# Three Essays in Financial Intermediation

by

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# Abstract

This thesis contains three chapters on financial intermediation. Chapter 1 considers whether the rating gap between "all-in" and "stand-alone" ratings for a bank can serve as a good measure of systemic risk, which is defined as the risk that a distressed bank may bring to the banking system. The gap between the stand-alone rating and the all-in rating is attributable to the external support that the bank would receive if it were in financial distress. With the motivation to provide a reliable and easily constructed systemic risk indicator, Chapter 1 contributes to the literature in providing several ways to calculate the rating gap and studies the link between it and a quantitative systemic risk measure, Co-independent Value at Risk (CoVar). This chapter finds that the rating gap is a good proxy for systemic risk for large banks.

Chapter 2 evaluates how the risks associated with mergers and acquisitions (M&As) affect banks' levels of solvency. This chapter hypothesizes that bank solvency is affected by M&As directly and indirectly through banks' market risk, geographical diversification and activity diversification. The relationship between bank solvency, diversification and market risk are estimated as a system using Generalized Method of Moments (GMM). The key finding is that M&As erode banks' solvency, both directly and indirectly through the effects associated with their geographical diversification.

Chapter 3 explores whether banks pursue different diversification strategies in response to time-varying market betas and spillover effects during upturns and downturns in markets. The main findings are: 1) banks use different diversification strategies in response to market movements conditional on market stability; 2) banks may need to consider market spillovers in activity diversification plans because spillovers change the link between activity diversification and a bank's return.

## Dedication

I dedicate this dissertation to my daughter, Sophia Wang Hu. May you understand that there is no end of learning.

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One of my favorite quotes from the movie Good Will Hunting: [a soul mate] is someone you can relate to, someone who opens things up for you. In this sense, I have found so many in the way of completing my thesis.

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## List of Abbreviations

| | |
|---|---|
| ARCH | Autogressive Conditional Heteroskedasticity |
| BHCs | Bank Holding Companies |
| BIX | Bank Index |
| BP | Breusch–Pagan |
| CAPM | Capital Asset Pricing Model |
| CRSP | Center for Research in Security Prices |
| CoVar | Co-independent Value at Risk |
| FDIC | Federal Deposit Insurance Corporation |
| FRB | Federal Reserve Bank |
| FSB | Financial Stability Board |
| G-SIB | Global Systemic Important Banks |
| GMM | General Moment Method |
| IV | Instrumental Variable |
| LR | Likelihood Ratio |
| MTB | Market-to-Book |
| M&As | Mergers and Acquisitions |
| OLS | Ordering Least Square |
| PERMCOs | Permanent Company Codes |
| REIT | Real Estate Investment Trusts |
| SPX | S&P 500 Index |
| S&P | Standard and Poor |
| SOD | Summary of Deposits |
| GARCH | General Autogressive Conditional Heteroskedasticity |
| OCC | Office of the Comptroller of the Currency |
| TBTF | Too Big to Fail |
| VaR | Value at Risk |
| VIX | Volatility Index |

# Introduction

Financial intermediation plays an important role in the economy and is distinct from other industries in terms of its three main functions: (i) the transmission of monetary policy, (ii) administration of the payment system, and (iii) allocation of credit to other sectors such as housing and agriculture (Saunders, 2000). Through its functions, it connects the processes of saving and investment. Extensive evidence shows that financial intermediation has an impact on the real economy (Del'Ariccia et al., 2008). Gorton and Winton (2002) state that financial intermediation is a central institution of economic growth.

In recent decades, financial intermediation has undergone rapid change. Globalization and industry integration, technology development in communications, financial innovations, and regulation amendments have all affected the process of financial intermediation. This dissertation intends to describe and analyze how some of these changes influence the risks of bank holding companies (BHCs; for the rest of this dissertation, referred to as "banks") and their strategic decisions in response to changing risks. National Information Center of the FRB (2009) define a BHC as "a company that owns and/or controls one or more U.S. banks or one that owns, or has controlling interest in, one or more banks. A bank holding company may also own another bank holding company, which in turn owns or controls a bank; the company at the top of the ownership chain is called the top holder. The Board of Governors is responsible for regulating and supervising bank holding companies, even if the bank owned by the holding company is under the primary supervision of a different federal agency (the office of the comptroller of the currency (OCC) or FDIC)."[1]

Chapter 1 considers whether or not the rating gap between "all-in" and "stand-alone" ratings for a bank can serve as a good measure of systemic risk, which is defined as the risk that a distressed bank may

[1] According to Avraham *et al*. (2012), although FRB holds the regulatory responsibility to all BHCs, under the Gramm-Leach-Bliley Act (GLBA) of 1999, non-banking subsidies of BHCs are under regulation of functional regulators. For example, broker dealers under BHCs are primarily regulated by the Securities and Exchange Commission (SEC), and insurance subsidiaries are regulated by state insurance regulators.

bring to the banking system. The three major rating agencies (Fitch Ratings, Moody's Investor Service, and Standard & Poor's) all provide two types of ratings for banks: "all-in" and "stand-alone". The "all-in" rating incorporates information not only about a bank's financial strength, but also about the external support a bank can receive from its holding institution and regulating authorities. A stand-alone rating looks only at a bank's individual financial strength. The gap between the stand-alone rating and the all-in rating is attributable to the external support that the bank would receive if it were in financial distress. With the motivation to provide a reliable and easily indicator to identify systemic important banks, Chapter 1 compares a CoVar systemic measure with the stand-alone and all-in rating gap. The CoVar systemic risk measure is defined as the marginal systemic importance of an individual bank; i.e., how much influence a bank in distress has on the banking system as a whole (Andrian & Brunnermerier, 2010). The linkage between the two measures is examined via an Ordered Probit model (of the relationship between the rating gap and the CoVar measure of systemic risk) in an attempt to answer whether or not the rating gap captures systemic importance. The analysis of this chapter shows that for banks with large book assets, ΔCoVar, a precise measure for systemic risk, has a positive and significant relationship with the rating gaps.

The findings of Chapter 1 have implications for both market investors and regulators. Instead of studying complicated quantitative models, they can use rating gaps as proxies for large banks' systemic risk. The finding of a linkage between large banks' systemic risk and their rating gaps provides convenience for investors to assess banks' credit risk, and for regulators to easily pin down banks with systemic importance.

Chapter 2 of this dissertation aims to evaluate the effects of mergers and acquisitions (M&As) on bank insolvency in a comprehensive manner. Many people consider that deregulation in the US banking system was a source for the 2008 financial crisis (Stiglitz, 2009; Krugman, 2009). Evidence in Appendix 1 and 2 shows that a significant increase in the amount of M&As is one of the most important consequences of deregulation. The estimation of the risk effect of M&As is a way to assess whether or not deregulation is indeed a source of high risk-taking in banking, which contributed to the 2008 financial crisis. Unlike the existing literature, which consists of separate examinations of single aspects of the issue (Hughes, 1999; Amihud et al., 2002; Meron & Weill, 2005), this chapter aims to provide a comprehensive evaluation of M&As on bank insolvency. It jointly examines: (i) how M&As contribute to bank geographic and activity diversification; (ii) how M&As change the relationship between an individual bank and the market; i.e., market risk; (iii) how the size of M&As cause changes a bank's insolvency while controlling for the M&As' effects from (i) and (ii); and (iv) overall, how M&As cause changes in insolvency risk for a bank. Panel data from the US, containing 591 annual cross-section observations of individual banks for a 14-year period are used. The key findings are: First, M&As negatively affect BHCs levels of solvency, regardless of risk caused by geographical diversification. Second, M&As affect BHCs geographical diversification, and this negatively impacts their financial solvency. Furthermore, on the whole, M&As erode BHCs' solvency, both directly and through the effects associated with geographical diversification.

Chapter 3 investigates how time-varying systematic risk and return spillovers affect bank diversification strategies. I ask three main questions: 1) Does systematic risk serve as a good indicator for bank diversification strategies? 2) Do banks adopt different diversification strategies during market ups and downs? 3) Do return spillovers within the banking industry affect bank diversification strategies? As in Chapter 3, banks are assumed to have two diversification choices: activity diversification (AI) and geographical diversification (GI). Bank strategies are assumed to belong to one of four sets: (high AI, high GI), (high AI, low GI), (low AI, high GI) and (low AI, low GI). The main hypothesis of Chapter 2 is that banks use a different set of strategies in response to systematic risk and spillover effects in market ups and downs. This chapter adds to the existing literature in two ways. First, it applies a time-varying beta as the indicator for diversification strategies in banking. Most studies (Montgomery & Singh, 1984; Barton, 1988; Baele et al., 2007; Stiroh, 2006) concentrate on how firm diversification strategies relate to firm systematic risk. Nevertheless, none of these studies explicitly view beta as an indicator for diversification strategy design. Moreover, being able to measure beta in a time-varying way help study bank diversification strategies in a dynamic fashion. Second, unlike the existing literature that examines spillover effects in banking from a macro perspective (Elyasiani & Mansur, 2003), this chapter incorporates data from bank balance sheets to study spillover effects at a micro level; i.e., the focus is on how the spillover among banks affects individual banks.

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# Chapter 1 . Bank Rating Gaps as Proxies for Systemic Risk

## 1.1 Introduction

Three major credit rating agencies, (Fitch, Moody's, and Standard & Poor's) each provide two types of ratings for individual banks: an "all-in" and a "stand-alone" rating. A stand-alone rating is referred to as an "individual rating" by Fitch, as a "bank financial strength rating" by Moody's, and as a "stand-alone credit profile" by Standard & Poor's. An all-in rating is referred to as a "long term issuer default rating" by Fitch, and an "issuer rating" by Moody's and Standard & Poor's. An all-in rating contains information about not only a bank's own financial strength itself, but also the external support a bank could receive from its parent holding institution and/or government authorities. A rating gap is the difference between an all-in and a stand-alone rating. Rating gaps capture the possible external support these banks may receive. This chapter investigates whether the rating gap between all-in and stand-alone ratings for a bank could serve as a useful measure for the systemic risk of the bank. Systemic risk is defined as systemic importance of an individual bank; that is, how much influence a bank in distress has on the banking system as a whole.

This chapter is motivated to explore whether the information contains in the rating gaps are useful to identify too-big-to-fail (TBTF) or systemic important banks. TBTF has become a major policy issue since the 2008 financial crisis. Most governments decided to offer subsidies to large financial institutions in order to avoid the collapse of their financial systems due to the failure of a financial institution such as Lehman Brother. The subsidies to TBTF banks generate externality cost to the society and induce moral hazard problems within banks. Thus, using public fund to save TBTF financial institutions may cause resource misallocation in the economy. It is the responsibility of regulators to supervise and to monitor TBTF risks on the banking system on a regular base. Rating gaps are convenient for regulators to use as proxies for systemic risk at a certain frequency since rating agencies publish ratings frequently. Research suggests that since investors expect that TBTF financial institutions are guaranteed to be bailed out, it helps them to receive cheaper funding cost, comparing to non-TBTF banks (Jacewitz and Pogach, 2014). Investors will be benefited by just looking at a simple indicator for systemic risk and distinguish between whether the funding discount they give to TBTF is because of the financial strength of banks themselves or for the potential support from their governments.

To the full extent of TBTF related studies, to identify which intuitions are TBTF should be the first step. Financial Stability Board (FSB) published an official list of global systemic important banks (G-SIB) in 2011 and has updated the list every November since then. Bank for International Settlements (BIS) provides an indicator based methodology to identify G-SIBs, which "reflect[s] the size of banks, their interconnectedness, the lack of readily available substitutes or financial institution infrastructure for the services they provide, their global (cross-jurisdictional) activity and their complexity" (BIS, 2013). Despite the publication of the official list of G-SIBs, studies related to the methodologies to identify TBTF are still in demand and in development. In Bank of England's recent paper about implicit subsidies to TBTF, Siegert and Willison (2015) address "Which banks are TBTF" as one of the core questions for future studies.

Rating gaps and size are two major approaches to measure the chance that TBTF banks may receive subsidies (Noss and Sowerbutts, 2012). The chance that a bank to be saved is related to how important this bank to the banking system. However, large banks are not necessarily systemically important. As pointed out by Packer and Tarashev (2011, p42), "banks role as financial intermediaries and their importance for financial stability determine the degree of external assistance they receive and shape the risk factors to which they are exposed. Assessments of bank creditworthiness thus need to account for the degree of external support, gauge the degree of systemic risk and address the inherent volatility of banks' performance".

Compared to only using asset size to identify TBTF , using rating gaps as proxies for banks' systemic importance have both pros and cons. Rating gaps might be a less noisy method because the rating agency have considered multiple factors for systemic importance, including size, interconnection, complexity and so on. On the other side, rating gaps may be a noisy way if the rating agency uses flawed methodologies and mistakenly estimate the likelihood that a bank may receive external support. However, as conjectured by

Siegert and Willison (2015), although the ratings may be imprecise, if investors believe in that the banks will be bailed out in distress anyway by taking the banks' rating face value only, these banks still enjoy benefits from the ex-ante expectation effects of being systemic important.

To explore whether rating gaps contain reliable information for systemic risk, this chapter contributes to the literature in proposing several methods to calculate the rating gaps, and studying whether the rating gaps are positively related with a quantitative systemic risk measure, Co-independent Value at Risk (CoVar), which is presented by Andrian and Brunnermerier (2010). Intuitively, CoVar is designed to measure how a single bank's distress affects the whole banking system. The main advantage of CoVar, compared to other quantitative systemic risk measures, is that it takes into account the fact that systemic risk tends to be cyclical, falling in booms and rising in crises. This chapter studies whether rating gaps capture the same risk that quantitative systemic risk measures (CoVaR) do. The main finding is that they do, but only in large banks. The confirmation of the existing linkage between banks' systemic risk and their rating gaps provides a simple and readily available measure to assess the systemic importance of an individual bank. Instead of studying complicated quantitative models, policymakers and investors can use rating gaps as proxies for banks' systemic risk and easily identify those TBTF banks.

The chapter is organized as follows. Section 1.2 provides a related literature review. Section 1.3 describes the methodology. Section 1.4 discusses the data and presents summary statistics. Section 1.5 presents results and section 1.6 concludes.

## 1.2 Related Literature

Few papers study the information contained in bank ratings for banks' systemic risk. Peresetsky and Karminsky (2008) use an Ordered Logit model and quantile regressions to study which factors contribute to the unobserved external support contained in the Moody's All-in ratings. They conclude that the "external support" component can be largely predicted by public information factors, such as county-specific volatility of economic growth and a corruption index, bank size, capital adequacy, asset quality, efficiency, and profitability. Rime (2005) examines whether being "too-big-to-fail" could boost the expectations for credit ratings for certain banks from Moody's and Fitch. The author regress all-in ratings on stand-alone ratings, bank asset size, and market share as proxies for "too-big-to-fail." The conclusion was that large banks do benefit from a significant increase in ratings. However, neither Peresetsky and Karminsky (2008) nor Rime (2005) use a precise measure for systemic risk, but rather employed indirect proxies for systemic risk.

Kaufman and Scott (2003) refer to systemic risk as "...the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by co-movements (correlation) among most or all the parts." In theory, a definition of systemic risk needs to trace back to externalities caused by networking among banks and fire-sale spillovers. Neither Peresetsky and Karminsky (2008) nor Rime (2005) uses measures that deal with the externality character of systemic risk. Network effects can lead to externalities, as emphasized by Allen, Babus and Carletti (2010). Banks connect to each other through their related businesses. Especially with the development of modern financial innovations, (e.g., derivatives and securitization), banks now are much more interconnected in terms of risk sharing relationships than in earlier times. Inter-linkages in the banking system can exacerbate the possibility that a run on an individual bank could cause a broader bank run. The theoretical bank run literature has clearly shown that such possibilities can dramatically reduce social welfare (Bhattacharya and Gale (1987)).

In recent years, several systemic risk measures have been proposed. These measures usually employ complicated econometric models. They generally define systemic risk as systemic importance of an individual bank; that is, how much influence a bank in distress has on the banking system as a whole. Acharya *et al.* (2010) focus on high-frequency marginal expected shortfalls as a systemic risk measure. Adams *et al.* (2010) study risk spillovers among financial institutions, including hedge funds, using quantile regressions. Zhou (2009) provides an estimation methodology, termed CoVaR, which uses a multivariate Extreme Value Theory framework. Andrian and Brunnermerier (2010) present a modified CoVaR measure that takes into account the fact that CoVaR tends to be cyclical, falling in booms and rising in crises.

Intuitively, CoVar in Andrian and Brunnermerier (2010) is designed to measure how a single bank's distress affects the whole banking system.

These econometric models provide quantitative measures of systemic risk. However, many market participants probably do not have the ability to develop and utilize such sophisticated models and may simply rely on rating agencies for their credit risk estimates of financial institutions. Policy makers and financial market supervision authorities thus, to some extent, ought to be aware of the information content of credit ratings for systemic risk. Since all three rating agencies publish both stand-alone and all-in ratings, it is surely convenient to take the gap between the two ratings as a measure of systemic risk.

## 1.3 Methodological Issues

### 1.3.1 Gap Calculation

The rating gap is the difference between the all-in rating and the stand-alone rating. A stand-alone rating reflects a bank's own financial strength. An all-in rating contains information about not only a bank's own financial strength, but also the external support a bank could receive from its parent company and government bodies in the event the bank's financial health is in jeopardy. The rating gap thus captures the external support a bank could receive if it were in distress.

There are some technical issues that have to be considered when calculating rating gaps. First, one must construct a map to compare the all-in and stand-alone ratings. Fitch (2011) provides a rating map which gives the equivalent category of each all-in rating and stand-alone rating. The map is presented in Table 1-1. My analysis uses the ratings from Fitch as Standard & Poor's has published financial strength ratings only for banks in the Asia-Pacific region and Moody's only began assigning stand-alone ratings in 2007.

Second, the stand-alone ratings and the all-in ratings do not have a one-to-one mapping for a given stand-alone rating, there are multiple all-in ratings. Moreover, a given all-in rating can be assigned to banks with different stand-alone ratings. To deal with these issues, I consider three approaches. First, the "rough mapping" approach ignores these issues and simply computes the gaps using the two ratings. The other two approaches, a "pessimist mapping" and an "optimist mapping", the assigned ratings are ordered so that they have a one-to-one relationship with no overlap.

The third consideration is that all ratings are provided as a set of characters, not quantitative measures. To obtain numerical rating gaps, I need to translate these ratings into numbers. The ways in which the various ratings, and thereafter rating gaps are translated into numbers depending on which method is chosen to deal with the overlaps.

The rough mapping approach is used to construct a variable "GAP". If the stand-alone rating is the same as any of the listed all-in equivalencies in Table 1-1, there is "no gap" and the variable GAP is recorded as 0. If the all-in rating is one category higher/ lower than the equivalencies in Table 1-1, there is a small positive / negative gap and the value for the variable GAP is +1/ -1. If the all-in rating is 2 or more cells above/ below, there is a large positive/ negative gap and the value for the variable GAP is +2/ -2. For example, if the stand-alone rating is A and the all-in rating is AA+, GAP is 0, where as if the stand-alone rating is A/B and the all-in rating is AAA, then GAP is +1. Summary statistics for the variable GAP are shown in Table 1-5.

The pessimist mapping approach assumes that the rating agency overstates a banks' all-in rating and thus overlaps with all-in ratings in Table 1-1 are moved to the next lower level. For example, all-in ratings of AA+ and AA both are equivalent in Table 1-1 to stand-alone ratings of A and A/B. The pessimist mapping assumes the all-in ratings AA+ and AA are equivalent to stand-alone ratings of only A/B. The pessimist mapping is shown in Table 1-2.

Similarly, the optimist mapping moves all-in ratings with overlaps up to the next higher rating category. That is, all-in ratings AA+ and AA in the example are assumed to be equivalent to a stand-alone rating of A. The optimistic mapping is shown in Table 1-3.

For each of the pessimist and optimist mappings stand-alone ratings are translated into ordered numbers from 0 to 8, increasing in increments of 1. I design two possible ways to assign numbers to the all-in ratings. The first one is termed the "grid method". This method assumes all-in ratings have the same numerical value as the equivalent stand-alone rating category. For example, under the optimist mapping, the rating gap would be the same for all-in ratings of BB and BB- as these are both in the same category for the stand-alone rating C/D. When translated into numbers, C/D equals to 3, so BB and BB- both equal to 3, and the rating gap is 0.

The second method for assigning values to all-in ratings is the "point method". All-in ratings are assigned values ordered from to 8.6, but the increments vary depending on how many all-in ratings are equivalent to the same stand-alone rating.

In summary, in addition to the rough mapping for constructing rating gaps, there are four measures constructed for calculating rating gaps: pessimist-grid, pessimist-point, optimist-grid and optimist-point. The variable names and the methods are listed in Table 1-4. Numerical gaps are shown in Tables 1-2 and 1-3.

### 1.3.2 Measuring Systemic Risk

Following Andrian and Brunnermerier (2010), I use a variable, $\Delta CoVaR_q^{system|i}$, to measure systemic risk. Intuitively, $\Delta CoVaR_q^{system|i}$ can be thought of as, when an individual bank *i* is in distress and its asset return is at or below the bottom *q*% of its historical asset return distribution, how much the banking system total asset return would be changed by the bank's distress compared to when the bank's asset return is at its median level. For example, in the first quarter of 1995, the estimated historical bottom 1% ($q = 1$) return of JPMorgan Chase is -23.76%. Conditional on JP. Morgan Chase's return dropping by 23.76%, it is estimated that the return of the banking system will drop by 3.85%. That is, $\Delta CoVaR_1^{system|JPMORGAN} = 3.85\%$.

Note that $VaR_q^i$ is defined as the *qth* quantile of the bank's asset return distribution, i.e.,$\left(X^i \leq VaR_q^i\right) = q$, where $X^i$ is the asset return of bank *i*. The market value of bank's assets is denoted as $A^i$, where:

$$A^i = BA^i \times \frac{ME^i}{BE^i} \tag{1.1 }$$

$BA^i$ is bank $i$'s book value of assets, $ME^i$ is its market value of equity, and $BE^i$ is the book value of equity.

$C()$ is denoted as some event that causes the bank's asset return change to $X^i$. $X^{system}$ is the market value weighted total asset return of the banking system. $CoVaR_q^{system|i}$ is the Value at Risk (VaR) of the banking system, conditional on the event $C()$ happens and bank $i$'s asset return is at or below $X^i$.

A special case is when $X^i = VaR_q^i$. That is, when bank $i$'s asset return is at its $q$th quantile historical level. The impact of Bank $i$'s distress on the system is defined as its systemic risk, which is

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{i|X^i=median^i} \tag{1.2}$$

Furthermore, I use quantile regressions to obtain $\hat{X}_q^{system}$

$$\hat{X}_q^{system} = VaR_q^{system}|X^i = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \tag{1.3}$$

$$CoVaR_q^{system|X^i=VaR_q^i} = VaR_q^{system}|VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{1.4}$$

$\Delta CoVaR_q^i$ is obtained by using equation (1.5)

$$\Delta CoVaR_q^{system|i} = \hat{\beta}_q^i (VaR_q^i - VaR_{50\%}^i) \tag{1.5}$$

The next step is to construct time series for *CoVaR* and *VaR*. Similar to Andrian and Brunnermerier (2010), I use a vector of state variables $S_{t-1}$ to capture time variation in conditional moments of asset returns. This state vector includes seven factors:

(i) The Chicago Board Options Exchange Market Volatility index (VIX), to capture the implied volatility in the stock market.

(ii) A short term liquidity risk measure, which is the difference between the three-month repo rate and the three-month T-bill rate.

(iii) The change in the three-month Treasury bill rate. Andrian and Brunnermerier (2010) find that the change in the three-month Treasury bill rate significantly explains the tails of financial sector asset returns.

(iv) The change in the slope of the yield curve, measured by the yield spread between the ten-year Treasury rate and the three-month T-bill rate.

(v) The change in the credit spread between BAA-rated bonds and the Treasury rate, both with maturity of ten years.

(vi) The quarterly equity market return using the S&P 500 index (SPX).

(vii) The change in the Dow Jones United States Real Estate Industry Group Index, represents Real Estate Investment Trusts (REIT) and other companies that invest directly or indirectly in real estate through development, management or ownership, including property agencies. This index is float-adjusted and market cap weighted.

I estimate time-varying $X_t^i$ and $\mathrm{X}_\mathrm{t}^{\mathrm{system}}$ as

$$X_t^i = \theta^i + \lambda^i S_{t-1} + \mu_t^i \tag{1.6}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} S_{t-1} + \varepsilon_t^{system|i} \tag{1.7}$$

The parameter $\widehat{\theta^\iota}$ , $\widehat{\lambda^\iota}$, $\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$ and $\hat{\gamma}^{system|i}$ from equation (1.6) and (1.7) are used to calculate:

$$VaR_t^i = \widehat{\theta^\iota} + \widehat{\lambda^\iota} S_{t-1} \tag{1.8}$$

$$CoVaR_t^{system|i} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} VaR_t^i + \hat{\gamma}^{system|i} S_{t-1} \tag{1.2}$$

Finally, I compute $\Delta CoVaR_t^{system|i}$ at the $q$th quantile for each bank:

$$\Delta CoVaR_t^{system|i}(q) = CoVaR_t^{system|i}(q) - CoVaR_t^{system|i}(50\%)$$
$$= \hat{\beta}^{system|i}(VaR_t^i(q) - VaR_t^i(50\%) \quad (1.10)$$

### 1.4 Bank Data and Summary Statistics

#### 1.4.1 Data

All observations in this chapter are for BHCs[2]. There are three data sources: Bloomberg, the FRB FRY-9C reports, and the CRSP database. Fitch Ratings and the factors discussed above are recorded on a quarterly basis. They are from Bloomberg. Quarterly data for banks' book value of assets and book value of equity are from FRY-9C reports. Both banks' quarterly stock price and outstanding shares are from CRSP. To calculate the banking system asset return, I begin with a pool of 589 banks. The final data set used to estimate the Ordered Probit model contains 1819 quarterly observations for 54 banks with the number of observations for a bank ranging from 13 to 54. The sample period is from the third quarter of 1994 to the fourth quarter of 2007.

#### 1.4.2 Summary Statistics

Summary statistics of the gaps and the gaps grouped by stand-alone ratings are listed in the Table 1-5 and the Table 1-6, respectively. There are negative numbers in the summary statistics. For example, the minimum values for all five types of gaps are negative. Negative external support could happen when the rating agency update all-in ratings and stand-alone ratings at different time. For example, the stand-alone rating for Wells Fargo & Company in the third quarter of 1997 switched from A/B to A but its all-in rating remained to AA. So the variable *PPGAP* is recorded as 0 for the second quarter of 1997 but as -1 in the third quarter.

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[2] The potential support to banks may come from two sources: their holding companies and regulating authorities. Since all observations are bank holding companies, for banks in the sample, support resource is only from regulating authorities. As stated in footnote 1, they might be FRB, SEC, insurance regulators and so on.

The correlation matrix for the five rating gaps is shown in Table 1-9. The correlations between gaps are all positive and significant at 1%. The highest correlation is 0.9600, which is between the optimist-point gap and the pessimist-point gap. The correlations between GAP and the other four types of rating gaps are much lower than the correlations among these four ratings gaps. It seems that ignoring the overlaps in ratings or not does make a big difference.

Overall, out of 1819 observations there are 1445 non-zero values for *PGGAP,* 1550 for *PPGAP*, 788 for *OGGAP*, 1550 for *OPGAP* and 219 for *GAP*. Further, there are 21 non-negative values for *PGGAP*, 126 for *PPGAP*, 621 for *OGGAP*, 1064 for *PPGAP* and 30 for *GAP*. Interestingly, most observations are concentrated on two to three values. Except for *PPGAP* and *OPGAP*, the other gaps have little variation, which are showed by the histograms for the gaps are presented in Figures 1-1 through 1-5, both for the full sample and sub-samples. for The sub-samples correspond to the quartiles of the book values of bank assets. The quartiles of book values of assets are listed in Table 1-7 and the summary statistics of all gap measures based on bank size are shown in Table 1-8.

For the variables *PGGAP* and *OGGAP* the observations are clustered on four values. I tried each of the five rating gaps as the dependent variable in equation (1.11), both by using the full sample and sub-samples. As expected, due to lack of variation with three of the gap measures, results were obtained only for *OPGAP* and *PPGAP*. I therefore use *PPGAP* and *OPGAP* for the final Ordered Probit regressions. Note that I translated *OPGAP* and *PPGAP* into integers starting from 0 to meet the programing requirement. The variables after translation are denoted *OP* and *PP*. The translation maps are presented in Table 1-10.

Variables used in the final regression are described in Table 1-11. In Table 1-12, I present summary statistics for each variable. The all-in rating, *RA*, varies from 7 to 20. The highest all-in rating in the sample is AA+, while the lowest all-in rating is B. The mean of *RA* is 15.7005, which means the average all-in rating is about A- to A. The mean of the variable *RI* is 8.0022, which means that the average stand-alone rating is about B. The maximum value for *RI* is 10 and the minimum value is 2. The stand-alone rating varies from E to A in the sample.

Both $\Delta CoVar005$ and $\Delta CoVar001$ are estimated variables based on equation (1.10). $\Delta CoVar$ stands for how the asset return of the banking system would change in response to a particular bank at its default level (I use 1% and 5% of historical asset return for default thresholds), compared to when the bank's asset return is at its historical median. The mean for $\Delta CoVar001$ is -0.0231 and for $\Delta CoVar005$ it is -0.0234. This means on average, when a bank is at a default threshold, the asset return of the banking system drops by 1.8%, compared to when this bank has asset returns equal to the median. The maximum for value for $\Delta CoVar005$ is 0.2705 and for $\Delta CoVar001$ it is 0.3678.

From 1994 to 2007, the VIX index varies from 11.38 to 40.95 in the sample. The mean of the Dow Jones Real Estate index return is 0.02, means the average return in the real estate market is about 2% quarterly for 1994-2007. The mean of *MKTA* is 0.0129, that is, the average quarterly asset return of banks from 1994 to 2007 is about 1%.

In Table 1-13, I present the correlation matrix for variables used in the Ordered Probit model. The correlation between the all-in rating variable *RA* and the stand-alone variable *RI* is positive and it is significant at 1% level. This indicates that banks with higher stand-alone financial strength usually receive higher all-in ratings. Both $\Delta CoVar005$ and $\Delta CoVar001$ are negatively correlated with *OP/PP*, and significant at 1%. A negative $\Delta CoVar$ means that the bank's default causes the banking system asset return to drop. The lower the value of $\Delta CoVar$ for a bank, the higher the systemic importance of the bank. The negative correlation between *OP/PP* and $\Delta CoVar$ may be a sign that banks with higher systemic importance usually have higher rating gap.

### 1.5 Ordered Probit Model

The systemic importance of a bank should be a continuous concept. However, the rating gaps are discrete. The rating gap between All-in and Stand-alone ratings can be seen as a proxy for the unobservable continuous real systemic importance of a bank, which is denoted by $G_i^*$. Following Kaplan and Urwitz's (1979) study of bond ratings, an Ordered Probit model is presented as:

$$G_{i,t}^* = \delta_i + \tau \Delta CoVaR_{i,t}^{system|i}(q) + \lambda MKTA_{i,t} + \theta_1 T_1 + \theta_2 T_2 + \cdots + \theta_t T_t + \omega_{i,t} \tag{1.3}$$

$$P(rating_i = r) = P(C_{r-1} < G_i^* < C_r) \tag{1.4}$$

where $MKTA_{i,t}$ is the market asset return of each bank, $G_{i,t}^*$ is the observed rating gap between a bank's all-in rating and its stand-alone rating, and $T_t$ are annual time dummies.[34]

The purpose of this chapter is to assess whether a rating gap is a useful proxy for a bank's systemic risk. This requires that rating gaps be positively related to systemic risk measures. In terms of equation (1.11), the hypothesis is: $\tau < 0$. This is because $\Delta CoVaR_{i,t}^{system|i}(q)$ measures how much the asset return of the banking system may drop because one of the banks is in distress, compared to the asset return of the banking system when this bank is not in distress. $\Delta CoVaR_{i,t}^{system|i}(q)$ is assumed to be a negative value by definition. Thus, the larger the systemic risk of a bank, the lower the value of $\Delta CoVaR_{i,t}^{system|i}(q)$.

### 1.5.1 Full Sample Results

Table 1-14 and Table 1-15 present the results of the Ordered Probit model by using the same group of control variables but two different independent variables, namely $\Delta CoVar$ at 1% and 5% respectively.[5] In both tables, the first and second columns present the results when using *OP* as the dependent variable. The only difference is that the results in the first column are obtained by using an Ordered Probit model in panel data with random effects, whereas the second column has fixed effects. The third column presents the results

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[3] I have tried to include bank asset size as an explanatory variable. However, the model crashed when I run the regressions. To exam whether asset size is a factor to affect the relationship between systemic risk and rating gaps, I then split the full sample into four subsamples based on quartile value of bank assets and run regressions on four subsamples.

[4] Quarterly dummies were also applied when both the full sample and the four sub-samples are used. However, due to multicollinearity, I am not able to obtain any results.

[5] For all regressions, I have tried both random effects and fixed effects. However, I fail to obtain any results when PP is the dependent variable with fixed effects estimation.

for *PP* as the dependent variable and the regression method is an Ordered Probit model in panel data with random effects.

To test the null hypothesis that the rating gaps are positively linked to systemic risk is equivalent to testing whether the coefficients on $\Delta CoVar$ are significantly negative. As showed in Table 1-14 and Table 1-15, coefficients on $\Delta CoVar005$ and $\Delta CoVar001$ are negative and significant at 1% in all regressions. This suggests that the rating gaps and banks systemic risk are significantly positively related. The more systemic importance the bank has, the higher the rating gap. For example, the coefficient on $\Delta CoVar005$ is -3.1663 when *OP* is the dependent variable. The marginal effect of ΔCoVar005 when fixed effect is applied, for example, when *OP=6*, is -0.6630 and significant at 1%. This means that when a bank is at its historical bottom 5% asset return level and it causes the asset return of the banking system to drop by 1%--the probability of the rating gap of this bank moving from 6 to 7 is 1.2%, holding other control variables constant. The estimated marginal effects of $\Delta CoVar$ for each gap notch are presented in Table 1-14 and 1-15 and are plotted in Figures 1-6, 1-7 and 1-8. For example, in the upper panel of Figure 1-6, the marginal effects of $\Delta CoVar005$ switch from positive to negative when $OP = 6$, and then switch back to positive when *OP= 12*. The summation of all the coefficients for all *OP* notches is naturally equal to 0. This is because the summation of all possibilities for a bank to receive a rating notch change must be zero.

It seems complicated to understand the interpretation of the marginal effects of $\Delta CoVar$. Arguably, the exact interpretation is not important for this chapter as the main focus here is whether the rating gap is an easy to construct and useful proxy for measuring the systemic risk of a bank. The evidence suggests it is.

However, as showed by Rime (2005), too-big-to-fail expectation boosts banks' all-in ratings. Although all-in ratings may not necessarily relate to the external support directly and rating gaps may be a better measure for systemic support, the conclusion of Rime (2005) implies that banks may not receive external support equally. Larger banks may enjoy more systemic support. The relationship between systemic risk and banks rating gap may shift depending on banks' size.

### 1.5. 2 Robustness Checks with Subsamples

In order to see if the relationship between rating gaps and $\Delta CoVar$ holds for banks of all sizes, I perform a "Chow" test of parameter equality. I split the full sample into four subsamples by using quartile values of book assets. Table 1-7 provides the minimum, lower quartile, medium and maximum of banks' book value of assets. Table 1-16 presents results for these subsamples. For each subsample, I run eight regressions corresponding to the relationships between *OP/PP* and $\Delta$*CoVar001 and* $\Delta$*CoVar005,* applying fixed and random effects. Note that when subsamples are applied, there are some gap measures with zero observations.

To test whether the estimations by using the subsamples are consistent with the estimation by using the full sample, I conduct four LR tests when random effects are applied.[6] The null hypothesis is that banks behavior the same in all four subsamples. The hypotheses are that the coefficients obtained by using four subsamples are all equal and they are all equal to the ones obtained by using the full subsample. $\chi^2$ values of the LR tests are presented in Table 1-17. At the 5% critical value, the null hypotheses are all rejected. That is, it may not be appropriate to pull all banks in one sample to do the estimation. The relationships between rating gaps and $\Delta CoVar$ may vary across banks, depending on which asset group they are in.

The relationships between rating gaps and $\Delta CoVar$ may vary across banks, depending on which asset quartile they are in. However, the coefficient on $\Delta$*CoVar005* is significant at 1% and is -8.57422 when the second quartile subsample is used and the dependent variable is *OP*. Also, the coefficients on $\Delta$*CoVar001* and $\Delta$*CoVar005* are both negative and significant at 1% when banks are in the subsample of the fourth quartile bank asset and fixed effects are applied. Note the rating gap calculation method includes both *OP* and *PP*. That is, no matter an investor is a pessimist or an optimist, rating gaps are related to banks' $\Delta CoVar$ negatively. This is consistent with the expectation that the coefficients on $\Delta CoVar$ are supposed to be

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[6] I don't test the results by using fixed effects because some of the estimation collapse due the potential invariance in cross-section dummy variables.

negative. As least I am able to draw the conclusion that higher rating gaps link to higher systemic risk when banks' book assets are greater than 83 billion dollars.

It is not surprising that the rating gaps can be proxies as systemic risk only for large banks. Table 1-18 presents the mean of *OP, PP,* $\Delta CoVar001$ *and* $\Delta CoVar005$ of four subsamples in quartiles. It shows that on average, banks in higher asset quartile have larger rating gaps and present lower value in $\Delta CoVar$, which suggests higher systemic risk. Large banks are likely to receive external support implicitly (funding discount comparing to small banks) or explicitly (bailed out by governments). Evidence shows that TBTF banks receive higher implicit external support no matter whether TBTF is identified by their asset size or their rating gaps. Acharya *et al.* (2014) find that only the largest 10% banks in their sample enjoy significant discount on finding. The bond spread between the largest 10% and the 90% rest of banks in their sample is about 30 basis point lower. Ueda and di Mauro (2013) show that on average, an uplift in rating gap leads to a funding cost advantage of 60 basis points at end of 2007 and 80 basis points at end-2009.

### 1.6 Conclusion

The relationships between rating gaps and $\Delta CoVar$ may vary across banks, depending on which asset group they are in. No matter an investor is a pessimist or an optimist, higher rating gaps link to higher systemic risk when banks' book assets are greater than 83 billion dollars. Banks with higher rating gaps are coincidently to be large banks. Large banks happen to be associated with higher systemic risk.

The analysis of this chapter shows that $\Delta CoVar$, a precise measure for systemic risk, has a positive and significant relationship with rating gaps in large banks. The findings of this chapter have important implications for both market participants and regulators. Instead of studying complicated quantitative models, they can use rating gaps as proxies for banks' systemic risk. The confirmation of a linkage between banks' systemic risk and their rating gaps provides great convenience for investors to assess banks' credit risk, and for regulators to easily identify banks with systemic importance.

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**Table 1-1 Rating Mapping from Fitch (2011)**

| Stand-alone | All-in |
|---|---|
| A | AAA |
| | AA+ |
| | AA |
| A/B | AA+ |
| | AA |
| | AA- |
| | A+ |
| B | AA- |
| | A+ |
| | A |
| | A- |
| B/C | A |
| | A- |
| | BBB+ |
| | BBB |
| C | BBB+ |
| | BBB |
| | BBB- |
| | BB+ |
| C/D | BBB+ |
| | BB+ |
| | BB |
| | BB- |
| D | BB |
| | BB- |
| | BB |
| | BB- |
| | B+ |
| | B |
| | B- |
| D/E | B+ |
| | B |
| | B- |
| | CCC |
| E | CCC |
| | CC |
| | C |

- This map issued by Fitch, which gives the connections between Stand-alone ratings and All-in ratings.

**Table 1-2 Pessimist Mapping**

| Stand-alone Letter Rating | Stand-alone Numerical Rating | All-in Letter Rating | All-in Grid Numerical Rating | All-in Point Numerical Rating |
|---|---|---|---|---|
| A | 8 | AAA | 8 | 8 |
| A/B | 7 | AA+ | 7 | 7.5 |
| | | AA | 7 | 7 |
| B | 6 | AA- | 6 | 6.5 |
| | | A+ | 6 | 6 |
| B/C | 5 | A | 5 | 5.5 |
| | | A- | 5 | 5 |
| C | 4 | BBB+ | 4 | 4.5 |
| | | BBB | 4 | 4 |
| C/D | 3 | BBB- | 3 | 3.5 |
| | | BB+ | 3 | 3 |
| D | 2 | BB | 2 | 2.5 |
| | | BB- | 2 | 2 |
| D/E | 1 | B+ | 1 | 1.7 |
| | | B | 1 | 1.3 |
| | | B- | 1 | 1 |
| E | 0 | CCC | 0 | 0.7 |
| | | CC | 0 | 0.3 |
| | | C | 0 | 0 |

- This map transfers Ratings from letters into numbers by using the Pessimist Method.

**Table 1-3 Optimist Mapping**

| Stand-alone Letter Rating | Stand-alone Numerical Rating | All-in Letter Rating | All-in Grid Numerical Rating | All-in Point Numerical Rating |
|---|---|---|---|---|
| A | 8 | AAA | 8 | 8.6 |
| | | AA+ | 8 | 8.3 |
| | | AA | 8 | 8 |
| A/B | 7 | AA- | 7 | 7.6 |
| | | A+ | 7 | 7.3 |
| | | A | 7 | 7 |
| B | 6 | A- | 6 | 6 |
| B/C | 5 | BBB+ | 5 | 5.5 |
| | | BBB | 5 | 5 |
| C | 4 | BBB- | 4 | 4.5 |
| | | BB+ | 4 | 4 |
| C/D | 3 | BB | 3 | 3.5 |
| | | BB- | 3 | 3 |
| D | 2 | B+ | 2 | 2.6 |
| | | B | 2 | 2.3 |
| | | B- | 2 | 2 |
| D/E | 1 | CCC | 1 | 1 |
| E | 0 | CC | 0 | 0.5 |
| | | C | 0 | 0 |

- This map transfers Ratings from letters into numbers by using the Optimist Method.

**Table 1-4 Variable Name and Method**

| Variable | Method |
|---|---|
| *GAP* | Rough Rating |
| *PGGAP* | Pessimism-grid |
| *PPGAP* | Pessimism-point |
| *OGGAP* | Optimistic-grid |
| *OPGAP* | Optimistic-point |

- This table indicates the method used to calculate the rating gap variables.

**Table 1-5 Summary Statistics**

| Variable | Mean | Maximum | Upper Quartile | Median | Lower Quartile | Minimum |
|---|---|---|---|---|---|---|
| *PGGAP* | -0.8851 | 1 | -1 | -1 | -1 | -2 |
| *PPGAP* | -0.6443 | 1.3 | -0.5 | -0.5 | -1 | -2 |
| *OGGAP* | 0.2793 | 2 | 1 | 0 | 0 | -1 |
| *OPGAP* | 0.4974 | 2.3 | 1 | 0.5 | 0 | -1 |
| *GAP* | -0.0874 | 1 | 0 | 0 | 0 | -1 |

- This table presents the summary statistics of the rating gap variables.

**Table 1-6 Summary Statistics --- by Stand-alone Ratings**

| *sa* | N Obs | Variable | Mean | Maximum | Upper Quartile | Median | Lower Quartile | Minimum |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 | *PGGAP* | 1 | 1 | 1 | 1 | 1 | 1 |
| | | *PPGAP* | 1.3 | 1.3 | 1.3 | 1.3 | 1.3 | 1.3 |
| | | *OGGAP* | 2 | 2 | 2 | 2 | 2 | 2 |
| | | *OPGAP* | 2.3 | 2.3 | 2.3 | 2.3 | 2.3 | 2.3 |
| | | *GAP* | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 2 | *PGGAP* | 0 | 0 | 0 | 0 | 0 | 0 |
| | | *PPGAP* | 0.7 | 0.7 | 0.7 | 0.7 | 0.7 | 0.7 |
| | | *OGGAP* | 1 | 1 | 1 | 1 | 1 | 1 |
| | | *OPGAP* | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 |
| | | *GAP* | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 23 | *PGGAP* | -0.6522 | 0 | 0 | -1 | -1 | -1 |
| | | *PPGAP* | -0.3522 | 0 | 0 | -0.3 | -0.7 | -0.7 |
| | | *OGGAP* | 0.3478 | 1 | 1 | 0 | 0 | 0 |
| | | *OPGAP* | 0.6217 | 1 | 1 | 0.6 | 0.3 | 0.3 |
| | | *GAP* | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 12 | *PGGAP* | -0.7500 | 1 | -1 | -1 | -1 | -1 |
| | | *PPGAP* | -0.3333 | 1 | -0.5 | -0.5 | -0.5 | -0.5 |
| | | *OGGAP* | 0.2500 | 2 | 0 | 0 | 0 | 0 |
| | | *OPGAP* | 0.6667 | 2 | 0.5 | 0.5 | 0.5 | 0.5 |
| | | *GAP* | 0.0833 | 1 | 0 | 0 | 0 | 0 |
| 4 | 12 | *PGGAP* | -0.6667 | 0 | 0 | -1 | -1 | -1 |
| | | *PPGAP* | -0.6250 | 0 | 0 | -1 | -1 | -1 |
| | | *OGGAP* | 0.3333 | 1 | 1 | 0 | 0 | 0 |
| | | *OPGAP* | 0.3750 | 1 | 1 | 0 | 0 | 0 |
| | | *GAP* | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 461 | *PGGAP* | -1.0434 | 1 | -1 | -1 | -1 | -2 |
| | | *PPGAP* | -0.8590 | 1 | -0.5 | -1 | -1 | -2 |
| | | *OGGAP* | 0.0347 | 2 | 0 | 0 | 0 | -1 |
| | | *OPGAP* | 0.1852 | 2.3 | 0.5 | 0 | 0 | -1 |
| | | *GAP* | -0.1757 | 1 | 0 | 0 | 0 | -1 |
| 6 | 785 | *PGGAP* | -0.6981 | 1 | 0 | -1 | -1 | -2 |
| | | *PPGAP* | -0.4847 | 1 | 0 | -0.5 | -1 | -1.5 |
| | | *OGGAP* | 0.5860 | 2 | 1 | 1 | 0 | -1 |
| | | *OPGAP* | 0.7396 | 2 | 1.3 | 1 | 0 | -0.5 |
| | | *GAP* | -0.0318 | 1 | 0 | 0 | 0 | -1 |
| 7 | 413 | *PGGAP* | -0.9976 | 0 | -1 | -1 | -1 | -2 |
| | | *PPGAP* | -0.6525 | 0 | -0.5 | -0.5 | -1 | -2 |
| | | *OGGAP* | 0.0993 | 1 | 0 | 0 | 0 | -1 |
| | | *OPGAP* | 0.5053 | 1 | 0.6 | 0.6 | 0.3 | -1 |
| | | *GAP* | -0.0654 | 0 | 0 | 0 | 0 | -1 |
| 8 | 110 | *PGGAP* | -1.2545 | -1 | -1 | -1 | -2 | -2 |
| | | *PPGAP* | -0.9909 | -0.5 | -0.5 | -1 | -1.5 | -1.5 |
| | | *OGGAP* | -0.2545 | 0 | 0 | 0 | -1 | -1 |
| | | *OPGAP* | -0.0200 | 0.3 | 0.3 | 0 | -0.4 | -0.4 |
| | | *GAP* | -0.2545 | 0 | 0 | 0 | -1 | -1 |

- This table presents the summary statistics of the rating gap variables grouped by stand-alone ratings.

**Table 1-7 Summary Statistics ---- Bank Book Assets in Dollars**

| Mean | Maximum | Upper Quartile | Median | Lower Quartile | Minimum |
|---|---|---|---|---|---|
| 117,797,366 | 2,358,266,000 | 83,856,300 | 32,175,286 | 9,423,099 | 486,418 |

- This table presents the quartiles of bank book assets in thousand dollars.

**Table 1-8 Summary Statistics by Bank Size**

| | Variable | Mean | Maximum | Upper Quartile | Median | Lower Quartile | Minimum |
|---|---|---|---|---|---|---|---|
| First Quartile | *PGGAP* | -1.3150 | 0 | -1 | -1 | -2 | -2 |
| | *PPGAP* | -1.1115 | 0 | -1 | -1 | -1.5 | -2 |
| | *OGGAP* | -0.2621 | 1 | 0 | 0 | -1 | -1 |
| | *OPGAP* | -0.0771 | 1 | 0 | 0 | -0.5 | -1 |
| | *GAP* | -0.2797 | 0 | 0 | 0 | -1 | -1 |
| Second Quartile | *PGGAP* | -1.0044 | 1 | -1 | -1 | -1 | -2 |
| | *PPGAP* | -0.8402 | 1.3 | -0.5 | -1 | -1 | -1.5 |
| | *OGGAP* | 0.1758 | 2 | 0 | 0 | 0 | -1 |
| | *OPGAP* | 0.2686 | 2.3 | 0.6 | 0 | 0 | -0.5 |
| | *GAP* | -0.0308 | 1 | 0 | 0 | 0 | -1 |
| Third Quartile | *PGGAP* | -0.7011 | 0 | 0 | -1 | -1 | -2 |
| | *PPGAP* | -0.4132 | 0.5 | 0 | -0.5 | -0.5 | -1.5 |
| | *OGGAP* | 0.6242 | 2 | 1 | 1 | 0 | -1 |
| | *OPGAP* | 0.8582 | 2 | 1.3 | 1 | 0.6 | -0.4 |
| | *GAP* | -0.0989 | 0 | 0 | 0 | 0 | -1 |
| Fourth Quartile | *PGGAP* | -0.5197 | 1 | 0 | -1 | -1 | -2 |
| | *PPGAP* | -0.2127 | 1 | 0 | -0.5 | -0.5 | -1.5 |
| | *OGGAP* | 0.5789 | 2 | 1 | 1 | 0 | -1 |
| | *OPGAP* | 0.9388 | 2.3 | 1.3 | 1 | 0.6 | -0.4 |
| | *GAP* | 0.0592 | 1 | 0 | 0 | 0 | -1 |

- This table presents summary statistics in four quartile groups by bank book assets.

**Table 1-9 Correlation between Five Rating Gap Measures**

| | *PGGAP* | *PPGAP* | *OGGAP* | *OPGAP* | *GAP* |
|---|---|---|---|---|---|
| *PGGAP* | 1 | | | | |
| | | | | | |
| *PPGAP* | 0.9080 | 1 | | | |
| | (0.0001)*** | | | | |
| *OGGAP* | 0.8342 | 0.8623 | 1 | | |
| | (0.0001)*** | (0.0001)*** | | | |
| *OPGAP* | 0.8391 | 0.9600 | 0.9285 | 1 | |
| | (0.0001)*** | (0.0001)*** | (0.0001)*** | | |
| *GAP* | 0.6268 | 0.5600 | 0.6422 | 0.5493 | 1 |
| | (0.0001)*** | (0.0001)*** | (0.0001)*** | (0.0001)*** | |

- This table shows the correlations among five types of rating gaps.

**Table 1-10 Translating opgap into Integers**

| ***OPGAP*** | ***OP*** | ***PPGAP*** | ***PP*** |
|---|---|---|---|
| -1 | 0 | -2 | 0 |
| -0.5 | 1 | -1.5 | 1 |
| -0.4 | 2 | -1 | 2 |
| 0 | 3 | -0.7 | 3 |
| 0.3 | 4 | -0.5 | 4 |
| 0.5 | 5 | -0.3 | 5 |
| 0.6 | 6 | 0 | 6 |
| 1 | 7 | 0.5 | 7 |
| 1.3 | 8 | 0.7 | 8 |
| 1.6 | 9 | 1 | 9 |
| 2 | 10 | 1.3 | 9 |
| 2.3 | 11 | | |

- This table shows how the *OPGAP* and *PPGAP* are translated into non-negative integers in order to fit the requirement as the dependent variables for the Ordered Probit Model.

**Table 1-11 Descriptions of Variables and Notations**

| **Variable Name** | **Description** |
|---|---|
| $X^i$ | The market value asset return of bank *i*. |
| $X^{system}$ | The market value weighted total asset return of the banking system. |
| $A^i$ | The market value asset of bank *i*. |
| $BA^i$ | Bank *i*'s book asset value. |
| $ME^i$ | Bank *i*'s market value of equity. |
| $BE^i$ | Bank *i*'s book value of equity |
| *C( )* | Some event that causes the bank's asset return to change to $X^i$. |
| $VaR_q^i$ | The *q*th quantile of the asset return $X^i$ |
| $CoVaR_q^{system\|i}$ | The *VaR* of the banking system, conditional on an event when bank i's asset return is at $X^i$. |
| $\Delta CoVaR_q^{system\|i}$ | How much the system total market value asset return would be changed when bank *i*'s asset return is at its bottom *q*% of historical asset distribution compared to when the bank's market asset return is at its median level. |
| *RA* | All-in ratings, transferred from characters into numbers. There are 21 gradations, from 1 to 21. |
| *RI* | Stand-alone ratings, transferred from characters into numbers. There are 10 gradations, from 1 to 10. |
| Δ*CoVar005* | ΔCoVar estimation for each bank at 5%. |
| Δ*CoVar001* | ΔCoVar estimation for each bank at 1%. |
| *VIX* | The VIX index available on Bloomberg, which is to capture the viability of the market. |
| *HOUSING* | The change in the Dow Jones United States Real Estate Industry Group Index represents Real Estate Investment Trusts (REIT) and other companies that invest directly or indirectly in real estate through development, management or ownership, including property agencies. Index is float-adjusted and market cap weighted. Base price is 100 as of 12/31/91. |
| *MKTA* | Quarterly market asset return of a bank. |
| *OP/OPGAP* | Rating gaps calculated by using the optimist point method. |
| *PP/PPGAP* | Rating gaps calculated by using the pessimist point method. |
| *PGGAP* | Rating gaps calculated by using the pessimist grid method. |
| *OGGAP* | Rating gaps calculated by using the optimist grid method. |

| | |
|---|---|
| *GAP* | Rating gaps calculated by using the Rough Rating Method. |
| *S* | A state vector to capture time variation in conditional moments of asset returns, which contains seven factors listed below. |
| *LIQUIDITY* | The difference between the three-month repo rate and the three-month bill rate, is to capture short-term liquidity risk. |
| *TBILL3M* | The quarterly change in the three-month Treasury bill rate. |
| *YIELD* | The quarterly change in the slope of the yield curve, measured by the yield spread between the ten-year Treasury rate and the three-month bill rate. |
| *CREDIT* | The quarterly change in the credit spread between BAA-rated bonds and the Treasury rate, both in the maturity of ten years. |
| *SPX* | The quarterly equity market return from the SPX index. |

- This table shows definitions for major variables.

**Table 1-12 Summary Statistics---Major Variables**

| Variable | N | Mean | Std Dev | Minimum | Maximum |
|---|---|---|---|---|---|
| *RI* | 1819 | 8.0022 | 1.0287 | 2 | 10 |
| *RA* | 1819 | 15.7108 | 2.3265 | 7 | 20 |
| $\Delta CoVar005$ | 1819 | -0.0234 | 0.0544 | -0.2873 | 0.2705 |
| $\Delta CoVar001$ | 1819 | -0.0231 | 0.0576 | -0.2873 | 0.3678 |
| *VIX* | 1819 | 19.2278 | 7.0160 | 11.3800 | 40.95 |
| *HOUSING* | 1819 | 0.0203 | 0.0761 | -0.1538 | 0.1521 |
| *LIQUIDITY* | 1819 | 0.2556 | 0.1924 | 0.0200 | 0.78 |
| *TIBILL3M* | 1819 | -0.0360 | 0.4637 | -1.4350 | 0.77 |
| *YIELD* | 1819 | -0.0140 | 0.5379 | -1.0624 | 1.29 |
| *CREDIT* | 1819 | 0.0062 | 0.3484 | -0.5750 | 0.9860 |
| *SPX* | 1819 | -0.0082 | 0.0795 | -0.1726 | 0.2141 |
| *MKTA* | 1819 | 0.0129 | 0.1906 | -2.0612 | 1.1614 |
| *OP* | 1819 | 5.0192 | 2.4661 | 0 | 11 |
| *PP* | 1819 | 3.4849 | 1.9149 | 0 | 9 |

- This table shows summary statistics for variables used to estimate CoVar and in the final Ordered Probit Model.

## Table 1-12 Correlation Matrix

| | *RI* | *RA* | *ΔCoVar005* | *ΔCoVar001* | *VIX* | *Housing* | *LIQUIDITY* | *TIBILL3M* | *YIELD* | *CREDIT* | *SPX* | *MKTA* | *OP* | *PP* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *RI* | 1.0000 | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | |
| *RA* | 0.8729 | 1.0000 | | | | | | | | | | | | |
| | (0.0001)*** | | | | | | | | | | | | | |
| *ΔCoVar005* | 0.0378 | -0.1007 | 1.0000 | | | | | | | | | | | |
| | (-0.1072) | (0.0001)*** | | | | | | | | | | | | |
| *ΔCoVar001* | 0.0302 | -0.1084 | 0.9824 | 1.0000 | | | | | | | | | | |
| | (-0.1987) | (0.0001)*** | (0.0001)*** | | | | | | | | | | | |
| *VIX* | 0.0921 | 0.0881 | -0.0950 | -0.0863 | 1.0000 | | | | | | | | | |
| | (0.0001)*** | (0.0002)*** | (0.0001)*** | (0.0002)*** | | | | | | | | | | |
| *Housing* | -0.0161 | -0.0355 | 0.0572 | 0.0511 | -0.4327 | 1.0000 | | | | | | | | |
| | (-0.4923) | -0.1301 | (0.0148)** | (-0.0293)** | (0.0001)*** | | | | | | | | | |
| *LIQUIDITY* | 0.0468 | 0.1342 | -0.0822 | -0.0746 | -0.1014 | -0.2338 | 1.0000 | | | | | | | |
| | (-0.0461)** | (0.0001)*** | (0.0004)*** | (0.0015)*** | (0.0001)*** | (0.0001)*** | | | | | | | | |
| *TBILL3M* | -0.0135 | 0.0077 | 0.0609 | 0.0564 | -0.5486 | 0.2376 | -0.1989 | 1.0000 | | | | | | |
| | (-0.5646) | -0.7419 | (0.0094)*** | (0.0162)** | (0.0001)*** | (0.0001)*** | (0.0001)*** | | | | | | | |
| *YIELD* | -0.0023 | -0.0237 | -0.0318 | -0.0337 | 0.1345 | -0.1122 | 0.0409 | -0.5665 | 1.0000 | | | | | |
| | (-0.9231) | -0.3116 | (-0.1755) | (-0.1511) | (0.0001)*** | (0.0001)*** | (0.0815)* | (0.0001)*** | | | | | | |
| *CREDIT* | 0.0165 | 0.0337 | -0.0402 | -0.0363 | 0.3680 | -0.4083 | 0.3084 | -0.2960 | -0.3638 | 1.0000 | | | | |
| | (-0.482) | -0.1503 | (0.0865)* | (-0.1215) | (0.0001)*** | (0.0001)*** | (0.0001)*** | (0.0001)*** | (0.0001)*** | | | | | |
| *SPX* | -0.0086 | -0.0445 | -0.0018 | -0.0041 | -0.0950 | 0.1562 | 0.0088 | -0.0852 | 0.1730 | -0.0620 | 1.0000 | | | |
| | (-0.7132) | (0.0577)* | (-0.9393) | (-0.8619) | (0.0001)*** | (0.0001)*** | -0.7090 | (0.0003)*** | (0.0001)*** | (0.0082)* | | | | |
| *MKTA* | 0.0431 | 0.0681 | 0.0142 | 0.0130 | -0.0716 | 0.2429 | -0.0502 | 0.0319 | 0.0804 | -0.2107 | 0.0553 | 1.0000 | | |
| | (-0.066)* | (0.0037)*** | (-0.5443) | (-0.5795) | (0.0022)*** | (0.0001)*** | (0.0322)** | -0.1740 | -0.0006 | (0.0001)*** | (0.0184)** | | | |
| *OP* | -0.0025 | 0.4664 | -0.3346 | -0.3336 | 0.0063 | -0.0365 | 0.1903 | 0.0525 | -0.0535 | 0.0341 | -0.0883 | 0.0688 | 1.0000 | |
| | (-0.9142) | (0.0001)*** | (0.0001)*** | (0.0001)*** | (-0.7877) | -0.1192 | (0.0001)*** | (0.0253)** | (-0.0226)** | -0.1461 | (0.0002)*** | (0.0033)*** | | |
| *PP* | -0.0417 | 0.4506 | -0.2750 | -0.2768 | 0.0107 | -0.0420 | 0.1887 | 0.0425 | -0.0455 | 0.0378 | -0.0764 | 0.0604 | 0.9600 | 1.0000 |
| | (0.0754)* | (0.0001)*** | (0.0001)*** | (0.0001)*** | (-0.6473) | (0.0736)* | (0.0001)*** | (0.0698)* | (0.0526)** | -0.1069 | (0.0011)*** | (0.0100)*** | (0.0001)*** | |

- This table shows the correlation matrix of variables used to estimate CoVar and in the final Ordered Probit Model.

## Table 1-14 Ordered Probit Regressions, Δ*CoVar 005*

| | *OP*/Random | *OP*/Fixed | *PP*/Random |
|---|---|---|---|
| Δ*CoVar005* | -2.4253 | -3.0915 | -3.0092 |
| | (-2.98)*** | (-3.67)*** | (-3.94)*** |
| *MKTA* | -0.0314 | -0.0867 | -0.0520 |
| | (-0.13) | (-0.42) | (-0.20) |
| *Y=0* | 0.0181 | 0.1886D-06 | 0.0148 |
| | 1.66* | (-0.57) | 1.81* |
| *Y=1* | 0.1601 | 0.0004 | 0.3829 |
| | 3.04*** | 0.39 | 3.51*** |
| *Y=2* | 0.0413 | 0.0222 | 0.1432 |
| | 1.17 | 0.84 | 1.58 |
| *Y=3* | 0.2827 | 1.1754 | -0.0038 |
| | 1.86* | 3.68*** | (-0.25) |
| *Y=4* | -0.0151 | -0.0206 | -0.3027 |
| | (-2.92)*** | (-.10) | (--3.90) |
| *Y=5* | -0.0255 | -0.1555 | -0.0034 |
| | (-2.60)*** | (-1.29) | (-0.20) |
| *Y=6* | -0.1215 | -0.6630 | -0.1582 |
| | (-2.61 )*** | (-3.61)*** | (--3.94 )*** |
| *Y=7* | -0.1798 | -0.3413 | -0.0544 |
| | (-2.32)** | (-1.58) | (-3.82)*** |
| *Y=8* | -0.1007 | -0.0312 | -0.0010 |
| | ( -2.36)** | (-.93) | (-0.62) |
| *Y=9* | -0.0284 | -0.0007 | -0.0175 |
| | (-2.50)*** | (-.66) | (-2.97)*** |
| *Y=10* | -0.0231 | 0.0000 | N/A |
| | (-3.08)*** | (-0.57) | |
| *Y=11* | -0.0081 | N/A | N/A |
| | (-2.44)** | | |
| Number of Observations | 1819 | 1819 | 1819 |
| Log Liklihood value | -2390.2785 | -2164.5377 | -1651.8039 |

- This table presents the results of Ordered Porbit regressions. The independent variables includes ΔCoVar005, MKTA, and a set of yearly dummies, which are presented in the first column. The coefficients on yearly dummies are not reported. Instead, the marginal effects of Δ*CoVar005* are reported for every rating gap grades.The second column presents the results by using *OP* as the dependent variable with random effect applied to the panel data. The third column presents the results by using *PP* as the dependent variable with fixed effect applied. The last column presents the results by using PP as the dependent variable with random effect applied.
- Limdep cannot compute the fixed effect ordered Porbit model when the dependent variable is *PP*.

## Table 1-15 Ordered Probit Regressions, Δ*CoVar 001*

| | *OP*/Random | *OP*/Fixed | *PP*/Random |
|---|---|---|---|
| Δ*CoVar001* | -3.6969 | -2.8014 | -2.9207 |
| | (-5.20)*** | (-3.49)*** | (-3.93) |
| *MKTA* | -0.0520 | -0.0869 | -0.0482 |
| | (-.20) | (-0.42) | (-0.18) |
| *Y=0* | 0.0443 | 0.18196D-06 | 0.0054 |
| | 2.96*** | (-0.57) | 1.60 |
| *Y=1* | 0.2350 | 0.0136 | 0.2705 |
| | 4.81*** | 1.05 | 3.11*** |
| *Y=2* | 0.0518 | 0.0201 | 0.2840 |
| | 1.62 | 0.84 | 2.68 |
| *Y=3* | 0.3506 | 1.0647 | -0.0006 |
| | 3.46*** | 3.49*** | (-0.31) |
| *Y=4* | -0.0065 | -0.0179 | -0.2228 |
| | -1.24 | (-.10) | (-3.83)*** |
| *Y=5* | -0.0197 | -0.1402 | -0.0036 |
| | (-3.35)*** | (-1.28) | (-0.20) |
| *Y=6* | -0.1196 | -0.6004 | -0.2003 |
| | (-4.03 )*** | (-3.44)*** | (-3.87)*** |
| *Y=7* | -0.2248 | -0.3106 | -0.0914 |
| | (-3.93)*** | (-1.57) | (-3.77)*** |
| *Y=8* | -0.1670 | -0.0286 | -0.0020 |
| | ( -4.05 )*** | (-0.93) | (-0.59) |
| *Y=9* | -0.0579 | -0.0007 | -0.0393 |
| | (-4.13)*** | (-0.67) | ( -3.44)*** |
| *Y=10* | -0.0567 | 0.0000 | N/A |
| | (-6.24)*** | (-0.57) | |
| *Y=11* | -0.0296 | N/A | N/A |
| | (-4.35)*** | | |
| Number of Observations | 1819 | 1819 | 1819 |
| Log Liklihood value | -2390.2785 | -2164.6313 | -1649.7160 |

- This table presents the results of Ordered Porbit regressions. The independent variables includes Δ*CoVar001, MKTA*, and a set of yearly dummies, which are presented in the first column. The coefficients on yearly dummies are not reported. Instead, the marginal effects of Δ*CoVar001* are reported for every rating gap grades.The second column presents the results by using *OP* as the dependent variable with random effect applied to the panel data. The third column presents the results by using *PP* as the dependent variable with fixed effect applied. The last column presents the results by using PP as the dependent variable with random effect applied.
- Limdep cannot compute the fixed effect ordered Porbit model when the dependent variable is *PP*.

## Table 1-16 Results Obtained by Using Subsamples

| | | Coefficient on $\Delta CoVar$ | Z-value | Log-likelihood Value |
|---|---|---|---|---|
| | $\Delta CoVar005$/Random | -4.03615 | -1.16 | -298.60188 |
| | $\Delta CoVar005$/Fixed | -6.49294* | -1.92 | -189.71264 |
| | $\Delta CoVar001$/Random | -3.7349 | -0.46 | -281.6185 |
| First/*OP* | $\Delta CoVar001$/Fixed | -4.1908 | -1.25 | -180.6571 |
| | $\Delta CoVar005$/Random | -2.9802 | -0.2 | -209.9631 |
| | $\Delta CoVar005$/Fixed | N/A | | |
| | $\Delta CoVar001$/Random | 0.8130 | 0.2 | -209.0740 |
| First/*PP* | $\Delta CoVar001$/Fixed | N/A | | |
| | $\Delta CoVar005$/Random | -5.9937 | -0.67 | -279.2676 |
| | $\Delta CoVar005$/Fixed | (-8.57422)*** | -2.46 | -178.6849 |
| | $\Delta CoVar001$/Random | -2.8549 | -0.47 | -281.2752 |
| Second/*OP* | $\Delta CoVar001$/Fixed | -4.2831 | -1.29 | -180.1973 |
| | $\Delta CoVar005$/Random | -3.7877 | -0.25 | -206.5844 |
| | $\Delta CoVar005$/Fixed | N/A | | |
| | $\Delta CoVar001$/Random | -1.3241 | -0.12 | -208.8856 |
| Second/*PP* | $\Delta CoVar001$/Fixed | N/A | | |
| | $\Delta CoVar005$/Random | 3.3948 | 0 | -555.7051 |
| | $\Delta CoVar005$/Fixed | 3.1049 | 1.53 | -477.2259 |
| | $\Delta CoVar001$/Random | 1.89153 | 0.08 | -566.8492 |
| Third/*OP* | $\Delta CoVar001$/Fixed | 3.1195 | 1.54 | -477.2087 |
| | $\Delta CoVar005$/Random | 1.1741 | 0.03 | -444.0385 |
| | $\Delta CoVar005$/Fixed | 1.7802 | 0.86 | -400.9266 |
| | $\Delta CoVar001$/Random | 1.1038 | 0.02 | -444.0742 |
| Third/*PP* | $\Delta CoVar001$/Fixed | 1.7979 | 0.87 | -400.9191 |
| | $\Delta CoVar005$/Random | -6.3981 | -.31 | -676.6547 |
| | $\Delta CoVar005$/Fixed | -6.48544*** | -4.08 | -636.1037 |
| | $\Delta CoVar001$/Random | -6.44695 | 0.0 | -675.52805 |
| Fourth/*OP* | $\Delta CoVar001$/Fixed | -6.59749*** | -4.28 | -634.94961 |
| | $\Delta CoVar005$/Random | -5.44806 | -.17 | -483.30478 |
| | $\Delta CoVar005$/Fixed | -5.03459*** | -2.97 | -454.65444 |
| | $\Delta CoVar001$/Random | -5.86028 | -1.23 | -483.33372 |
| Fourth/*PP* | $\Delta CoVar001$/Fixed | -5.61198*** | -3.44 | -455.24416 |

- This table presents results when regressions are run under subsamples. The full sample are divided into four subsamples by the quartile values of the bank book assets. For each subsample, I run eight regressions in order to see the relationship between *OP/PP* and $\Delta CoVar001$ *and* $\Delta CoVar005$, applying fixed and random effects. For example, in the table First/OP stands for when *OP* is the dependent variable and the data is the subsample when bank book assets are in the first quartile. $\Delta CoVar005$/Random stands for when $\Delta CoVar005$ is the major independent variable (other independent variables are the same as the full sample regressions) and random effect is applied.
- I drop some yearly dummies in some of the regressions due to singularity.

**Table 1-17 LR Tests for the Estimation Consistency in Subsamples and the Full sample**

| | $\Delta CoVar005/OP$ | $\Delta CoVar001/OP$ | $\Delta CoVar005/PP$ | $\Delta CoVar001/PP$ |
|---|---|---|---|---|
| LR $\chi^2$ Value | 1149.3536 | 2294.3021 | 612.06184 | 610.01016 |
| Degree of Freedom | 97 | 97 | 88 | 88 |

- This table presents the LR test $\chi^2$ values. The LR tests are employed to test whether the estimations by using subsuamples are the same as the estimation by using the full sample.

**Table 1-18 The Mean of *OP*, *PP*, Δ*CoVar001* and Δ*CoVar005* by Asset Quartile**

| Variable | First Quartile Mean | Second Quartile Mean | Third Quartile Mean | Fourth Quartile Mean |
|---|---|---|---|---|
| *OP* | 2.7621 | 4.0857 | 6.4571 | 6.7675 |
| *PP* | 1.9493 | 2.6989 | 4.3363 | 4.9539 |
| Δ*CoVar001* | -0.0016 | -0.0298 | -0.0306 | -0.0332 |
| Δ*CoVar005* | -0.0019 | -0.0284 | -0.0304 | -0.0326 |

- This table presents the mean of four variables: *OP*, *PP*, Δ*CoVar001* and Δ*CoVar005* by quartile. It shows that on average, banks in higher asset quartile have larger rating gaps and present higher systemic risk.

**Figure 1-1 *OPGAP***

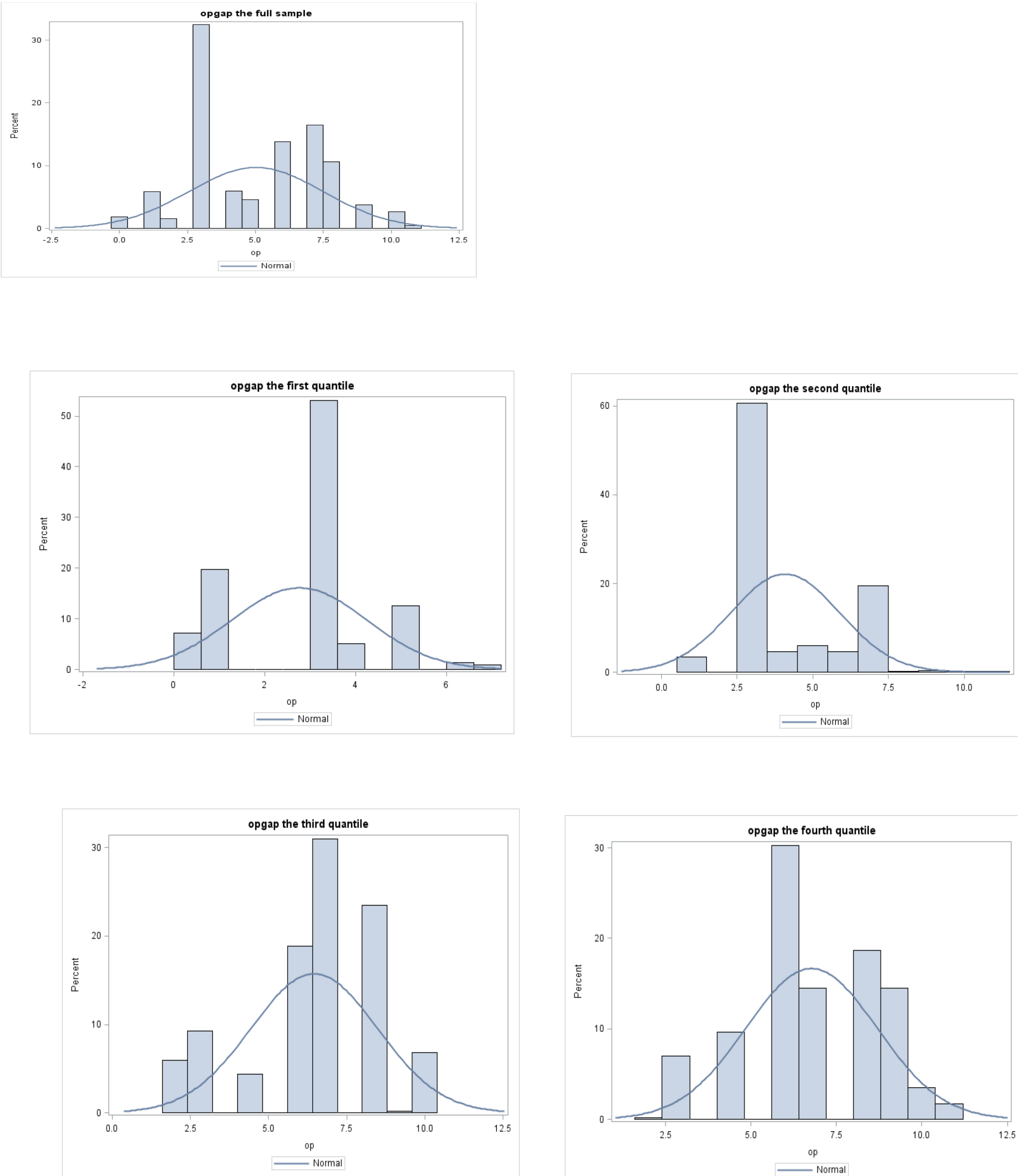


Figure 1-2 *PPGAP*

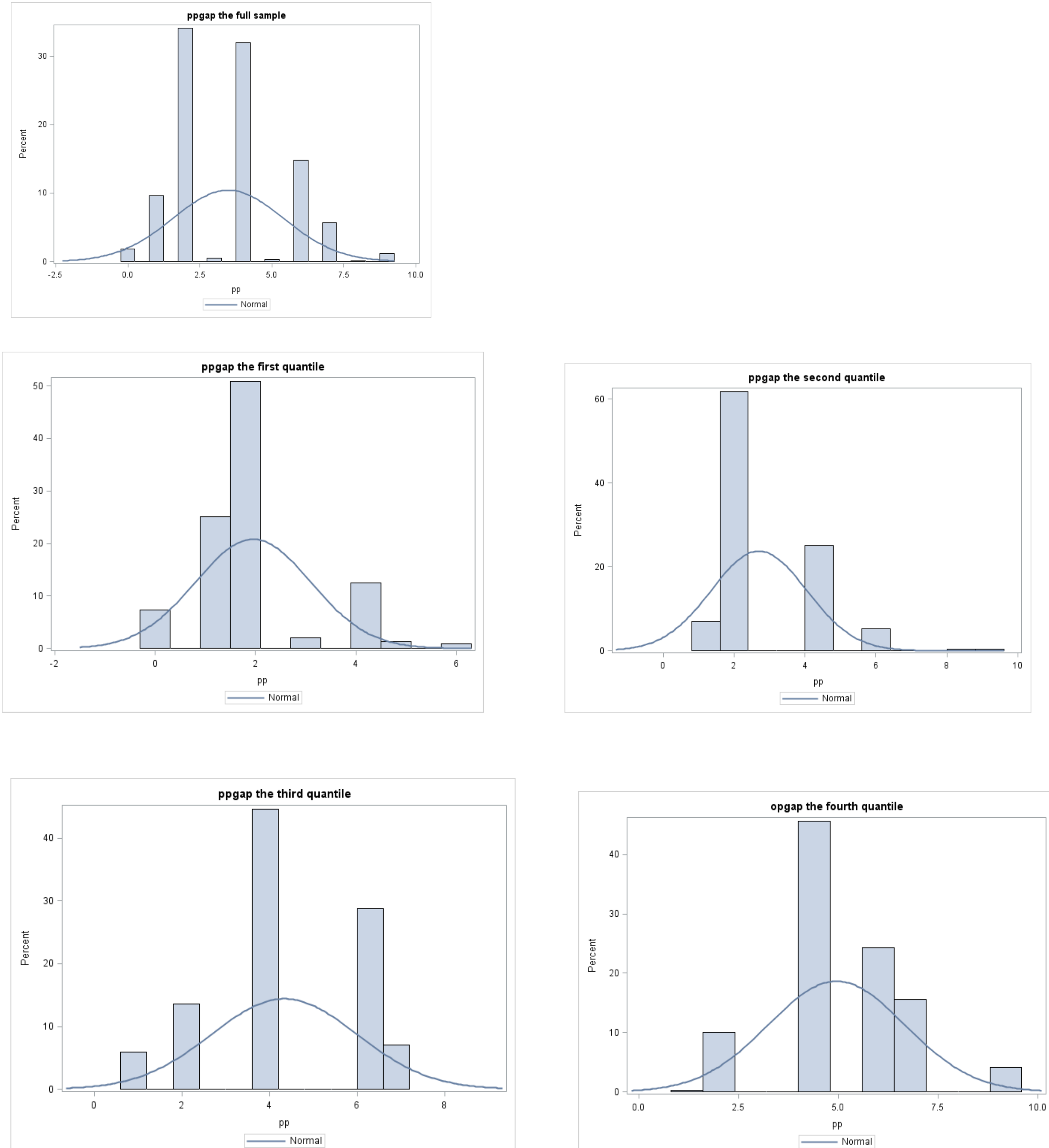
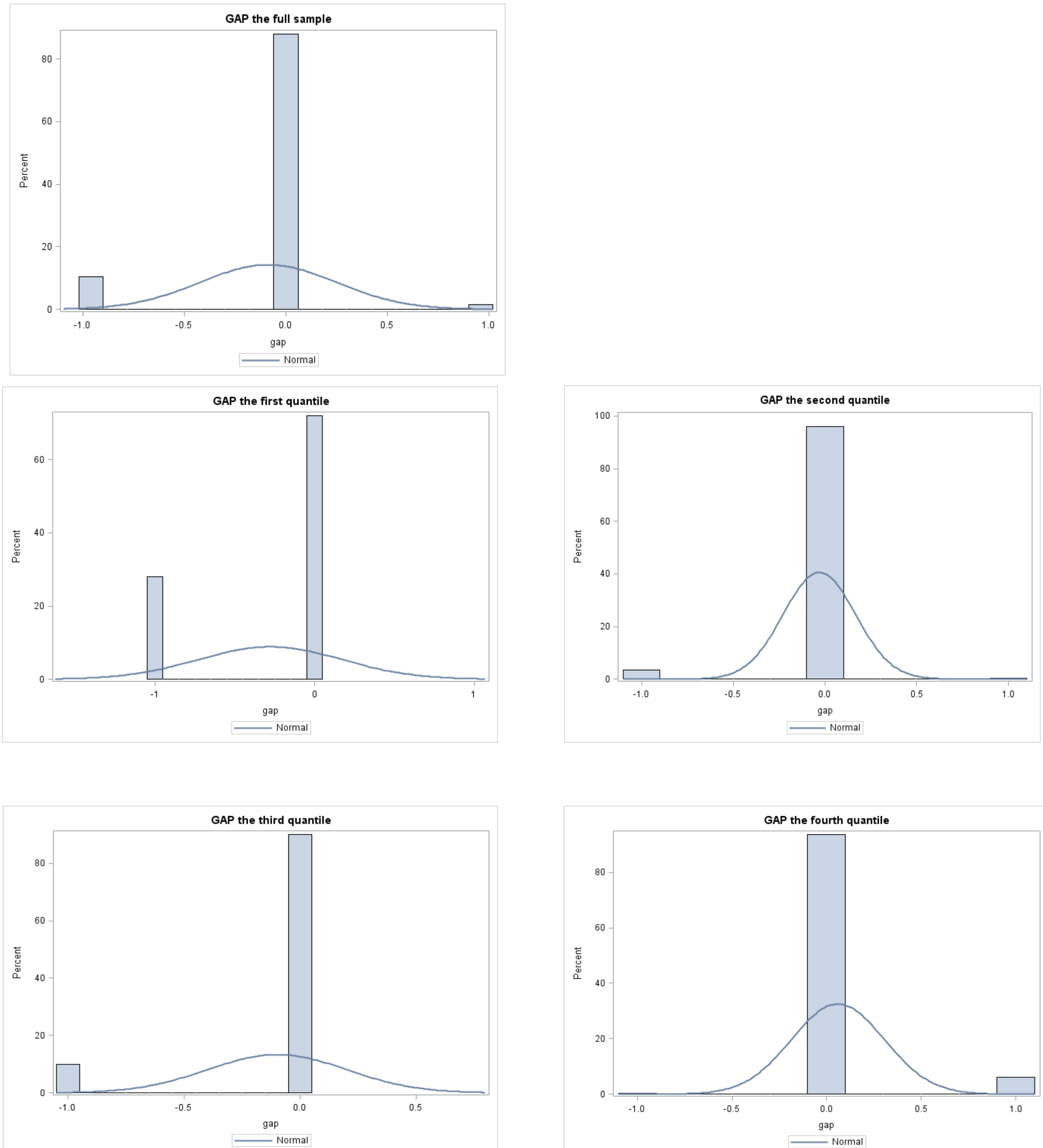


**Figure 1-3 *GAP***



## Figure 1-4 *PGGAP*

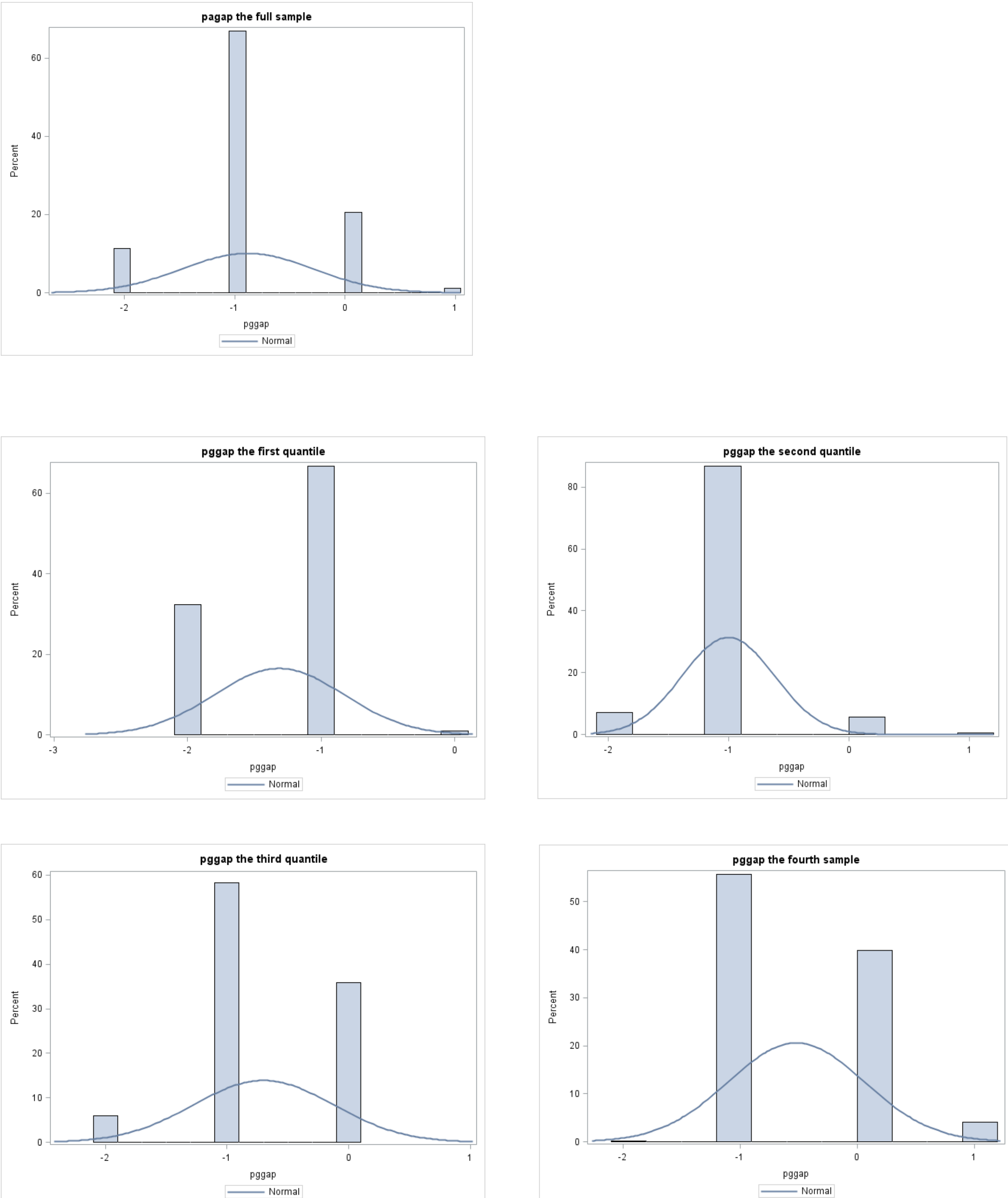


Figure 1-5 *OGGAP*

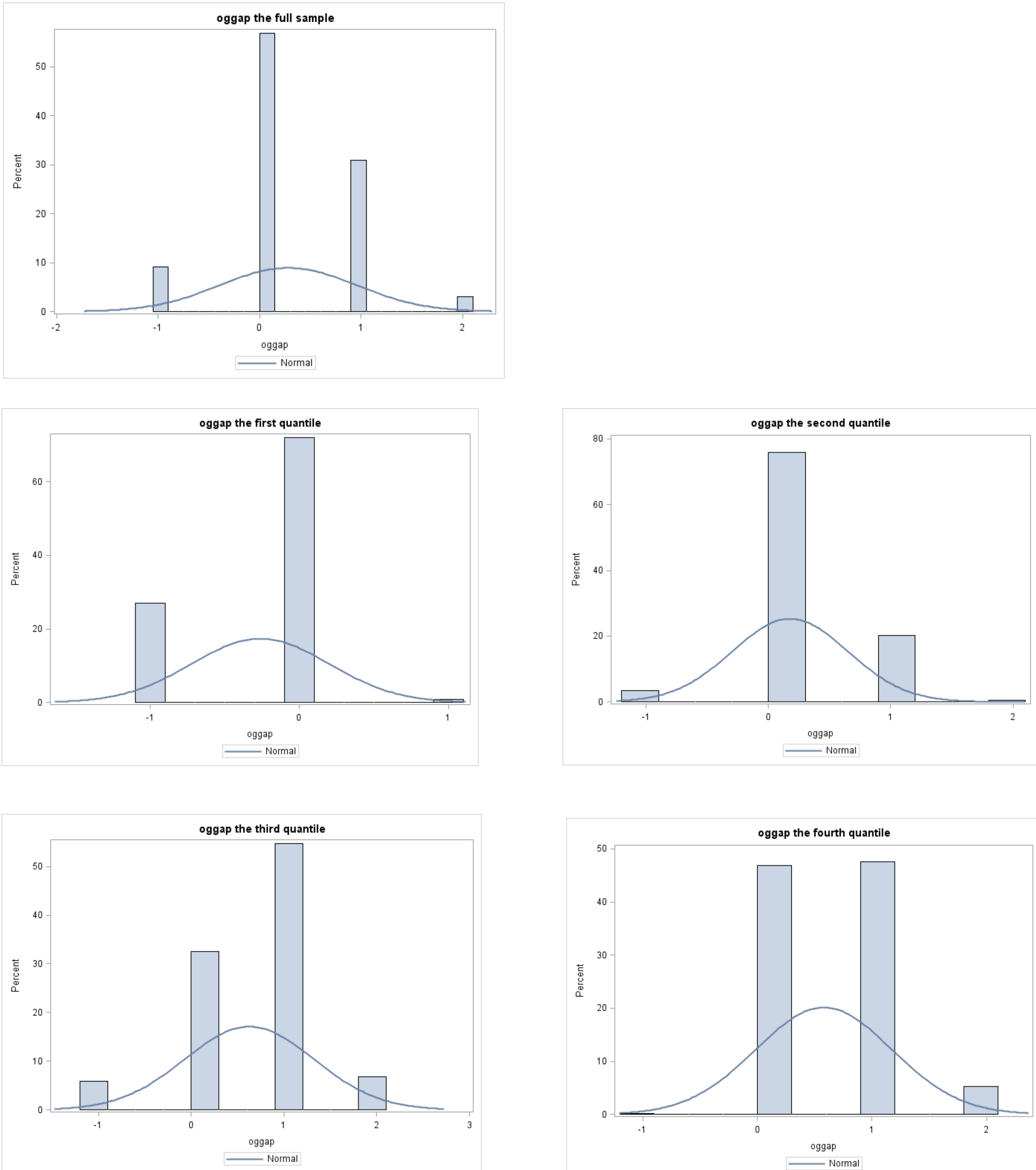
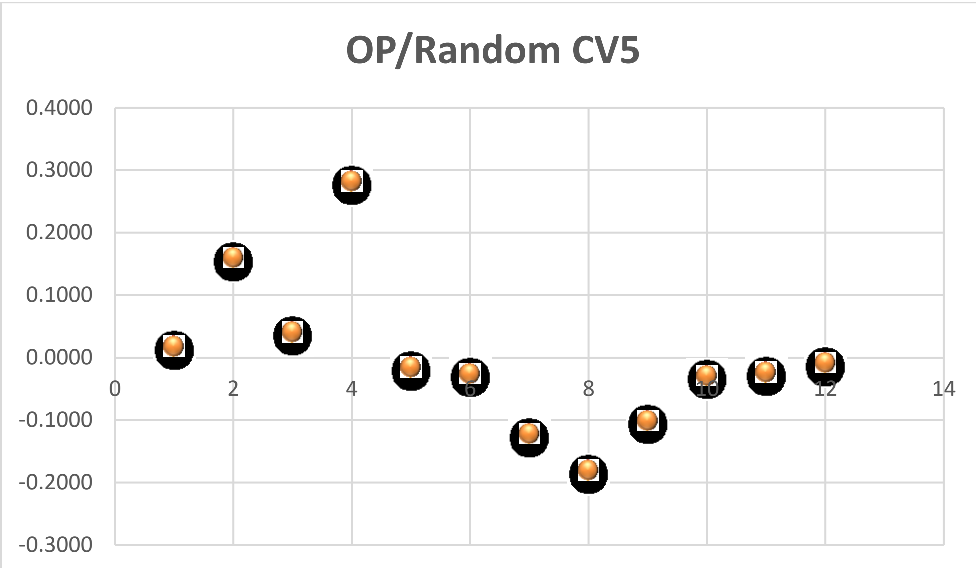


**Figure 1-6 Marginal Effects/*OP-CV5***



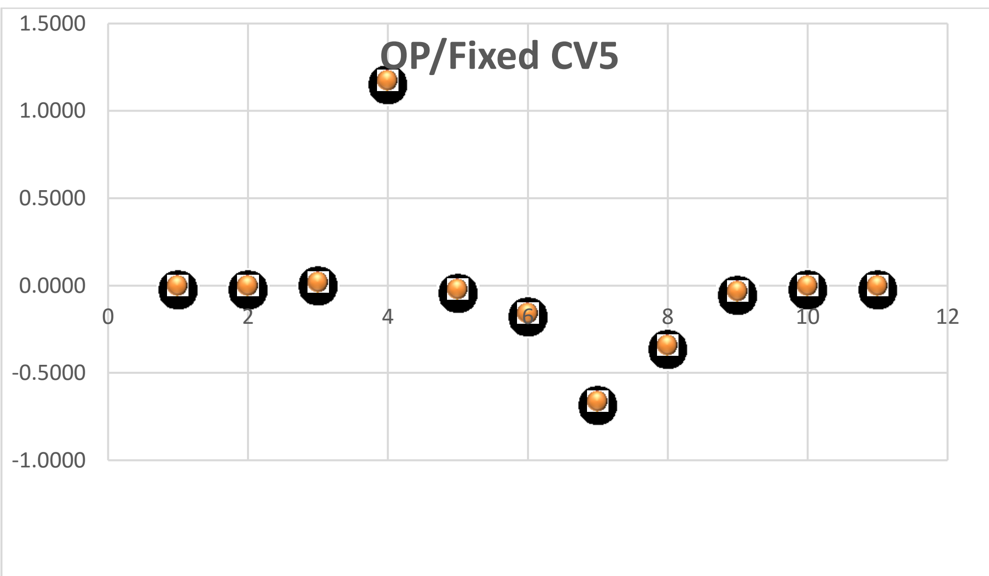
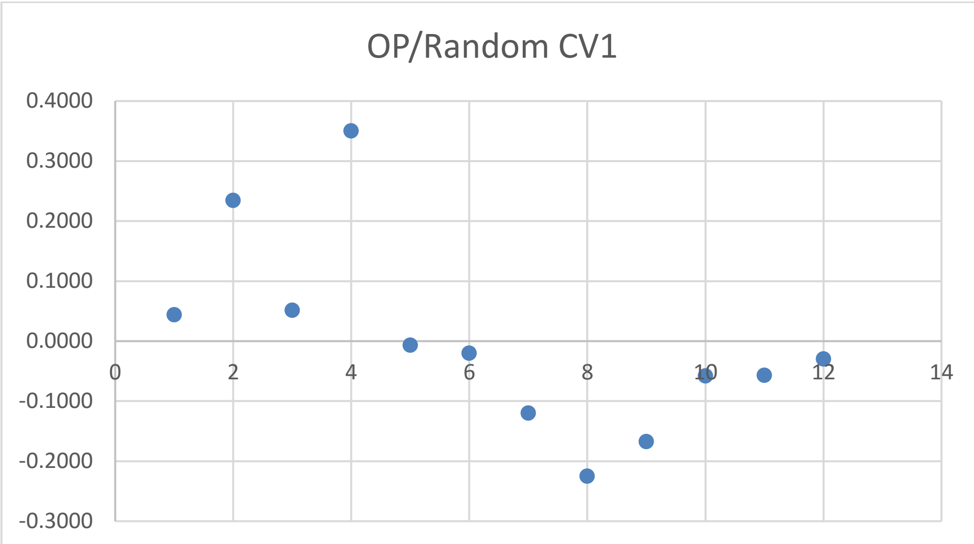



**Figure 1-7 Marginal Effects/*OP-CV1***



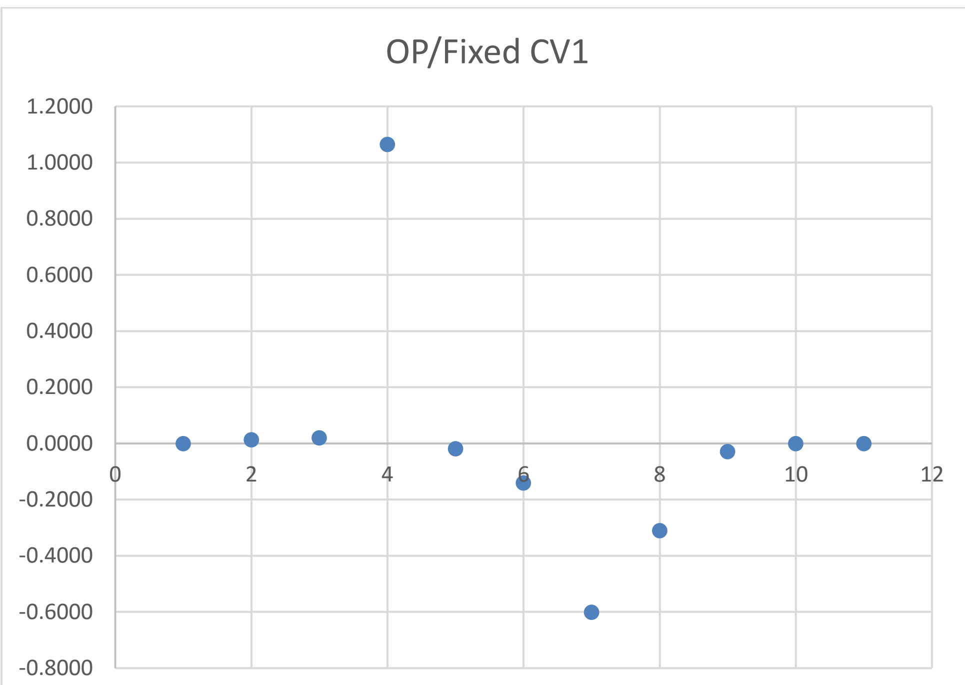
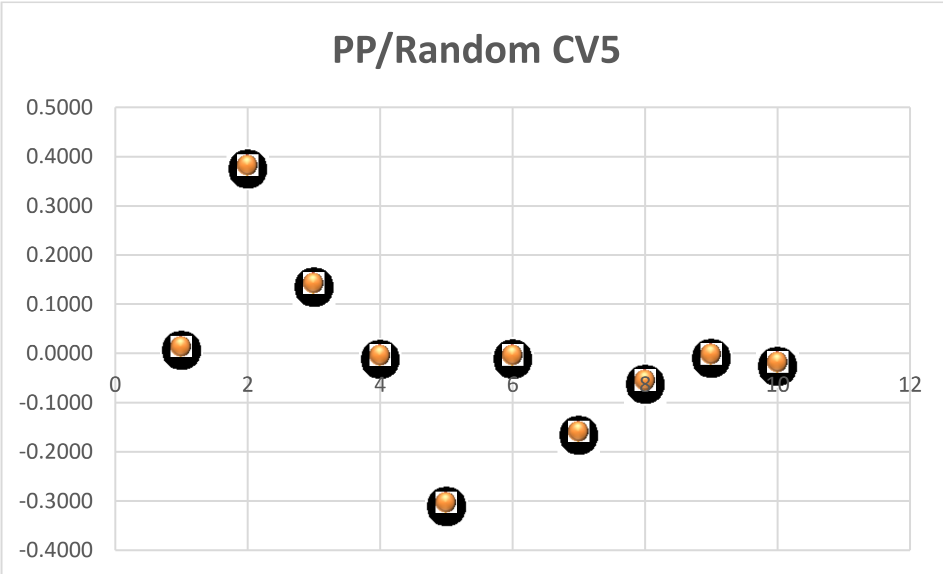
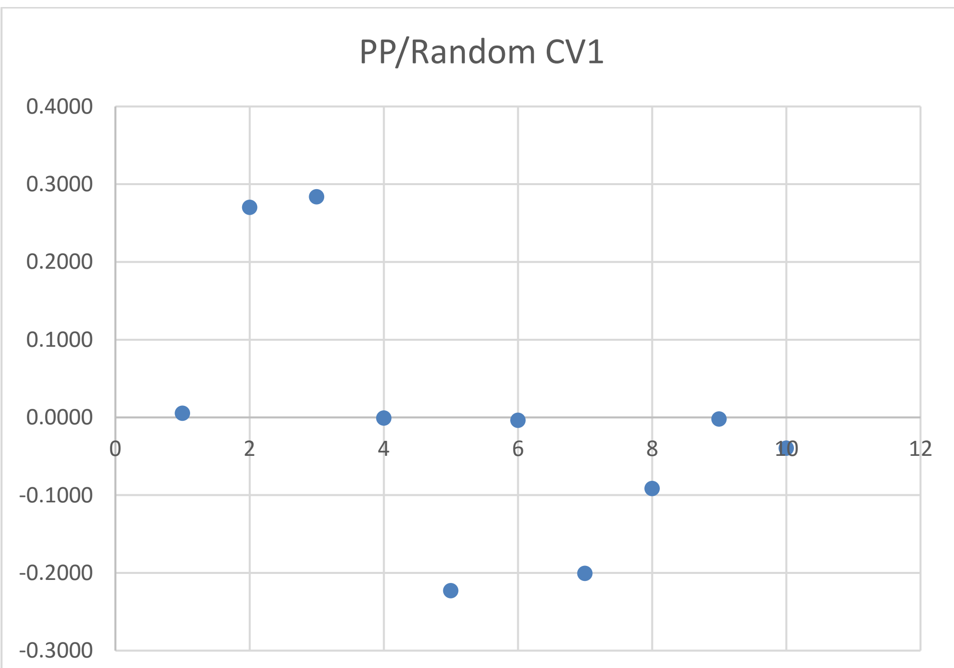



**Figure 1-8 Marginal Effects/*PP***



# Chapter 2 . The Effect of Mergers and Acquisitions on Bank Risk Taking

## 2.1 Introduction

This paper aims to comprehensively evaluate how the risks associated with M&As affect banks' levels of financial solvency. I explore how M&As contribute to banks' geographic and activity diversification, how they alter a bank's market risk, how the size of a merger or acquisition changes a bank's degree of solvency by impacting diversification and market risk, and how M&As globally affect banks' financial solvency.

This study has important policy implications. Many authors (Stiglitz, 2009 and Krugman, 2009) have pointed to financial deregulation as the cause of recent financial crisis in the US. Some researchers have argued that deregulation has spurred a spike in the number of M&As (Berger et al., 1999 and Pilloff, 2004). Thus, by estimating M&A risk effects, this study attempts to determine whether deregulation has caused banks to engage in increasingly risky activities, which, in turn, may have fostered financial crisis.[7] This study also attempts to resolve some inconsistencies in the theoretical and empirical research on the subject of M&As. Portfolio theory suggests that M&As enable banks to diversify their risk both geographically and across business lines in order to achieve higher risk-adjusted returns on capital. However, M&As may increase a bank's risk. M&As lead banks to develop similar internal structures therefore increase interdependence between banks and raise market or systematic risk.[8] Moreover, M&As create mega-banks, which become so large that when one of these fails, it may topple the entire banking system. In this sense,

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[7] In 1987, the U.S. Federal Reserve System's Board of Governors began allowing some bank holding companies (BHCs) to engage in activities listed under Section 20 of Glass-Steagall Act of 1933. The 1994 Riegle-Neal Act allowed banks and BHCs to conduct acquisitions and to establish branches in more than one state. In 1996, the Federal Reserve further removed several firewalls between BHCs' bank and nonbank subsidiaries. Appendix 2 gives the trend of M&As of commercial banks between 1994 to 2003.

[8] Systematic risk is "the degree to which the firm's performance co-varies with the economy as a whole" (Olibe, et al., 2008, p. 683). Systematic risk is also called market risk.

many of these banks are deemed TBTF and bank regulators are compelled to offer extra protections to them. The belief that a bank is TBTF may increase moral hazard for bank managers to expand banks' businesses and take extra risk. In sum, theory provides two contradictory predictions for the risk effect of M&As. This leaves a puzzle: what is the sign of the risk effect of M&As in terms of bank insolvency in the data when all of these various influences are accounted for? This is the objective of this chapter.

This chapter studies interactions among diversification, market risk, bank solvency. Market risk affects a bank's level of diversification, and diversification, in turn, affects a bank's market risk. Moreover, banks' solvency situations could impact how much they are willing to diversify, and, conversely, diversification may impact a bank's level of solvency.

Using data from U.S. BHCs, I estimate a system of equations. The first equation explores how M&As, solvency, activity and geographic diversification affect a bank's market risk. The second and the third equations are used to capture how M&As, market risk and insolvency risk are related to bank activity and geographic diversification. Finally, a fourth equation is developed to investigate how M&As, market risk, and geographic and activity diversification affect insolvency risk. The key finding is that M&As negatively affect bank levels of solvency when all these interactions are accounted for.

The paper is organized as follows. Section 2.2 is a review of related literature. In section 2.3 I discuss sample selection issues, describe data sources and explain variable construction. In Section 2.4 the econometric model and underlying hypotheses are presented along with a discussion of estimation methods. In Section 2.5 I present the results. I offer concluding remarks in Section 2.6.

## 2.2 Related Literature

Empirical research to date has found that M&As, as a means of risk diversification, have been shown to have conflicting empirical effects on bank risk-taking. In theory, M&As may help banks diversify their risks geographically and across business lines because risks differ from region to region and across financial business lines (Craig and Dos Santos, 1997; Meron and Weill, 2005). Some studies suggest that geographic diversification reduces bank risk (Deng and Elyasiani, 2008; Hughes et al., 1996, 1999) but that activity diversification does not foster higher risk-adjusted profitability (Stiroh, 2002). Related, some researchers have found evidence that diversification increases systematic risk (Olibe et al., 2008).

The literature varies in terms of how M&As are defined and measured. Most scholars use one of three measures to characterize M&As. Rather than directly estimating a merger or acquisition's effects, the majority of the research on this subject attempts to analyze the risk effects associated with diversification. Hughes et al. (1999) use geographic diversification as a proxy for M&As, but they neglect the M&As are also used for bank diversification into various business lines.

Some studies measure M&As directly, but with a lack of precision. Nicolo and Kwast (2002) measure M&As as “the change in an institution’s, or pair of institutions', market share[s]” during a given period before and after an M&A, where market share is defined as the ratio between an individual bank’s assets and the entire sample of banks' consolidated assets. This measure is problematic because it fails to acknowledge that factors other than M&As contribute to changes in banks' assets.

Other research does not directly measure M&As; rather, it compares banks’ risk characteristics before and after a M&A to test whether there have been significant changes in risk levels (Amihud et al., 2002 and Craig and Dos Santos, 1997). These studies answer questions about M&As' effects on bank risk taking; however, they do not allow to determine how the magnitude of an M&A relates to risk taking.

Moreover, various scholars apply different definitions of "risk". Deng and Elyasiani (2008) and Amihud et al. (2002) define risk as volatility in stock and market returns. Hughes et al. (1996, 1999) describe risk as the relationship between profit volatility and the probability of insolvency. Olibe *et al. (*2008) discuss systematic risk, measured as the correlation between banks’ excess returns and market returns. To date, the literature separates firm-specific and systematic risk as two unrelated risks, but in reality, bank managers generally consider systematic risk as part of their own individual risk (Montgomery & Singh, 1984).

Moreover, much of the literature employs datasets from diverse regions and various time periods. This makes it nearly impossible to meaningfully compare results. Amihud et al. (2002) use data from 33 countries to analyze cross-border mergers. Meron and Weill (2005) use data from across the European Union. Craig and Santos (1997) employ a dataset from the United States that covers the period from 1984 to 1993 and captures some of the effects of the loosening of restrictions between bank and non-bank businesses. However, this study has the disadvantage of not being able to test the effect of the 1994 Riegle-Neal Act that allowed interstate M&As. Hughes et al. (1999) use a dataset starting from 1994, the year when the Riegle-Neal Act was passed, in order to evaluate the Act's effects; yet, this may ignore delayed effects. Nicolo and Kwast (2002) use data from the period between 1988 to1999; but these data are from too early a period to explore what lead to the 2008 financial crisis.

## 2.3 Data Sources, Sample Selection Issues, Variable Construction and Summary Statistics

### 2.3.1 Data Sources

To evaluate the effects of M&As, I use annual data from Federal Reserve Bank (FRB) FR Y-9C reports, Summary of Deposits (SOD), and Center for Research in Security Prices (CRSP) databases. The unbalanced panel covers the 1994-2007 periods, and includes 591 BHCs. The total sample size is 3633. Data after 2007 are not included, as the focus is on how increases in M&As, as one of consequences of deregulation, affect the risk taking of banks. Post-2008 involves a structural break and may be the topic for future research.

I focus on BHCs for two reasons. First, top-tier BHCs submit FRY-9C reports to the FRB, and these contain information about their subsidiaries and branches. If a BHC is allowed to operate insurance and securities underwriting businesses, its subsidiaries may include commercial banks, insurance companies and securities brokers. Thus these reports include information about all of the other types of financial institutions under a BHC's control. Second, BHCs, in contrast with other types of financial institutions, are able to engage in M&As in any of their allowed business lines. Therefore, by studying BHCs, I am better able to evaluate the effects of different types of M&As.

Top-tier BHCs that hold consolidated assets exceeding $500 million submit financial statements to the FRB in the form of FRY-9C reports. I utilize these data to determine total assets, total equity capital and net income. The SOD database contains information about levels of deposits and about BHCs' associated bank names, headquarters and branch locations. I use these data to construct indices that measure BHCs' levels of geographic diversification. I rely on the CRSP database to provide information about stock and market returns.

Not all BHCs are publicly-listed. The FRB in New York has developed a dataset called the CRSP-FRB Link. I use this to match the three data sources. The dataset contains details about banks that were operating during the period January 1990 through December 2007 and notes their bank regulatory entity codes and CRSP Permanent Company Codes (PERMCOs). The FRB assigns each bank, including those now defunct, a unique regulatory entity code (RSSD ID), and the FRY-9C reports and the SOD database identify banks according to their RSSD IDs. A publicly-listed US bank must have both a RSSD ID and a PERMCO. I have excluded BHCs that are not publicly-listed because I am unable to calculate their systematic risk.

Businesses submit FR Y-9C reports on a quarterly basis. The SOD database is updated annually and the CRSP database is refreshed monthly. In order to create a consistent data series, I have converted all data into annual figures. All SOD reports are submitted June 30th. I therefore use the FRY-9C second quarter figures as the basis for annual figures. The monthly CRSP data is used to compute annual betas in a 60-month rolling window. I use the betas for June as the annual betas, to match the SOD reports.

Finally, the SOD database only provides data starting from 1994. The time period is therefore 1994-2007. The entire panel data contains 591 cross-section units, with the number of observations for an individual BHC ranging from 1to 14.

### 2.3.2 Sample Selection Issues

Estimating systematic risk requires that stock return data be available for banks. Unlisted banks whose betas cannot be estimated are eliminated from the sample. It could be argued that a potential sample selection bias exists due to the choice of whether or not to publicly list a bank. Compared to non-publicly-listed BHCs, a publicly-listed bank is under closer supervision, which may help to reduce insolvency risk; on the other hand, publicly-listed banks partially finance their investment from the market and are more exposed to market risk. It may be a potential problem, however, there is no good solution based on the information in my hand.

### 2.3.3 Main Variable Construction

#### *2.3.3.1 Insolvency Risk*

Insolvency means that an individual, corporation, or organization is not able to meet its obligations σfor paying debt that is due. I follow Hughes et al. (1999) and Laeven and Levine (2008) and use a "*Zscore*" to measure a BHC's insolvency risk.

$$Zscore_{i,t} = \frac{ROA_{i,t} + ROE_{i,t}}{\sigma_{i,t}} \tag{2.1}$$

$ROA_{i,t}$ is the rate of annual return on assets of bank $i$ at year $t$.

$EOA_{i,t}$ is the ratio of annual equity to assets of bank $i$ at year $t$.

$\sigma_{i,t}$ is the standard deviation of bank $i$'s quarterly $ROA$s at year $t$.

The *Zscore* numerator represents a bank's solvency status. The difference between $ROA$ and $EOA$ divided by the standard deviation of $ROA$ measures the distance to insolvency, that is, how many standard deviations the bank is from insolvency (Roy, 1952). When a bank is suffering a loss, it has a negative return and so a negative $ROA$. When the loss of a bank eats all its equity capital, that is the negative return (or loss) plus equity is zero. The numerator of Z*score*, $ROA + EOA = \frac{Return+Equity}{Asset}$, equals zero. *Zscore* is also zero. When the loss is even larger than its equity capital, the difference between $ROA$ and $ROE$ becomes negative and the *Zscore* is negative. A bank is considered insolvent when its equity capital equals or is less than its loss. At this point, *Zscore* is zero or negative. For positive *Zscore*s, the larger the *Zscore*, the more stable the bank. I use FR Y-9C accounting data to calculate all the components of *Zscore*s.[9]

*2.3.3.2 Geographic Diversification Index*

I use Deng and Elyasiani's (2008) measures of geographic diversification, which is a distance-adjusted deposit dispersion index. The geographic diversification index, *GI*, quantifies a bank's geographic diversification status within a given year. Bank *i*'s geographic diversification level is monotonically related to its *GI* index:

$$GI_{i.t} = (DepositDispersion\_st_{i.t}) \times [(DistBHC\_br_{i,t})/MedianDistance_{i,t}] \qquad (2.2)$$

There three parts of $GI_{i.t}$. The first part is $DepositDispersion\_st_{i.t}$, which is a measure of how widely bank *i*'s deposits are geographically dispersed over states (indexed by *q*) at year *t* and is calculated as

[6] There are three elements that are needed to calculate *Zscore*: bank returns, bank assets and bank equities. Data on bank returns, bank equities and bank assets are obtained from account BHCK 4340, account BHCK 3210 and account BHCK2170 in the FRY-9C reports, respectively.

$$DepositDispersion\_st_{i,t} = 1 - \sum_{q} \left( \frac{deposit_{q,t}}{\sum_q deposit_{q,t}} \right)^2 \tag{2.3}$$

where $q = 1,2,..,s$ $(s = total\ number\ of\ states)$.

$deposit_{q,t}$ represents bank $i$'s total deposits within a particular state $q$ at year $t$.

The second part is $DistBHC\_br_{i,t}$. It is the deposit share ratios of BHC $i$ at year $t$ weighted by a calculation of the distance between the headquarters of a BHC and its branches.[10]

It is calculated as:

$$DistBHC\_br_{i,t} = \sum_{p=1}^{m} \frac{TD_{p,t}}{\sum TD_{p,t}} \times d_{p,t} \tag{2.4}$$

where $p = 1, 2, \dots, m$, while m is total number of branches.

$d_{p,t}$ is the distance in miles between bank $i$'s headquarters and its branch $p$, at year $t$, and is computed as the geodetic distance between the two zip codes rather than the distance between two precise locations. $d_{p,t} = 0$ if a branch is in the same zip code as its headquarters;

$TD_{p,t}$ represents each branch's total deposits; and $\sum TD_{p,t}$ describes a bank $i$'s total deposits at year $t$. Thus, for banks with all branches in a single zip code, $DistBHC\_br_{i,t} = 0$ and $GI_{i.t} = 0$.

The last part is $MedianDistance_{i,t}$. It is the median distance of bank $i$'s branches to its headquarters at time $t$.

I use the SOD database to compile all data related to geographic diversification.

[10] The alternative could be the loan ratio. Nevertheless, bank spatial information and deposits for their branches are provided by the SOD database from FDIC. Information for branch assets and loans are not available from this database.

*2.3.3.3 Activity Diversification Index*

I use the activity diversification Index (*AI*) of Stiroh (2002) and Stiroh and Rumble (2006) to determine how diversified a bank's businesses are. Some banks may only engage in traditional banking businesses (such as loans), and others may also manage non-traditional businesses in securities underwriting, insurance and the like. I classify banks' operating revenue into two broad categories: Net interest income (*NET*), which is the income from loan services minus deposit service expenses, and non-interest revenue (*NON*), which includes fiduciary income, fees and service charges, trading revenue and other non-interest income sources.[11] I obtain these data from the FRY-9C reports. Based on this information, *AI* is built as a Herfindahl-like Index and is computed as:

$$AI = 1 - (SHNET_{i,t}^2 + SHNON_{i,t}^2) \tag{2.5}$$

where

$$SHNET_{i,t} = \frac{|NET_{i,t}|}{|NET_{i,t}| + |NON_{i,t}|} \tag{2.6}$$

$$SHNON_{i,t} = \frac{|NON_{i,t}|}{|NET_{i,t}| + |NON_{i,t}|} \tag{2.7}$$

*AI* varies from 0 to 0.5. The most diversified bank has *AI* equaling 0.5 when the bank has equal shares in both the absolute value of net interest income and the absolute value of non-interest income. The most

[11] Net interest income is the difference between interest income and interest expense. Interest income does not just include the loan income, but also other items. However, the main component of interest income comes from the loan business. Also, the interest income and dividend on securities, which includes mortgage-backed securities, is a big part of interest income.

According to the FRY-9C form, interest income includes seven parts: 1) interest and fee income on loans; 2) income from lease financing receivables; 3) interest income on balances due from depository institutions; 4) interest and dividend income on securities; 5) interest income from trading assets; 6) interest income on federal funds sold and securities purchased under agreements to resell; and 7) other interest income. The interest expense includes: 1) interest on deposits; 2) expense on federal funds purchased and securities sold under agreements to repurchase; 3) interest on subordinated notes and debentures and on mandatory convertible securities; 4) interest on trading liabilities and other borrowed money (excluding subordinated notes and debentures); and 5) other interest expense.

undiversified bank has *AI* equaling 0 when it does not have any income from non-interest or net interest business.[12]

*2.3.3.4 Systematic Risk Index*

I measure systematic risk or market risk, within the framework of the classic Capital Asset Pricing Model (CAPM) ((Lintner, 1965; Sharpe 1964). In this setting, the *BETA* generally measures how a bank's excess returns relate to the excess market returns. I use *BETA* as a proxy for market-based risk. For each bank, the *BETA* is estimated by

$$R_{i,t} = \partial_i + BETA_i R_t^M + \varepsilon_i \tag{2.8}$$

$t=1, 2, \ldots, 60$, where $t$ refers to the number of months, $R_{i,t}$ indicates bank $i$'s monthly excess returns, and $R_t^M$ is the value weighted excess monthly market return index from CRSP. $\varepsilon_i$ is the error term.

I use a sixty-month rolling window to calculate the CAPM *BETA* for each BHC. This means that excess returns from the last 60 months (including the current month) form the data series for the dependent variables, and excess market returns from the last 60 months are the data series for the independent variable in the above regression. Since the SOD reports are issued in June, to be consistent, I use *BETA*s from June as the annual *BETA*s in the panel dataset.

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[12] Slightly different to Stiroh (2002) and Stiroh and Rumble (2006), I use the absolute value of *NON* and *NET*. This is to avoid a negative value of an *AI* index. When *NET* or *NON* is negative, $SHNET^2$ or $SHNON^2$ may exceed 1 and *AI* may become a negative number. In this case, the *AI* index fails to rank banks activity diversification properly. This is because a bank with a negative *AI* cannot be less diversified than the one with an *AI* equaling zero. The bank with a negative *AI* at least has some business in both business lines. The absolute values of *NET* and *NON* allow me to measure how much a bank involves in either business line, no matter it is at a loss or at a profit.

*2.3.3.5 M&As*

I measure M&As as a ratio of the net changes in assets from M&As to the amount of a bank's total assets in a given year. Data are from the accounts of (Equity) Changes incident to business combinations, net, which are numbered 4356 in the FR Y-9C reports.

This measure is more direct than other ones. Unlike Hughes *et al*. (1999), Amihud *et al.* (2002) and Craig & Dos Santos (1997), the net changes in assets due to business combinations measure M&As in a direct manner. Hughes et al. (1999), use the number of states that a bank diversifies in as a measure of M&As. Nicolo and Kwast (2002) take M&As as the market share changes in a given period before and after a M&A. The market share is defined as the ratio of a bank's assets to total assets of the full set of banks in their sample. The measure adopted here will likely be more accurate, as a bank's market share may change for many reasons in a given period. A M&A may be just one of the reasons shifting a bank's market share.

Definitions of other variables used in the empirical exercises that follow are provided in Table 2-1.

### 2.3.4 Summary Statistics

In Table 2- 2, I present summary statistics. In the sample, there is wide variation in the measure of distances to insolvency. The standard deviation of *Zscore* among banks over time is 18.9541, with a minimum value of 0.5757, and a maximum of 437.2823. This means that the bank with the poorest performance demonstrates a degree of insolvency that is about half of its quarterly standard deviation of *ROA* in a given year. According to this measure, the best performing bank would become insolvent only if its annual return drops 437 times the quarterly standard deviation of its *ROA*. Overall, there are about 0.5% of banks in the sample with *Zscore*s less than 10; these banks might be considered to the highest probability to become insolvent.

I measure M&As by the ratios of the changes in their net assets due to M&A events to their total assets, and I scale this ratio up by 1000. I obtain these data from businesses' accounts of "net changes incident to business combinations" that are listed in their FR Y-9C reports. This variable, denoted *MA,* displays a minimum value of -13.3907, which means that this particular bank is selling parts of its business. Additionally, the average for *MA* is 13.2920, which means that, on average, a merger or acquisition accounts for approximately 1.3% of a bank's total assets. The largest M&A deal in the sample is $5.7336 billion dollars.

The variable *SIZE* is the total assets of a bank. *SIZE* exhibits a mean of $21.7696 billion. The variable *SIZE* varies from $15 million to $110 billion, which means the largest bank in a given year holds around $110 billion and the smallest bank has $15 million.

More variable descriptions are provided in Table 2-1.The minimum values for *CASH* (cash flow from operations divided by total assets), *DIV* (ratio of dividends to total earnings) and *CIA* (sum of cash and investment divided by total assets) are -0.1105, -46.9123 and -0.1598, respectively. The *CASH* variable becomes negative when a bank is short of cash (i.e., when it has negative cash flow). The *CIA* variable is negative when the sum of cash flow and investment is negative. If a bank makes an investment, this usually appears as negative cash flow, particularly if a bank's investment is greater than its incoming cash; thus, it displays a negative *CIA*. When a bank has negative net income, its declared dividends may still be positive; therefore, *DIV* exhibits a negative value. The mean of *CASH*, *DIV* and *CIV* are 0.0064, 0.3979 and -0.0036, respectively. On average, banks have positive cash-flow-to-asset and dividend-to-asset ratios but negative cash-and- investment- to- asset ratios.

In Table 2-3, I present the correlation matrix for the major variables. M&As are positively and significantly correlated with banks' solvency. *BETA* is significantly negatively correlated with *Zscore*. Both diversification indices, *AI* and *GI,* exhibit a significant negative correlation with *Zscore*, which means that, generally, diversification negatively correlates with banks' levels of solvency. Both *AI* and *GI* are positively related to *BETA*, which suggests that banks experience greater degrees of market risk when they are more highly diversified. These relationships are explored further in the econometric analysis that follows.

### 2.4 Estimation Equations and Methodology

I utilize four estimation equations to investigate how M&As affect banks' levels of solvency.

#### 2.4.1 The *BETA* Equation

I term the following equation as the *BETA* Equation:

$$\begin{aligned} BETA_{i,t} &= \alpha_1 MA_{i,t} + \alpha_2 Zscore_{i,t} + \alpha_3 GI_{i,t} + \alpha_4 AI_{i,t} + \alpha_5 SIZE_{i,t} + \alpha_6 MTB_{i,t} \\ &\quad + \alpha_7 DEBT_{i,t} + \alpha_{0i} + \alpha_8 T_t + \varepsilon_{1i,t} \end{aligned} \tag{2.9}$$

where *i* indexes an individual bank, t indexes a year. Variables are defined as below.

$BETA_{i,t}$: *BETA*s from equation (2.8);

$MA_{i,t}$: annual net asset changes due to business combinations;

$Zscore_{i,t}$: *Zscore*s from equation (2.1);

$GI_{i,t}$: geographic diversification indexes from equation (2.2);

$AI_{i,t}$: indexes for activity diversification from equation (2.5);

$SIZE_{i,t}$: a bank's total assets;

$MTB_{i,t}$: market-to-book value for a bank;

$DEBT_{i,t}$: total debt divided by total assets for a bank;

$T_t$: a time index. *T=0* for year of 1994 and incrementally increases by 1 for each year.[13]

$\varepsilon_{1i,t}$: an idiosyncratic error.

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[13] Instead of using time dummies, a time trend is employed to capture the potential time effect. When time dummies are included in the equations, multicollinearity problems occur with GMM estimation. To make the results comparable, I employ the time index for all types of estimation methods.

Nicolo and Kwast (2002) suggest that M&As contribute to systematic risk. Olibe *et al.* (2008) find evidence that diversification also significantly increases banks' systematic risk. In Equation (2.9), I consider how M&As and geographic and activity diversification impact banks systematic risk. I include *Zscore* in the equation to control for potential simultaneous relationships between systematic risk and insolvency risk. I also follow Olibe et al. (2008) and use *SIZE*, *MTB*, and *DEBT* as control variables.

I utilize the *MTB* as a proxy for a firm's growth opportunities. Firms with high *MTB* values are considered to be fast growers.[14] Olibe et al. (2008) refer to La Porta's (1996) findings that companies with stocks that exhibit high expected growth are associated with higher standard deviations of returns and higher market betas. On the other hand, diversification provides firms with growth opportunities and enhances their competitive positions. The variable *MTB* is therefore related to the right-hand variables *GI*, *AI* and *MA* and to the left-hand-side variable *BETA*. Olibe *et al.* (2008) also refer to Hamada's (1972) assertion that systematic risk is positively related to the extent of financial leverage in firms' capital structures. I therefore include the control variable *DEBT*, a ratio of total debt to total assets.

Finally, I assume that large firms have economies of scale, which should correlate with less stock market variation. I include the *SIZE* variable to control for the effects of economies of scale on market risk.

### 2.4.2 The GI and AI Equations

Equation (2.10) and equation (2.11) are the *GI* and *AI* equations, respectively.

$$\begin{aligned} GI_{i,t} = {} & \beta_1 MA_{i,t} + \beta_2 BETA_{i,t} + \beta_3 AI_{i,t} + \beta_4 Zscore_{i,t} + \beta_5 \ln(SIZE_{i,t}) + \beta_6 CASH_{i,t} \\ & + \beta_7 MTB_{i,t} + \beta_8 DIV_{i,t} + \beta_9 CIA_{i,t} + \beta_{10} CUMMA_{i,t} + \beta_{0i} + \beta_{11} T_t \\ & + \varepsilon_{2i,t} \end{aligned} \tag{2.10}$$

[14] Growth refers to the increase in firms' stock market returns. The statement that firms with high MTB values are considered to be fast growers is consistent to the Fama and French's (1993) finding that firms with lower Book-to-Market yield higher return, since the variable MTB is exactly the inverse of the Book-to-Market ratio.

$$AI_{i,t} = \lambda_1 MA_{i,t} + \lambda_2 BETA_{i,t} + \lambda_3 GI_{i,t} + \lambda_5 Zscore_{i,t} + \lambda_6 \ln\left(SIZE_{i,t}\right) + \lambda_7 CASH_{i,t} + \lambda_8 MTB_{i,t} + \lambda_9 DIV_{i,t} + \lambda_{10} CIA_{i,t} + \lambda_{11} DG_{i,t} + \lambda_{12} OBSA_{i,t} + \lambda_{0i} + \lambda_{13} T_t + \varepsilon_{3i,t} \quad (2.11)$$

The variables not defined previously are:

$CASH_{i,t}$: cash flow from operations divided by total assets. It is used to measure a bank's operating performance.

$CIA_{i,t}$: cash and investment divided by assets, and is a proxy for resources available for diversification.

$DIV_{i,t}$: the ratio of dividends to total earnings, and is a proxy for constraints facing managers from free cash flow and thus diversification ambitions.

$DG_{i,t}$: the ratio of total deposits to total assets. A higher ratio is expected to decrease the desire to enter other financial markets.

$OBSA_{i,t}$: the ratio of gross amount of derivative contracts on interest rates to total assets.

$CUMMA_{i,t}$ : Cumulative M&As, in dollars, exclusive of time period *t* for bank *i*.

$\varepsilon_{2i,t}$ and $\varepsilon_{3i,t}$: idiosyncratic errors.

Little research has investigated why banks diversify. I borrow from the Management Science literature in the specification of equations (2.10) and (2.11), in an effort to explain why banks diversify and to determine whether M&As are positively correlated with diversification. Montgomery (1994) indicates that researchers can use three theories to explain why firms diversify. The first of these is Power Theory, which suggests that firms diversify in order to expand and gain market power. Second, Agency Theory posits that managers use diversification as a tool to build their empires and show their ability, rather than focusing on maximizing stakeholder benefits. The agency view suggests that managers who are holding fewer stocks are more likely to diversify. Additionally, this theory asserts that managers are more likely to use spare cash to expand the firm instead of distributing dividends. Third, Resource Theory contends that firms that have extra resources and capacity seek to diversify in order to capitalize on their economies of scale.

I use the *SIZE* variable to capture the power view, implicitly assuming that banks with large assets have more market power. I expect that banks that have large assets will also be more diversified in their activities and in their geographical scope. I follow Hyland (2002) and include variables *CASH*, *MTB* and *DIV* in the equations to reflect the agency view, while variables *CIA* and *DG* are used to reflect the resource theory. *CASH* is the ratio of cash flow from operations divided by total assets, and I use this variable to measure banks' operating performance. Substantial cash flow leads to good performance, and banks with less cash flow are lower performers. Agency Theory posits that lower performing firms are more likely to diversify; therefore, I expect that *CASH* will be negatively related to both *GI* and *AI*. Additionally, given that the agency view indicates that banks that give large dividend distributions have less incentive to expand, *DIV* will be negatively related to the *GI* and *AI* diversification indices. Finally, the resource theory suggests that banks that have larger off-balance-sheet items (derivatives) will have lower book values, and that highly geographically diversified banks will have more physical assets, such as branch buildings, and thus retain higher book values. *MTB* is expected to negatively related to *GI* but positively related to *AI*.

I define *CIA* as the ratio of cash and investments to total assets, a proxy for the resources that a firm has available to diversify. *DG* is the ratio of total deposits to total assets. The Resource and Power theories predict that banks with large deposit market businesses will have fewer resources or incentives to expand into other business areas, but they may have more power to build additional branches. Based on the resource and power theories, I expect *DG* to be negatively related to *AI*, but positively correlated with *GI*.

If a bank intends to acquire more branches through an M&A deal, it may keep these branches for some time after the deal. This may change the bank’s geographic diversification not only in the year the deal happens but also in subsequent years. To capture this possibility, I include the variable *CUMMA*, the cumulative amount of M&As as of the current year, in the *GI* Equation. A bank may have fewer resources to engage in other geographic diversification if it has had many M&As in the past.

In the *AI* equation, the *OBSA* variable represents off-balance-sheet activities and related risks. The Basel Committee (1986) classifies off-balance-sheet assets into four categories: (i) Guarantees and similar contingent liabilities, where a bank is obligated to stand behind a third party. Standby letters of credit are an example of this; (ii) Commitments, where "a bank has committed itself to a future transaction that will normally result in the bank acquiring a credit exposure". Asset sales and repurchase agreements or lines of credit fall into this category; (iii) Foreign exchange, interest rate and stock index-related transactions. Interest rate swaps are an illustration of these types of activities; (iv) Advisory, management and underwriting functions.

Interest rate derivatives are a particularly popular risk hedging tool. The proxy for measuring off-balance-sheet risk is the ratio of a bank's gross notional amounts of interest rate contracts to its total assets. The FR Y-9C report lists four types of derivative contracts: Interest Rate Contracts, Foreign Exchange Contracts, Equity Derivative Contracts, and Commodity and other Contracts. In my sample, there are only data on Interest Rate Contracts and Foreign Exchange Contracts. Therefore, it is impossible to use the total derivative notional amounts as the proxy. I have to choose between the notional amounts on Interest Rate Contracts and on Foreign Exchange Rate Contracts. There are 316 observations out of 3633 have no zero records on Foreign Exchange Contracts, and 990 out of 3633 have no zero records on Interest Rate Contracts. The average percentage of notional amounts to total assets on Interest Rate Contracts is 16.41%; and on Exchange Rate Contracts is 0.91%. Moreover, in my sample, the number of interest rate contracts a bank manages strictly positively correlates with its total amount of off-balance-sheet assets (interest rate contracts plus foreign exchange rate contracts). Thus, the notional amounts of interest rate contracts is adequately as a qualified proxy for off-balance-sheet risk.

On the right side of the *GI* Equation (2.10), I include the variables *BETA*, *Zscore* and *AI* in order to allow for simultaneous relationships. Similarly, I incorporate the variables *BETA*, Zscore and GI into the right side of the *AI* Equation (2.11).

### 2.4.3 The *Zscore* Equation

Equation (2.12) is the *Zscore* equation, used to study how M&As influence banks' insolvency risk.

$$Zscore_{i,t} = \theta_1 MA_{i,t} + \theta_2 BETA_{i,t} + \theta_3 AI_{i,t} + \theta_4 GI_{i,t} + \theta_5 \ln(SIZE_{i,t}) + \theta_6 MTB_{i,t} + \theta_7 DEBT_{i,t} + \theta_8 OBSA_{i,t} + \theta_9 Netchargeoff_{i,t} + \theta_{10} CASH_{i,t} + \theta_{11} DIV_{i,t} + \theta_{12} Liquidity_{i,t} + \theta_{0i} + \theta_{13} T_t + \varepsilon_{4i,t} \quad (2.12)$$

$Netchargeoff_{i,t}$: the net-charge-off ratio, which is used as a measure of credit risk.

$Liquidity_{i,t}$: the ratio of total loan divided by total assets, which is a proxy for a bank's liquidity condition.

$\varepsilon_{4i,t}$: the idiosyncratic error.

Following Deng and Elyasiani (2008) I utilize control variables *OBSA*, *Netchargeoff* and *Liquidity*. Deregulation and technology development in the banking sector stimulated a growth in off-balance-sheet assets. Off-balance-sheet risk exposes banks to greater credit risks. Thus, I expect that a bank's level of solvency will be directly tied to the quantity of off-balance-sheet assets it maintains. For example, a third party's default may cause a guarantee-providing bank to pay for an obligation, thereby shrinking that bank's assets and negatively impacting its profitability.

The variable *Liquidity* is a proxy for actual liquidity by using the ratio of total loans to total assets. A bank with a large loan-to-asset ratio is considered less liquid because loans take longer to be liquidated than do some other kinds of assets, such as cash, securities and federal funds. The relationship between liquidity and insolvency is ambiguous. During an extreme economic downturn, a lack of liquidity may cause a bank to become insolvent. Although it may have enough assets on book to cover its losses, a bank may still default when it cannot sell its assets for a fair value. In prosperous times, however, it is usually more profitable for a bank to hold more of its assets in loans instead of holding cash or securities.

*Netchargeoff* is the ratio of the net-charge-off to total loans, a means to determine how credit risk influences bank solvency. Banks with higher *Netchargeoff* ratios are those that have higher losses, lower profits and are likely to be less solvent on the whole.

Per Nicolo (2001, 2002), I include the variable *SIZE* in natural logarithm. Nicolo suggests that insolvency risk increases when banks grow in size within the category of small banks, but that this risk decreases when banks have grown big enough to enter the category of large banks. Given that the average assets of banks in the sample are $21.8 billion, which is rather large, I expect that banks' size will positively relate to their *Zscore*s. That is, larger banks should exhibit lower insolvency risks.

I use *MTB* to control for the market's expectation about a bank's degree of solvency. *Zscore*, which measures insolvency risk as the units of standard deviation of the difference between earnings to assets and equity to assets, is positively related to a bank's equity returns. In the market, banks that have high *MTB* ratios are often considered to be overpriced and their stocks are expected to trend downward. I therefore expect that *MTB* will have a negative relationship with *Zscore*. I also include the *CASH* and *DIV* variables which also capture bank performance, and are related to *Zscore* and to *AI* and *GI*. I consider those banks that hold sufficient cash and distribute generous dividends to be good performers, and thus in good solvency positions. I therefore expect that *CASH* and *DIV* will be positively related to Zscore.

Moreover, I use *DEBT* as a proxy for leverage. It is difficult to predict the exact relationship between banks' leverage levels and their degrees of solvency. Banks with unreasonably high leverage levels are generally considered unsafe; however, reasonable leverage may enhance bank profitability and contribute to solvency. Thus, the sign on the coefficient of *DEBT* is ambiguous.

### 2.4.4 Total Effects of M&As

In order to develop a measure of M&As' total effects and the impact of mergers and acquisitions on distance to insolvency, I take the derivative of the *Zscore* (from the *Zscore* Equation), as it relates to *MA*, and apply the chain rule that relates to the *BETA, AI* and *GI* equations. The *Zscore* Equation indicates that M&As' effects consist of four components: $\theta_1$, the direct effect caused by a change in the size of a M&A; $\theta_4\beta_1$and $\theta_3\alpha_1$, indirect effects created by geographic and activity diversification; and$\theta_2\lambda_1$, indirect effects in the form of changes in market risk. The interactions between these components determine the direction of M&As' total effects.

$$\frac{\partial Zscore_{i,t}}{\partial MA_{i,t}} dMA_{i,t} = (\theta_1 + \theta_2\alpha_1 + \theta_4\beta_1 + \theta_3\lambda_1)dMA_{i,t} \tag{2.13}$$

## 2.5 Discussion of Estimation Approaches and Results

It has been argued above that M&As' effects should be investigated jointly. Therefore, an ideal methodology might be a system equation estimation that controls for potential simultaneous relationships between *BETA, AI, GI* and *Zscore*. GMM provides an appropriate methodology, in that it is able to deal with the endogeneity that simultaneous relationships may produce. To compare methodologies, I begin with single equation General Least Squares (GLS) fixed effects estimation, which I expect to be inconsistent because it ignores simultaneous relationships. I then use a system GMM estimator in an effort to obtain consistent results after I select a group of reasonable Instrumental Variables (IV).[15]

I discover, however, that when using the system GMM estimation, most coefficients are not significant (using a 5% critical value). I consider the possibility that the insignificant results may be caused

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[15] The order condition states that the numbers of exogenous variables excluded from each equation in the system must be at least as many as the number of endogenous variables on the right-hand-side of this equation. For every equation, there are three endogenous variables on its right-hand-side. All equations satisfy the order condition.

by misspecifications in the system, and thus consider estimating the equations one by one while continuing to rely on GMM estimation to control for endogeneity relationships.

### 2.5.1 Generalized Least Squares (GLS) Panel Regressions with Fixed Effects

I begin by estimating the *BETA, GI, AI* and the *Zscore* equations as single equations. As stated above, most of the literature focuses on one of these equations without considering the potentially simultaneous relationship among geographic and activity diversification, M&As and insolvency risk.

In Table 2-4, I present the results from single equation estimation. Column (1), (2), (3) and (4) list the estimates for the *BETA* equation, the *GI* equation, the *AI* equation and the *Zscore* equation, respectively. F-statistics of the Wooldridge tests for first order autocorrelation are also presented. The null hypothesis for the Wooldridge test is that there is no first order autocorrelation associated with the residuals. At the 5% level, the test results suggest that, except for the Zscore equation, first order autocorrelation exists in the other equations. Baltagi and Wu (1999) provide a GLS estimation approach to deal with autocorrelation problems. However, Breusch-Pagan tests, shown at the bottom of Table 2-4, suggest that there are also heteroskedasticity problems. Also, based on the Hausman test, a fixed effects framework should be used. Therefore, I use GLS with fixed effects that account for heteroskedasticity and first order autocorrelation.

With single equation estimation, there is no accounting for simultaneous relationships among the four key variables *BETA*, *GI*, *AI* and *Zscore*. The estimation results could therefore be biased. In Column (4), the coefficient on *MA* is positive and significant at 1% level, suggesting that M&As increase banks' solvency. This is in line with the finding of Craig and Dos Santos (1997) that acquisitions generally lower solvency risk. Note that these authors did not consider the potential simultaneity problem.

### 2.5.2 Instrumental Variable (IV) Selection

When I use the single equation GLS method, potential simultaneous relationships between *BETA, GI, AI, MA* and *Zscore* may yield endogeneity in the *BETA, GI, AI* and *Zscore* equations. An estimation with IVs provides solution with taking the potential endogeneities into account. A suitable IV must satisfy two conditions: It must be related to the potentially endogenous variable, but have no relationship to the error term of the equation that includes the endogenous variable. IV candidates that may satisfy both of these conditions include time-lagged values of the endogenous variables. I use the second time lags as IVs for *AI, BETA, GI, Zscore* and *MA*, respectively.

In the *BETA* equation, for example, *Zscore[-2]* (the second time lag for *Zscore*) is an IV for the endogenous variable *Zscore* (a bank's current solvency condition), and should relate to *Zscore* because a bank continues to remain in the same solvency condition for a period of time. Poorly-run and well-run banks are likely to have considerable persistence in Zscores. .

I employ weak IV tests to determine whether the IVs are related to endogenous variables.[16] The results suggest that the IV group (*AI[-2]*, *BETA[-2]*, *GI[-2]*, *Zscore[-2]*, and *MA[-2]*) is not weak.

### 2.5.3 System GMM Estimation with IVs and Fixed Effects

The potential simultaneous relationships between *MA*, *BETA*, *GI*, *AI* and *Zscore* suggest that system estimation may be an appropriate approach. I therefore choose to apply the GMM system equation method. Moreover, the GMM method is able to handle heteroskedasticity and autocorrelation and is as efficient as

[16] I test this by running a regression that uses an endogenous variable on the left-side and includes all exogenous variables from the system equations and the group of IVs on the right-side. I use an F-test to test the null hypothesis that the group of IVs is weak. If the F-statistics suggests that the null hypothesis should be rejected, the group of IVs is considered not "weak." I estimate five regressions to test the "weakness" of the IVs and present the results in Table 2-5.

other estimations when no heteroskedasticity and autocorrelation presents.[17] The results are reported in Table 2-6.

Overall, the results are poor. None of the coefficients are significant. Compared with the results using single equation GLS estimation: (1) In the *BETA* Equation, the coefficient on *MA* becomes significant at the 10% level; (2) In the *Zscore* Equation, the coefficient on *MA* becomes insignificant; (3) In the *GI* equation, the coefficient on *BETA* stays positive and changes from significant at the 1% level to insignificant; (4) In the *AI* equation, the coefficient on *MA* is still negative but switches from significant at the 1% level to insignificant.

### 2.5.4 Single Equation Estimation with GMM and Fixed Effects

I recognize that misspecification of any equation in the system may have affected the system GMM estimation. The system GMM have the errors from all of the equations included. Thus, a misspecification in any equation leads to misspecification of the whole system. If there is no misspecification, single equation GMM estimation should be less efficient than system GMM estimation, but no less consistent. In order to avoid a system-wide misspecification, I next estimate each equation separately. In Table 2-7, I present the results of the single equation GMM estimation.

The outcomes of this estimation are far more interesting than those from the system GMM. The significance of the coefficients improves tremendously when I estimate the equations separately. In the *Zscore* equation, all coefficients are significant at the 1% level. Given that most of the existing literature uses single equation estimation, I will next compare the results of the single equation GLS results with those of the single equation GMM estimates.

[17] A Newey-West variance covariance matrix is applied when use the GMM method.

For the *BETA* equation, with GMM the coefficient on *GI* becomes insignificant. The coefficient on *MA* switches from insignificant to significant at the 10% level and it is positive, which is consistent with the idea that banks have more diversified businesses have greater market risk in their stock prices.

In regard to the *GI* equation, with GMM the coefficients on *MA* and *CUMMA* become significant at 1%. As expected, the positive sign associated with *CUMMA* suggests that more M&As in the past years increase the bank’s geographical diversification. The negative sign on *MA* suggests that M&As reduce banks’ geographical diversification in the same year. This seems counterintuitive, unless perhaps the M&A causes the bank to close some branches but invest in other business lines. Given that the coefficient on *AI* in this equation is negative and significant at 1%, this explanation appears plausible. The coefficient on *BETA* remains positive and significant at the 1% level. The positive coefficient on *BETA* suggests that banks with higher market risk are more likely to diversify geographically. For the *AI* Equation, the coefficient on *Zscore* switches from insignificant to significantly negative at the 5% level. This suggests that more solvent banks are less likely to diversify into different business lines.

The significance of the coefficients for the *Zscore* Equation changes dramatically. All coefficients become significant at the 1% level. The sign on the *MA* variable shifts from positive to negative, thus predicting that when a M&A event occurs, it will be detrimental to a bank's financial health. M&As' pure effect on BHCs' solvency is -0.8288. Recall that *MA* is the ratio of the dollar amount of M&As divided by a bank’s total assets, and *Zscore* is the sum of *ROA* and *EOA* divided by the standard deviation of *ROA* of the same year. Thus, on average, when a bank engages in a M&A that affects approximately 1% of its assets, it will negatively affect the bank's level of solvency by 0.8 of the yearly *ROA* standard deviation.

The facts that the coefficients on *BETA*, *GI* and *AI* are all significant at the 1% level, provide evidence that supports the simultaneous relationship among *BETA, GI, AI* and *Zscore*. Moreover, the *MA*'s effect on *Zscore* can be decomposed into two parts: indirectly through *GI* and *MA*’s direct effect. The effect of *MA* through *GI* on *Zscore* is the coefficient of *MA* in the *GI* equation multiplies the coefficient of *GI* in the *Zscore* equation, that is, $\theta_3\beta_1 = (-0.5404) * (-0.0550) = 0.0297$. This positive number suggests when a M&A only contributes to geographical diversification, it increases a bank's solvency. The coefficient on *MA* in the *Zscore* equation is $\theta_1 = -0.8288$ , suggesting that the direct effect of *MA* on *Zscore* is negative. Without considering the effect through geographical diversification, M&As decreases banks solvency. The total effect of *MA* on *Zscore* can be expressed mathematically as:

$$\frac{\partial Zscore_{i,t}}{\partial MA_{i,t}} = \theta_1 + \theta_3\beta_1 = -0.8288 + (-0.5404) * (-0.0550)$$

$$= -0.7991$$

On the whole, M&As erode BHCs' solvency, both directly and through the effects associated with their geographical diversification.

*BETA* affects *Zcore* in two ways: a positive direct effect and a negative indirect effect through *GI*. The positive sign on *BETA* in the *GI* equation suggests that banks with higher market risk are more likely to expand geographically. The effect of *BETA* through *GI* on *Zscore* is the coefficient of *BETA* in the *GI* equation multiplies the coefficient of *GI* in the *Zscore* equation, that is, $\hat{\theta}_4 \times \hat{\beta}_1 = (-0.5404) \times 5.0380 = -2.7225$. This suggests that geographical diversification spurred by market risk decreases banks solvency. The coefficient on *BETA* in the *Zscore* equation is $\hat{\theta}_2 = 5.7469$ , suggesting that the direct effect of *BETA* on *Zscore* is postive. Without considering the effect through geographical diversification, market risk increases banks solvency. *BETA*'s total effect on *Zcore* is calculated as below:

$$\frac{\partial Zscore_{i,t}}{\partial BETA_{i,t}} = \hat{\theta}_2 + \hat{\theta}_4 \times \hat{\beta}_1 = 5.7469 + (-0.5404) \times 5.0380$$

$$= 3.0244$$

This indicates that overall, *BETA* affects *Zscore* positively. That is, banks with higher market risk may lead to higher solvency.

## 2.6 Conclusions

This paper investigates four channels through which M&As affect BHC's insolvency risk: the effect through market risk; the effects through geographic and activity diversification; the effect directly from M&As. The main question is, after controlling for these indirect effects, what is the total effect of M&As on BHCs' solvency?

The main findings are as follows. First, there does exist a simultaneous relationship between banks' market risk, diversification, and solvency. Market risk and diversification--both geographically and by different business lines--are confirmed to affect bank solvency directly. Market risk affects banks solvency directly and also through geographical diversification. Second, M&As affect BHCs geographical diversification, and this negatively impacts their financial solvency. Third, on the whole, M&As erode BHCs' solvency, both directly and through the effects associated with their geographical diversification.

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## Table 2-1 Descriptions of Variables

| Variable Name | Definitions |
|---|---|
| *Zscore* | Distance to insolvency. See equation (2.1). |
| *MA* | Net asset changes due to M&As divided by the total assets. (Scaled up by $10^3$ in regressions) |
| *BETA* | Correlation between a bank's excess return and the market return. |
| *AI* | Activity Diversification Index. See equation (2.5), (2.6) and (2.7). |
| *GI* | A distance-adjusted deposit dispersion index. (Scaled up by 100 in regressions). See equation (2.2), (2.3) and (2.4) |
| *SIZE* | Total assets of a bank, measured in billions of dollars. |
| *MTB* | Market-to-book value. |
| *Netchargeoff* | Net Charge off ratio, a measure of credit risk. |
| *CASH* | Cash flow from operations divided by total assets. |
| *DIV* | Ratio of dividends to total earnings. |
| *CIA* | Sum of cash and investment divided by total assets. |
| *DEBT* | Total debt divided by total assets. |
| *Liquidity* | Total loans divided by total assets. |
| *OBSA* | Gross amount of derivative contracts on interest rates divided by total assets. |
| *DG* | Ratio of total deposits to total assets. |
| *CUMMA* | Cumulative sum of *MA*s, as of current year, inclusive. |

- This table shows definitions for major variables.

**Table 2-2 Summary Statistics**

| Variables | Number of Obs. | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| *Zscore* | 3616 | 30.7532 | 18.9541 | 0.5757 | 437.2823 |
| *MA* | 3616 | 3.3488 | 10.1493 | -13.3907 | 129.1556 |
| *BETA* | 3616 | 0.4822 | 0.4086 | -1.1178 | 2.7586 |
| *AI* | 3616 | 0.3476 | 0.0968 | 0.0265 | 0.4999 |
| *GI* | 3616 | 2.5973 | 7.6150 | 0 | 100.5306 |
| *SIZE* | 3616 | 21.7696 | 110.0479 | 0.1501 | 2187.6310 |
| *MTB* | 3616 | 2.0298 | 1.3310 | 0.3073 | 39.2297 |
| *Netchargeoff* | 3616 | 0.0044 | 0.0054 | 0 | 0.0805 |
| *CASH* | 3616 | 0.0064 | 0.0091 | -0.1105 | 0.2426 |
| *DIV* | 3616 | 0.3979 | 1.2584 | -46.9123 | 29.0536 |
| *CIA* | 3616 | -0.0036 | 0.0106 | -0.1598 | 0.0890 |
| *DEBT* | 3616 | 0.1394 | 0.0695 | 0.0353 | 0.7349 |
| *Liquidity* | 3616 | 0.6463 | 0.1251 | 0.0349 | 0.9414 |
| *OBSA* | 3616 | 0.3536 | 2.3687 | 0.0000 | 43.3613 |
| *DG* | 3616 | 0.7374 | 0.1366 | 0.0000 | 0.9522 |
| *CUMMA* | 3616 | 20.3417 | 34.5721 | -1.3292 | 351.0144 |

- Among 3616 observations for MA, 2706 carry value 0, which means that M&As never happen in these banks. The mean, Std.Dev, and max values are calculated by including only non-zero values from M&As.

## Table 2-3 Correlation Matrix for Main Variables

| | *Zscore* | *MA* | *BETA* | *AI* | *GI* | *SIZE* | *MTB* | *Netcharge-off* | *CASH* | *DIV* | *CIA* | *DEBT* | *Liquidity* | *OBSA* | *DG* | *CUMMA* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Zscore* | 1.0000*** | | | | | | | | | | | | | | | |
| | (0.0000 | | | | | | | | | | | | | | | |
| *MA* | 0.1274*** | 1.0000 | | | | | | | | | | | | | | |
| | (0.0000) | (0.0000) | | | | | | | | | | | | | | |
| *BETA* | -0.1063*** | 0.0571*** | 1.0000 | | | | | | | | | | | | | |
| | (0.0000) | (0.0006) | (0.0000) | | | | | | | | | | | | | |
| *AI* | -0.0628*** | 0.0345** | 0.1984*** | 1.0000 | | | | | | | | | | | | |
| | (0.0002) | (0.0379) | (0.0000) | (0.0000) | | | | | | | | | | | | |
| *GI* | -0.0556*** | 0.0940*** | 0.3240*** | 0.2833*** | 1.0000 | | | | | | | | | | | |
| | (0.0008) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | | | | | | | | | | |
| *SIZE* | -0.1722*** | 0.1562*** | 0.4979*** | 0.2236*** | 0.5629*** | 1.0000 | | | | | | | | | | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | | | | | | | | | |
| *MTB* | -0.1987*** | 0.0073 | 0.1322*** | 0.1060*** | 0.0790*** | 0.1431*** | 1.0000 | | | | | | | | | |
| | (0.0000) | (0.6625) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | | | | | | | | |
| *Netchargeoff* | 0.0201 | -0.0174 | 0.1973*** | 0.1197*** | 0.1435*** | 0.1887*** | -0.0366** | 1.0000 | | | | | | | | |
| | (0.2269) | (0.2943) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0276) | (0.0000) | | | | | | | | |
| *CASH* | -0.1411*** | -0.0002 | 0.0604*** | 0.1345*** | 0.1063*** | 0.1980*** | 0.0776*** | 0.0044 | 1.0000 | | | | | | | |
| | (0.0000) | (0.9898) | (0.0003) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.7894) | (0.0000) | | | | | | | |
| *DIV* | 0.0956*** | 0.0280* | -0.0318* | 0.0250 | 0.0209 | 0.0075 | -0.0093 | -0.0077 | 0.0272* | 1.0000 | | | | | | |
| | (0.0000) | (0.0918) | (0.0550) | (0.1321) | (0.2078) | (0.6504) | (0.5749) | (0.6438) | (0.1012) | (0.0000) | | | | | | |
| *CIA* | 0.0305* | -0.1015*** | -0.0303* | -0.0517*** | -0.0821*** | -0.0821*** | -0.0077 | 0.0134 | -0.1838*** | 0.0181 | 1.0000 | | | | | |
| | (0.0661) | (0.0000) | (0.0685) | (0.0018) | (0.0020) | (0.0000) | (0.6442) | (0.4187) | (0.0000) | (0.2759) | (0.0000) | | | | | |
| *DEBT* | 0.0243 | 0.0877 | 0.0646*** | 0.0898* | 0.1168*** | 0.2113*** | -0.0353** | 0.0711*** | 0.0767*** | 0.0277* | 0.0060 | 1.0000 | | | | |
| | (0.1430) | (0.0000) | (0.0001) | (0.0000) | (0.0000) | (0.0000) | (0.0337) | (0.0000) | (0.0000) | (0.0949) | (0.7204) | (0.0000) | | | | |
| *Liquidity* | -0.0027 | 0.0084 | -0.1569*** | 0.0256* | -0.0353** | -0.1584*** | 0.0235 | -0.1355*** | -0.0178 | 0.0205 | 0.0384** | -0.0353** | 1.0000 | | | |
| | (0.8688) | (0.6140) | (0.0000) | (0.1213) | (0.0334) | (0.0000) | (0.1574) | (0.0000) | (0.2845) | (0.2156) | (0.0207) | (0.0338) | (0.0000) | | | |
| *OBSA* | -0.0329* | -0.0077 | 0.3012*** | 0.1564*** | 0.1898*** | 0.3956*** | 0.0292* | 0.1238*** | 0.0123 | -0.0099 | -0.0579*** | -0.0157 | -0.3181** | 1.0000 | | |
| | (0.0583) | (0.6588) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0930) | (0.0000) | (0.4792) | (0.5689) | (0.0009) | (0.3666) | (0.0338) | (0.0000) | | |
| *DG* | 0.0328** | -0.0549*** | -0.3152*** | -0.2669*** | -0.3396*** | -0.5854*** | -0.0579*** | -0.1023*** | -0.0761*** | 0.0028 | 0.1279*** | -0.4329*** | 0.3741*** | -0.4900*** | 1.0000 | |
| | (0.0479) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0005) | (0.0000) | (0.0000) | (0.8656) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | |
| *CUMMA* | 0.0175 | 0.4214*** | 0.0922*** | 0.1701*** | 0.2655*** | 0.1685*** | 0.0543*** | 0.0415*** | 0.1138*** | 0.0355** | -0.0194 | 0.2518** | -0.0418*** | 0.0613*** | -0.2356*** | 1.0000 |
| | (0.2907) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0011) | (0.0124) | (0.0000) | (0.0325) | (0.2426) | (0.0000) | (0.0117) | (0.0004) | (0.0000) | (0.0000) |

- p-values are in parentheses.
- ***,**,* represent statistical significance at the 1%, 5% and 10% level.

## Table 2-4 GLS Panel Regressions with Fixed Effects

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *BETA* | *GI* | *AI* | *Zscore* |
| *MA* | 0.00002 | 0.0096 | -0.0002*** | 0.3131*** |
| | (0.06) | (0.89) | (-2.39) | (10.29) |
| *BETA* | n/a | 0.6519*** | -0.0073* | 1.6325 |
| | | (2.33) | (-1.80) | (1.15) |
| *GI* | 0.0003** | n/a | -0.0004 | 0.1707* |
| | (2.08) | | (-1.44) | (1.67) |
| *AI* | -0.1175 | -3.0555* | n/a | -2.6742 |
| | (-0.28) | (-1.92) | | (-0.34) |
| *Zscore* | -0.00006 | 0.0060* | -0.0000 | n/a |
| | (0.51) | (1.64) | (-0.22) | |
| *Ln(SIZE)* | -0.0271 | 0.4179 | 0.0175*** | -0.1529 |
| | (-1.37) | (1.74) | (6.69) | (-0.12) |
| *MTB* | -0.0006 | -0.0341 | 0.0023*** | -1.3592*** |
| | (-0.13) | (-0.50) | (2.62) | (-4.05) |
| *DEBT* | 0.0537 | n/a | n/a | 15.4768* |
| | (0.48) | | | (1.84) |
| *CIA* | n/a | -4.4356 | -0.0270 | n/a |
| | | (-0.92) | (-0.45) | |
| *Netchargeoff* | n/a | n/a | n/a | 335.0976*** |
| | | | | (3.69) |
| *OBSA* | n/a | n/a | 0.0003** | -0.4286 |
| | | | (0.20) | (-1.08) |
| *CASH* | n/a | 0.9544 | -0.0740 | -120.9888 |
| | | (0.16) | (-1.00) | (-3.83)*** |
| *DIV* | n/a | 0.0036 | 0.0004 | 1.4341*** |
| | | (0.92) | (1.06) | (6.20) |
| *Liquidity* | n/a | n/a | n/a | 13.1920** |
| | | | | (2.05) |
| *DG* | n/a | 1.3187 | 0.0026 | n/a |
| | | (0.87) | (0.13) | |
| *CUMMA* | n/a | 0.0017 | n/a | n/a |
| | | (0.25) | | |
| *T* | 0.0240*** | -0.1856 | 0.0009 | 0.5374*** |
| | (5.61) | (-0.40) | (1.31) | (2.86) |
| Intercept | 0.6826*** | -3.6830** | 0.0834*** | 17.7612 |
| | (7.01) | (-2.06) | (5.94) | (1.17) |
| No. of Obs | 3021 | 3016 | 2731 | 2731 |
| | | | | |
| R-squared | 0.1756 | 0.2349 | 0.2385 | 0.0777 |
| | | | | |
| Fixed vs Random Huasman $\chi^2(20)$ | 111.10 | 36.82 | 90.12 | 30.22 |
| | $\chi^2(20)$ | $\chi^2(23)$ | $\chi^2(23)$ | $\chi^2(24)$ |
| FE/RE | FE | FE | FE | FE |
| Breusch-Pagan hetero $\chi^2$ | 147.14 | 7345.20 | 231.80 | 4490.90 |
| | $\chi^2(20)$ | $\chi^2(23)$ | $\chi^2(23)$ | $\chi^2(24)$ |
| Wooldridge Test F-statistic for error term AR(1) | 508.764 | 7.696 | 247.029 | 2.981 |
| | F(1,459) | F(1,428) | F(1,458) | F(1,425) |

- This table presents the results of each equation by using GLS GLS Panel Regressions with Fixed Effects.
- Z-values are in parentheses.

## Table 2-5 Weak IV Tests

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | *MA* | *BETA* | *GI* | *AI* | *Zscore* |
| *CIA* | -77.9000*** | 0.3584 | -13.5528** | 0.0324 | 67.1889 |
| | (-3.22) | (0.80 | (-1.96) | (0.40) | (1.13) |
| *DG* | 7.9855 | -0.4120** | 3.1738 | -0.0219 | 18.4935 |
| | (1.14) | (-2.18) | (1.06) | (-0.72) | (1.37) |
| *liquidity* | -0.1424 | 0.11 | 0.1442 | -0.0126 | 6.9131 |
| | (-0.03) | (0.91) | (0.07) | (-0.35) | (1.19) |
| *OBSA* | -0.5320* | -0.0090 | 0.1431 | -0.0008 | -0.0801 |
| | (-1.95) | (1.15) | (1.22) | (-0.84) | -(0.16) |
| *Ln(SIZE)* | -10.0275*** | -0.03285 | 1.4813** | -0.1454 | -4.7569 |
| | (-4.31) | (-0.71) | (2.02) | (-1.74) | (-1.19) |
| *MTB* | -0.0391 | 0.0090 | -0.0264 | 0.0013** | -1.3042 |
| | (-0.18) | (1.85) | (-0.52) | (2.46) | (-1.33) |
| *Netcharge-off* | 14.8278 | 1.9477 | 25.6508 | 0.6486 | 318.8284 |
| | (0.32) | (1.08) | (1.18) | (1.12) | (1.71) |
| *CASH* | -28.9488 | 0.9658** | -6.9069 | -0.0957 | -109.9630** |
| | (-1.26) | (2.32) | (-1.05) | (-1.18) | (-2.19) |
| *DIV* | 0.0389 | 0.0019 | 0.0728 | 0.0006 | 1.4036 |
| | (0.28) | (1.25) | (1.14) | (0.53) | (1.16) |
| *DEBT* | -3.2101 | -0.0951 | 1.0749 | 0.0347 | 13.8261 |
| | (-0.46) | (-0.78) | (0.54) | (1.09) | (1.24) |
| *CUMMA* | 0.4211*** | 0.0002 | -0.0033 | 0.00004 | 0.1794*** |
| | (20.42) | (0.58) | (-0.46) | (0.73) | (3.18) |
| *T* | -0.6616*** | 0.0079** | -0.1401 | 0.0027** | 0.4672 |
| | (-3.89) | (2.07) | (-2.05) | (2.48) | (1.55) |
| *AI[-2]* | -15.7395*** | 0.1586 | -0.7563 | 0.2533*** | -10.3151 |
| | (-2.95) | (1.26) | (-0.32) | (4.31) | (-1.03) |
| *BETA[-2]* | 3.0628** | 0.2886*** | 1.0538* | 0.0086 | 1.3056 |
| | (2.40) | (8.40) | (1.69) | (1.41) | (0.71) |
| *GI[-2]* | -0.0307 | 0.0012 | 0.2940*** | 0.0001 | -0.0752 |
| | (-0.42) | (0.68) | (3.06) | (0.23) | (-0.77) |
| *Zscore[-2]* | -0.0207* | 0.0004 | 0.0040 | 0.0001 | -0.1208*** |
| | (-1.79) | (0.85) | (1.00) | (1.61) | (-4.10) |
| *MA[-2]* | -0.0820*** | 0.0004 | -0.0095 | -0.0001 | 0.0818 |
| | (-4.56) | (1.06) | (0.75) | (-1.03) | (1.46) |
| Intercept | 111.8119*** | 0.8947 | -22.0588*** | -22.0588*** | 77.9514 |
| | (3.56) | (1.58) | (-2.06) | (-2.06) | (1.24) |
| No. of Obs | 2440 | 2461 | 2461 | 2461 | 2461 |
| R-squared | 0.2266 | 0.5636 | 0.7762 | 0.7762 | 0.0566 |
| Group Test F-st | 13.21 | 15.86 | 9.01 | 7.26 | 3.80 |
| | F(5,457) | F(5,457) | F(5,457) | F(5,457) | F(5,457) |

- This table presents the results of weak IV tests.

## Table 2-6 System GMM

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *BETA* | *GI* | *AI* | *Zscore* |
| *MA* | -0.0122* | -0.012 | -0.0054 | 1.4051 |
| | (-0.0004) | (-0.0004) | (-0.0006) | (0.0004) |
| *BETA* | n/a | 2.2250 | -0.0187 | 5.3237 |
| | | (0.0002) | (-0.0003) | (0.0004) |
| *GI* | -0.0002 | n/a | -0.0000 | 0.1451 |
| | (0.0000) | | (0.0000) | (0.0004) |
| *AI* | -0.1891 | -0.0676 | n/a | 20.5015 |
| | (-0.0003) | (0.0000) | | (0.0005) |
| *Zscore* | 0.0050 | 0.1635 | -0.0021 | n/a |
| | (0.0006) | (0.0007) | (0.0008) | |
| *Ln(SIZE)* | 0.1252 | 2.6932 | 0.0411 | -4.7925 |
| | (0.0021) | (0.0016) | (0.0020) | (-0.0008) |
| *MTB* | 0.0339 | 0.1974 | 0.0067 | -1.5975 |
| | (0.0011) | (0.0003) | (0.0011) | (-0.0005) |
| *DEBT* | -0.0602 | n/a | n/a | 11.3133 |
| | (-0.0001) | | | (0.0003) |
| *CIA* | n/a | -17.5746 | -0.8617 | n/a |
| | | (-0.002) | (-0.0005) | |
| *Netcharge-off* | n/a | n/a | n/a | 199.7994 |
| | | | | (0.0003) |
| *OBSA* | n/a | n/a | -0.0031 | 0.6708 |
| | | | (-0.0009) | (0.0010) |
| *CASH* | n/a | 28.5350 | 0.0942 | -160.9599 |
| | | (0.0003) | (0.0000) | (-0.0007) |
| *DIV* | n/a | -0.0946 | -0.0012 | 1.3821 |
| | | (-0.0001) | (-0.0001) | (0.0004) |
| *Liquidity* | n/a | n/a | n/a | -12.4128 |
| | | | | (-0.0005) |
| *DG* | n/a | 1.1800 | 0.0728 | n/a |
| | | (0.0001) | (0.0005) | |
| *CUMMA* | n/a | 0.0138 | n/a | n/a |
| | | (0.0001) | | |
| *T* | -0.0312 | -0.1464 | -0.0007 | 1.1298 |
| | (-0.0021) | (-0.0005) | (-0.0002) | (0.0010) |
| Intercept | -1.2342 | -43.7968 | -0.3586 | 86.4181 |
| | (-0.0015) | (-0.0016) | (-0.0010) | (0.0014) |
| No. of Obs | 2450 | 2487 | 2450 | 2487 |
| R-squared | -0.0164 | 0.2557 | -0.0164 | -0.1622 |
| Durbin-Watson | 0.7246 | 0.4074 | 0.7246 | 1.5617 |

- This table presents results of GMM system equations.
- When IV estimation is applied, the R-squared can be negative because SSR for IV can actually be larger than SST. R-square may present negatively (Wooldridge, 2003).

## Table 2-7 GMM Single Equations

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *BETA* | *GI* | *AI* | *Zscore* |
| *MA* | -0.0070 | -0.0550*** | -0.0004 | -0.8288*** |
| | (-0.90) | (-2.25) | (-0.03) | (-24.04) |
| *BETA* | n/a | 5.0380*** | 0.0529* | 5.7469*** |
| | | (11.44) | (1.90) | (14.64) |
| *GI* | 0.0039 | n/a | -0.0008 | -0.5404*** |
| | (0.88) | | (-0.67) | (-19.20) |
| *AI* | 0.5325 | -13.4871*** | n/a | -23.2873*** |
| | (0.24) | (-4.98) | | (-10.19) |
| *Zscore* | 0.0056 | -0.0748*** | -0.0016** | n/a |
| | (0.81) | (-4.52) | (-1.98) | |
| *Ln(SIZE)* | -0.0176 | 1.6278*** | -0.0091 | 11.32*** |
| | (-0.05) | (5.00) | (-0.40) | (31.86) |
| *MTB* | 0.0095 | -0.1532*** | -0.0003 | -1.4665*** |
| | (0.76) | (-4.90) | (-0.14) | (-60.32) |
| *DEBT* | -0.0857 | n/a | n/a | 14.2018*** |
| | (-0.14) | | | (22.03) |
| *CIA* | n/a | -14.0844*** | -0.1081 | n/a |
| | | (-4.05) | (-0.37) | |
| *Netcharge-off* | n/a | n/a | n/a | 263.6933*** |
| | | | | (31.54) |
| *OBSA* | n/a | n/a | -0.0021* | -0.2591*** |
| | | | (-1.74) | (-9.81) |
| *CASH* | n/a | -27.9451*** | -1.0825 | -179.7630*** |
| | | (-5.91) | (-1.37) | (-52.14) |
| *DIV* | n/a | 0.1925*** | 0.0031 | 1.6658*** |
| | | (6.16) | (1.46) | (82.88) |
| *Liquidity* | n/a | n/a | n/a | 11.8307*** |
| | | | | (23.47) |
| *DG* | n/a | 4.4367*** | -0.0525 | n/a |
| | | (6.59) | (-0.88) | |
| *CUMMA* | n/a | 0.0296*** | n/a | n/a |
| | | (2.64) | | |
| *T* | -0.0127 | -0.1185 | 0.0062*** | -0.6670*** |
| | (-0.30) | (-4.93) | (3.96) | (-14.72) |
| Intercept | 0.5035 | -19.2410 | 0.5113 | -131.4837 |
| | (0.11) | (-3.65) | (1.43) | (-25.93) |
| No. of Obs | 2487 | 2483 | 2450 | 2450 |
| R-squared | 0.6443 | 0.8495 | 0.7920 | 0.2274 |
| Durbin-Watson | 1.06 | 1.54 | 1.33 | 2.42 |

- This table presents results of GMM system equations.

# Chapter 3 . Time-Varying Systematic Risk, Return Spillovers, and Dynamic Bank Diversification Strategies

## 3.1 Introduction

The aim of this chapter is to investigate how time-varying systematic risk and return spillovers affect bank diversification strategies. Three questions are posed: 1) Does the conditional beta-return relationship exist in banking so banks should make their diversification strategies base on the beta of their assets? 2) Should banks adopt different diversification strategies during market ups and downs? 3) Should banks consider return spillovers when they make diversification strategies?

This chapter contributes to the existing literature in two ways. First, it is the first to test whether or not beta can be considered as an effective indicator for bank asset allocation in a dynamic fashion. Beta, as a risk measure obtained from the traditional CAPM, provides information about how portfolio returns relates to market returns. Pettengill *et al.* (1995) further explore the conditional beta-return relationship. That is, beta and return relate positively when the market is up, and beta-return relationship is negative when the market is down? The study of the relationship between beta and diversification has been extended from portfolio management to firm asset allocation (Leibowitz and Bova, 2010). Based on assets' beta values, portfolio managers allocate their assets and form their portfolios. Does the conditional beta-return relationship exist in banking so banks should make their diversification strategies base on the beta of their assets?

Nevertheless, most studies have concentrated on how firm diversification is related to firm systematic risk. Few studies have explicitly used beta as an indicator for diversification strategy design. Montgomery and Singh (1984) examine the relationship between betas and diversification, concluding that diversifications unrelated to firms' original products were associated with higher betas. Barton (1988) suggests that firm diversification may indicate future market risk to investors. Baele *et al.* (2007) investigates whether investors value bank diversification in term of different business-lines. The authors confirm the findings of Stiroh

(2006) that banks that rely more on non-interest sources of income have systematically higher market betas and hence higher systematic risk. All of the above literature only explores how diversification connects to beta, and have not examined whether banks proactively take beta into consideration for diversification strategy making. Moreover, most studies in this area have only considered a static approach, without allowing for time-varying betas. In this chapter, this shortcoming is addressed with the use of a dynamic analysis.

Second, unlike the existing literature that examines spillovers in banking between different countries, this chapter incorporates bank balance sheet data to study spillovers between individual banks within a country. Elyasiani and Mansur (2003) investigate the spillover effects of interest rate volatility and systematic risk across the banking sectors of the US and Japan, and the US and Germany. They studied bank spillovers using market indexes, to capture the linkages between banks operating in different countries. In contrast, to capture how return spillovers affect individual banks, this chapter uses an industrial spillover measure for each bank--which is a time-varying factor--by regressing individual bank returns against the S&P's Bank index (BIX).[18]

There are three key findings. First, time-varying systematic risk (beta) is a useful variable for bank to make diversification strategies when the market is moderately volatile, i.e. when the monthly change in the market excess return is less than one standard deviation. Second, banks may use different diversification strategies to respond to market ups and downs, conditional on market stability. Finally, banks may wish to consider spillovers when they make activity diversification decisions because spillovers from the banking industry affect bank returns through banks activity diversification.

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[18] According to S&P index methodology, the index series is equal-weighted, with adjustments to individual constituent weights to ensure concentration and liquidity requirements. Also, a final adjustment is made to ensure that no stock in the index has a weight greater that 4.5%.

The rest of this chapter is structured as follows. Section 3.2 discusses related literature. Section 3.3 explores the methodology for time-varying beta estimation. Section 3.4 presents a bank return model in order to test hypotheses about whether beta can be a useful indicator for bank diversification decision-making, and how return spillovers within the banking industry affect individual banks. Section 3.5 provides data and summary statistics, while section 3.6 presents the results. Concluding remarks are presented in section 3.7.

### 3.2 Related Literature

The CAPM (Sharpe, 1964 and Linter, 1965) is widely used to price assets like stocks. Empirical evaluation of the CAPM typically takes the form of a time-series regression equation with the expected excess stock return (a return minus a risk-free interest rate) on the left side and an intercept and the expected market excess return or a market excess return proxy on the right side as explanatory variables. The estimated coefficient on the expected market excess return, beta, provides a measure for the systematic risk, that is, the risk of holding the market portfolio.

Inspired by the portfolio management literature, this chapter examines whether banks use their betas (market risk) as an input into their diversification decisions. In the investment industry, some portfolio managers may think of beta as an indicator of their portfolios' exposure to systematic risk. Consequently, they may adjust their diversification strategies by modifying their portfolios. For example, Leibowitz and Bova (2010) introduced the Beta-Range Rebalancing strategy, to suggest that portfolio managers should rebalance portfolios based on the portfolio beta value. Regarding the banking industry, one question that could be raised is: Do banks make their diversification strategies base on the beta of their assets?

There is a long history of testing for a positive relationship between betas and returns. Early tests of the CAPM, produced by Linter (1965), Fama and MacBeth (1973) and Black *et al.* (1972) support a positive relationship between betas and returns. However, according to Morelli (2011), subsequent studies fail to find evidence of such a relationship. This includes the research of Grinold (1993), Davis (1994), and Fama and

French (1992) on the US markets, Chan and Chui (1996), Fletcher (1997), Strong and Xu (1997), Levis and Liodakis (2001), and Hung et al. (2004) all on the UK market, *Ho et al.* (2000) on the Hong Kong market, Isakov (1999) on the Swiss market, Faff (2001) on the Australian market, and Elsas *et al.* (2003) on the German stock market.

The positive relationship between beta and returns implied by the CAPM indicates that the risk premium of the market, i.e. the difference between the market return and the risk free interest rate, is always positive. Pettengill *et al.* (1995) showed that in US monthly data, over the period 1936 through 1990, there are 280 out of 660 months where the market return (the CRSP equally-weighted market index) is less than the risk free rate (90-day T-bill rate). Based on this observation, Pettengill et al. (1995) hypothesized that there is a conditional relationship between beta and return. When the realized return on the market exceeds the risk-free rate (up markets) there exists a positive relationship between beta and return, and when the realized market return is negative (down markets), the beta-return relationship is negative. Pettengill et al. (1995) thus examined the role of beta conditional on the sign of the realized market net return. They found a significant conditional relationship between betas and returns in the US market over their entire sample period, sub-periods, and when the data was split according to the month of the year.

Morelli (2011) developed the study of Pettengill et al. (1995) in testing the beta-return relationship further by adopting ARCH models to estimate beta, allowing beta to be time-varying. The empirical results of Morelli (2011) are in agreement with Pettengill et al. (1995) and confirm the importance of using the conditional approach in testing the relationship between beta and return. When the sign of the excess market return is ignored, beta is found to be an insignificant risk factor.

As outlined in Faff (2000), the works of Fabazzi and Francis (1978), Sunder (1980), Bos and Newbold (1984), Collins *et al.* (1987), Faff *et al.* (1992), Kim (1993), Bos and Fetherston (1995), and Pope and Warrington (1996), extensive evidence suggests that systematic risk is time-varying. Moreover, evidence show that the time-varying relationship between market and return may exist in the banking industry. Baele et al. (2007) found that market betas for many European banks increased after the 1989 Second Banking Directive, which allowed banks to also engage in non-traditional banking activities, such as insurance and investment banking. Inspired by this literature, this chapter studies the conditional beta-return relationship in the U.S. banking industry, in a framework that incorporates time-variation in banks' betas.

My first step is to estimate time-varying betas. I consider three approaches: a General Autoregressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1990), a state space model (Hamilton, 1994) and one type of Conditional CAPM, Beta-regression Premium (Petkova and Zhang, 2005). The GARCH model of time-varying beta estimation assumes that bank stock returns and market returns can be modeled via an autoregressive process. How the current information set is updated by previous information depends on the nature of the autoregressive process. The State Space model assumes that beta evolves via a specific dynamic process, which can be represented by a state equation. I use an AR (1) specification for the state equation, which implies that banks' current market risks are determined by their market risk from the previous period and a random shock. The Conditional CAPM approach (Jagannathan and Wang, 1996) that I use follows Petkova and Zhang (2005) in specifying that the conditioning information includes four main factors--the dividend yield, the default spread, the term spread and the short-term Treasury bill rate--with the time-varying beta expressed as a linear combination of these four factors.

After obtaining time-varying betas, I follow the methodology of Pettengill *et al.* (1995) to test the beta-return relationship conditional on market ups and downs. Pettengill *et al.* (1995) considered the market as up when the excess market return is positive and vice versa. They created a dummy variable to indicate market states (ups or downs) based on the signs of the excess market return. Returns are regressed against two interactive terms: beta interacted with (i) the market state dummy and (ii) one minus the market state dummy. Pettengill *et al.* (1995) hypothesized that when the market is up, the beta-return relationship would be positive, and beta-return relationship is negative when the market is down. The coefficient on the first interaction term is expected to be positive. The coefficient on the second term is expected to be negative. In considering that in practice banks may experience some extreme market conditions, I also explore including dummy variables that capture large market movements.

Banks engage in two types of diversification: diversification among business activities and geographical locations. Recall that in Chapter 2, AI and GI indexes were used to measure activity diversification and geographical diversification. In this chapter, bank strategies are assumed to divisible into four sets: (high AI, high GI), (high AI, low GI), (low AI, high GI), and (low AI, low GI).[19] Banks are assumed to know their current period betas using historical information, and it is hypothesized that they then adjust their diversification strategies conditional on market ups and downs and whether their beta is high or low. The conjectured process for bank diversification decisions is shown in Figure 3-1.

This chapter also explores the link between bank return spillovers and banks' diversification decisions. The "domino effect" in the banking industry during times of crisis has been widely noted in the literature. Empirical results have shown that shocks are transferred from one bank to another through the interdependence of banks (Nicolo &Kwast, 2002). Peek and Rosengren (1997) examined the transmission of domestic financial shocks in Japan to the US via the Japanese banking sector. They found that shocks to the capital of Japanese parent banking institutions resulted in substantial loan shrinkage at their US branches, though not at their US subsidiaries. Elyasiani and Mansur (2003) investigated the spillover effects of interest rate volatility and of unsystematic risk between banking sectors in the US and Japan, and between the US and Germany. Except for Baele and Koen (2009), little of the existing literature links return spillovers with diversification, and their study was not specific to banking. The

[19] Abbreviated as (HA HG) (HA LG) (LA HG) (LA LG) in Figure 3-1.

authors investigated the impact of globalization and integration on the relative benefits of country and industry diversification. They concluded that globalization and integration have led to a gradual convergence of country-to-industry betas, and geographical diversification continues to be superior to industry diversification. According to Kaufman (1994), compared with non-financial companies, spillovers are more likely to occur among financial firms and spread more quickly from financial firms to the overall economy. Further study is needed to explore how spillovers affect bank diversification.

In this chapter, a spillover is defined as how the return of a single bank is affected by the overall return of the banking industry. Based on this definition, bank returns are regressed against an intercept and the S&P's BIX. The methodology used to estimate spillovers is similar to the Beta-premium Regression approach (Petkova and Zhang, 2005) to estimate beta. Instead of using a stock market return index as the proxy for the overall market, S&Ps' BIX is employed as a proxy for banking industry performance. The coefficient on the BIX, which is called *SO*, is used to measure the spillover from the banking industry. Specifically, to test whether spillovers are a factor in the effects of diversification on bank returns, I regress banks' excess return against two interactive terms: $SO \times GI$ and $SO \times AI$. The effects of diversification on returns are functions of *SO*. If *SO* contributes to the total effects of diversification on banks return, the coefficients on the interactive terms should be non-zero.

### 3.3 Methodology for Estimating Time-Varying Betas

This chapter uses three methods to estimate a time-varying beta. The conditional covariance between banks return at time *t* and the market excess return at time *t*, and the conditional variance of the market excess return at time *t* on the information set $\Phi_{t-1}$ from period *t-1*, are estimated by using a Generalized Autogresssive Conditional Heteroskedasticity (GARCH) model.

*3.2.1.1 Conditional CAPM and GARCH models*

The conditional version of the CAPM can be written as:

$$E(r_{it}|\Phi_{t-1}) = \beta_{it}|\Phi_{t-1}(E(r_{mt}|\Phi_{t-1})) \tag{3.1}$$

where

$r_{i,t}$ is the excess return for bank $i$ at time *t*.

$r_{mt}$ is the excess return on the market at time *t* (data from CRSP).

$\Phi_{t-1}$is the information set at time *t-1*.

$E(|\Phi_{t-1})$ is the expectation operator conditional on the information set $\Phi_{t-1}$.

$\beta_{it}$ is the beta of bank $i$, so-called systematic risk, computed as:

$$\beta_{it}/\Phi_{t-1} = \frac{cov(r_{it}, r_{mt}/\Phi_{t-1})}{var(r_{mt}/\Phi_{t-1})} \tag{3.2}$$

*3.2.1.2 GARCH model set-up.*

Stock market volatility is often modeled using Engle's (1982) Autogresssive Conditional Heteroskedasticity (ARCH) model and Bollerslev's (1986) GARCH model. Studies by Bollerslev et al. (1988), Bodurtha and Mark (1991), Ng (1991), and Hansson and Hordahl (1998) have allowed for time variation in covariance and variances in tests of the conditional CAPM. The (G) ARCH model can be written:

$$r_{it} = \beta_{it} r_{mt} + \varepsilon_{it} \tag{3.3}$$

$$\sigma_{it}^2 = \omega + \rho \sum_{j=1}^{q} \varepsilon_{it-j}^2 + \gamma \sum_{l=1}^{p} \sigma_{it-l}^2 \tag{3.4}$$

Equation (3.3) presents a time series linear regression model of $r_{it}$ on $r_{mt}$ with an error term $\varepsilon_{it}$. It incorporates heteroskedasticity and the variance of $\varepsilon_{it}$ , $\sigma_{it}^2$ changes over time. The variance of the error term $\sigma_{it}^2$ is represented is a GARCH (*q,p*) term. The lagged squared error term $\varepsilon_{it-j}^2$ is called the ARCH (q) term, and the lagged squared term of variance $\sigma^2_{it-i}$ is called the GARCH (*p*) term. Portmanteau Q Tests (McLeod & Li, 1983) are used to check whether the squared residuals of Equation (3.4) follow the GARCH construction. To test the null hypothesis that the process is identically and independently distributed, the test statistics are compared to the $\chi^2(q)$ distribution at the required level of significance. If the test statistic is greater than the value found for $\chi^2$(q), reject the null hypothesis. The formula for the Q test is as follows.

$$Q(q) = M(M+2)\sum_{m=1}^{q}\frac{w(m;\hat{\varepsilon}_t^2)}{(m-1)} \tag{3.5}$$

where

$$w(m;\hat{\varepsilon}_t^2) = \frac{\sum_{t=m+1}^{m}(\hat{\varepsilon}_t^2 - \hat{v}^2)(\hat{\varepsilon}_{t-m}^2 - \hat{v}^2)}{\sum_{t=1}^{M}(\hat{\varepsilon}_t^2 - \hat{v}^2)} \tag{3.6}$$

$$\hat{v}^2 = \frac{1}{M}\sum_{t=1}^{M}\hat{\varepsilon}_t^2 \tag{3.7}$$

ε is the error term of ($y_t = \beta x_t' + v$) for equation (3.7) and q is the qth order of the ARCH progress. I test for up to the12$^{th}$ order for ARCH process. Overwhelmingly, for the 879 banks used in this study, over half of them have no evidence of even an ARCH (1) process. Thus, the GARCH model is not a reasonable specification for a time-varying beta in this study.

### 3.2.2 A State-Space model with the Kalman Filter

I next consider a linear state space model for time-varying beta estimation, given that the variance of stock returns and/or covariance between stock returns and the market return do not appear to follow a (G)ARCH process.

Hamilton (1994) describes a state-space model as a representation of a complicated system to capture the dynamics of an observed vector, $y_t$, in terms of a possibly unobserved vector, $\xi_t$, known as the state vector. A dynamic system can be presented in state space form with two equations: an observation equation and a state equation. Assume that the underlying true vector $\xi_t$ follows an AR (1) process:

$$\xi_t = \delta\xi_{t-1} + v_t \tag{3.8}$$

where $v_t$is an error term.

Equation (3.8) is a state equation. An observable variable,$y_t$, differs from $\xi_t$ by the error term $w_t$ in a dynamic fashion through the observation equation:

$$y_t = \xi_{t-1} + w_t \tag{3.9}$$

where $w_t$ is white noise and unrelated to $v_t$.

I adopt the state-space model for the time-varying beta estimation, as suggested by Nicholls and Pagan (1985). For an individual bank, the observation equation is (2.3) and $\beta_{it}$ follows an AR (1) process:

$$\beta_{it} = \rho\beta_{it-1} + \mu_{it} \tag{3.10}$$

where $\mu_{it}$ is the white noise and unrelated to $\varepsilon_{it}$.

The AR (1) process for beta assumes that the current market risk of banks is affected by their market risk from the previous period and a random shock. In practice, the estimation does not converge when I use the state space model to estimate beta. I thus consider the third method: the Beta-premium regression suggested by Petkova and Zhang (2005).

### 3.2.3 The Beta-premium regression

Petkova and Zhang (2005) suggest using a factor model to estimate a time-varying beta. They consider four factors, the dividend yield ($DIV_{t-1}$), the default spread ($DEF_{t-1}$), the term spread ($TERM_{t-1}$) and the short-term Treasury bill rate ($TB_{t-1}$). They estimate the conditional market return and the conditional individual return by equation (3.11) and (3.12) as below:

$$r_{mt} = \delta_0 + \delta_1 DIV_{t-1} + \delta_2 DEF_{t-1} + \delta_3 TERM_{t-1} + \delta_4 TB_{t-1} + e_{mt} \tag{3.11}$$

$$r_{it} = \alpha_i + (b_{i0} + b_{i1}DIV_{t-1} + b_{i2}DEF_{t-1} + b_{i3}TERM_{t-1} + b_{i4}TB_{t-1})r_{mt} + \varepsilon_{it} \tag{3.12}$$

$$\hat{\beta}_{it} = \hat{b}_{i0} + \hat{b}_{i1}DIV_{t-1} + \hat{b}_{i2}DEF_{t-1} + \hat{b}_{i3}TERM_{t-1} + \hat{b}_{i4}TB_{t-1} \tag{3.13}$$

Because both $r_{mt}$ and $\beta_{it}$ are estimated with the same factors, Petkova and Zhang use GMM to estimate equation (3.11) and (3.12) as a system:

$$E[(r_{mt} - Z_{t-1}\delta)Z'_{t-1}] = 0 \tag{3.14}$$

$$E\big[[r_{it} - \alpha_i - (Z_t r_{mt})b_i](IZ_t r_{mt})'\big] = 0 \tag{3.15}$$

where

$$Z_{t-1} = [IDIV_{t-1}DEF_{t-1}TERM_{t-1}TB_{t-1}] \tag{3.16}$$

I is a vector of ones, and:

$$\delta = [\ \delta_{20}\ \delta_1\ \delta_2\ \delta_3\ \delta_4]' \tag{3.17}$$

$$b_i = [b_{i0}\ b_{i1}\ b_{i2}b_{i3}b_{i4}] \tag{3.18}$$

There are a total of 10 parameters and 10 moment conditions. The system consisting of the equation (3.14) and the equation (3.15) is exactly identified.

### 3.3 The Bank Return Model

The model of bank returns takes the form:

$$\begin{aligned} R_{i,t} = \alpha &+ \lambda_1 D_t \beta_{i,t} + \lambda_2(1 - D_t)BETA_{i,t} + \lambda_3 D_t AI_{i,t} + \lambda_4(1 - D_t)AI_{i,t} \\ &+ \lambda_5 D_t GI_{i,t} + \lambda_6(1 - D_t)GI_{i,t} \\ &+ \lambda_7 SO_{i,t} + \lambda_8 AI_{i,t}SO_{i,t} + \lambda_9 GI_{i,t}SO_{i,t} + \lambda_{10} SIZE_{i,t} \quad + e_{i,t} \end{aligned} \tag{3.19}$$

$R_{i,t}$ is bank *i*'s excess return in percentage at time *t*.

$\beta_{i,t}$ *is* the time-varying beta obtained from the beta premium regression.[20]

$GI_{i,t}$ and $AI_{i,t}$ are the geographic diversification index, and an activity diversification index, respectively. The method for generating these two indices is discussed in Chapter 2.

$SO_{i,t}$ is to measure how the return of a single bank is affected by the return of the banking industry. The final methodology used to estimate spillovers is similar to the Beta-premium Regression (Petkova and Zhang, 2005) to estimate beta. Instead of using a stock market return index as the proxy for the overall market, S&Ps' BIX is employed as a proxy for the banking industry performance. Bank returns are regressed against an intercept and S&P's BIX index. The coefficient on the BIX index is called *SO*.

$SIZE_{i,t}$ is total assets of bank *i* at time *t*.

$e_{i,t}$ is the error term, where *i* individual banks and t indexes for year.

$D_t$, is a dummy variable, used to indicate whether the market is in "up" or "down". There are three types of $D_t$: $D_{1t}$, $D_{2t}$ and $D_{3t}$, conditional on the degree of the market's volatility. $D_{1t}$ equals 1, when the market excess return is positive (the market is said to be in an up state). It equals 0 when the market excess return is negative (the market is said to be in a down state). $D_{2t}$ equals 1, when the change between *t* and *t-1* in market excess return exceeds one standard deviation using a 60-month rolling window. $D_2$ equals to 0 when the change in market excess return is less than one standard deviation using a 60-month rolling window. $D_{3t}$ equals 1, when the change between *t* and *t-1* in the market excess return exceeds two standard deviations using a 60-month rolling window. $D_{3t}$ equals 0 when the monthly change in market excess return is less than two standard deviations of the market excess return using a 60-month rolling window.

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[20] $\beta_{i,t}$ is a generated regressor. As suggested by Murphy and Topel (1985), a generated regressor on the right-hand of the regression may cause biased estimation. The common method to treat generated regressor is to use IVs. However, it is hard to find a good IV for $\beta_{i,t}$. This is because, by definition, $\beta_{i,t}$ is the relationship between the market returns and firm individual returns. It always obtained by using regression methods. Thus, while $\beta_{i,t}$ is a generated regressor, it is standard in the finance literature to ignore this potential problem. This is an issue to explore in the future research.

The hypotheses I examine are as follows:

1) During a boom, taking more market risk would generate higher returns, but during a downturn, taking more market risk would bring losses to banks, i.e. $\lambda_1>0$ and $\lambda_2<0$. If parameters are significant and have the expected signs, this will suggest that a conditional beta-return relationship exists within the banking industry.

2) Intuitively, a bank decides to develop its activity/geographical diversification if this diversification will increase its returns. A bank makes its decision about diversification depending on the effect of the diversification on its returns. In Equation (3.19), the effect of *AI* on bank *i*'s return consists of three components: $\lambda_4(1-D_t)$, $\lambda_3 D_t$, and $\lambda_8 SO_{i,t}$. When in a market up, $D_t = 1$ and the effect of *AI* on bank *i*'s return is $\lambda_3 + \lambda_8 SO_{i,t}$; and when in a market down, $D_t = 0$ and the effect of *AI* on bank *i*'s return is $\lambda_4 + \lambda_8 SO_{i,t}$. If the effect of *AI* on bank *i*'s return is different during a market up or a market down, $\lambda_4 + \lambda_8 SO_{i,t} \neq \lambda_3 + \lambda_8 SO_{i,t}$ or $\lambda_4 \neq \lambda_3$.[21] Therefore, the hypothesis that $\lambda_3 = \lambda_4$ will be tested.

3) If the impact of geographic diversification on banks returns is different from market up to market down, $\lambda_5 \neq \lambda_6$. Therefore, the hypothesis that $\lambda_5 = \lambda_6$ will be tested.

4) If the effects of bank activity diversification on banks' returns are affected by spillovers, $\lambda_8 \neq 0$. The interaction terms, $AI_{i,t}SO_{i,t}$ and $GI_{i,t}SO_{i,t}$ are included in Equation (3.19) to test whether or not spillovers affect the impact of bank diversification strategies on banks' return. The effect of *AI* on bank *i*'s return, is $\lambda_2(1-D_t) + \lambda_3 D_t + \lambda_8 SO_{i,t}$, which is a function of

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[21] $SO_{i,t}$ is time-varying, i.e., for each time t, there is a value for *SO* for each bank *i*. However, I assume that, in a given time period *t*, *SO* is invariant to whether the market is up or down. In this chapter, I only explore whether bank betas and market returns are conditional on market states.

$SO_{i,t}$. When a bank designs its activity diversification, it has to include the effect of the spillover from the banking sector into its consideration if the spillover affects its return via activity diversification. Therefore, the hypothesis that $\lambda_8 = 0$ will be tested.

5) If the impact of bank geographic diversification on returns is affected by spillovers, $\lambda_9 \neq 0$. Therefore, the hypothesis that $\lambda_9 = 0$ will be tested to assess whether banks need to take spillovers into consideration when they design their geographic diversification strategies.

## 3.4 Data and Summary Statistics

### 3.4.1 Data

The primary focus is on individual BHCs. The data come from five sources: Federal Reserve Board (FRB) FRY-9C reports (Chicago branch office); Federal Deposit Insurance Corporation (FDIC) SOD database; Center for Research in Securities Prices (CRSP) databases; Professor Kenneth R. French's online data library; and Bloomberg.

The geographic diversification index *GI* and the activity diversification index *AI* are as described in Chapter 2. This chapter uses five factors to estimate the time-varying *beta* and the spillover index within the banking industry, *SO*. The dividend yield is the sum of dividends accruing to the CRSP value-weighted market portfolio over the previous 12 months divided by the level of the market index. The default premium is the yield spread between Moody's Baa and Aaa corporate bonds, and the term premium is the yield spread between the ten-year and the one-year Treasury bonds. The default yields and the government bond yields are from Bloomberg. The short-term interest rate is the one month Treasury bill rate from CRSP. The data source for the market excess return used to estimate the time-varying *beta* is the market excess return index from Professor Kenneth R. French's online data library. Finally, the BIX index is used to calculate excess return within the banking industry and is from Bloomberg.

Banks submit FRY-9C reports on a quarterly basis. The SOD database is updated annually and the CRSP database is refreshed monthly. I convert all figures to annual figures. As all SOD reports are dated June 30th, I use the FRY-9C second quarter figures as the basis for the annual figures. I use the estimated *beta*s and *SO*s for June as the annual records.

Finally, the time period covered in the full dataset is 1994-2007. The panel contains 589 cross-section units, with the number of annual observations for an individual BHC ranging from 1to 14.

### 3.4.2 Summary Statistics

Table 3-2 presents summary statistics for all variables. The minimum value of *AI* is 0.0265 and the maximum value of *AI* is 0.5. The mean of *AI* is 0.3476, which means on average banks are moderately diversified between interest-income businesses and non-interest businesses. The returns of banks vary widely. The lowest bank return in a particular year is -68.04 percent, while the highest return is 50.90 percent. The minimum estimated time-varying *beta* is -287.25 and the maximum is 194.73. Recall that $D_{1t}$, $D_{2t}$ and $D_{3t}$ are market state dummy variables. For $D_{1t}$, 2168 out 3619 observations (almost 60%) are equal to 1. This means that for 2168 bank-year observations, the market excess return is greater than zero. About 66 percent of observations on $D_{2t}$ equal 1, which means that two-thirds of bank-year observations correspond to a monthly change in the market excess return greater than one standard deviation calculated on a 60-month rolling basis. There are 479 out of 3619 observations (13%) for which $D_{3t}$ equal 1, where the monthly change in market excess returns is greater than two standard deviations. The variable *SIZE* is total assets of a bank. It has a mean of \$21.76 billion, and ranges from \$0.15 billion to \$2187.63 billion.

In Table 3-3, I present the correlation matrix for all variables. Both diversification indexes *AI* and *GI* are negatively correlated with bank returns and are significant at the 1% level. This means, generally, diversification may reduce bank returns. The time-varying market risk measure, *BETA*, is not significantly correlated with bank returns. The banking industry spillovers index *SO* is negatively correlated with bank returns and is significant at the 1% level. This suggests that banks affected more by spillovers within the banking industry tend to perform worse.

## 3.5 Results

### 3.5.1 The Return Model

In Table 3-4, I report the regression results for the return model for the three alternative market state dummy variables, $D_{1t}$, $D_{2t}$ and $D_{3t}$. In the following discussion, the market states represented by these three dummy variables are referred to as Type 1, Type 2 and Type 3.

A Hausman test is used to test whether a fixed effects or random effects model is preferred. I also use Breusch–Pagan (BP) tests for heteroskedasticity. Test results are shown at the bottom of Table 3-4. Based on these test results I choose a fixed effects approach with robust standard errors to estimate equation (3.19).

The coefficients on $D^*\beta$, $\lambda_1$ , are positive under all three market state definitions, and are significant at the 5% level for the Type 2 and Type 3 definitions. This suggests that when the market is up and comparatively volatile, a higher *beta* leads to higher returns. The coefficients on $(1\text{-}D)^*\beta$, $\lambda_2$, are negative but only significant under the Type 2 definition of market states. This may imply that in market downturns with moderate volatility, a higher *beta* is associated with lower bank returns. The coefficients on $AI \times SO$, $\lambda_8$, are negative under all three definitions. They are all significant at 10%, and under Type 1 and Type 3 definitions are significant at the 5% level. This suggests that spillovers within the banking industry matter for banks' returns. Moreover, spillovers contribute negatively to the overall banks return through activity diversification.[22]

[22] The total effect of *SO* on bank returns is $\lambda_7 + \lambda_8 AI_{i,t} + \lambda_9 GI_{i,t}$. However, since $\lambda_7$ and $\lambda_9$ are both insignificant at 5% under all three market condition definitions, the effect of *SO* on bank return is $\lambda_8 AI_{i,t}$. That is, the effect of *SO* on banks' return only depends on banks' activity diversification.

### 3.5.2 Hypothesis Tests

In Table 3-5, I present tests pertaining to the five hypotheses. The first row of Table 3-5 examines the first part of the hypothesis 1: whether banks taking more market risk during market ups have higher returns. The null hypothesis, $\lambda_1 \leq 0$, is rejected under all three definitions of market conditions, suggesting that taking more market risk during market ups leads to higher bank returns.

The second row of Table 3-5 examines the link between bank returns and beta during market downturns. There is some evidence that a higher beta during market downturns lowers bank returns (except for the Type 3 case).

In the third row of Table 3-5, I test the null hypothesis $H_o$: $\lambda_3=\lambda_4$ in order to determine whether activity diversification strategies have different impacts on banks returns in market ups and downs. Except when a market up/down is defined as Type 1, the null hypothesis is rejected. This suggests that bank activity diversification may have different consequences for bank returns in market ups than in market downs, at least in relatively volatile markets.

The fourth row of Table 3-5 examines a similar hypothesis but in regards to geographic diversification. The null hypothesis is $H_o$: $\lambda_5=\lambda_6$. The null hypothesis is rejected only for the Type 1 case. This suggests that when geographic diversification has different impacts on bank returns in market ups than in market downs for the Type 1 case only.

In the fifth row of Table 3-5, I test whether spillovers within the banking industry affect bank returns through bank activity diversification. The null hypothesis that $\lambda_8=0$ is rejected. Recall that the effect of *AI* on bank $i$'s return is $\lambda_3 + \lambda_8 SO_{i,t}$ when the market is up and $\lambda_4 + \lambda_8 SO_{i,t}$ in a down market. If the null hypothesis that $\lambda_8=0$ is rejected, $SO_{i,t}$ is a part of the total impact of activity diversification on bank returns. When the bank considers activity diversification, spillovers within the banking system should be taken into consideration. The test results do indeed generally reject the null hypothesis that $\lambda_8=0$. The effect of the spillover on banks' return are suggested to come through banks' activity diversification. Moreover, $\lambda_8$ is significantly negative at 5% for the type1 and type 3 market state. When *SO* becomes larger, banks are better-off by less diversifying among different businesses (lower the value of *AI*).

Recall that *SO* is the coefficient on the BIX index, which is to measure how closely that a bank's return volatile with the banking industry. Higher *SO* means the bank's return follow the banking industry's return more tightly. In other words, larger spillover effect from other banks. For example, JP Morgan Chase's estimated *SO* is 0.56 in 1995. In 2001, the value of *SO* of JP Morgan Chase increased to 1.48. Compare to 2001, the spillover from the banking industry on JP Morgan is larger than it was in 1995. Comparing to 1995, in 2001, JP Morgan might be better off if it could one of the two types of businesses, either traditional loan-related business or no-loan related businesses, such as insurance or underwriting.

In the last row of Table 3-5, I test the null hypothesis $H_o$: $\lambda_9=0$. Rejecting the null hypothesis means that bank returns are affected by spillovers within the banking industry through bank geographic diversification. The test results fail to reject the null hypothesis under all three definitions for market conditions. The conclusion is that spillovers do not affect bank returns through geographic diversification.

### 3.6 Concluding Remarks

This chapter has three main findings. First, time-varying systematic risk (beta) could be considered by banks as an important variable for their returns. As stated previously, to serve as a qualified indicator for diversification strategy-making, a conditional beta-return relationship has to exist in the banking industry. Beta has to be associated with market ups/downs with bank returns increasing/decreasing accordingly. That is, when the market is up, higher beta is associated with higher bank returns; when the market is down, lower beta leads to higher banks returns. Under all three definitions for market conditions, evidence shows that taking more market risk benefits banks during market ups. However, banks only benefited by cutting their systematic risk in downturns when the market is comparatively stable.

Second, the influences of both activity diversification and geographical diversification on banks' return are state dependent. Test results suggest that when the market is comparatively volatile, activity diversification has different impacts on bank returns depending on the market state. However, when the market is rather stable, the impact from geographic diversification on banks return is different in market ups and downs. It might be that it is more difficult for banks to adjust their geographic diversification position than their activity diversification, especially when the market is volatile. Banks are suggested to adopt different diversification strategies conditioning on the market state and market vitality.

Third, spillovers within the banking industry do not directly affect bank returns, but spillovers do affect bank returns through activity diversification. Moreover, the effect of the spillovers through activity diversification is negative, which means the spillovers reduce the impact of activity diversification on bank returns. Banks should consider spillovers when they consider the consequence of their activity diversification strategies on their returns.

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**Figure 3-1 Bank Diversification Decision-Making Process**

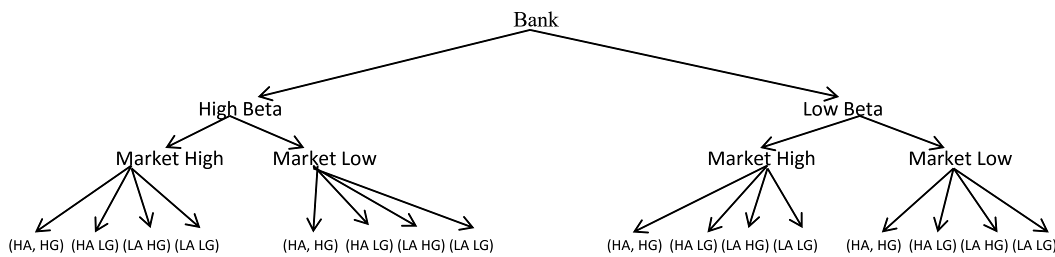

**Table 3-1 Descriptions of Variables**

| Variable Name | Description |
|---|---|
| *AI* | 1 minus the sum of the square of the share of absolute value of net interest income to absolute value of net operating revenue plus the share of noninterest income to net operating revenue. |
| $\beta$ | Estimated time-varying systematic risk for a bank. |
| $D_{1t}$ | $D_{1t}$ equals 1, when the market excess return is positive (the market is said to be in an up state). It equals 0 when the market excess return is negative (the market is said to be in a down state). |
| $D_{2t}$ | $D_{2t}$ equals 1, when the change between *t* and *t-1* in market excess return exceeds one standard deviation using a 60-month rolling window. $D_2$ equals to 0 when the change in market excess return is less than one standard deviation using a 60-month rolling window. |
| $D_{3t}$ | $D_{3t}$ equals 1, when the change between *t* and *t-1* in the market excess return exceeds two standard deviations using a 60-month rolling window. $D_{3t}$ equals 0 when the monthly change in market excess return is less than two standard deviations of the market excess return using a 60-month rolling window. |
| *GI* | A distance-adjusted deposit dispersion index, scaled up by $10^6$. |
| *R* | Excess return of a bank |
| *SIZE* | Total assets of a bank, measured in billions. |
| *SO* | How the return of a single bank is affected by the return of the banking industry. The final methodology used to estimate spillovers is similar to the Beta-premium Regression applied to estimate beta by Petkova and Zhang (2005). Instead of using a stock market return index as the proxy for the overall market, S&Ps' BIX is employed as a proxy for the banking industry performance. Bank returns are regressed against an intercept and S&P's BIX index. The coefficient on the BIX index is called *SO*. |

- This table provides description of major variables.

**Table 3-2 Summary Statistics**

| Variable Name | Number of Obs. | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| *AI* | 3633 | 0.3476 | 0.0968 | 0.0265 | 0.5000 |
| *beta* | 3619 | 0.5152 | 7.1037 | -287.2513 | 194.7356 |
| $D_1$ | 3619 | 0.5991 | 0.4902 | 0 | 1 |
| $D_2$ | 3619 | 0.6593 | 0.4740 | 0 | 1 |
| $D_3$ | 3619 | 0.1324 | 0.3389 | 0 | 1 |
| *GI* | 3633 | 2.5973 | 7.6150 | 0 | 100.5306 |
| *R* | 3619 | 0.7117 | 8.8141 | -68.0486 | 50.9066 |
| *SIZE* | 3633 | 21.7696 | 110.0479 | 0.1501 | 2187.6310 |
| *SO* | 3619 | 0.4621 | 0.4837 | -5.4061 | 3.6857 |

- This table provides summary statistic of major variables.

**Table 3-3 Correlation Matrix**

| | *AI* | *beta* | $D_1$ | $D_2$ | $D_3$ | *GI* | *R* | *SIZE* | *SO* |
|---|---|---|---|---|---|---|---|---|---|
| *AI* | 1.0000 | | | | | | | | |
| | (0.0000) | | | | | | | | |
| *BETA* | 0.0170 | 1.0000 | | | | | | | |
| | (0.3076) | (0.0000) | | | | | | | |
| $D_1$ | -0.0206 | 0.0318* | 1.0000 | | | | | | |
| | (0.2147) | (0.0558) | (0.0000)) | | | | | | |
| $D_2$ | 0.0230 | 0.0167 | 0.2553*** | 1.0000 | | | | | |
| | (0.1665) | (0.3159) | (0.0000) | (0.0000) | | | | | |
| $D_3$ | -0.0463*** | 0.0224 | -0.0465*** | 0.2808*** | 1.0000 | | | | |
| | (0.0054) | (0.1771) | (0.0051) | (0.0000) | (0.0000) | | | | |
| *GI* | 0.2833*** | 0.0218 | -0.0167 | 0.0088 | 0.0032 | 1.0000 | | | |
| | (0.0000) | (0.1904) | (0.3151) | (0.5953) | (0.8496) | (0.0000) | | | |
| *R* | -0.0483*** | 0.0054 | 0.0130 | -0.1219*** | -0.0817*** | -0.0576*** | 1.0000 | | |
| | (0.0036) | (0.7432) | (0.4327) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | |
| *SIZE* | 0.2236*** | 0.0129 | -0.0203 | -0.0157 | -0.0185 | 0.4419*** | -0.0627*** | 1.0000 | |
| | (0.0000) | (0.4361) | (0.2215) | (0.3447) | (0.2651) | (0.0000) | (0.0002) | (0.0000) | |
| *SO* | 0.2297*** | 0.0207 | 0.0285* | 0.0227 | 0.0093 | 0.2807*** | -0.0715*** | 0.2297*** | 1.0000 |
| | (0.0000) | (0.2136) | (0.0861) | (0.1727) | (0.5747) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |

- This table shows the correlation matrics of major variables.

**Table 3-4 Return Model Estimation**

| | $D_1$ | $D_2$ | $D_3$ |
|---|---|---|---|
| $\lambda_1$ | 0.02735* | 0.0479*** | 0.0598*** |
| | (1.74) | (6.71) | (7.71) |
| $\lambda_2$ | -0.0149 | -0.0046*** | -0.0011 |
| | (-1.39) | (-3.12) | (-0.51) |
| $\lambda_3$ | 5.5747 | 3.9573 | -3.2255 |
| | (1.53) | (1.08) | (-0.75) |
| $\lambda_4$ | 5.3404 | 11.1918*** | 4.4325 |
| | (1.45) | (2.96) | (1.20) |
| $\lambda_5$ | -0.0234 | -0.0472 | -0.2112 |
| | (-0.39) | (-0.82) | (-1.53) |
| $\lambda_6$ | -0.0890* | -0.0605 | -0.0709 |
| | (-1.91) | (-1.30) | (-1.31) |
| $\lambda_7$ | 1.3709 | 1.2468 | 1.4284 |
| | (1.07) | (0.93) | (1.13) |
| $\lambda_8$ | -8.0245** | -7.2383* | -8.1569** |
| | (-2.16) | (-1.88) | (-2.19) |
| $\lambda_9$ | 0.0758 | 0.0998* | 0.0882 |
| | (1.30) | (1.65) | (1.35) |
| $\lambda_{10}$ | 0.0153 | -0.0000 | -0.0177 |
| | (0.91) | (-0.03) | (-0.83) |
| Intercept | -0.5356 | 0.9511 | 0.3106 |
| | (-0.43) | (-0.76) | (0.24) |
| R-sq | 0.0050 | 0.0255 | 0.0214 |
| Hausman $\chi^2(9)$ | 2.47 | 7.64 | 14.24 |
| FE/RE model | Fixed Effect | Fixed Effect | Fixed Effect |
| BP test for Heteroskedasticity $\chi^2(10)$ | 62.26 | 30.52 | 36.90 |

- This table presents the results of the return model.
- ***,**,* represent statistical significance at the 1%, 5% and 10% level.
- All results are obtained by using fixed robust standard errors.
- t-statistics are in parentheses.

**Table 3-5 Test Results**

| | D1 (p-value) | D2 (p-value) | D3 (p-value) |
|---|---|---|---|
| $H_o$: $\lambda_1 \leq 0$; $H_1$:$\lambda_1 > 0$ | 0.0414 | 0.0000 | 0.0000 |
| $H_o$: $\lambda_2 \geq 0$; $H_1$:$\lambda_2 < 0$ | 0.0829 | 0.0009 | 0.3068 |
| $H_o$:$\lambda_3 = \lambda_4$; $H_o$:$\lambda_3 \neq \lambda_4$ | 0.7878 | 0.0000 | 0.0000 |
| $H_o$:$\lambda_5 = \lambda_6$; $H_o$:$\lambda_5 \neq \lambda_6$ | 0.0440 | 0.7706 | 0.1937 |
| $H_o$: $\lambda_8 = 0$; $H_1$:$\lambda_8 \neq 0$ | 0.0311 | 0.0605 | 0.0291 |
| $H_o$: $\lambda_9 = 0$; $H_1$:$\lambda_9 \neq 0$ | 0.1932 | 0.0989 | 0.1768 |

- This table provides p-values for each test statistic.

# Appendix 1. Major Regulation Changes

| Year | Description |
|---|---|
| 1980 | Depository Institutions Deregulation and Monetary Control Act (DIDMCA). Raised federal deposit insurance coverage limit from $40,000 to $100,000. Phased out interest-rate ceilings. Allowed depositories to offer negotiable order of withdrawal (NOW) accounts nationwide. Eliminated usury ceilings. Imposed uniform reserve requirements on all depository institutions and gave them access to Federal Reserve services. |
| 1982 | Garn-St Germain Act. Permitted money market deposit accounts. Permitted banks to purchase failing banks and thrifts across state lines. Expanded thrift lending powers. |
| 1987 | Competitive Equality in Banking Act (CEBA). Allocated $10.8 billion in additional funding to the Federal Savings and Loan Insurance Corporation (FSLIC). Authorized forbearance program for farm banks. Reaffirmed that the full faith and credit of the U.S. Department of the Treasury (Treasury) stood behind federal deposit insurance. |
| 1987 | Board of Governors of the Federal Reserve System (Federal Reserve) authorized limited underwriting activities for Bankers Trust, J.P. Morgan, and Citicorp with a 5% revenue limit on Section 20 ineligible securities activities. |
| 1989 | Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA). Provided $50 billion in taxpayer funds to resolve failed thrifts. Replaced Federal Home Loan Bank Board with the Office of Thrift Supervision to charter, regulate, and supervise thrifts. Restructured federal deposit insurance for thrifts and raised premiums. Re-imposed restrictions on thrift lending activities. Directed the Treasury to study deposit insurance reform. |
| 1989 | Federal Reserve expanded Section 20 underwriting permissibility to corporate debt and equity securities, subject to revenue limit. |
| 1989 | Federal Reserve raised limit on revenue from Section 20 eligible securities activities from 5% to 10%. |
| 1991 | Federal Deposit Insurance Corporation Improvement Act (FDICIA). Directed the Federal Deposit Insurance Corporation (FDIC) to develop and implement risk-based deposit insurance pricing. Required prompt corrective action of poorly capitalized banks and thrifts and restricted too big to fail. Directed the FDIC to resolve failed banks and thrifts in the least costly way to the deposit insurance funds. |
| 1993 | Court ruling in Independent Insurance Agents of America v. Ludwig allowed national banks to sell insurance from small towns. |
| 1994 | Riegle-Neal Interstate Banking and Branching Efficiency Act (Riegle-Neal). Permitted banks and bank holding companies (BHCs) to purchase banks or establish subsidiary Banks in any state nationwide. Permitted national banks to open branches or convert subsidiary banks into branches across states lines. |
| 1995 | Court ruling in NationsBank v. Valic allowed banks to sell annuities. |
| 1996 | Court ruling in Barnett Bank v. Nelson overturned states' restrictions on bank insurance sales. |
| 1996 | Federal Reserve announced the elimination of many firewalls between bank and nonbank subsidiaries within BHCs. |
| 1996 | Federal Reserve raised limit on revenue from Section 20 eligible securities activities from 10% to 25%. |
| 1997 | Federal Reserve eliminated many of the remaining firewalls between bank and nonbank subsidiaries within BHCs. |
| 1999 | Gramm-Leach-Bliley Financial Modernization Act (GLB). Authorized financial holding companies (FHCs) to engage in a full range of financial services such as commercial banking, insurance, securities, and merchant banking. Gave the Federal Reserve, in consultation with the Treasury, discretion to authorize new financial activities for FHCs. Gave the Federal Reserve discretion to authorize complementary actives for FHCs. Established the Federal Reserve as the umbrella regulator of FHCs. Provided low-cost credit to community banks. Reformed the Community Reinvestment Act. Eliminated the ability of commercial firms to acquire or charter a single thrift in a unitary thrift holding company. |
| 2001 | Federal Reserve issued revisions to Regulation K. Expanded permissible activities abroad for U.S. banking organizations. Reduced regulatory burden for U.S. banks operating abroad and streamlined the application and notice process for foreign banks operating in the United States. Allowed banks to invest up to 20% of capital and surplus in |

| | |
|---|---|
| | Edge Corporations. Liberalized provisions regarding the qualification of foreign organizations for exemptions from the nonbanking prohibitions of Section 4 of the Bank Holding Company Act. Implemented provisions of Riegle-Neal that affect foreign banks. |

- Sources: Jones, D. Kenneth and Critchfield Tim, 2006. Consolidation in the U.S. Banking Industry, FDIC Banking Review, http://www.fdic.gov/bank/analytical/banking/2006jan/article2/index.html

## Appendix 2. Trends of M&As from 1994 to 2003

1. Number of Bank Mergers, and Assets, Deposits, and Number of Offices Acquired, by Year, 1994–2003
Millions of dollars except as noted

| Year | Number of mergers | Assets | | | | Deposits | | | | Number of offices | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Median | Total | | Mean | Median | Total | | Mean | Median | Total | |
| | | | | Amount | Percent of industry | | | Amount | Percent of industry | | | Amount | Percent of industry |
| **All** | **3,517** | **874** | **102** | **3,073,017** | . . . | **601** | **86** | **2,114,228** | . . . | **13.4** | **3** | **47,283** | . . . |
| 1994 | 475 | 394 | 77 | 187,012 | 3.8 | 302 | 70 | 143,651 | 4.4 | 8.3 | 3 | 3,932 | 5.1 |
| 1995 | 475 | 537 | 86 | 254,851 | 4.9 | 394 | 75 | 186,968 | 5.5 | 10.5 | 3 | 4,981 | 6.5 |
| 1996 | 446 | 912 | 87 | 406,695 | 7.5 | 656 | 76 | 292,740 | 8.4 | 14.7 | 3 | 6,549 | 8.5 |
| 1997 | 422 | 739 | 93 | 311,871 | 5.3 | 545 | 79 | 230,148 | 6.1 | 13.5 | 3 | 5,687 | 7.3 |
| 1998 | 493 | 1,698 | 112 | 836,970 | 13.3 | 1,178 | 97 | 580,972 | 14.7 | 23.0 | 3 | 11,351 | 14.3 |
| 1999 | 333 | 831 | 108 | 276,643 | 4.2 | 560 | 88 | 186,440 | 4.6 | 10.4 | 3 | 3,477 | 4.3 |
| 2000 | 255 | 788 | 125 | 200,963 | 2.8 | 385 | 104 | 98,190 | 2.2 | 10.6 | 4 | 2,693 | 3.3 |
| 2001 | 231 | 1,556 | 139 | 359,495 | 4.6 | 1,022 | 109 | 236,067 | 5.0 | 21.5 | 4 | 4,958 | 6.0 |
| 2002 | 203 | 740 | 115 | 150,186 | 1.8 | 454 | 97 | 92,102 | 1.8 | 9.4 | 3 | 1,914 | 2.3 |
| 2003 | 184 | 480 | 135 | 88,330 | 1.0 | 364 | 103 | 66,950 | 1.2 | 9.5 | 3 | 1,741 | 2.1 |

- Source: Pilloff, J. Steven, 2004. Bank Merger Activity in the United States, 1994-2003, The Board of Governors of the Federal Reserve System Staff Study 176

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