1 represents the short-run risk adjustment and year t+5 represents the long-run risk adjustment model. The partial risk adjustment Model 1 is as follows:

$$\Delta EV_{(t+1)} = \alpha_0 + \alpha_1 * \mu_t + \alpha_2 * EV_t + \varepsilon_{t+1}, \text{ with the intercept term } \alpha 0.$$

$$\Delta EV_{(t+5)} = \alpha_0 + \alpha 1 * \mu_t + \alpha_2 * EV_t + \varepsilon_{t+1}, \text{ with the intercept term } \alpha 0.$$

The dependent variable is change in Earnings Volatility (EV), where $\Delta EV_{(t+1)} = EV_{t+1} - EV_t$ and $\Delta EV_{(t+5)} = EV_{t+5} - EV_t$. The independent variables are the Cross-sectional mean of EV of year t ($CSEV_t$_Mean) and Earnings volatility of year t (EV_t). Here μ(t) represents the Cross-sectional mean of EV_t. Earnings volatility winsorized at the first and 99th percentiles. The model includes bank fixed effects and the t-values (reported in parentheses) are based on robust standard errors clustered by bank and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

	(1) $\Delta EV_{(t+1)}$	(2) $\Delta EV_{(t+5)}$
$CSEV_t$ Mean	0.2300^{**}	-0.0481
	(2.38)	(-0.41)
EV_t	-0.2378^{***}	-1.1163^{***}
	(-9.20)	(-20.13)
_cons	0.0225	0.4585^{***}
	(0.72)	(5.96)
N	14732	9393
Bank FE	Yes	Yes
Cluster by bank and year	Yes	Yes
adj. R^2	0.092	0.564

Table 2.3: Baseline Regression- Partial Risk Adjustment Model 2

Table 3 presents the results of my baseline regressions using partial risk adjustment model 2 for analysing the dynamics of risk-taking behavior in Banks where year t+1 represents the short-run risk adjustment and year t+5 represents the long-run risk adjustment. The partial risk adjustment Model 2 is as follows:

$$\Delta EV_{t+1} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t - EV_t) + \varepsilon_{t+1}, \text{ No intercept term}$$
$$\Delta EV_{t+5} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t - EV_t) + \varepsilon_{t+5}, \text{ No intercept term}$$

The dependent variable is change in Earnings Volatility (EV), where $\Delta EV_{(t+1)} = EV_{t+1} - EV_t$ and $\Delta EV_{(t+5)} = EV_{t+5} - EV_t$. The independent variables are DTS and DCS. DTS is the proxy of whole-sector risk adjustment and which is equal to $(\bar{\mu} - \mu(t)) = (TS\bar{\mu} - CS\mu(t))$; and DCS is the proxy of cross-sectional risk adjustment which is equal to $(\mu(t) - EV(t)) = (CS\mu(t) - EV(t))$. Here, $\mu(t)$ represents the Cross-sectional mean of EV(t) in year t, and $\bar{\mu}$ represents Time-series mean of $\mu(t)$. Earnings volatility winsorized at the first and 99th percentiles. The model includes bank fixed effects; t-values (reported in parentheses) are based on robust standard errors clustered by bank and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

	(1) $\Delta EV_{(t+1)}$	(2) $\Delta EV_{(t+5)}$
DTS	0.0078	1.1644***
	(0.09)	(7.85)
DCS	0.2378***	1.1163***
	(9.20)	(20.13)
N	14732	9393
Bank FE	Yes	Yes
Cluster by bank and year	Yes	Yes
adj. R^2	0.092	0.564

Table 2.4: Determinants of Banks' Risk-taking

To model the partial risk adjustment mechanism using models 1 and 2, here I use bank-level characteristics that appear frequently in literature to infer the target risk-taking (EV*) of banks. Table 4 presents the results of my baseline regressions for analyzing the determinants of optimal risk-taking behavior in Banks from year t+1 to t+5. The pooled regression model is as follows:

$$\Delta EV_{i,\,t+1} = \lambda_1 (EV^* - EV_{i,\,t}) + \varepsilon_{t+1} \qquad \text{Eq. (1)}$$

$$EV_{i,t+1} = (\lambda\beta)X_{i,t} + (1-\lambda)EV^* + \varepsilon_{i,t+1}$$

$$EV_{i,t+1} = \beta_1 EV_{i,t} + \beta_2 \text{Size}_{i,t} + \beta_3 \text{Deposit ratio}_{i,t} + \beta_4 \text{Loan ratio}_{i,t} + \beta_5 \text{LLP ratio}_{i,t} + \beta_6 \text{NPL}_{i,t} + \beta_7 \text{CAPR1}_{i,t} + \beta_8 \text{ROA}_{i,t} + \text{Bank FE} + \varepsilon_{i,t+1}, \text{ No intercept term}$$

The dependent variable is the Earnings Volatility (EV) from t+1 to t+5. The lagged X variables infer the optimal risk-taking. The main independent variable is earnings volatility of time t. The control variables are Bank size (log of total assets), Deposit ratio (Ln of total deposit to total assets), Loan ratio (Ln of total loan to total assets), LLP ratio (Ln of loan loss provision to total assets), NPL (Non-performing loan to total assets), CAPR1(Tier 1capital ratio), and ROA (Earnings before extraordinary item deflated by average total asset), MTB (market to book ratio of equity). Earnings volatility and all independent variables are winsorized at the first and 99th percentiles. The model includes bank fixed effects; t-values (reported in parentheses) are based on robust standard errors clustered by bank and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

	(1) EV_{t+1}	(2) EV_{t+2}	(3) EV_{t+3}	(4) EV_{t+4}	(5) EV_{t+5}
$EV_{i,t}$	0.7662***	0.4376***	0.1495*	-0.1494*	-0.3165***
	(11.17)	(5.24)	(1.77)	(-1.94)	(-3.48)
Bank size $_{i,t}$	0.0003*	0.0007**	0.0009**	0.0011**	0.0016***
	(1.82)	(2.07)	(2.08)	(2.37)	(3.14)
Deposit ratio $_{i,t}$	-0.0034**	-0.0049*	-0.0049**	-0.0044**	-0.0051**
	(-2.08)	(-1.84)	(-2.12)	(-2.26)	(-2.81)
Loan ratio $_{i,t}$	0.0010	0.0020	0.0027**	0.0036***	0.0032***
	(1.23)	(1.55)	(2.13)	(3.55)	(3.26)
LLP ratio $_{i,t}$	0.0002**	0.0002	-0.0000	-0.0004*	-0.0005**
	(2.24)	(1.33)	(-0.20)	(-1.97)	(-2.34)
NPL $_{i,t}$	0.0407***	0.0464***	0.0383***	0.0297**	0.0527***
	(2.98)	(3.71)	(3.35)	(2.30)	(3.14)
$CAPR1_{i,t}$	-0.0000	-0.0000	-0.0001*	-0.0001**	-0.0002***
	(-0.35)	(-1.26)	(-2.04)	(-2.11)	(-2.97)
MTB $_{i,t}$	-0.0022	-0.0005	-0.0008	-0.0002	0.0052
	(-0.44)	(-0.09)	(-0.13)	(-0.03)	(0.69)
ROA $_{i,t}$	-0.0609**	-0.1120***	-0.1886***	-0.2872***	-0.1401***
	(-2.22)	(-4.43)	(-6.68)	(-8.71)	(-6.11)
_cons	0.0018	-0.0005	-0.0002	-0.0022	-0.0121
	(0.37)	(-0.08)	(-0.03)	(-0.31)	(-1.40)
N	11109	9925	8847	7928	7124
Bank Fixed Effect	Yes	Yes	Yes	Yes	Yes
Cluster by Bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.733	0.574	0.519	0.500	0.485

Table 2.5 Alternative measures of Banks' Risk-taking

Table 5 presents the results of partial risk adjustment model 1 and 2 using the alternative measures of Banks' risk-taking behavior. In Panel A, the dependent variable is defined as change in stock return volatility (SRV) for year t+1 and t+5. The dependent vaiable in Panel B is the change in z-score. Z-score represents the probability of default and defined as z-score = (ROA+EAR)/SD of ROA (use the logarithm of z-score). In Panel C, I use the change in Equity Capital Ratio (ECR) as the dependent vaiable for year t+1 and t+5, where, EC Ratio is defined as log of total stock holder's equity to total assets ratio. The independent variables are DTS and DCS. In Panel A, DTS is the proxy of whole-sector risk adjustment and which is equal to (μ¯ - μ(t)) = (TSμ¯ - CSμ(t)); and DCS is the proxy of cross-sectional risk adjustment which is equal to (μ(t) –SRV(t)) = (CSμ(t) – SRV(t)). In panel B and C, DCS is the cross sectional risk adjustment proxy which is equal to (CSμ(t) – Z-score(t)) and (CSμ(t) – ECR(t)) respectively. Here, μ(t) represents the Cross-sectional mean of SRV(t) in year t, and μ¯ represents Time-series mean of μ(t). Earnings volatility winsorized at the first and 99th percentiles. The model includes bank fixed effects; t-values (reported in parentheses) are based on robust standard errors clustered by bank and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

Panel A: Stock Return Volatility

Model 1: $\Delta SRV_{(t+1)} = \alpha_0 + \alpha_1 * \mu_t + \alpha_2 * SRV_t + \varepsilon_{t+1}$, with the intercept term α0.

$\Delta SRV_{(t+5)} = \alpha_0 + \alpha 1 * \mu_t + \alpha_2 * SRV_t + \varepsilon_{t+1}$, with the intercept term α0.

	(1) $\Delta SRV_{(t+1)}$	(2) $\Delta SRV_{(t+5)}$
CSRVt_mean	0.4700***	-0.2919*
	(3.88)	(-1.88)
SRVt	-0.7741***	-1.2749***
	(-9.66)	(-17.67)
_cons	0.0289*	0.1406***
	(2.02)	(8.03)
N	9651	5552
Bank Fixed Effect	Yes	Yes
SE Clustered by bank and year	Yes	Yes
adj. R^2	0.133	0.477

Model 2: $\Delta SRV_{t+1} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t - EV_t) + \varepsilon_{t+1}$, No intercept term

$\Delta SRV_{t+5} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t - EV_t) + \varepsilon_{t+5}$, No intercept term

	(1) ΔSRV_{t+1}	(2) ΔSRV_{t+5}
DTS	0.2702*	1.4863***
	(1.71)	(9.89)
DCS	0.7786***	1.0823***
	(11.51)	(19.59)
N	9651	5552
Bank Fixed Effect	Yes	Yes
SE Clustered by bank and year	Yes	Yes
adj. R^2	0.254	0.524

Panel B: Z-score (probability of default)

Model 1: ΔZ-score $_{(t+1)} = \alpha_0 + \alpha_1 * \mu_t + \alpha_2 *$ z-score$_t + \varepsilon_{t+1}$, with the intercept term α0.

ΔZ-score $_{(t+5)} = \alpha_0 + \alpha 1 * \mu_t + \alpha_2 *$ z-score$_t + \varepsilon_{t+1}$, with the intercept term α0.

	(1) ΔZ-score $_{(t+1)}$	(2) ΔZ-score $_{(t+5)}$
CSmeanZ$_t$	0.2090***	-0.1357
	(3.65)	(-1.13)
z-score$_t$	-0.3898***	-1.1767***
	(-10.58)	(-28.43)
_cons	1.5103***	11.0513***
	(2.79)	(12.20)
N	6250	3517
Bank Fixed Effect	Yes	Yes
SE Clustered by bank and year	Yes	Yes
adj. R^2	0.179	0.698

Model 2: ΔZ-score $_{(t+1)} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t -$z-score$_t) + \varepsilon_{t+1}$, No intercept term α0.

ΔZ-score $_{(t+5)} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t -$z-score$_t) + \varepsilon_{t+1}$, No intercept term α0.

	(1) ΔZ-score $_{(t+1)}$	(2) ΔZ-score $_{(t+5)}$
DTS	0.1797**	1.3048***
	(2.70)	(11.95)
DCS	0.3876***	1.1515***
	(10.63)	(28.46)
N	6250	3517
Bank Fixed Effect	Yes	Yes
SE Clustered by bank and year	Yes	Yes
adj. R^2	0.186	0.701

Panel C: Equity Capital Ratio

Model 1: $\Delta ECR_{(t+1)} = \alpha_0 + \alpha_1 * \mu_t + \alpha_2 * ECR_t + \varepsilon_{t+1}$, with the intercept term α0.

$\Delta ECR_{(t+5)} = \alpha_0 + \alpha 1 * \mu_t + \alpha_2 * ECR_t + \varepsilon_{t+1}$, with the intercept term α0.

	(1) $\Delta ECR_{(t+1)}$	(2) $\Delta ECR_{(t+5)}$
$CSER_t$_mean	0.2059***	0.6765***
	(4.64)	(7.10)
ECR_t	-0.3488***	-1.0391***
	(-15.17)	(-15.95)
_cons	0.3099***	0.8163***
	(3.51)	(4.51)
N	18545	12005
Bank Fixed Effect	Yes	Yes
SE Clustered by bank and year	Yes	Yes
adj. R^2	0.115	0.470

Model 2: $\Delta ECR_{(t+1)} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t - ECR_t) + \varepsilon_{t+1}$, No intercept term α0.
$\Delta ECR_{(t+5)} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t - ECR_t) + \varepsilon_{t+1}$, No intercept term α0.

	(1) $\Delta ECR_{(t+1)}$	(2) $\Delta ECR_{(t+1)}$
DTS	0.1458***	0.3530***
	(3.41)	(4.33)
DCS	0.3551***	1.0106***
	(11.98)	(18.78)
N	18545	12005
Bank Fixed Effect	Yes	Yes
SE Clustered by bank and year	Yes	Yes
adj. R^2	0.148	0.544

Table 2.6: Alternative Control variables (Control variables are estimated at year t-5)

Table 6 presents the results of robustness check for analyzing the determinants of optimal risk-taking behavior in Banks from year t+1 to t+5. To model the partial risk adjustment mechanism using models 1 and 2, here I use bank-level characteristics that appear frequently in literature to infer the target risk-taking (EV*) of banks. For the alternative test, I measure the control variables that estimated at year t-5. Because I use the past 5-year rolling window to measure dependent variable (earnings volatility). The pooled regression model is as follows:

$$\Delta EV_{i,\,t+1} = \lambda_1 (EV^* - EV_{i,\,t}) + \varepsilon_{t+1} \qquad \text{Eq. (1)}$$

$$EV_{i,t+1} = (\lambda\beta)X_{i,t} + (1\text{-}\lambda)EV^* + \varepsilon_{i,t+1}$$

$$EV_{i,t+1} = \beta_1 EV_{i,t\text{-}5} + \beta_2 \text{Size}_{i,t\text{-}5} + \beta_3 \text{Deposit ratio}_{i,t\text{-}5} + \beta_4 \text{Loan ratio}_{i,t\text{-}5} + \beta_5 \text{LLP ratio}_{i,\text{-}5t} + + \beta_6 \text{CAPR1}_{i,t\text{-}5} + \beta_7 \text{ROA}_{i,\,t\text{-}5} + \text{Bank FE} + \varepsilon_{i,t+1}, \text{No intercept term}$$

The dependent variable is the Earnings Volatility (EV) from t+1 to t+5. The lagged X variables infer the optimal risk-taking. The main independent variable is earnings volatility of time t. The control variables are Bank size (log of total assets), Deposit ratio (Ln of total deposit to total assets), Loan ratio (Ln of total loan to total assets), LLP ratio (Ln of loan loss provision to total assets), CAPR1(Tier 1capital ratio), and ROA (Earnings before extraordinary item deflated by average total asset), MTB (market to book ratio of equity). Earnings volatility and all independent variables are winsorized at the first and 99th percentiles. The model includes bank fixed effects; t-values (reported in parentheses) are based on robust standard errors clustered by bank and year. * p < 0.10, ** p < 0.05, *** p < 0.01 represents significance at the 10%, 5% and 1% level, respectively.

	(1) EV_{t+1}	(2) EV_{t+2}	(3) EV_{t+3}	(4) EV_{t+4}	(5) EV_{t+5}
EV_t	0.7990***	0.4504***	0.1965	-0.0520	-0.2949***
	(17.58)	(4.62)	(1.63)	(-0.45)	(-3.67)
Bank size $_{t-5}$	0.0005***	0.0009***	0.0010***	0.0009**	0.0009*
	(3.53)	(3.60)	(3.22)	(2.40)	(1.89)
Deposit ratio $_{t-5}$	-0.0017	-0.0014	-0.0016	-0.0030	-0.0039*
	(-1.53)	(-0.78)	(-0.83)	(-1.66)	(-1.91)
Loan ratio $_{t-5}$	-0.0001	-0.0016	-0.0012	-0.0004	0.0003
	(-0.16)	(-1.44)	(-0.91)	(-0.26)	(0.19)
LLP ratio $_{t-5}$	-0.0001	-0.0001	0.0000	0.0002	0.0003
	(-1.62)	(-0.57)	(0.21)	(0.98)	(1.56)
CAPR1 $_{t-5}$	-0.0001*	-0.0002**	-0.0002***	-0.0001**	-0.0001*
	(-1.77)	(-2.83)	(-3.66)	(-2.79)	(-1.93)
MTB $_{t-5}$	-0.0164**	-0.0216*	-0.0259*	-0.0321**	-0.0405***
	(-2.15)	(-1.85)	(-2.08)	(-2.38)	(-2.93)
ROA $_{t-5}$	0.0661***	0.1287***	0.1517***	0.1703***	0.1508***
	(4.56)	(4.15)	(4.43)	(4.85)	(5.10)
N	6118	4742	4168	3700	3886
Bank Fixed Effect	Yes	Yes	Yes	Yes	Yes
Cluster by bank and year	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.730	0.555	0.505	0.490	0.548

Table 2.7: Post-estimation Test of the Model 2

Panel A: Testing the equality hypothesis of the two coefficients ($\beta_1 = \beta_2$) from Model 2

Table 5 presents the results of post estimation test of Model 2. Panel A presents the equality hypothesis using partial risk adjustment model 2. The partial risk adjustment Model 2 is as follows:

$$\Delta EV_{t+1} = \beta_1 * (\bar{\mu} - \mu_t) + \beta_2 * (\mu_t - EV_t) + \varepsilon_{t+1}, \text{ No intercept term}$$

The null hypothesis is presented as to whether the two parameters of Model 2 are equal. I use the Wald test statistics to test the equality hypothesis. DTS is the proxy of whole-sector risk adjustment and which is equal to ($\bar{\mu}$ - μ(t)) = (TS$\bar{\mu}$ - CSμ(t)); and DCS is the proxy of cross-sectional risk adjustment which is equal to (μ(t) – EV(t)) = (CSμ(t) – EV(t)). Here, μ(t) represents the Cross-sectional mean of EV(t) in year t, and $\bar{\mu}$ represents Time-series mean of μ(t). The result shows that the null hypothesis is accepted with a p-value of 0.6817.

H0: $\beta_1 = \beta_2$

F (1, 30) = 0.17
Prob > F = 0.6817

(D_ts_cs - Dx = 0
F (1, 30) = 0.17
Prob > F = 0.6817

Constrained coefficients
(Std. err. adjusted for clustering on gvkey and year)

Variables	Coefficients	Robust Standard Error	z	P>|z|	95% Confidence Interval	
DTS	1.10656	0.050247	22.020	0.000	1.008078	1.205042
DCS	1.10656	0.050247	22.020	0.000	1.008078	1.205042

Panel B: Testing the value of the two coefficients equal 1 ($\beta_1 = 1$; $\beta_2 = 1$) from Model 2

Panel B presents testing the value of coefficients equal to 1 using partial risk adjustment model 2. The null hypothesis is presented as to whether the two parameters of Model 2 are equal to 1. The result shows that the null hypothesis is accepted with a p-value of 0. 1142. The results show that we cannot reject the hypothesis or at least we cannot reject it at any significance level below 11.42%.

H0: $\beta_1 = 1$; $\beta_2 = 1$

(1) Dx = 1
(2) D_ts_cs = 1
F(2, 30) = 2.33
Prob > F = 0.1142

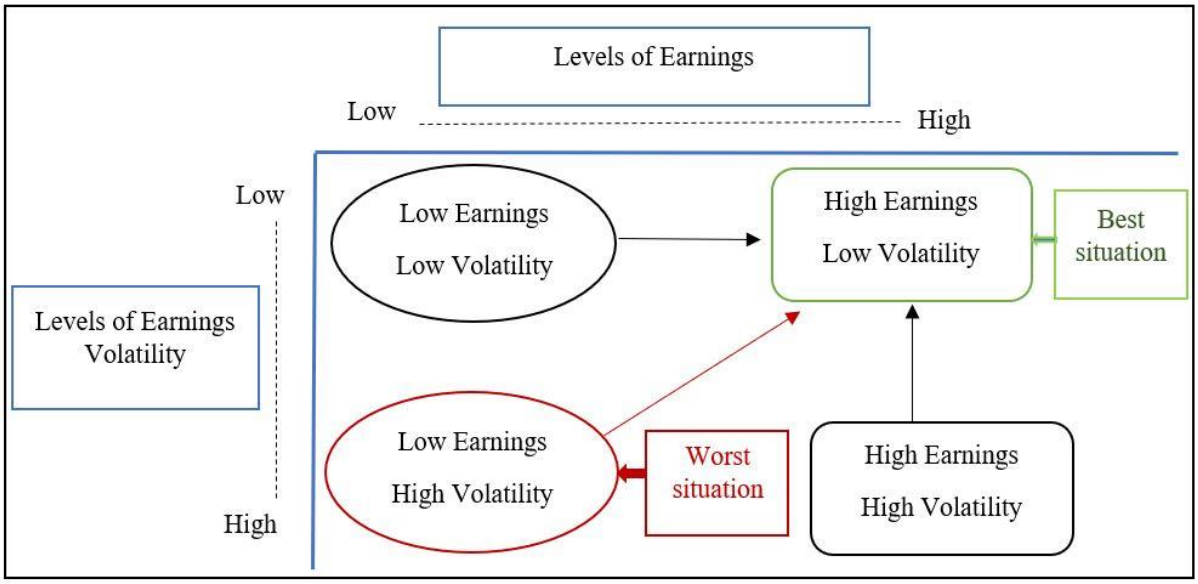


Figure 2. 1: Flow chart of Earnings and Earnings Volatility

The figure depicts the implications of earnings and earnings volatility dynamics in terms of low to high levels, where the vertical axis represents the levels of earnings volatility and the horizontal axis represents the levels of earnings. From the implications of Dichev and Tang's hypothesis in banks' risk-taking behavior, I portray the banks' risk-taking scenario as follows. For banks the best situation is "High earnings with Low volatility" and the worst situation is "Low earnings with High volatility". When banks are in the situation of low earnings volatility with low levels of earnings, bank managers should take more risk to increase their levels of earnings. Even banks with low earnings and high volatility should take more risk to increase their earnings levels. When banks are in the situation of high earnings and high volatility, bank managers should reduce risk because high volatility reduces the future earnings. Since earnings are the main measures to analyze firm's performance.

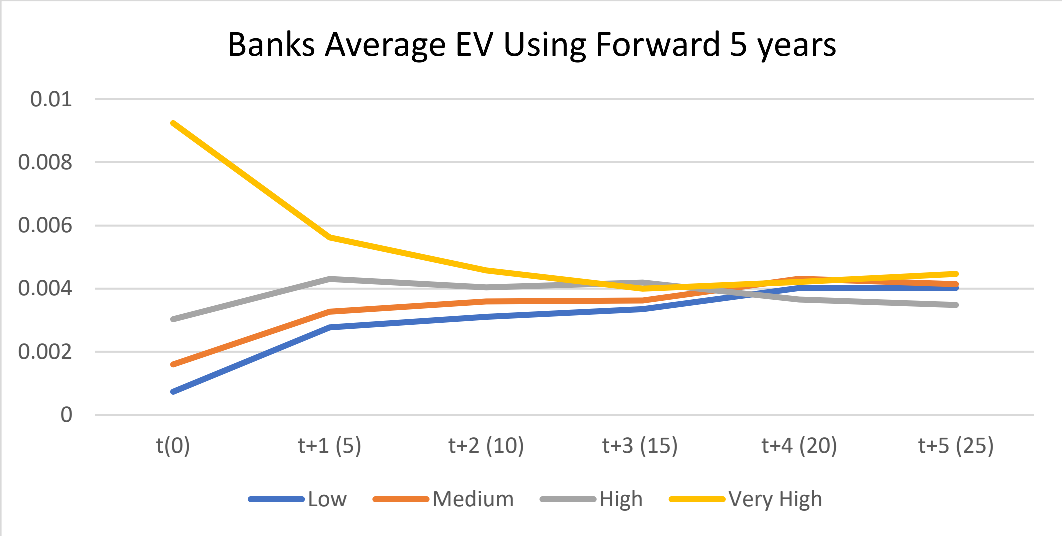
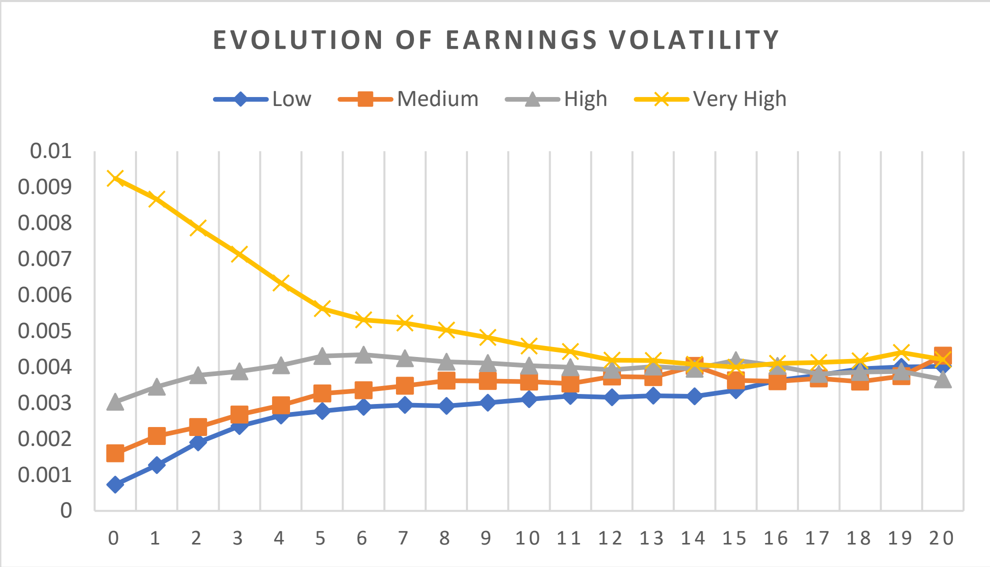


Figure 2.2: Dynamics of Banks Earnings Volatility

The figure illustrates the dynamics of banks' risk-taking behavior. I use average earnings volatility using forward five years. The sample consists of all banks fundamental in the Compustat database from 1988–2020. Each panel presents the average earnings volatility of four portfolios in event time, where year zero is the portfolio formation period. That is, for each calendar year, we form four portfolios: very high, high, medium, and low by ranking banks based on their actual earnings volatility. Holding the portfolios fixed for the next 25 years, we compute the average earnings volatility for each portfolio. For example, in 1988 we sort firms into four groups based on their leverage ratios. For each year from 1988 to 2013, we compute the average earnings volatility for each of these four portfolios. We repeat this process of sorting and averaging for every year in our sample horizon. After performing this sorting and averaging for each year from 1988–2020, we then average the average earnings volatility across "event time" to obtain the bold lines in the figure. The surrounding dashed lines represent 95% confidence intervals.

Panel A: Banking firms Earnings Volatility Dynamics for 20 event years



Panel B: Industry firms Earnings Volatility Dynamics for 20 event years

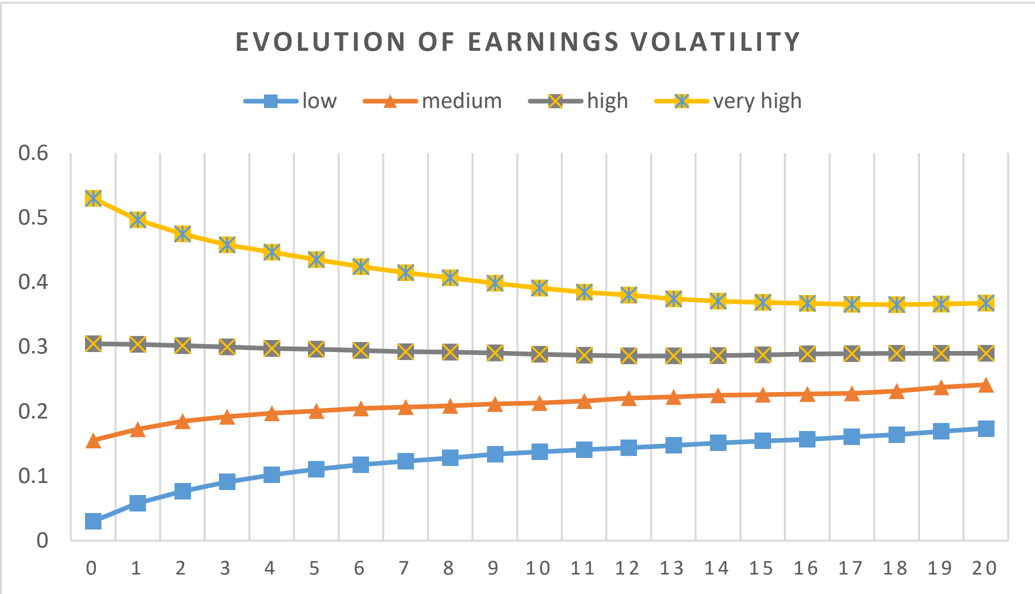


Figure 2.3: Comparison between Banks and Industry (Non-banking) Risk (Earnings Volatility)

The figure accentuates the differences between banking firm and industry firm risk dynamics behavior over the 20 years period. Panel A shows that banks' earnings volatility dynamics which starts to converges irrespective of the portfolio (very high, high, medium, and low) after 15 years. Panel B shows that industry firms earnings volatility dynamics which also take more risk to ensure future earnings. However, unlike banks, the portfolio volatility of industry firms does not converge over time, but rather diverge from one other. Banking firms differ from industry firms because their devastation can have a systemic effect on the economy, which puts them under pressure to converge risk.

Table 2.8: Asymmetry in Cross-sectional Risk Adjustment Model

Table 6 presents the results of asymmetric effects of partial risk adjustment model for analysing the dynamics of risk-taking behaviour in Banks. The short-run asymmetric effects of risk adjustment presented in year t+1 and the long-run asymmetric effects of risk adjustment presented in year t+5. The asymmetric effects presented as follows:

$$\Delta EV_{t+1} = \beta 1 * DCS^{(+)} + \beta 2 * DCS^{(-)} + \varepsilon_{t+1}, \text{ no intercept term}$$

$$\Delta EV_{t+5} = \beta 1 * DCS^{(+)} + \beta 2 * DCS^{(-)} + \varepsilon_{t+5}, \text{ no intercept term}$$

The dependent variable is change in Earnings Volatility (EV), where $\Delta EV_{(t+1)} = (EV_{t+1} - EV_t)$ and $\Delta EV_{(t+5)} = (EV_{t+5} - EV_t)$. The independent variable DCS which is calculated as the difference between Cross-sectional mean of EV_t and Earnings Volatility of year t ($CS\mu_t - EV_t$) where, DCS $^{(positive)}$ represents cost of less risk taking which is equal to ($\mu_t - EV_t$) if ($\mu_t - EV_t$) >0 and zero otherwise; and DCS $^{(negative)}$ represents cost of taking excess risk which is equal to ($\mu_t - EV_t$) if ($\mu_t - EV_t$) <0 and zero otherwise. Here, μ_t represents the Cross sectional mean of EV_t. Earnings volatility winsorized at the first and 99th percentiles. The model includes bank and year fixed effects and the t-values (reported in parentheses) are based on robust standard errors clustered by bank and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

	(1) $\Delta EV_{(t+1)}$	(2) $\Delta EV_{(t+5)}$
$DCS^{(positive)}$	0.0680	0.9800***
	(1.16)	(8.66)
$DCS^{(negative)}$	0.2685***	1.1487***
	(10.64)	(20.89)
N	14732	9393
Bank and Year FE	Yes	Yes
Cluster by bank and year	Yes	Yes
adj. R^2	0.187	0.647

Table 2.9: The Interaction between Asymmetry of Risk Adjustments and Banks Earnings

Table 7 presents the results of interaction between asymmetric effects of partial risk adjustment and banks' earnings for analysing the dynamics of risk-taking behaviour in Banks. The short-run interaction effects of earnings and risk adjustment presented in year t+1 and the long-run interaction effects of earnings and risk adjustment presented in year t+5. The interaction effects presented as follows:

$$\Delta EV_{t+1} = \beta 1^*DCS^{(+)} + \beta 2^*DCS^{(-)} + \beta 3^*ROA + \beta 5^*(DCS^{(+)}*ROA) + \beta 6^*(DCS^{(-)}*ROA) + \varepsilon_{t+1}, \text{ no intercept term}$$

$$\Delta EV_{t+5} = \beta 1^*DCS^{(+)} + \beta 2^*DCS^{(-)} + \beta 3^*ROA + \beta 5^*(DCS^{(+)}*ROA) + \beta 6^*(DCS^{(-)}*ROA) + \varepsilon_{t+5}, \text{ no intercept term}$$

The dependent variable is change in Earnings Volatility (EV), where $\Delta EV_{(t+1)} = EV_{t+1}-EV_t$ and $\Delta EV_{(t+5)} = EV_{t+5}-EV_t$. The independent variable ROA represents the return of assets (earnings) of banks and DCS is the difference between Cross-sectional mean of EV_t and Earnings Volatility of year t (CSμ(t) – EV(t)). DCS $^{(positive)}$ represents cost of taking less risk, which is equal to (μ(t) – EV(t)) if (μ(t) – EV(t)) >0 and zero otherwise; and DCS $^{(negative)}$ represents cost of taking excess risk which, is equal to (μ(t) – EV(t)) if (μ(t) – EV(t)) <0 and zero otherwise. Here, μ(t) represents the Cross sectional mean of EV_t. Earnings volatility and ROA are winsorized at the first and 99th percentiles. I include bank and year fixed effects and the t-values (reported in parentheses) are based on robust standard errors clustered by bank and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

	(1) $\Delta EV_{(t+1)}$	(2) $\Delta EV_{(t+5)}$
$DCS^{(positive)}$	0.1073^{*}	1.1810^{***}
	(1.71)	(8.49)
$DCS^{(negative)}$	0.3060^{***}	1.1937^{***}
	(9.75)	(21.43)
ROA	-7.8229^{***}	-7.5548^{***}
	(-4.03)	(-2.77)
Dxpos*ROA	6.4251	-9.0583
	(1.52)	(-1.07)
Dxneg*ROA	-2.4708^{**}	3.4082
	(-2.35)	(1.67)
N	14724	9389
Bank and Year Fixed	Yes	Yes
Effect	Yes	Yes
Cluster by Bank and Year		
adj. R^2	0.202	0.659

Table 2.10: The Interaction between Asymmetric Effect of Risk Adjustments and Banks Specific Characteristics

Table 8 presents the results of the interaction between asymmetric effects of partial risk adjustment and banks' earnings for analysing the dynamics of risk-taking behavior in Banks. The short-run interaction effects of earnings and risk adjustment presented in year t+1 and the long-run interaction effects of earnings and risk adjustment presented in year t+5. The equation for interaction effects is presented as follows:

$\Delta EV_{t+1} = \beta1*DCS^{(+)} + \beta2*DCS^{(-)} + \beta3*ROA + \beta4*LLP + \beta5*Leverage + \beta6*(DCS^{(+)}*ROA) +\beta7*(DCS^{(-)}*ROA)+\beta8*(DCS^{(+)}*LLP)+\beta9*(DCS^{(-)}*LLP)+\beta10*(DCS^{(+)}*Leverage)+ \beta11*(DCS^{(-)} * Leverage) + \varepsilon_{t+1}$**,** no intercept term

$\Delta EV_{t+5} = \beta1*DCS^{(+)} + \beta2*DCS^{(-)} + \beta3*ROA + \beta4*LLP + \beta5*Leverage + \beta6*(DCS^{(+)}*ROA) +\beta7*(DCS^{(-)}*ROA)+\beta8*(DCS^{(+)}*LLP)+\beta9*(DCS^{(-)}*LLP)+\beta10*(DCS^{(+)}*Leverage)+ \beta11*(DCS^{(-)} * Leverage) + \varepsilon_{t+5}$**,** no intercept term

	(1) $\Delta EV_{(t+1)}$	(2) $\Delta EV_{(t+5)}$
Dx positive	0.2794***	1.5324***
	(3.31)	(8.94)
Dx negative	0.2941***	1.1742***
	(11.08)	(19.36)
ROA	-4.1607***	-1.6725
	(-3.07)	(-0.51)
LLP	9.1381***	15.8295***
	(3.41)	(6.16)
Leverage	-0.0012	-0.0003
	(-0.64)	(-0.05)
Dxpos*ROA	1.4646	-18.1536**
	(0.35)	(-2.25)
Dxneg*ROA	-0.9798	5.1080**
	(-1.31)	(2.21)
Dxpos*LLP	-11.2227**	-29.3142***
	(-2.04)	(-3.69)
Dxneg*LLP	0.8877	2.8966
	(0.96)	(1.05)
Dxpos*Leverage	-0.0033	-0.0064
	(-1.29)	(-1.17)
Dxneg*Leverage	-0.0000***	-0.0000**
	(-2.82)	(-2.63)
N	14379	9180
Bank & Year Fixed Effects	Yes	Yes
Cluster by Bank & Year	Yes	Yes
adj. R^2	0.209	0.666

The dependent variable is changes in Earnings Volatility (EV), where $\Delta EV_{(t+1)} = EV_{t+1} - EV_t$ and $\Delta EV_{(t+5)} = EV_{t+5} - EV_t$. The independent variable DCS is the difference between the Cross-sectional mean of EV_t and Earnings Volatility of year t (CSμ(t) – EV(t)). DCS $^{(positive)}$ represents cost of taking less risk, which is equal to (μ(t) – EV(t)) if (μ(t) – EV(t)) >0 and zero otherwise; and DCS $^{(negative)}$ represents cost of taking over risk which, is equal to (μ(t) – EV(t)) if (μ(t) – EV(t)) <0 and zero otherwise. Here, μ(t) represents the Cross-sectional mean of EV_t. The bank-specific independent variables are ROA which represents bank's return of assets calculated as earnings deflated by total average assets. LLP is defined as loan loss provisions of a year scaled by total assets and Leverage is defined as total assets divided by total equity. Earnings volatility and All the variables are winsorized at the first and 99th percentiles. I include bank and year fixed effects and the t-values (reported in parentheses) are based on robust standard errors clustered by bank and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ represents significance at the 10%, 5% and 1% level, respectively.

Appendix: Variable Definitions

Variable Names	Definitions	Data Sources
Earnings	Earnings before extraordinary item deflated by average total asset	COMPUSTAT/Banks Fundamental
EV_t	Earnings Volatility is the S.D. of earnings, over most recent (past) 5yrs [t, t-4].	COMPUSTAT/Banks Fundamental
ΔEV_{t+1}	Change in Earnings Volatility with differences between Earnings Volatility of year t+1 and t (EV_{t+1} - EV_t)	COMPUSTAT/Banks Fundamental
ΔEV_{t+5}	Change in Earnings Volatility with differences between Earnings Volatility of year t+5 and t (EV_{t+5} - EV_t)	COMPUSTAT/Banks Fundamental
CS mean EV_t	Cross-sectional mean of Earnings Volatility of year t	COMPUSTAT/Banks Fundamental
DTS	The deviation between time-series mean of cross-sectional mean of earnings volatility and cross-sectional mean of earnings volatility of year t (TS mean – CS mean)	COMPUSTAT/Banks Fundamental
DCS	The deviation between cross-sectional mean of earnings volatility and earnings volatility of year t (CS mean of EV_t - EV_t)	COMPUSTAT/Banks Fundamental
Size	Bank size calculated by taking the natural log of average total assets of year t-1	COMPUSTAT/Banks Fundamental
Deposit Ratio	Total deposits divided by total assets	COMPUSTAT/Banks Fundamental
Loan Ratio	The natural log of Net loans divided by total assets	COMPUSTAT/Banks Fundamental
LLP Ratio	The natural log of total loan loss provision divided by total assets	COMPUSTAT/Banks Fundamental
NPL	Non-performing loans divided by total loans	COMPUSTAT/Banks Fundamental
CAPR1	Tier 1 risk-based capital ratio at the end of year t-1.	COMPUSTAT/Banks Fundamental
MTB	Tobin's q calculated as total equity divided by book value of common equity	COMPUSTAT/Banks Fundamental
ROA	Earnings before extraordinary item deflated by average total asset	COMPUSTAT/Banks Fundamental