ESSAYS ON MERGER THEORY.

NEW EVIDENCE FROM THE U.S. BANKING INDUSTRY

by

ROBERT PHILIP LOVELAND

(Under the Direction of J. HAROLD MULHERIN)

ABSTRACT

This dissertation comprises three independent essays that use empirical evidence from merger activity in the US banking industry to provide new evidence on merger, auction and market efficiency theories. The first essay examines the valuation effects of FDIC auctions of failed banks and provides new evidence from tests of auction theory. I find that bidder abnormal returns around the announcement date of the purchase of a failed bank are significantly positive. I also find that winning bidders in FDIC auctions do not fall victim to the winner's curse. Instead, I find some evidence that conditions commonly cited as driving industry fire sales (low levels of industry liquidity combined with industry distress) appear to significantly drive acquirer returns. The second essay uses data from the past 30 years of merger activity in the US banking industry to determine empirically whether shocks to industry fundamentals or stock price misvaluation drive observed merger activity. The study adds to our understanding of merger activity by examining the specific mechanism through which industry changes are translated into an industry-wide merger wave. I show that deregulation in the banking industry led to an increased level and dispersion of risk throughout the industry over time which, in turn, drove increases in both merger activity and aggregate industry stock misvaluation. The third essay examines the effect of market valuation on the loan portfolios and regulatory capital levels of U.S. banks during the financial crisis. I use unique data on bank asset values, gathered from SEC merger documents, to provide a benchmark for asset fair values for a sample of US banks during the financial crisis. Using a sample of banks from 2008 to 2010, I find that bank financial statements consistently underreport the level of impairment in loan portfolios implied by market prices. An examination of failed banks, ex-post, finds significant evidence that distressed assets were not properly accounted for, helping market value insolvent banks to report adequate capital for regulatory purposes. A conservative estimate of the costs of forbearance to the deposit insurance fund in 2009 and 2010 is roughly $15 billion.

INDEX WORDS: Mergers and Acquisitions, Auction Theory, Asset Reallocation, Uncertainty, Fire-Sales, Deregulation, Banking, Idiosyncratic Risk

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DEDICATION

To my family for their endless, and ever-present, support and encouragement.

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CHAPTER 1

INTRODUCTION

Because corporate mergers and acquisitions are such a large part of corporate capital expenditures, aggregate U.S. mergers and acquisitions (M&A) deal value totaled over $850 billion in 2011, determining the cause(s) of such a large turnover in corporate control has implications for investors, corporate managers and public policy makers alike. The various theories proffered to identify the determinants of M&A generally fall into one of two categories: neoclassical or behavioral. Neoclassical explanations argue that broad fundamental factors such as economic, regulatory and/or technological shocks drive industry merger activity. Behavioral explanations posit that corporate managers take advantage of temporary market misvaluation of the firm's stock to acquire assets or growth options; essentially buying only if "the price is right".

My dissertation research uses the modern U.S. banking industry to contribute to our understanding of the determinants of corporate M&A activity, the mechanisms used to effect the transactions and the resulting valuation of the deals.

The first essay of my dissertation examines the valuation effects during times of financial crisis of an oft-used mechanism for the change of corporate control: the auction. Whether putting themselves in play through a formal public auction, a private formal auction or a less structured informal auction, many firms are sold through an auction process. I use a sample of 225 bank sales from 1985 to 2010 to examine the valuation effects of FDIC auctions of failed banks. I find that bidder abnormal returns around the announcement date of the purchase of a failed bank are significantly positive. On average over a (-1, +1) window, bidders gain roughly 2% during the Savings and Loan crisis of the late 1980's to early 1990's, and over 3.75% during this latest industry crisis. Bidders gain roughly 3%, on average, over the full sample period 1985 to 2010. Using recent FDIC auctions to test potential explanations for realized prices and returns to bidders in FDIC auctions, I find that the level of uncertainty in the value of the target lowers the realized bid level (price) and increases acquirer abnormal returns, which is inconsistent with the winner's curse hypothesis. Instead, I find that conditions commonly cited as driving industry fire sales (constrained industry liquidity along with indications of industry distress) lead to significant auction price discounts.

The second essay uses data from the past 30 years of merger activity in the U.S. banking industry to show that deregulation in the banking industry led to an increased level and dispersion of risk throughout the industry over time which, in turn, drove increases in both merger activity and aggregate industry stock misvaluation. Test results indicate that merger activity is positively and significantly linked to both industry growth options and aggregate stock misvaluation. However, we also find that aggregate stock misvaluation increases significantly with increases in industry cash flow volatility, and that cash flow volatility increases with increases in average industry revenue volatility and revenue from fee-based products; evidence suggesting that changes in industry fundamentals drive merger activity and that stock misvaluation reflects these changes in industry fundamentals. We show that the increase in industry revenue and cash flow volatility is caused by increases in industry competition after several deregulatory events. Our second major finding supports evidence from the extant literature that merger activity is significantly related to structural industry change; merger activity increases significantly following the two deregulatory acts examined (1994 and 1999) while showing a weaker positive link to a broader proxy for economic shock.

The final essay examines the effect of market valuation on the non-traded loan portfolios of U.S. banks during the financial crisis. Past studies have shown that US financial regulators are inclined to practice capital forbearance during financial crises. Recent work and anecdotal evidence suggest that banks during the recent crisis overstate the value of distressed assets with the intent of bolstering their profitability and levels of regulatory capital, providing suggestive evidence of regulatory forbearance. Using a sample of banks from 2008 to 2010, I find that bank financial statements consistently underreport the level of impairment in loan portfolios. Ex-post examination of failed banks shows significant evidence that distressed assets were not properly accounted for, helping market value insolvent banks to report adequate capital for regulatory purposes. A conservative estimate of the costs of forbearance to the deposit insurance fund for failed banks in 2009 is almost $9 billion.

These studies contribute to the M&A literature by 1) adding to the extant evidence on the existence of fire-sales. Prior work is limited to transactions involving specific asset types and/or international locations. This study helps to expand the application of, and empirical evidence supporting, the fire-sale hypothesis by utilizing data from sales of medium- and large-sized U.S. corporations. 2) adding to our understanding of merger activity by examining the specific mechanism through which industry shocks are translated into the critical mass of change necessary to create an industry-wide merger wave. And 3) providing evidence suggesting significant capital forbearance by regulators in the process of seizure and subsequent sale of failed banks during the financial crisis.

CHAPTER 2

DOES IT PAY TO WIN AN FDIC AUCTION?

Introduction

Whether putting themselves in play through a formal public auction, a private formal auction or a less structured informal auction, many firms are sold through an auction process. Auctions are also used extensively in the bankruptcy process. Baird and Rasmussen (2003) find that more than half of all large Chapter 11 cases resolved in 2002 used an auction process[1].

Given the prevalence of auctions in corporate finance, the auction process has received considerable academic interest. A sizeable strand of literature examines auctions in corporate finance for evidence of the winner's curse. The winner's curse hypothesis predicts that, in the presence of incomplete information, winning bidders are likely those that most overestimate the fundamental value of the target and underestimate the effect of competition on bid levels. Because winning bidders are likely to have paid more than fundamental value, returns will be inversely related to the amount of uncertainty in the value of the target and the level of competition in the auction. Predictions from the winner's curse hypothesis are that the level of negative abnormal return will be positively related to the number of bidders participating in the auction (Kagel and Levin, 1986) and the level of uncertainty in the asset being sold (Bazerman and Samuelson, 1983).

The winner's curse has been examined in various situations, including bidding on oil and gas leases (Capen et al., 1971). Among others, Thaler (1988) argues that the nonpositive return to bidders shown in empirical research is consistent with the winner's curse. Giliberto and Varaiya (1989) study FDIC failed bank auctions in the 1980s and conclude that winning banks do suffer from the winner's

[1] Klemperer (1999) surveys the literature on auction theory, while Dasgupta and Hansen (2007) review the applications of auction theory to corporate finance.

curse. However, Boone and Mulherin (2008) find no support for the winner's curse in the corporate takeover market of the 1990s.

An alternative explanation of the returns to bidders in corporate auctions is the fire-sale hypothesis. The fire-sale hypothesis posits that industry-wide distress and illiquidity cause assets to be sold at discounts to fundamental values, generating positive returns to the winning bidder. Accordingly, a central prediction of the fire-sales hypothesis is that realized prices are negatively correlated with measures of industry illiquidity and distress. Shleifer and Vishny (1992) explore the determinants of asset liquidation values when a distressed firm, as well as its industry peers, is experiencing problems. They argue that during periods of industry-wide shock, surviving industry peers are able to acquire liquidated assets only at fire-sale prices because they themselves are likely to be financially stressed. Past studies on fire-sale discounts include Pulvino (1998) who finds evidence of fire-sale discounts in aircraft sales and Officer (2007) who documents evidence of liquidity discounts in the purchase of unlisted firms. Eckbo and Thorburn (2008) study Swedish bankruptcy auctions and also find some evidence of fire-sale discounts.

This study uses data from Federal Deposit Insurance Corporation (FDIC) auctions of failed banks to contrast the winner's curse hypothesis against the industry fire-sale hypothesis and information asymmetry hypotheses as explanations for returns to winning bidders in corporate auctions. FDIC auctions provide a powerful setting to contrast the above hypotheses; this formal structure is seen infrequently in a corporate finance environment and thus provides a natural setting to test the winner's curse. FDIC auctions, called purchase and assumption (P&A) auctions are first-price sealed bid auctions. Because the auction process is tightly controlled by the FDIC, all targets are subject to a single uniform selling mechanism (see section 2 and the Appendix for a detailed outline of the FDIC failed bank resolution process). Furthermore, because the bulk of failed bank auctions occur in down markets, the setting is an attractive one to test the fire-sale hypothesis. The considerable uncertainty inherent in a distressed industry, and failed target banks, during down markets also provides an attractive setting to test the information asymmetry hypothesis.

To distinguish between the hypotheses, I compare the valuation effects of failed bank acquisitions for the time period 1985-2010. If the winner's curse holds in FDIC P&A auctions, then the wealth effects for auctions should be nonpositive. By contrast, if the industry fire-sale hypothesis is correct, then the wealth effects will be significantly positive, on average. My results demonstrate that acquisitions of failed banks at FDIC and Federal Savings & Loan Insurance Corporation[2] (FSLIC) auctions are wealth creating events during periods of industry shock. On average over a (-1, +1) window, abnormal returns to the bidder for acquisitions of failed banks are found to be roughly 2% during the Savings and Loan (S & L) crisis of the late 1980's to early 1990's, and 3.75% during this latest industry crisis. Abnormal gains are roughly 3%, on average, over the full sample period 1985 to 2010. Bidder abnormal returns are found to be -1% during the relatively stable economic expansionary period 1995 to 2004. Results are robust to both event window and model specifications.

Using failed bank acquisitions from the 2008-2010 period to test the competing merger theories, I find results consistent with the fire-sale hypothesis: during periods of industry distress, realized prices are significantly lower and returns to winning bidders significantly higher. Detailed empirical tests show that several conventional fire-sale factors that proxy for industry illiquidity and distress lead to significant auction price discounts. It appears the overall predictions for the industry fire-sale hypothesis hold during the 2008-2010 subperiod; the mechanism most often theorized to produce the effects, industry illiquidity along with high levels of industry financial distress, lowers the average price fetched for target firms. Notably, I find that presence of industry outside buyers does not have a significant impact on price, contrary to anecdotal evidence in financial press reports.

I find that bidder returns increase, and realized bid prices decrease, with measures of uncertainty in the value of the target; however, the effect does not significantly drive returns. Moreover, the level of competition does not have a significant influence on realized bid prices. Both of these findings are inconsistent with the winner's curse. The positive, but insignificant, relation between bidder

[2] For pre- Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA) auctions the FSLIC agency conducted the auctions of failed savings and loans

announcement returns and the target valuation uncertainty is robust to different measures. Finally, using a measure of private competition modeled in Boone and Mulherin (2007), I provide evidence that the level of competition at recent FDIC auctions is greater than that of the voluntary banking takeover market as well as the broader 1990's corporate takeover market.

This paper extends the literature by comparing failed bank sales over an extended period of time (1985-2010) for a larger data set of 225 failed bank acquisitions. Much of the extant work on failed bank acquisitions has focused around prior time periods; from the 1970s to early 1990's. This larger sample period allows for identification of intertemporal trends in returns to failed bank sales and provides context for results from the current period. Furthermore, this study adds to the extant evidence on the existence of fire-sales. Prior work is limited to transactions involving specific asset types and/or international locations. This study helps to expand the application of, and empirical evidence supporting, the fire-sale hypothesis by utilizing data from sales of medium- and large-sized U.S. corporations. Finally, the work adds richness to the empirical evidence from tests of auction theory by utilizing data from a formal corporate finance auction setting.

The paper proceeds as follows: Section 2 reviews relevant literature and details the FDIC resolution process. Section 3 reports sample statistics. Section 4 reports the wealth effects of failed bank acquisitions. Section 5 and 6 report tests of winner's curse and industry fire-sale hypotheses, respectively. Section 7 concludes.

Background and Hypothesis Development

Research on the valuation effects of mergers within the banking industry has produced findings generally consistent with the broader corporate merger literature; that is, significant positive abnormal returns to the target and breakeven returns, on average, to the bidder. Becher (2000) finds that for a sample of 558 mergers of solvent banks from 1980 to 1997, targets gain on average over 22% while bidders break even. Prior event studies on bank mergers from 1972 to 1992 found large returns for targets, ranging from 9.66% to 36.22%, and no meaningful returns for bidders, with values ranging from

3.12% to -3.25% (James and Wier (1987), Neely (1987), Trifts and Scanlon (1987), Cornett and De (1991), Houston and Ryngaert (1994 and 1997).

The findings for acquisitions of failed banks is somewhat mixed, however, there is evidence that failed bank auctions produce positive abnormal returns for the winning bidder. James and Wier (1987) study FDIC failed bank auctions and find that average announcement period abnormal returns to winning P&A bidders are positive and significant for 19 sales from 1973 to 1983. They conclude that, based on these and other cross-sectional-test results, winning purchase and assumption (P&A) auction bidders pay less than "true" value and gain as a result of over subsidization by the FDIC insurance fund. However, Pettway and Thrifts (1985) find that average geometric abnormal returns are negative for a sample of 11 P&A bidders from 1972-1981 and conclude that winning bidders overbid for failed banks. Giliberto and Varaiya (1989) also test whether acquirers of failed banks overpay when bidding at FDIC failed bank auctions and find that winning bids tend to increase as the level of competition increases. They conclude that their findings support the winner's curse hypothesis.

Further, Gupta, et al. (1997) and Stover (1997) find that winning bidders in Resolution Trust Corp. (RTC) auctions did not experience statistically significant abnormal returns. Gupta, et al. conclude that the RTC procedures appear to have eliminated any over-subsidization observed in prior studies. Further supporting this observation Stover concludes that, when combining the abnormal return results with cross-section regression results, there is no evidence of a wealth transfer in the acquisition process. Cochran, et al (1995) find that, overall, winning bidders do not overpay. However, they find that acquiring banks undertaking large failed bank transactions experience large wealth transfers. Table 2.1 summarizes the pertinent literature on failed bank sales.

During the full sample period studied in this paper (1985-2010), more than 2,500 banks failed and were seized by regulators. Of those 2,500, almost 1,900 failures were resolved via a P&A auction. The FDIC is the regulatory body responsible for the resolution of a federal or state chartered bank or S & L once that institution's banking charter has been revoked by its chartering authority (typically the primary regulator). I provide a brief outline of the resolution process below. A full outline of the FDIC resolution process is presented in the Appendix.

The FDIC is required by law to choose the resolution option that is least costly to the FDIC Deposit Insurance Fund. If a P&A auction is identified as the likely least costly option, the FDIC begins the process of confidentially marketing the failing institution to potential acquirers consisting of approved financial institutions and private investors. Once the (least cost) winning bid has been chosen from the sealed bids submitted at auction and the failed bank sold to the acquiring bank, the FDIC reimburses the acquiring bank for the amount of the deposits purchased.

"The final step in the resolution process occurs when the institution is closed, and the assets that the acquirer purchased and the deposits that it assumed are transferred to the acquirer. The chartering authority closes the institution and appoints the FDIC as receiver (usually on a Friday)." The announcement of the bank's seizure and subsequent sale is released to the public via a FDIC press release usually the next calendar day following the seizure (usually on a Saturday). The entire resolution process is generally carried out in 90 to 100 days. Figure 2.1 depicts the steps in the process and the approximate timeframes. Table 2.2 presents a more detailed timeline of the process summarized in Figure 1.

The winner's curse arises in a common value (CV) auction setting when a bidder fails to recognize that if his/her bid is the winning bid, it is likely because he/she is the bidder that assigned the highest value to the auctioned asset. A key assumption of the CV model is that the auctioned asset has a true value which is the same for all bidders. However, the bidders do not know this value at the time of auction. Winning bidders may correct for this problem by discounting bids to reflect the number of competing bidders participating in the auction as well as the degree of uncertainty about the true value of the auctioned asset (Kagel and Levin, 1986). Therefore, the optimal winning bid in a CV auction will significantly decrease with increases in the level of competition for the auction asset and/or the degree of uncertainty about the true value of the auctioned asset. This (significant) decrease in the level of the optimal winning bid in response to an increase in competition and asset value uncertainty will then produce a (significant) increase in returns to the winning bidder.

The FDIC P&A auction has many elements of the CV model that spawns the winner's curse. Giliberto and Varaiya (1986) argue a case in which the value of a failed bank's charter and deposit base may be considered sufficiently equal across all bidders, such that it has a "true" value that may be determined by all bidders. Furthermore, they note, the FDIC's capital adequacy and other bidder eligibility guidelines may effectively limit the pool of eligible bidders for each auction to be relative homogeneous and thus nearly equally able to use the failed bank's funding base and charter. Even if this assumption is relaxed and the effect of synergies is considered, Asquith, et al. (1993) notes that the corporate takeover literature considers synergies to be unique to the target, which implies no special synergies to the bidder, on average. In this context, it may be argued that synergies have a common value element.

Given the assumption of a CV environment in FDIC P&A auctions, my tests of the winner's curse investigates whether the level of competition in P&A auctions and / or the uncertainty regarding the value of the failed bank sold at auction are related to the winning bid and, ultimately, the return to the winning bidder for purchasing the failed bank. Testable predictions of the winner's curse are that (i) the returns to the winning bidder are significantly inversely related to the level of bid competition (Kagel and Levin, 1986) and (ii) the returns to the winning bidder are significantly inversely related to the uncertainty in the value of the auctioned asset (Bazerman and Samuelson, 1983).

The fire-sale hypothesis posits that industry-wide distress, illiquidity and excess leverage cause assets to be sold at discounts to fundamental values. A central prediction of the fire-sales hypothesis, then, is that realized prices are negatively correlated with measures of industry illiquidity, distress and leverage. Shleifer and Vishny (1992) explore the determinants of asset liquidation values when a distressed firm, as well as its industry peers, is experiencing problems. They argue that during periods of industry-wide shock, surviving industry peers are able to acquire liquidated assets only at fire-sale prices because they themselves are likely to be financially stressed. Their industry equilibrium model identifies one determinant that is particularly important in determining liquidation value, namely, asset redeployability. If an asset is not easily redeployable, due either to the nature of the asset or such limits as government-imposed regulatory constraints, assets in liquidation fetch only fire-sale prices (Williamson, 1988). Furthermore, the more severe the industry-wide distress, the less likely that illiquid high-value users within the industry purchase the asset and the more likely that the asset will go to a well-financed, low-value industry outsider.

Testable predictions of the fire-sale hypothesis are that (i) fire-sale discounts in auction prices increase with industrywide financial distress and illiquidity and (ii) are greater when the winning bidder is an industry outsider (Eckbo and Thorburn, 2008).

FDIC Failed Bank Sample

The sample of failed banks P&A auction transactions was obtained from the FDIC's Historical Banking Failures and Assistance Transactions on-line database. The FDIC database contains detailed information on bank and thrift failures since the FDIC was established in 1934. For each transaction in the sample, I review the detailed information posted to the Failed Bank Information section of the FDIC website. In order to quantify the wealth effects to failed bank acquisitions, an initial event study sample of 264 failed banks P&A auction transactions with public acquirers was obtained from the FDIC's database for the period 1985–2010. The FDIC database was used to obtain accounting and deal data for failed banks. Stock price information for both types of transactions was obtained from the CRSP database. If neither CRSP price nor FDIC accounting data was available the deal was dropped from the sample. 39 failed bank transactions were thus dropped from the sample to produce a final sample of 225 failed bank transactions.

In order to provide a benchmark for the wealth effects of failed bank acquisitions, a control sample of voluntary takeover transactions of "going concern" banks was obtained from the Security Data Corporation (SDC) Mergers & Acquisitions database for the period 1985–2010. Data restrictions are as follows: for firms, the bidders were required to be either domestic or the domestic subsidiary of a foreign corporation, publicly traded and engaged in the banking, savings & loan or credit union industries. The target was required to be either domestic or the domestic subsidiary of a foreign corporation. The target was allowed to be either public or private. Once the final sample of failed bank transactions was determined, the sample of bidders in both cash/stock and cash-only voluntary M&A deals were matched against the range of values within the minimum and maximum of total assets of the bidders in the failed bank deals for the subsample periods 1985-1994, 1995-2004 and 2008-2010. Subsequent accounting and price data restrictions described above produced a final sample of 1,008 cash/stock voluntary M&A deals and 458 cash-only voluntary M&A deals.

In order to conduct tests of the two competing merger theories I need detailed bid and deal valuation data. I compile this data for the 2005-2010 period by hand collecting from the FDIC database: 1) bid data from the auction bid sheets submitted by each bidder submitting a bid in the P&A auction 2) details about the timing of the seizure of the failed bank, pricing of the sold bank, size of the assets and liabilities sold and FDIC loss sharing information from FDIC press releases announcing the seizure and auction results and 3) deal-specific pricing and loss share terms from the P&A agreement signed by the FDIC and the purchasing bank.

Because I test theories of company sales, as opposed to asset sales, I examine failed bank sales in which the company is sold as a whole, vs. piecemeal asset sales often seen in bankruptcy proceedings or in some forms of P&A auctions. For each whole bank P&A transaction in the period 2005-2010, I review filings from the EDGAR system of the U.S. Securities and Exchange Commission (SEC). I obtain details of the valuation of the failed bank purchased at auction from acquirer 8K, 10Q or 10K filings. Generally Accepted Accounting Principles (GAAP) require that purchased assets and liabilities be marked to market before being booked on the purchaser's financial statements. For those winning bidders for which the purchased bank was material to their financial results, the details of the valuation are disclosed in SEC filings. From these filings I hand collect the market values of both the assets and liabilities of the purchased bank reported on the winning bidder's balance sheet. From this valuation I am also able to determine any bargain purchase gain / goodwill booked to the income statement of the winning bidder as well as any cash received / paid to the FDIC as a result of the purchase.

As a benchmark against which to measure the price of, and returns from, the purchase of a failed bank, I select a control subsample of voluntary takeover transactions of "going concern" banks for the period 2005-2010 from the SDC data. In order to match the characteristics of the FDIC P&A auctions the selected deals are those in which the compensation is cash-only and for which the target is either domestic or the domestic subsidiary of a foreign corporation. The target is allowed to be either public or private.

For each voluntary takeover in the control sample I review the filings from the SEC EDGAR system to obtain details of the valuation of the target at auction from acquirer 8K, 10Q or 10K filings. As with the failed bank deals, I hand collect the same information: market values of both the assets and liabilities of the target bank, any goodwill or bargain purchase gain booked to the income statement, and the cash purchase price. For each voluntary takeover in the control sample I also review 14A, 14D and S-4 filing from the SEC EDGAR system to document the level of competition in each takeover. I follow Boone and Mulherin (2007) and characterize the private takeover process by identifying 1) the number of potential buyers contacted, 2) the number of potential buyers signing confidentiality/standstill agreements and 3) the number of potential buyers making written private bids.

I obtain accounting data on the targets in both the failed bank and voluntary takeover samples from the call reports accessible via the FDIC website. I use financial data of the target bank as of the quarter preceding the announcement date of the FDIC auction announcement and the takeover announcement date for failed and voluntary deals, respectively.

Table 2.3 presents the distribution of bank failures during the period 1985 to 2010. Several notable trends are evident in the data. The spike in bank failures during the years 1985 to 1992 is evidence of the concurrent oil bust in Texas and real estate meltdown in New England that prompted the S&L crisis of that period. The effects of the subprime crisis that began in 2007 can be seen with the increase in failures in the years 2008 and 2010. Finally, the small number of failures during the intervening years 1994 to 2007 is reflective of the relative prosperity and economic growth experienced during that period.

Table 2.4 provides summary statistics for the full event study sample of target and acquiring banks in P&A auctions, as well as some details regarding the transactions. The data is adjusted for inflation using the CPI-U annual index with the period 1982 - 84 = 100. The acquiring banks have, on average, inflation-adjusted assets 20 times that of targets over the full sample period and 21 times that of targets for the period 2008-2010. The mean (median) asset size of the failed and acquiring banks during the period 2008-2010 are $1.6 billion ($195 million) and $33.5 billion ($2.3 billion), respectively. Many of the failed banks were small community / regional banks, while the average acquiring bank is a small to medium size national bank.

Panel B presents information on 97 whole bank P&A sales of failed banks during the period 2008-2010 for which detailed deal valuation data is available. Financial information is for the quarter-end preceding bank failure and sale at auction. The mean (median) price paid for a failed bank is $-71.9 million ($-23.6 million), meaning that on average the winning bidder was paid cash by the FDIC upon completion of the auction. The mean (median) fair value adjustment of the auctioned loan pools is $348.2 ($96.7) million. This equates to a 34% mark down on average, consistent with the average loss on assets of 29.88% to 32.33%, for the years 1985 to 1988 documented by James (1991) in his analysis of losses realized in bank failures during the savings and loan crisis. As Panel B also reports, the mean (median) pre-tax gain on purchase booked by the winning bidder is $26.2 ($8.3) million. 74 of the 96 winning bidders with available data booked a one-time bargain purchase gain as a result of buying a failed bank below market value.

The Wealth Effects of FDIC Auctions of Failed Banks

As an initial test to distinguish between the hypotheses, I use a conventional event study to examine the wealth effects of purchasing a failed bank at FDIC auction. If the winner's curse is at play the wealth effects for the announcement of the purchase should be non-positive. By contrast, if the fire-sale hypothesis is correct, the wealth effects should be positive, on average, as a result of paying less than "true" value for the failed bank. If the fire-sale hypothesis is at work bid levels will be negatively associated with fire-sale factors (liquidity, distress and leverage) and returns positively related.

To provide a benchmark against which to compare the wealth effects of purchasing a failed bank at FDIC auction I tabulate the wealth effects of purchasing a going concern bank in a voluntary takeover. Wealth effects for both forms of takeover are tabulated for a 25 year period in order to examine intertemporal variation in returns across economic cycles. I compare mean returns and perform tests of equality on the mean returns of both forms of takeover. I next conduct a set of empirical tests on both returns and realized auction price that examine whether the returns (price) to (paid by) a winning bidder are related to the level of competition in an FDIC auction and/or uncertainty regarding the true value of the failed bank. The regression analysis includes control variables that prior work shows to be correlated with target returns and/or price.

Table 2.5, Panel A presents estimates of the wealth effects for the target banks in both forms of takeover - FDIC auction and voluntary M&A - for the period 2008-2010. Estimates from the (-1,+1) window of the market model, where day 0 is the initial announcement date, show that the mean bidder returns for the purchase of a failed bank are 3.75% and are statistically significant. Mean bidder returns for the purchase of a viable bank using cash-only consideration are 1.82% but not significant, while stock and cash deals return a statistically significant -1.81% over the same window and using the same model.[3]

A two sample test of means was employed to test the null hypothesis that the mean difference between the failed bank sample and each of the forms of voluntary takeover time series is zero. The resulting test statistic vs. cash-only voluntary M&A deals is 1.13 (p value = .134) and 3.06 (p value = .001) when testing against cash/stock voluntary M&A deals. Thus, while bidder returns for the purchase of a failed bank are greater than for the purchase of a financially viable bank, the difference is significant only when compared against combined stock and cash deals.

To put this result in historical context, I estimate the wealth effects for both FDIC auction and voluntary M&A for the period 1985-2010. Table 2.5, Panel B reports the wealth effects for the period 1985-2010; results from the (-1,+1) window of the market model show that the mean bidder returns for the purchase of a failed bank are 3.02% and statistically significant. Conversely, bidder returns for the purchase of a viable bank using cash-only consideration and cash/stock consideration are 0.52% and -0.29% and statistically significant. These results for bidder returns from voluntary takeovers are roughly

[3] One outlier cash deal, the acquisition of United Commercial Bank by acquirer East West Bancorporation, was discarded; evidence of concurrent capital restructuring during the event window combined to produce a 62% return over the three day window.

consistent with those in prior research, including Andrade et al. (2001), Fuller, Netter et al. (2002) and Moeller et al. (2005). A two sample test of means produces a test statistic vs. cash-only voluntary M&A deals of -4.11 (p value < .001). When testing against cash/stock voluntary M&A deals, the resulting test statistic is -5.63 (p value < .001). These results indicate that mean bidder returns for the purchase of a failed bank are statistically greater than for the purchase of a financially viable bank over the past 25 years.

But are mean bidder returns *consistently* greater for failed bank purchases over the past 25 years? Because the period 1985-2010 spans times of economic expansion and contraction, as well as times of significant industry evolution and shock, the returns may best be examined by subperiod. For the periods 1985-1994 and 1995-2004, the mean bidder returns for the purchase of a failed bank over the (-1,+1) window using the market model are 2.02% and -0.98%. The return for the 1985-1994 period is statistically significant. The mean returns for cash-only voluntary M&A deals are 0.31% and 0.47% while the returns for cash/stock voluntary M&A deals are -0.05%, and -0.36% for the same periods; all results are statistically significant. A two sample test of means produces a test statistic vs. cash-only voluntary M&A deals of -2.31 (p value = .01) for the subperiod 1985-1994 and -3.05 (p value .002) when testing against cash/stock voluntary M&A deals. Of note is the fact that the mean bidder return for the purchase of a failed bank during the economically stable period of 1995-2004 is negative, in-line with the returns to bidders found in the literature, and less than the returns for voluntary takeovers. The small number of bank failures resolved by selling to a public bidder during this time frame makes reliable statistical testing problematic, however. Overall, the results suggest that conditions during economic downturn are associated with positive abnormal returns to failed bank purchases.

In order to ensure that the results are robust to both event window and model specifications, I use three different model specifications (market, net of market and raw returns) and four different event windows (0 to +1, -1 to +1, -1 to +3, -1 to +5) to compute the bidder CARs for all three types of transactions (failed bank, voluntary M&A – cash only, cash and stock). Unreported results across model and event window are qualitatively similar; any differences do not affect the findings in this paper. I next examine possible drivers of these returns.

OLS Analysis – Tests of the Winner's Curse

Testable predictions of the winner's curse are that (i) the returns to the winning bidder are significantly inversely related to the level of bid competition (Kagel and Levin, 1986) and (ii) the returns to the winning bidder are significantly inversely related to the uncertainty in the value of the auctioned asset (Bazerman and Samuelson, 1983). I test only prediction (ii) using bidder returns as I do not have a sufficient number of publicly traded firms with bid data for years 2008-2010 to test prediction (i) with adequate statistical power. To address this shortcoming I use a comparable test of prediction (i) with bid prices (as opposed to bidder returns) in later analysis. I test prediction (ii) by analyzing the relation between bidder returns and a variable that proxies for uncertainty in the value of the failed bank. I follow the model used by Boone and Mulherin (2008) in regressing the (-1, +1) window of abnormal bidder returns presented in Section 5 on target intangible assets. If winning bidders in P&A auctions are subject to the winner's curse, bidder returns should be negatively and significantly related to intangible assets. I define intangible assets as the target's Goodwill and Other Intangibles at calendar quarter-end preceding failure. Intangible assets include goodwill, mortgage servicing rights, purchased credit card relationships and other identifiable intangible assets such as a core deposit intangible.

As per Boone and Mulherin (2008), I include in the regression analysis control variables that have been shown in the extant literature to be related to bidder returns. Relative size of the target as compared to size of the winning bidder has been shown to have a positive effect on bidder returns (Jarrell and Poulsen, 1989). Bidder size has been shown by Moeller, Schlingemann, and Stulz (2004) to have a negative effect on bidder returns. However, Cochrane (1995) posits that the FDIC would prefer to sell the reconstituted failed banks to the healthiest and most well-capitalized bidding banks. Because large firms with relatively greater capital cushions are generally better able to weather downturns one might also expect the bidder size variable to have a positive effect on bidder returns in a banking context. Variables related to form of compensation, unsolicited bid and use of investment bank are not needed as P&A

auctions are cash only while the transaction take places directly between the bidder and the FDIC solely at the invitation of the FDIC (there is no investment bank involvement in the deals).

Table 2.6 presents sample statistics for the explanatory variables examined in this paper while Table 2.7 presents correlations. Variables are log transformed to produce normally distributed data. Table 2.8 presents the results of OLS analysis. I use two-way cluster robust errors (Cameron, Gelbach and Miller, 2006) to adjust for both time and acquirer clustering for the reported t-statistics. I present two models: the first with the controls outlined above and the second with an additional control to represent the loan loss mitigation support provided by the FDIC on many of the whole bank deals. As shown, the coefficient on the intangible assets variable is positive in both models but is not statistically significant. The winner's curse predicts a negative and significant relation between the level of intangible assets of the target and winning bidder returns. Similar to the finding from the means test of bidder abnormal returns in Section 5, this result is inconsistent with the winner's curse. The coefficient for the relative size and bidder size control variables both have the expected sign but are statistically insignificant in both models. The coefficient on the FDIC loss share variable is negative, the opposite of prediction, but is insignificant.

Because tests using bidder abnormal returns are limited to the transactions with winning bidders that have actively traded common shares, I next perform tests using observed bids from P&A auctions. This not only allows me a larger sample and increased statistical power but it more completely represents the population of P&A transactions during the two year period 2008-2010. I follow the model used by Giliberto and Varaiya (1986) and use a pooled regression to regress bid amounts on proxies for level of competition and for uncertainty regarding the value of the auctioned asset. I use the number of bids per auction as a proxy for the level of competition in each auction and the standard deviation of the bid amounts for each auction to measure the distribution of value estimates of the auctioned assets (uncertainty). If winning bidders in P&A auctions are subject to the winner's curse, bids should be positively and significantly related to both the number of bids per auction (competition) and the standard deviation of the distribution of value estimates (uncertainty). I include additional variables to control for factors that may drive difference in the value of the reconstituted failed banks across auctions.

An important caveat to the above specification is the fact that my sample of bid data does not contain the number of potential bidders who chose not to submit a bid. Because the FDIC does not release information regarding bidders invited to participate in a P&A auction, nor about those who choose not to submit bids, this omission has the potential to reduce the magnitude of the uncertainty measure: the standard deviation of the bid amounts. Therefore it is useful to recognize that the data used in this analysis will, in effect, produce a lower bound on the estimated coefficient for uncertainty.

Figure 2.2 shows the frequency distribution of bids across the subsample of P&A auctions used in the subsequent analysis. The number of bids ranges from 1 to 17, with a mean of 2.3. There are multiple bids in 37% of whole bank auctions in this sample. The auction competition reported here is greater than that found in private negotiations by Boone and Mulherin (2007) but significantly less than those involved in Swedish automatic bankruptcy auctions as reported by Eckbo and Thorburn (2008). The following section analyses the level of auction competition in further detail.

I follow guidance from past research to select appropriate variables for the set of controls. James (1991) and Giliberto and Varaiya (1986) find that an important determinant of bank value is the value of the bank's charter. Bank charters have value because it allows the bank to operate as a deposit-taking institution. The core deposit base of the bank is viewed as a stable source of low cost funding and because regulations restrict entry into local deposit markets a bank charter is valuable to institutions seeking to expand their footprint. Following James (1991) and Giliberto and Varaiya (1986), I use the level of core deposits (deposit accounts less than $100,000) as a proxy for charter value. James (1991) also finds the value of risky assets assumed by the winning bidder to be a significant driver of bank value. While risky assets may include both securities and loans; for most banks loans make up a majority of the risky assets held on the balance sheet. For this reason, I use the fair value of loans of the target bank as a proxy for risky assets. I include calendar quarter dummies to capture any differences in FDIC subsidization packages or cyclical economic variation.

Table 2.9 presents the results of the OLS regression for the sample of P&A and whole bank P&A auctions deals. The competition variable, number of bids per auction, is negative in univariate tests, positive in multivariate, but not significantly different from zero in any specification. Like the means test in Section 5, this finding is inconsistent with the winner's curse hypothesis. The value uncertainty variable, bid standard deviation, is negative but not statistically significant. This implies that bids are lower as uncertainty is greater, opposite to the prediction of the winner's curse hypothesis. To test the robustness of the results, I substitute bid variance and bid range for bid standard deviation. Results are indistinguishable. The direction of the results resemble those of James (1991) who finds a negative and statistically significant relation between the premium paid at P&A auction and the measure of bidder uncertainty concerning the asset values, and Giliberto and Varaiya (1986) who also find a significant negative relation between value uncertainty and average bid levels. Both James (1991) and Giliberto and Varaiya (1986) find a positive and statistically significant relation between the premium paid and the measure of auction competition.

Table 2.9 reports a positive but insignificant relation between the number of bids per auction and observed bids in P&A auctions, a finding inconsistent with the winner's curse hypothesis. In this section I report results of an additional test of bidder competition in P&A auctions. Because the FDIC privately determines the set of banks invited to participate in the auctions (only relatively healthy, well capitalized banks with no potential anti-competitive issues are eligible to participate) the ensuing restriction on competition may be a determinant of the observed positive abnormal returns for P&A auctions reported in Section 5. Previous research has argued that bidder restrictions may, in some cases, have a negative impact on bid levels in first price sealed bid auctions (French and McCormick ,1984; and Johnson, 1979). James and Weir (1986) test a sample of P&A auctions from the 1980's and conclude that "FDIC procedures limit competition to acquire the failed banks' assets" and therefore "FDIC procedures reduce competitive pressure on the price of the auctioned banks".

I follow Boone and Mulherin (2007) in modeling the private takeover process for a control sample of voluntary bank takeovers with no FDIC assistance. For each voluntary takeover in the control sample I review 14A, 14D and S-4 filing from the SEC EDGAR system to quantify the level of competition in each takeover. I identify 1) the number of potential buyers contacted, 2) the number of potential buyers signing confidentiality/standstill agreements and 3) the number of potential buyers making written private bids. I use the last statistic, the number of binding, written private bids submitted for the target as the primary measure of deal competition. A simple means tests of the number of bids submitted, on average, for P&A vs. voluntary takeover auctions gives an indication of how restrictive the P&A environment is as compared to the voluntary corporate takeover market. This is an important test as the extant research has shown the corporate takeover market to be sufficiently competitive as to produce roughly breakeven returns to winning bidders, on average. If P&A auctions do not allow for sufficient competition among bidders, this may be a potential driver of the observed positive abnormal returns. Andrade, Mitchell, and Stafford (2001) hypothesize that a competitive takeover market is responsible for the breakeven return seen to winning bidders in the 1990s and Boone and Mulherin (2007 and 2008) demonstrate this empirically using data from the 1990s.

Table 2.10 provides summary statistics for the steps in the private sales process for both the P&A and voluntary takeover sample as compared to the sample statistics for corporate takeovers from Boone and Mulherin (2007). Panel B reports that the average target firm in the voluntary sample contacts roughly 13 potential bidders. Approximately 6 of those 13 contacted, on average, sign a confidentially agreement in order to receive private information from the bidder and move forward with formulating a potential bid. On average, 1.409 bidders make private written offers for the purchase of the target bank. As compared to the 308 voluntary corporate deals sampled by Boone and Mulherin (2007), and reported in Panel A, the distribution of the 3 competition variables for the 22 cash-only voluntary bank deals sampled in this study are skewed higher. The Boone and Mulherin (2007) sample is comprised of publicly traded, large-cap corporations taken from the Value Line Investment Survey; the incidence of auctions and negotiations are reported to be comparable to a random sample of deals taken from the merger database of SDC. Thus, to the extent that the takeover market for large public companies provides sufficient competition to produce breakeven returns to the winning bidder (and thus, one indication of a “fair” price paid for the target) for the period sampled, their sample provides a benchmark of the level of competition for takeovers executed in an auction environment.

Panel C of Table 2.10 reports the summary statistics for the 147 whole bank P&A auctions from 2008-2010 included in this sample. The written bids submitted to the FDIC as part of the auction are binding. On average, 2.24 bids are submitted for each whole bank P&A auction in the sample. The median binding private bid is equal to one across the samples reported in all three panels of Table 2.10, while the maximum reported number of bids is higher in the FDIC sample as compared to the control sample and the Boone and Mulherin (2007) sample, 17 vs. 4 vs. 2, respectively. As noted previously, the FDIC does not make publicly available information on the number of banks 1) invited by the FDIC to participate in the auction process, or 2) signing a confidentiality agreement to receive the FDIC information packet regarding the failed bank and the FDIC’s estimate of its value. A two sample test of means to test for differences in the number of binding bids in the P&A auction in Panel C and versus voluntary bank deals in Panel B (assuming unequal sample size and variance) produces a test statistic of -2.99 (p value = 0.002) implying that the level of competition is greater for banks sold at P&A auctions than banks sold in the voluntary, cash-only corporate takeover market for the period 2005-2010.

The simple comparison performed in this section demonstrates that the level of competition in P&A auctions is greater than that of a control sample of voluntary takeovers of banks unassisted by the FDIC. When benchmarked against the measures of competition from Boone and Mulherin (2008), both samples prove to be at least as competitive. Together with the reported findings in Table 2.9 that the number of bids in an auction has a statistically insignificant effect on bid price, it seems that a lack of bidder competition in P&A auctions is not driving the positive abnormal returns to winning bidders in a P&A auction.

Tests of the Auction Fire-Sale Hypothesis

In this section, I test for the existence of fire-sale discounts in P&A auction prices. I follow the approach used by Pulvino (1998) and use a two-step hedonic regression methodology to test whether industry distress / illiquidity pushes realized auction prices significantly lower than estimated fundamental values. Rosen (1974) provides the theoretical motivation for estimating hedonic pricing and concludes "When goods can be treated as tied packages of characteristics, observed market prices are also comparable on those terms." In order to estimate the fundamental value of the target banks in the first step of the procedure I identify hedonic prices by regressing realized auction prices on target asset quality factors using the following equation:

$$\boldsymbol{Price = \widehat{\alpha} + \widehat{\beta_1} AssetQuality + \widehat{\beta_2} Earnings + \widehat{\beta_3} Size + \varepsilon} \quad \textbf{(1)}$$

I estimate two sets of regression to test the fire-sale hypothesis. In the first set of regression tests, I use the sample of 68 whole bank P&A auctions during 2008-2010 for which detailed asset valuation information is publicly available. In the first step regression, used to estimate the fundamental value of the target banks, I utilize explanatory variables drawn from both the available 8k deal valuation filings and call reports at the quarter end preceding the announcement of failure. Variable definitions can be found in the Appendix.

Because the first stage identifies the fundamental values by controlling for $\boldsymbol{AssetQuality}$, $\boldsymbol{Earnings}$ and $\boldsymbol{Size}$, residuals from this estimation are independent of asset characteristics that drive fundamental value across all market conditions. In the second step, residuals from the first step are regressed on fire sale factors such as industry distress and illiquidity variables. The fire sale factors are drawn from call reports at the quarter end preceding the announcement of failure. I draw on the insights from Cornett, et al. (2011) on bank liquidity management during the financial crisis of 2007 – 2009 for the formation of the fire sale explanatory variables. The specification for the second step is (variable definitions can be found in the Appendix):

$$\boldsymbol{\varepsilon = \widehat{\alpha} + \widehat{\Phi_1} IndustryDistress + \widehat{\Phi_2} IndustryLiquidity + \widehat{\Phi_3} Outsider + \varphi} \quad \textbf{(2)}$$

I focus on the estimated OLS coefficients $\widehat{\boldsymbol{\Phi_1}}$, $\widehat{\boldsymbol{\Phi_2}}$, and $\widehat{\boldsymbol{\Phi_3}}$ to determine whether the fire sale factors are significant in forcing realized prices lower than their estimated fundamental values. Viewed this way, the second-step coefficients can be considered the marginal impact of any industry-wide illiquidity and financial distress. Note that, in addition to the sample formation process described in Section 4, I follow the following process to classify a winning bidder as an industry outsider: for each transaction in the sample I review the age of the winning bidder's bank charter through the FDIC on-line database. For any bank determined to de novo (defined as a bank that has been in operation for five years or less), I review the history of the winning bank through financial press stories. In addition, I catalog the number of bidders described in FDIC press releases as non-bank entities (primarily private equity and individual investor consortiums). If, through this process, the primary business of the winning bidder is determined to be anything other than banking the bidder is classified as an outsider.

Table 2.11 reports the results of the first-step regressions for the sample of 68 whole bank P&A auctions during 2008-2010 for which detailed asset valuation information is publicly available. To enable proper estimation of standard errors I adjust for both time and acquirer clustering using two-way cluster robust errors (Cameron, Gelbach and Miller, 2006).

The first stage of the model presented in Table 2.11 is statistically significant with an R^2 of .76. The large R^2 values are consistent with Pulvino (1998) who reports adjusted R^2 values of .76 and .95 in his fundamental price regressions of prices in aircraft sales. Table 2.11 shows that realized auction prices increase significantly in the $\boldsymbol{AssetQuality}$ measure *Fair value adjustment purchased loans*. Because the *Fair value adjustment* variable is a contra asset account (which implies a negative balance), the interpretation is that as the price paid for a failed bank falls the more the loan portfolio is marked down post-sale. This also suggests that buyers are successful, on average, in measuring the level of asset impairment during bid-formation. The $\boldsymbol{Size}$ measure *LN(number of branches sold)* is positive but not statistically different than zero. The $\boldsymbol{Earnings}$ measure *Cost of funding earning assets* is positive but insignificant, the opposite of the predicted direction.

The second-step regression is used to assess the effects of industry illiquidity on price residuals from the first-step hedonic regression. A significant relation between the explanatory fire-sale factors and the price residual would provide evidence of fire-sale discounts. The $\boldsymbol{IndustryDistress}$ measure *# Banks failed following quarter* measures the number of institutions seized in the quarter following the announcement of failure. If, as predicted by theory, increasing industry distress drives auctions prices lower a negative relation would be expected. The *Median industry core capital (leverage) ratio* measures the effects of the industry-wide constraints caused by over leveraged, capital constrained banks. Because it is the ratio of equity capital to total assets, as the ratio declines, leverage increases. If, as predicted by theory, increased leverage restricts free cash flow available for acquisitions, a positive relation to realized prices would be expected.

The measure of $\boldsymbol{IndustryLiquidity}$, (*Change in industry median liquid assets(t)) / asset(t-1)* measures the change in industry median liquid assets. As average industry liquidity decreases a negative effect on prices would be expected as banks have less free cash to finance asset purchases; thus, a positive relation would be expected. (*Change in industry commitments + loans(t)) / asset(t-1)* reflects the change in industry median illiquid assets. As banks hold a greater percentage of assets in illiquid assets and credit commitments, less cash will be available to finance asset purchases. A negative relation is expected. *Acquirer commitments + loans / assets* reflects the acquirer's level of illiquid assets. A negative relation is expected. The *Outsider Dummy* variable captures the impact of purchases by industry outsiders. Theory would predict a negative relation between the # of sales to outsiders and realized auction prices. *Acquirer core deposits* and *liquid assets* should produce a positive relation to prices.

Table 2.11 also reports the results of the second-step regressions of whole bank P&A auctions. The explanatory power of all four regressions presented in Table 2.11 is much lower than the first stage, however the R^2 values for the second stage are again roughly consistent with those from Pulvino (1998). The regressions reveal that the measure of industry liquidity, (*Change in industry median liquid assets(t)) / asset(t-1)* is significant and positively related to prices realized at auction, showing that decreasing ratios of industry liquid assets reduced the price paid for banks at P&A auction. As documented by Cornett, et al., banks experienced significant liquidity demands during the crisis as large numbers of corporate clients drew down on existing backstop credit commitments. A proxy for that demand on bank liquidity, (*Change in industry commitments + loans(t)) / asset(t-1),* is significant and negatively related to prices realized at auction. Thus, as the average level of credit outstanding grew, banks became less liquid and available cash for acquisitions dropped, reflected in lower auction prices. Finally, the industry distress proxy, *# of banks failed the following quarter,* is negative and significant in some model specifications, at both the 5% and 10% levels. This indicates that as the industry as a whole experienced more financial distress, prices realized at auction fell.

A negative relation between the *Median industry leverage* ratio and realized auction prices is reported, although the estimated coefficients are not significant. The coefficient for the *Outsider Dummy* variable has a mixed sign depending on the specification but is not statistically different than zero. From this analysis, then, it appears that industry outsiders do not significantly influence auction prices; a finding consistent with Eckbo and Thorburn (2008) but inconsistent with Stromberg (2000) who finds that outsiders purchase at lower prices, on average, than industry insiders. Controls for acquirer size and liquidity, the log transform of acquirer core deposits and liquid assets, are both insignificant.

As a robustness check, I next add the sample of voluntary bank takeovers to the failed whole bank sample and run a pooled regression using the same model specification as presented in Table 2.11. To account for the significant economic differences between the two samples I include an indicator variable in the first stage regression to capture the effect of any economic or legal liability dichotomy between going concern targets and seized targets. To the extent that liquidity and industry distress influence target prices for both going concern and failed banks this approach, although somewhat crude, should be adequate to disentangle the effects of asset price fundamentals from liquidity pressures. Table 2.12 presents the results of the first and second-step regressions for the pooled sample of 105 whole bank P&A and voluntary takeover deals over the sample period 2005-2010. The explanatory power of both regression steps is roughly similar to that presented in Table 2 11, although the R^2 value for the second stage of the pooled regression is lower than that of the whole bank P&A only sample.

Most of the fire-sale variables in the second stage retain the same signs, however, at lower levels. Including the voluntary takeover deals reduces the statistical significance of almost all of the fire-sale variables in the second stage. None of the fire-sale variables significantly explain the realized prices of acquired banks. The (*Change in industry median liquid assets(t)) / asset(t-1)* variable has a negative relation in this specification. This is not surprising since the sample period includes 2005-2007, a time when financial markets as a whole were considered to be much more liquid than post-2007. This is reflected in the regression results that show, in aggregate, liquidity factors play a smaller role in asset pricing over the wider sample period 2005-2010.

Conclusion and Summary

This study uses recent FDIC P&A auctions of failed banks to contrast the winner's curse hypothesis against the industry fire-sale and target-firm information asymmetry hypotheses as potential explanations for realized prices and returns to bidders in FDIC auctions. I find that acquisitions of failed banks at FDIC (and FSLIC) auctions are wealth creating events during periods of industry shock. Mean abnormal returns to winning bidders for the acquisition of a failed bank are 3.75% during the financial crisis of 2007-2010 and roughly 2% during the S&L crisis of the late 1980's to early 1990's. Importantly, bidder abnormal returns are found to be -1.0% during the relatively stable economic expansionary period 1995 to 2004, roughly consistent with findings on bidder returns in the extant literature on voluntary takeovers. Overall, abnormal gains are roughly 3% over the full sample period 1985 to 2010.

Analyses of FDIC bid data shows that although bidder returns increase, and realized bid prices decrease, with measures of uncertainty in the value of the target, the effect does not significantly drive returns. Moreover, the level of competition does not have a significant influence on realized bid prices. Both of these findings are inconsistent with the winner's curse hypothesis. Using a measure of private competition, I provide evidence that the level of competition at recent FDIC auctions is greater, on average, than that of the voluntary banking takeover market as well as the broader 1990's corporate takeover market. In all, evidence from tests using stock return data and direct bid level data from FDIC auctions indicate that bidder's do not fall victim to the winner's curse when purchasing a failed bank at FDIC auction.

However, tests of the alternative hypothesis that industry fire-sale conditions drive prices for failed bank assets below their "true" value show that increases in measures of industry illiquidity, along with high levels of industry financial distress, lower the average price fetched for target firms. Not all fire-sale variables follow their predicted direction or magnitude, however; industry leverage and outsider activity do not drive prices significantly lower. Because liquidity trends and measures within the banking industry are complicated by regulatory intervention during times of economic distress, disentangling their effects in this context may be a fruitful area for further research. Overall, this evidence is consistent with the notion that, during periods of industry distress, prices are driven significantly lower by fire-sale conditions, pushing returns to winning bidders significantly higher. The finding that the presence of industry outside buyers does not have a significant impact on price is notable given anecdotal evidence to the contrary in financial press reports.

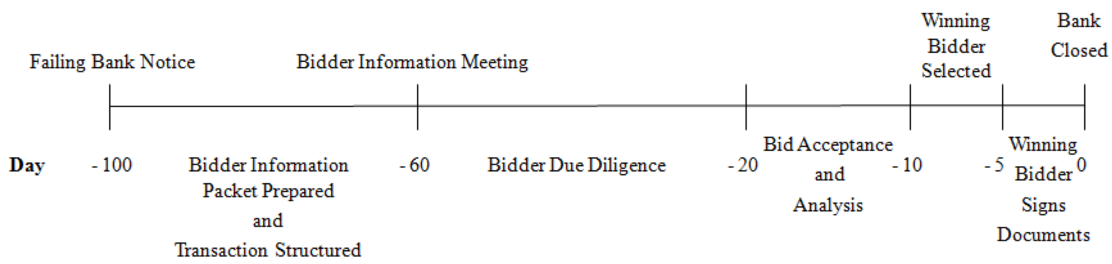

Figure 2.1: Timeline of FDIC P&A auction process

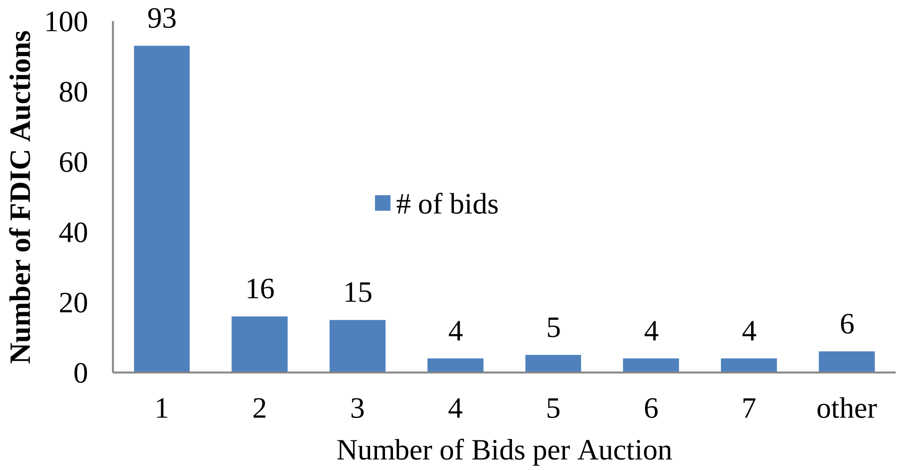

Figure 2.2: Frequency distributions of bids in FDIC P&A auctions

This figure displays the frequency distributions of the number of bids in P&A auctions for the subsample period 2008-20010. The number of bids range from 1 to 17, with a mean of 2.3. There are multiple bids in 37% of auctions in this sample.

Table 2.1: Comparison of event studies on failed bank mergers and acquisitions
This table provides an overview of the results of seven studies on failed bank acquisitions. Authors, time period, event window around announcement date, number of observations and bidder return taken from the original studies. Simple averages are the sum of all the available returns for bidder firms divided by the number of papers.

Number	**Authors**	**Time Period**	**Event Window Around Announcement Date**	**Number of Observations**	**Bidder Return (%)**
1	Giliberto and Varaiya (1989)	1975 - 1985	n/a	219 acquisitions	n/a
2	James and Wier (1987b)	1973 - 1983	(-1,0)	19 acquisitions	2.36
3	Pettway and Trifts (1985)	1972 - 1981	(-10, +50)	11 acquisitions	-3.43% AGRR*
4	Gupta, LeCompte and Misra (1997)	1979 - 1992	(-1,0)	138 acquisitions	-0.75
5	Zhang (1997)	1980 - 1990	(-1,0)	128 acquisitions	0.68
6	Cochran, Rose and Fraser (1995)	1982 - 1991	(-2,0)	58 acquisitions	1.16
7	Stover (1997)	1990 - 1992	(0,+2)	71 acquisitions	1.71
				Simple Average	0.29

* Average geometric residual return (AGRR). AGRR is a theoretically superior measure of residual returns over time because it duplicates the actual returns available to an investor, assuming a buy-and hold strategy of an equally weighted portfolio.

Table 2.2: FDIC P&A auction detailed timeline

This table provides a timeline of the process used by the FDIC to resolve a failing bank through a P&A auction. A *Failing Bank Notice* is sent by the bank's regulator to the FDIC notifying it of the bank's impending failure and triggering the FDIC to begin due diligence on the failing bank. An *Information Package is Assembled* by the FDIC which will be given to prospective bidders selected by the FDIC. The package provides bidders with financial data on the failed institution as well as the FDIC's estimate of the liquidation value of the assets. Concurrently, an *Asset Valuation Review (AVR) Package is Assembled* that is used to document the minimum price the FDIC is willing to accept for those assets from prospective bidders. The *AVR is Reviewed by Region* such that the OCC, OTS, Federal Reserve and state bank regulators may approve the preliminary pool of prospective bidders. Early in the process, a *Capital Call is Made* in order to formalize the failing bank's deficient capital position and document the bank's seizure by regulators. The FDIC conducts a Bid *Information Meeting* to brief approved bidders on details of the auction procedure and assets up for sale. Bidders conduct their *Due Diligence* of bank assets and liabilities and submit sealed bids to the FDIC. *Bid Acceptance/Analysis/Board Authority:* The FDIC accepts bids and selects the winning bidder based on the bid that creates the least cost to the insurance fund. The *Winning Bidder Signs Documents* and closes the acquisition on *Closing Date.*

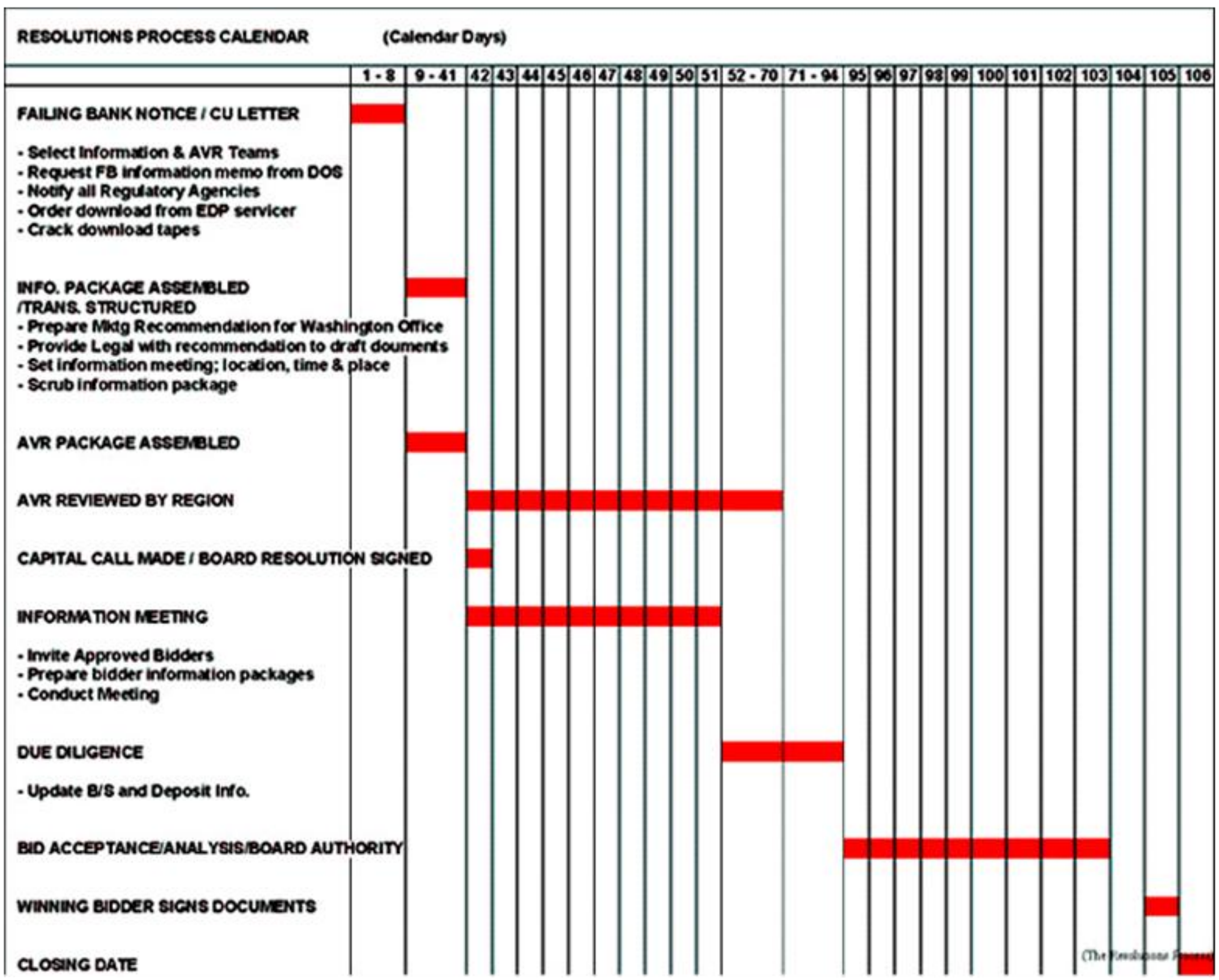

Table 2.3: Sample summary - failed banks

This table reports the number of bank failure and assistance transactions and the number of failures resolved through P&A auctions per year in the sample period of 1985– 2010. Transactions are classified by year of announcement. Data are reported for the full sample used in the event study analysis. Data sample reports the number and percentage of transactions used in the event study analysis by year.

	Total Failure & Assistance Transactions			FDIC Purchase & Assumption	Data Sample	
Year	**Total**	**Failure**	**Assistance**		**Final**	**%**
1985	180	139	41	87	1	1%
1986	204	162	42	98	2	2%
1987	262	217	45	133	1	1%
1988	470	232	238	165	3	2%
1989	534	531	3	319	7	2%
1990	382	381	1	291	15	5%
1991	271	268	3	241	27	11%
1992	181	179	2	153	20	13%
1993	50	50	-	42	1	2%
1994	15	15	-	13	2	15%
1995	8	8	-	7	1	14%
1996	6	6	-	6	2	33%
1997	1	1	-	1	-	-
1998	3	3	-	3	-	-
1999	8	8	-	8	1	13%
2000	7	7	-	7	-	-
2001	4	4	-	3	-	-
2002	11	11	-	7	1	14%
2003	3	3	-	3	-	-
2004	4	4	-	3	1	33%
2005	-	-	-	-	-	-
2006	-	-	-	-	-	-
2007	3	3	-	3	-	-
2008	30	25	5	25	10	40%
2009	148	140	8	130	56	43%
2010	154	154	0	146	74	51%
Total	**2939**	**2551**	**388**	**1894**	**225**	**12%**

Table 2.4: Sample statistics

This table reports financial, deal, and target characteristics for the subsample period 2008-2010. Panel A reports data on the failed (target) bank for failed bank P&A auctions. Financial data are from FDIC call report data at the quarter end preceding the announcement of failure. Deal data are from acquirer 8K, 10Q or 10K filings. Total Assets is total assets of the bank. Total Deposits is total deposits of the bank. Purchase Price is net cash due to/received from the FDIC in exchange for the failed bank acquired at auction. Book Value Loans is book value of total loans of the failed bank as of the purchase date. Fair Value Adjustment Loans is the adjustment to book value used to properly record loans of the failed bank at market value as of the purchase date. FDIC Loss Share Receivable is the present value of the estimated cash payments expected to be received from the FDIC for future losses on covered assets. Total Gain on Purchase is the excess of the fair value of net assets over the total purchase consideration paid at auction. # of Branches Sold is the number of bank branch offices purchased by the acquiring bank. N is the number of observations. N is the number of observations. All reported financial figures are in $ million.

Variables	N	Mean	Median	Max	Min
Panel A - Full Sample: 1985 - 2010					
Acquiring Banks					
Total Assets	225	33,834	4,822	967,097	194
Total Deposits		22,774	3,669	639,236	139
Failed Banks					
Total Assets		1,674	230	137,609	6
Total Deposits		1,175	210	84,380	6
Panel B - Subsample: 2008-2010					
Acquiring Banks					
Total Assets	140	33,523	2,319	967,097	194
Total Deposits		21,148	1,597	639,236	139
Failed Banks					
Total Assets		1,588	195	137,609	6
Total Deposits		1,088	170	84,380	6
Failed Banks (Deal Data)					
Purchase Price	97	(72)	(24)	5,822	(4,121)
Book Value Loans		1,024	324	14,328	32
Fair Value Adjustment Loans		(348)	(97)	(5)	(6,164)
FDIC Loss Share Receivable		214	66	3,443	-
Total Gain on Purchase (pre-tax)		26	8	471	-
# of Branches Sold		15	7	346	-

Table 2.5: Event study analysis: (-1,+1) window

This table reports event study returns for the full event study sample of 225 target firms in which the bidder is a U.S. publicly traded firm and bidder equity value data are available. Data are reported for the full sample period used in the event study analysis (1985–2010), as well as by subsample period. The results are net-of market returns for the (−1,+1) window, where day 0 is the initial announcement date and the market index is the CRSP value-weighted index. The p-Values are for a t-test of the null hypothesis that the mean difference between the failed bank sample and each of the forms of voluntary takeover is zero.

	Bidder CARs - Failed Bank Acquisitions		**Bidder CARs - Voluntary M & A (Cash Only)**		**Bidder CARs - Voluntary M & A (Stock and Cash)**	
	Market Model		**Market Model**		**Market Model**	
Window	**Coeff**	**Patell Z**	**Coeff**	**Patell Z**	**Coeff**	**Patell Z**
Panel A - Subsample: 2008-2010						
N	140		20		33	
(-1,+1)	3.75%	7.759***	1.82%	1.304	-1.81%	-4.136***
Panel A - Means Test - t-Statistic (p-Value)						
			1.12731	(.134)	3.061354	(.001)
Panel B - Subsample: 1985-2010						
N	225		458		1008	
(-1,+1)	3.02%	8.636***	0.52%	3.275***	-0.29%	-4.492***
Panel B - Means Test - t-Statistic (p-Value)						
			-4.11	(<0.001)	-5.63	(<0.001)
Panel C - Subsample: 1985-1994						
N	79		219		279	
(-1,+1)	2.02%	4.529***	0.31%	2.023*	-0.05%	-2.102*
Panel C - Means Test - t-Statistic (p-Value)						
			-2.31	(0.01)	-3.05	(0.002)
Panel D - Subsample: 1995-2004						
N	6		242		688	
(-1,+1)	-0.98%	-0.951	0.47%	2.644**	-0.36%	-3.634***

Table 2.6: Summary statistics of explanatory variables

This table presents summary statistics for the explanatory variables employed in regression analysis presented in this study. Panel A reports statistics for the analysis reported in Table 8; variable definitions are presented in Table 8. Panel B reports statistics for the analysis reported in Table 9; variable definitions are presented in Table 9. Panel C reports statistics for the analysis (second stage) reported in Table 11; variable definitions are presented the Appendix. Data are reported only for whole bank P&A auctions for which deal-specific valuation data is publicly available.

Variables	**Mean**	**Median**	**Min**	**Max**	**Std. Dev.**	**# of Obs.**
Panel A: Summary Statistics for Variables in Table 8						
LN (Intangible assets)	2.97	0.00	0.00	12.82	3.71	114
LN (Bidder size)	12.06	12.24	6.07	18.26	3.49	114
LN (Relative size)	-2.61	-2.52	-10.02	-0.06	1.66	114
LN (FDIC loss share)	4.37	5.34	0.00	9.62	2.85	114
Panel B: Summary Statistics for Variables in Table 9						
LN(Core Deposits)	19.32	19.21	16.25	23.49	1.15	331
LN(Fair Value Loans)	18.39	19.16	0.00	23.96	4.49	331
# of bids	4.89	3.00	1.00	17.00	4.21	331
LN(# of bids)	1.20	1.10	0.00	2.83	0.92	331
LN(Bid Std. Dev.)	11.64	15.20	0.00	20.41	7.51	331
LN(Bid Range)	12.19	15.87	0.00	21.22	7.88	331
LN(Bid Variance)	23.29	30.41	0.00	40.81	15.02	331
Panel C: Summary Statistics for Variables in Table 11						
Change in ind. med liquid assets(t)/asset(t-1)	0.0061	0.0043	0.0011	0.0124	0.0042	82
Change in ind. commts + loans(t)/asset(t-1)	(0.0013)	(0.0011)	(0.0032)	0.0019	0.0015	82
# Banks failed following quarter	38.95	41.00	24.00	50.00	7.85	82
(Acquirer commitments + loans) / assets	0.74	0.76	0.11	1.05	0.18	82
Outsider dummy (1=yes, 0=no)	0.04	0.00	0.00	1.00	0.19	82
Ind. med. leverage ratio	9.36	9.35	9.28	9.51	0.08	82
Acquirer core deposits	4,365,781	1,864,196	238,164	80,761,984	9,383,386	82
LN(Acquirer core deposits)	14.56	14.44	12.38	18.21	1.11	82

Table 2.7: Correlations of explanatory variables

This table presents correlations for the explanatory variables employed in regression analysis presented in this study. Panel A reports correlations for the analysis reported in Table 8. Panel B reports correlations for the analysis reported in Table 9. Panel C reports correlations for the analysis (second stage) reported in Table 11; variable definitions are presented Table 8, Table 9 and the Appendix, respectively.

Panel A	LN (Intangible assets)	LN (Bidder size)	LN (Relative size)	LN (FDIC loss share)
LN (Intangible assets)	1.00			
LN (Bidder size)	-0.18	1.00		
LN (Relative size)	0.32	-0.20	1.00	
LN (FDIC loss share)	0.24	0.32	0.26	1.00

Panel B	LN (Core Deposits)	LN (Fair Value Loans)	# of bids	LN (# of bids)	LN (Bid Std. Dev.)	LN (Bid Range)	LN (Bid Variance)
LN(Core Deposits)	1.00						
LN(Fair Value Loans)	0.26	1.00					
# of bids	0.35	-0.07	1.00				
LN(# of bids)	0.28	-0.11	0.92	1.00			
LN(Bid Std. Dev.)	0.30	-0.03	0.66	0.85	1.00		
LN(Bid Range)	0.30	-0.04	0.67	0.86	1.00	1.00	
LN(Bid Variance)	0.30	-0.03	0.66	0.85	1.00	1.00	1.00

Panel C	Change in ind. med liquid assets(t)/asset (t-1)	Change in ind. commts + loans(t)/asset(t-1)	# Banks failed following quarter	Acquirer commitments + loans / assets	Outsider dummy (1=yes, 0=no)	Ind. med. leverage ratio	LN(Acquirer core deposits)
Change in ind. med liquid assets(t)/asset(t-1)	1.00						
Change in ind. commts + loans(t)/asset(t-1)	-0.82	1.00					
# Banks failed following quarter	0.51	-0.38	1.00				
Acquirer commitments + loans / assets	-0.01	-0.07	0.08	1.00			
Outsider dummy (1=yes, 0=no)	0.04	0.09	0.13	-0.14	1.00		
Ind. med. leverage ratio	-0.28	0.28	-0.77	-0.06	-0.12	1.00	
LN(Acquirer core deposits)	0.13	-0.12	0.20	0.18	-0.02	-0.10	1.00

Table 2.8: OLS regression analysis of bidder returns, (-1,+1) window

This table reports regression analysis of bidder returns on variables that capture the absolute and relative bidder size, level of intangible assets and FDIC financial assistance. Bidder data are for the winning bidder. The dependent variable is net-of-market bidder returns for the (-1,+1) window in which day 0 is the date the seizure and auction results are concurrently announced by the FDIC and the market index is the Center for Research in Security Prices value-weighted index. Intangible assets is the target's Goodwill and Other Intangibles at the quarter end preceding the announcement of failure. Intangible assets include goodwill, mortgage servicing rights, purchased credit card relationships and other identifiable intangible assets such as a core deposit intangible. Relative size is the ratio of the total assets of the target divided by the total assets of the bidder at the quarter end preceding the announcement of failure. Bidder size is the total assets of the bidder at the quarter end preceding the announcement of failure. FDIC Loss Share is the face amount of covered assets (in $mm) for which the FDIC will share any future realized losses. Two-way cluster robust errors are employed to adjust reported t-statistics for both time and acquirer clustering. To facilitate comparison with previous research both standard errors and cluster robust errors are reported. The t-statistics of the regression coefficients are reported in parentheses. The model F-statistic, p-value and R-squared are reported at the bottom of the table.

		Model 1	**Model 2**
	Predicted Direction of Coefficient	LN (-1,+1) Cumulative Abnormal Return	LN (-1,+1) Cumulative Abnormal Return
Intercept		0.09	0.09
		(3.60)	(3.64)
LN (Intangible assets)	(-)	0.001	0.002
		(0.57)	(0.76)
LN (Bidder size)	(+)/(-)	-0.002	-0.002
		(1.16)	(0.84)
LN (Relative size)	(+)	0.01	0.01
		(1.05)	(1.32)
LN (FDIC loss share)	(+)		-0.002
			(0.47)
# of Observations		114	114
R^2		0.05	0.06
F Statistic		2.11	1.66
P-value of F-stat		0.10	0.16

Table 2.9: OLS regression analysis of auction bid level, whole bank and P&A ($)

This table reports regression analysis of observed bids from whole bank and standard P&A auctions on variables that capture the level of competition in each auction, the uncertainty regarding the value of the auctioned asset, target franchise value, level of target risky assets and time dummies. The dependent variable is the bid amount submitted by each participating bidder in each auction for the sample period 2008-20010. LN(Core Deposits) is the natural log of total domestic demand, savings and time deposits under $100,000 at the quarter end preceding the announcement of failure. LN(Fair Value Loans) is the market value of total loans of the failed bank as of the purchase date. # of Bids is the number of bids per auction; it proxies for the level of competition in each auction. LN(# of Bids) is the natural log transformation of # of Bids. LN(Bid Std. Dev.) is the standard deviation of the bid amounts for each auction; it proxies for the level of uncertainty regarding bidder value estimates of the auctioned assets in each auction. LN(Bid Range) is the range of the bid amounts for each auction; it is an alternate proxy for the level of uncertainty regarding bidder value estimates of the auctioned assets in each auction. LN(Bid Variance) is the variance of the bid amounts for each auction; it is another alternate proxy for the level of uncertainty regarding bidder value estimates of the auctioned assets in each auction. Time Dummies is a dummy variable equal to one if failure occurred in quarter x, zero otherwise. Two-way cluster robust errors are employed to adjust reported t-statistics for both time and acquirer clustering. The t-statistics of the regression coefficients are reported in parentheses. The model F-statistic, p-value and R-squared are reported at the bottom of the table.

Auction Bid ($)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Intercept	26.68	22.51	22.15	22.26	27.54	27.22	27.23	27.23
	(7.83)	(71.67)	(63.58)	(36.37)	(6.97)	(7.32)	(7.32)	(7.32)
LN(Core Deposits)	-0.24				-0.27	-0.25	-0.25	-0.25
	(1.32)				(1.35)	(1.35)	(1.35)	(1.35)
LN(Fair Value		-0.02			0.004	0.005	0.005	0.005
		(1.13)			(.47)	(.58)	(.56)	(.58)
# of bids					0.04			
					(1.13)			
LN(# of bids)			-0.06			0.19	0.21	0.19
			(1.31)			(1.04)	(1.05)	(1.04)
LN(Bid Std. Dev.)				-0.01	-0.03	-0.03		
				(1.24)	(1.19)	(1.13)		
LN(Bid Range)							-0.03	
							(1.13)	
LN(Bid Variance)								-0.02
								(1.13)
Time Dummies	No	No	No	No	Yes	Yes	Yes	Yes
# of Observations	331	332	333	333	331	331	331	331
R^2	0.05	0.01	0.00	0.01	0.08	0.07	0.07	0.07
F Statistic	17.1	2.4	0.6	2.7	4.4	4.2	4.2	4.2
P-value of F-stat	0.00	0.12	0.44	0.10	0.00	0.00	0.00	0.00

Table 2.10: Summary of the sales process

This table summarizes the sales process for a sample of 308 corporate takeovers from 1990-1999 (Boone and Mulherin, 2008), 22 voluntary bank takeovers from 2005-2009 and 147 P&A auctions from 2008-2010. Panel A describes the sales process for the 308 corporate takeovers reported in Boone and Mulherin (2008). Contact reports the average number of potential buyers contacted by the selling firm and its investment bank. Confidential reports the average number of potential buyers that engage in a confidentiality/standstill agreement. Binding reports the average number of potential buyers that submit a private written offer. In Panel B, the aspects of the sales process are reported for the 22 voluntary bank takeovers from 2005-2009. Panel C reports the information available for FDIC P&A auctions: the number of (binding) bids submitted per auction.

	Mean	**Median**	**Max**	**Min**
Panel A: Boone and Mulherin Statistics (1990 - 1999)				
# of Obs.	308			
Contact	7.10	2.0	150	1
Confidential	3.25	1.0	50	1
Binding	1.240	1.0	2	1
Panel B: Voluntary Bank M&A (2005 - 2009)				
# of Obs.	22			
Contact	13.50	8.0	52	1
Confidential	6.36	4.5	30	1
Binding	1.41	1.0	4	1
Panel C: FDIC P&A (2008 - 2010)				
# of Obs.	147			
Contact	n/a			
Confidential	n/a			
Binding	2.24	1.0	17	1

Table 2.11: Two stage hedonic regression - whole bank P&A

This table reports a pooled regression analysis of realized sales price for target banks from whole bank P&A auctions, standard P&A auctions and voluntary bank takeovers on fundamental value factors and fire-sale factors. The regression analysis used is a two-step hedonic regression. The first step estimates the fundamental value of the target banks by regressing realized auction prices on target asset quality factors. Variables definitions are presented in the Appendix. The dependent variable is the net cash payment made to/received from the FDIC at transaction closing (realized sales price) for each auction for the sample period 2005-2010.

Dependent variable: Purchase Price ($, thousands)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: First Stage						
Intercept	(21,918)	(21,918)	(21,918)	(21,918)	(21,918)	(21,918)
	(0.39)	(0.39)	(0.39)	(0.39)	(0.39)	(0.39)
Cost of funding earning assets	0.31	0.31	0.31	0.31	0.31	0.31
	(1.07)	(1.07)	(1.07)	(1.07)	(1.07)	(1.07)
Fair Value Adjustment Loans	0.39	0.39	0.39	0.39	0.39	0.39
	(10.26)	(10.26)	(10.26)	(10.26)	(10.26)	(10.26)
Core Deposit Intangible	(40)	(40)	(40)	(40)	(40)	(40)
	(1.54)	(1.54)	(1.54)	(1.54)	(1.54)	(1.54)
Noncurrent assets plus OREO	(255)	(255)	(255)	(255)	(255)	(255)
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
LN(# of Branches Sold)	57,020	57,020	57,020	57,020	57,020	57,020
	(1.55)	(1.55)	(1.55)	(1.55)	(1.55)	(1.55)
Return on assets (ROA)	-100	-100	-100	-100	-100	-100
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
# of Observations	68	68	68	68	68	68
R^2	0.76	0.76	0.76	0.76	0.76	0.76
F Statistic	32.75	32.75	32.75	32.75	32.75	32.75
P-value of F-stat for Regression	0.00	0.00	0.00	0.00	0.00	0.00

Table 2.11: Two stage hedonic regression - whole bank P&A, continued

This table reports a pooled regression analysis of realized sales price for target banks from whole bank P&A auctions, standard P&A auctions and voluntary bank takeovers on fundamental value factors and fire-sale factors. The regression analysis used is a two-step hedonic regression. In the second step, residuals from the first step are regressed on fire sale factors. Variables definitions are presented in the Appendix. The dependent variable is the residuals from the first step regression for the sample period 2005-2010.

Dependent variable: First step residual	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel B: Second Stage						
Intercept	6,374,512	9,361,405	9,133,903	4,356,138	7,195,282	6,939,455
	(.95)	(.92)	(1.08)	(.66)	(.72)	(.83)
Change in ind. med. liquid assets(t)/asset(t-1)	22,260,672	25,226,479	25,904,122			
	(3.20)	(3.34)	(3.25)			
Change in ind. commts + loans(t) / asset(t-1)				-45,773,599	-52,700,823	-54,361,562
				(1.70)	(2.02)	(1.97)
# Banks failed following quarter	-11,871	-15,140	-15,590	-7,843	-10,791	-11,185
	(1.94)	(1.59)	(2.11)	(1.61)	(1.31)	(1.83)
Acquirer commts + loans / assets	-309,583	-214,747	-242,159	-359,165	-272,493	-301,221
	(1.16)	(1.06)	(1.21)	(1.32)	(1.34)	(1.50)
Outsider dummy (1=yes, 0=no)	-70,251	-29,279	-39,306	-30,250	17,905	9,784
	(.69)	(.42)	(.51)	(0.28)	0.20	0.11
Ind. med. leverage ratio	-707,235	-921,418	-942,488	-497,412	-693,418	-711,220
	(.90)	(.83)	(1.01)	(0.64)	(0.63)	(0.77)
Acquirer core deposits	-0.01			-0.01		
	(2.01)			(2.01)		
LN (Acquirer core deposits)		(8,853)			-9,689	
		(.17)			(.18)	
R^2	0.15	0.11	0.12	0.13	0.09	0.09
F Statistic	1.48	1.24	1.33	1.29	0.99	1.06
P-value of F-stat for Regression	0.19	0.30	0.26	0.27	0.44	0.39

Table 2.12: Two stage hedonic regression - whole bank P&A

This table reports a pooled regression analysis of realized sales price for target banks from whole bank P&A auctions, standard P&A auctions and voluntary bank takeovers on fundamental value factors and fire-sale factors. The regression analysis used is a two-step hedonic regression. The first step estimates the fundamental value of the target banks by regressing realized auction prices on target asset quality factors. Variables definitions are presented in the Appendix. The dependent variable is the net cash payment made to/received from the FDIC at transaction closing (realized sales price) for each auction for the sample period 2005-2010.

Dependent variable: Purchase Price ($, thousands)	**(1)**	**(2)**	**(3)**	**(4)**
Panel A: First Stage				
Intercept	-11,004	-11,004	-11,004	-11,004
	(.22)	(.22)	(.22)	(.22)
Cost of funding earning assets	-0.45	-0.45	-0.45	-0.45
	(9.33)	(9.33)	(9.33)	(9.33)
Fair Value Adjustment Loans	0.37	1.37	2.37	3.37
	(4.57)	(5.57)	(6.57)	(7.57)
Core Deposit Intangible	30	31	32	33
	(60.90)	(61.90)	(62.90)	(63.90)
Noncurrent assets plus OREO	3,106	3,107	3,108	3,109
	(2.12)	(2.12)	(2.12)	(2.12)
LN(# of Branches Sold)	-74,337	-74,337	-74,337	-74,337
	(0.99)	(0.99)	(0.99)	(0.99)
Return on assets (ROA)	545	545	545	545
	(1.61)	(1.61)	(1.61)	(1.61)
Liability Idemnification Dummy	78,459	78,459	78,459	78,459
	(0.99)	(0.99)	(0.99)	(0.99)
# of Observations	105	105	105	105
R^2	0.96	0.96	0.96	0.96
F Statistic	326.40	326.40	326.40	326.40
P-value of F-stat for Regression	0.00	0.00	0.00	0.00

Table 2.12: Two stage hedonic regression - whole bank P&A, continued

This table reports a pooled regression analysis of realized sales price for target banks from whole bank P&A auctions, standard P&A auctions and voluntary bank takeovers on fundamental value factors and fire-sale factors. The regression analysis used is a two-step hedonic regression. In the second step, residuals from the first step are regressed on fire sale factors. Variables definitions are presented in the Appendix. The dependent variable is the residuals from the first step regression for the sample period 2005-2010.

Dependent variable: First step residual	**(1)**	**(2)**	**(3)**	**(4)**
Panel B: Second Stage				
Intercept	-2,024,570	-2,402,135	-3,380,346	-3,688,805
	(.68)	(.81)	(.93)	0.98
Change in ind. med. liquid assets(t)/asset(t-1)	-24,551	(14,904)		
	(.14)	(.10)		
Change in ind. commts + loans(t) / asset(t-1)			-211,918	-186,698
			0.59	0.55
# Banks failed following quarter	392	308	1,501	1,337.62
	(.22)	(.19)	0.72	0.67
Acquirer commts + loans / assets	-105,020	-136,574	-32,224	-71,432
	(.84)	(1.18)	0.16	0.38
Outsider dummy (1=yes, 0=no)	98,563	97,451	156,623	151,992.17
	(.9)	(.95)	1.59	1.54
Ind. med. leverage ratio	244,303	262,104	381,362	391,657.75
	(.68)	(.76)	0.90	0.92
LN (Acquirer core deposits)	-15,047.36		-17,022	
	(.35)		(.39)	
R^2	0.01	0.01	0.02	0.01
F Statistic	0.20	0.16	0.25	0.20
P-value of F-stat for Regression	0.98	0.99	0.96	0.98

CHAPTER 3

WHAT DRIVES TAKEOVER ACTIVITY IN THE BANKING INDUSTRY?

Introduction

Neoclassical explanations of corporate mergers and acquisitions (M&A) argue that broad fundamental factors such as economic, regulatory and/or technological shocks drive industry merger activity, often in waves (Mitchell and Mulherin, 1996; Harford, 2005). More recent studies use evidence such as the correlation of the bull market of the 1990s with increased merger activity to support the behavioral explanation that managers use temporary market misvaluation of the firm's stock to acquire assets or growth options (Shleifer and Vishny, 2003; Rhodes-Kropf, Robinson, and Viswanathan, 2005). Because M&A are such a large part of corporate capital expenditures, aggregate U.S. M&A deal value totaled over $850 billion in 2011[4], determining the cause(s) of such a large turnover in corporate control has implications for investors, corporate managers and public policy makers alike.

While these two contrasting explanations of M&A activity have generally been a focal point of the merger literature, more recent research builds on the notion that industry-level M&A builds into a wave-like concentration of activity only when other industry conditions are in place. Specifically, Harford (2005) shows that, in addition to the economic shocks that initiate the wave, capital liquidity is needed to provide sufficiently low transaction costs to allow for large scale reallocation of assets. More recent work by Garfinkel and Hankins (2011) provides evidence that cash flow uncertainty, typically created by industry shocks or increased competition, spurs companies to vertically integrate to hedge against future cash flow volatility, which helps produce merger waves.

We use data from the past 30 years of merger activity in the U.S. banking industry to determine empirically whether shocks to industry fundamentals or stock price misvaluation drive merger activity.

[4] Factset, 2012

The U.S. banking industry provides an excellent setting to contrast these two broad hypotheses because the industry has experienced several structural shocks via deregulation and technological change over the sample period (Mitchell and Mulherin, 1996; Winston, 1998; Harford, 2005); while simultaneously benefitting from several bull markets (mid-1980's, 1990's and mid-2000's) that provide fertile ground for behaviorally-driven market irrationality. Moreover, past multi-industry merger studies exclude banking because it's historically regulated nature is viewed to have muted natural market responses, such as takeover activity, to industry change. The study of this single industry provides an opportunity to test these theories with new data.

The U.S banking industry is somewhat unique in that it continues to this day to be subject to significant government regulation, despite having undergone significant deregulatory changes over the last 30 years. Importantly, deregulation did not simply slow the economic decline of the industry as happens in some other industries (Ovtchinnikov, 2010); it helped produce an increasingly profitable and heterogeneous industry characterized by product innovation and diversification. This, in turn, resulted in higher levels of growth options and widening product margins. Many studies examine the impact of product diversification on the risk / return profile of U.S. banks (DeYoung and Roland, 2001, Kwan, 1998, Boyd, et al., 1980, among others). While some find that shifts to a larger share of revenue from non-interest income sources (fee-based income, commissions, trading profits) produce a lower *expected* risk-return relationship, some studies also find that the diversification impacts on realized returns are short-lived. Moreover, some non-interest income activities increase risk and lead to increased leverage (due to lower capital requirements) producing a significant increase in earnings volatility (DeYoung and Roland, 2001, Stiroh, 2004, Stiroh and Rumble, 2006).

Based on this evidence, we hypothesize that deregulation ultimately caused an increase in the level and dispersion of risk throughout the industry which, in turn, led to increases in industry stock misvaluation. Increases in firm-level cash flow volatility have been shown to increase firm-level risk as proxied by idiosyncratic stock return volatility (Irvine and Pontiff, 2008). We draw on their insights and theorize that the increasingly heterogeneous and risky nature of the banking industry made it increasingly difficult for investors to forecast future revenues and profitability. This increased uncertainty let to larger discounts to estimates of long run value over the sample period. We provide evidence to show that the Rhodes-Kropf, Robinson, and Viswanathan (RRV) misvaluation proxy (a variable used in the literature to capture aggregate stock misvaluation) increases significantly with increases in industry cash flow volatility.

However, this same increase in firm-level cash flow uncertainty has been shown to lead to the start of merger waves. We confirm this relationship in our study; test results show that firm-level cash flow volatility significantly drives merger activity in the U.S banking industry during the time period studied. Furthermore, we find that cash flow volatility increases with increases in average industry revenue volatility and revenue from fee-based products; evidence suggesting that changes in industry fundamentals drive merger activity and that the RRV stock misvaluation measure reflects these changes in industry fundamentals.

We also show that the increase in industry revenue and cash flow volatility is caused by increases in industry competition after several deregulatory events. This finding supports evidence from the extant literature that merger activity is significantly related to structural industry change; merger activity increases significantly following the two deregulatory acts examined (1994 and 1999) while showing a weaker positive link to a broader proxy for economic shock.

The paper proceeds as follows: Section 2 briefly reviews the literature and establishes the framework for testing the hypotheses. Section 3 lays out the recent history of bank deregulation, Section 4 discusses the patterns of industry merger activity, Section 5 reviews the data sample construction of variables, Section 6 presents the empirical tests and results, and Section 7 concludes.

Literature Review and Hypothesis Development

Given that mergers have received much scholarly interest, there exists a substantial body of work covering many aspects of M&A. This section outlines the strands of the literature most relevant to developing testable hypotheses.

Two broad and contrasting explanations of M&A activity have emerged in the literature over the past 40-odd years. Neoclassical theory posits that corporate M&A are an efficient response to economic shocks. Gort (1969) is one of the earlier researchers to argue that economic shocks drive the reallocation of assets within an industry. Mitchell and Mulherin (1996) examine merger activity at the industry level and find that economic, regulatory and technological shocks create clusters of merger activity that vary in time and intensity across industries. Andrade, Mitchell, and Stafford (2001) and Mulherin and Boone (2000) confirm the clustering of merger activity by industry during the 1990s. Harford (2005) also finds evidence of merger waves driven by economic, regulatory and technological shocks but contends that sufficient levels of capital liquidity are needed to make merger activity cluster into a wave-like pattern over time. Ovtchinnikov (2010) shows that merger waves often follow industry deregulation, while Homstrom and Kaplan (2001) confirm this they also attribute merger waves to issues in corporate governance.

Behavioral explanations link M&A activity and (relative) stock valuations. Shleifer and Vishny (2003) create a model that explains many of the empirical regularities about the characteristics and returns of merging firms. They argue that an inefficient market allows for periods of high stock market valuations that drive M&A activity as rational managers use their overvalued stock as currency to buy undervalued, or less overvalued, firms. As a bull market runs higher, M&A tend to cluster in time until a market pull-back ends the bull market run. Rhodes-Kropf et al. (2005), in a follow up to an earlier theoretical paper, develop several proxies for short and long run misvaluation via a decomposition of the market-to-book ratio and show that short-term overvaluation is a significant drivers of M&A activity. Dong et al. (2003) evaluate the misvaluation theory and find that bidders are more highly valued than their targets; the effect is stronger in the 1990s than the 1980s. Ang and Cheng (2003) also examine firm-level valuation and conclude that stock overvaluation is an important motive for firms to make acquisitions. However, distinguishing between uncertainty and misvaluation is not always straightforward. For example, Pastor and Veronesi (2006) argue that the fundamental value of technology firms listed on the NASDAQ in the late 1990's increased with uncertainty about average future profitability; they conclude the valuations seem reasonable in this context and do not constitute a bubble.

Past research on bidder returns from bank mergers provides support for various theories about the determinants of mergers. While most studies find slightly negative returns to bidders, findings support various theories for the determinants of those returns. Cornett and De (1991), Gupta et al. (1997) and Becher (2000) find support for the synergy hypothesis. Houston and Ryngaert (1994) find no support for the cost savings hypothesis while Gupta et al. (1997) finds support for the agency and hubris theories. Houston, James and Ryngaert (2001) find positive combined gains to bank mergers and attribute the majority of announcement period gains to estimated cost savings rather than projected revenue enhancements.

A sizable literature studies post-merger efficiency gains. Berger, Demsetz and Strahan (1999) find little or no cost efficiency improvement, on average, but do find some evidence consistent with increases in market power. Jayaratne and Strahan (1998) find that M&A activity increases in states subsequent to joining an interstate banking agreement and that bank performance improves significantly after restrictions on bank expansion are lifted. Calomiris (1999) studies bank merger waves and finds evidence of substantial efficiency gains from reduced operating costs and enhanced diversification. Amel, et al. (2004) note that they find little evidence that mergers yield economies of scope or gains in managerial efficiency. Nail and Parisi's (2005) survey of bank merger literature concludes that benefits of geographic diversification result more from revenue growth and lower risk associated with deposit and loan diversity than from the cost-cutting of in-market mergers designed to increase operating efficiency.

Wheelock and Wilson (2004) examine the determinants of merger activity and conclude that supervisory evaluations of bank performance affect expected mergers (the expected number of mergers is largest for banks with top-rated management) and that expected mergers fall with a rating downgrade. Hagendorff, Collins and Keasey (2008) study international merger patterns and report that bidding banks realize higher returns when targeting low protection economies (most European economies) than bidders targeting institutions which operate under a high investor protection regime (the US). Finally, Esty, Narasimhan and Tufano (1999) examine how interest rate levels and exposure affect the level of takeover activity and find that the level of acquisition activity is positively correlated with equity indices and negatively correlated with interest rates. A summary of bank-related merger studies is presented in Table 3.1.

Testable predictions for merger activity in the banking industry, synthesized from the discussions in Sections 1 and 2, are as follows:

Neoclassical Structural Shock Hypothesis

H_O1: Merger activity, measured as the number of annual industry mergers, will increase significantly following deregulation, measured by the passage of the 1994 Riegle-Neal Interstate Banking Act and the 1999 Graham-Leach-Bliley Act.

H_A1: Merger activity is independent of deregulation, measured by the passage of the 1994 Riegle-Neal Interstate Banking Act and the 1999 Graham-Leach-Bliley Act.

H_O2: Merger activity, measured as the number of annual industry mergers, will increase significantly following economic shocks, measured as the proxy variables *economic shock index* and *cash flow volatility*.

H_A2: Merger activity is independent of economic shocks, measured as the proxy variables *economic shock index* and *cash flow volatility*.

H_O3: Merger activity, measured as the number of annual industry mergers, will increase significantly following significant increases in growth opportunities, measured as the *RRV Value/Book* ratio.

H_A3: Merger activity is independent of increases in growth opportunities, measured as the *RRV Value/Book* ratio.

Behavioral Stock Misvaluation Hypothesis

H_O4: Merger activity, measured as the number of annual industry mergers, will occur during periods of industry stock misvaluation, captured by the variable *RRV valuation error*.

H_A4: Industry merger activity is independent of industry stock misvaluation, captured by the variable *RRV valuation error*.

H_O5: Industry stock misvaluation, captured by the variable *RRV valuation error,* is correlated with, and responds to, changes in industry financial fundamentals, captured by the variable *cash flow volatility*.

H_A5: Industry stock misvaluation is independent of changes in industry fundamentals, captured by the variable *cash flow volatility.*

Recent Bank Deregulation

The U.S. banking industry has traditionally been one of the most heavily regulated industries in the county. Following the stock market crash of the late 1920's, increased regulatory oversight produced many new restrictions, including the separation of deposit taking from securities underwriting. Beginning in the late 1970's, federal and state governments began to gradually ease restrictions on banking activity. State banks, thrifts and bank holding companies were allowed bank branch networks across state lines. In 1994, the Riegle-Neal Interstate Banking and Branching Efficiency Act amended the laws governing federally chartered banks to allow them interstate branch networks as well. This deregulatory act essentially marked the end of geographic restrictions on banking activity as it had existed in the U.S. for the past century. Much work has been done to study the effects of interstate banking; a common empirical finding is that bank deregulation spurred merger activity (Winston, 1998; Mitchell and Mulherin, 1996), the end result of which was a more competitive industry made up of more profitable banks (Winston, 1998; Stiroh and Strahan, 2003). Because the extant literature has shown the Riegle-Neal act to have a significant effect on several facets of the banking industry, including merger activity, we include it in this study.

The second major deregulatory event to occur during our sample period concerns the restrictions on permissible banking products. In response to active bank lobbying, the Federal Reserve, beginning in the mid-1980s, gradually relaxed restrictions on securities underwriting and trading imposed by the Banking Act of 1933, also known as the Glass-Steagall act. The Glass-Steagall act severely limited bank securities activity and the affiliation between banks and securities firms. The restrictions on the permissible products, and related revenues, were repealed in a series of regulatory interpretations from the late 1980's to late 1990's. In 1999, the Financial Modernization Act, also known as the Gramm-Leach-Bliley Act, finally eliminated the last remaining restriction around the combination of banking, securities and insurance operations. Arguably more so than any other deregulatory event, the gradual repeal of the Glass-Steagall restrictions during the 1990's changed the nature of commercial banking and its competitive position in the financial services industry. Due to the significance of the Gramm-Leach-Bliley Act and its effects on the industry, we include it in this study.

Data Sample and Variable Construction

The sample period used for this study includes the years 1979 to 2009. This time period has several characteristics useful for this study: it is long enough to span several decades of change, including three significant deregulatory acts in 1982, 1994 and 1999; it includes the bull markets runs in the mid-1980's, 1990's and mid-2000's; and it includes periods of technological innovation, the most significant of which was the early 1990's period. We construct the data sample by first selecting firms belonging to the Fama and French 49 industry classification code 45 (Banks) from the CRSP monthly stock file, which is made up of publicly traded firms on the NYSE, AMEX and Nasdaq stock exchanges. The Fama and French code 45 (Banks) comprises SIC codes from 6000 to 6199 and includes commercial banks, savings and loans and other depository institutions. We identify firms with CRSP Share Code 10 and 11 (ordinary common shares), and exclude foreign firms (incorporated outside the U.S. and ADRs). The remaining sample of firms consists only of domestic public U.S. banks. We track every firm using its unique CRSP identifier, PERMNO, each year over the sample period. Entry, exit and merger activity is confirmed against SDC IPO data or manually confirmed against financial press stories from LexisNexis.

The proxy for economic shocks used in this paper is a modified version of the variable used in Harford (2005). Harford's "economic shock index" is the first principal component of seven economic shock variables. The variable is intended to capture the magnitude of multiple indicators of economic shock; each economic shock variable is measured as the median absolute change in the underlying economic variable, per industry year. The variables are: return on sales (ROS), return on assets (ROA), asset turnover, research and development scaled by assets, capital expenditures scaled by assets, employee growth and sales growth. Because banks, on average, spend relatively little on research and development and physical capital expenditures, we remove from the index calculation the variables research and development scaled by assets and capital expenditures scaled by assets. Robustness checks using the complete index of seven variables do not change the qualitative findings in this paper. These variables are computed using annual data from the CRSP/Compustat Merged Fundamentals Annual file for the firms belonging to the banking industry.

Figure 3.1 displays the time-series of the calculated economic shock index. As evidenced by Figure 3.1, the index spikes sharply during the economic recovery following the 1987 stock market crash. The index declines during the subsequent savings and loan crisis but rises steadily until 2000 when it begins to decrease steadily throughout the 2000's. Notably, the times series increases in the years immediately preceding the deregulatory events. More importantly, when compared with the merger activity in Figure 3.4 it becomes apparent that increases in the economic shock index precede large increases in merger activity. This initial result is consistent with evidence in Winston (1998) and Mitchell and Mulherin (1996).

We next build on recent research by Garfinkel and Hankins (2011) who find that merger activity is significantly driven by increases in firm cash flow uncertainty. While Garfinkel and Hankins (2011) use two measures of uncertainty, we use the measure that is most applicable to income uncertainty in an industry like banking that does not produce physical goods. The measure of uncertainty used in this study is the volatility of operating income before depreciation (OIBD). We also measure OIDB quarterly by firm and use the last 20 periods to calculate the measure. We scale OIDB by Total Assets (TA) to remove any skewness attributable to large firms. The uncertainty measure is calculated as follows:

$$\sigma\left(\frac{OIDB}{TA}\right) = standard\ deviation\ of\ \left(\frac{OIDB}{TA}\right) over\ quarters\ t = 0, \dots, -19$$

We also employ two measures used by Garfinkel and Hankins (2011) to capture the effects of cash flow shocks:

5% increase = 1 if the current quarter's value of $\sigma\left(\frac{OIDB}{TA}\right)$ *is at least 5% higher than the previous years' (same quarter) value*

10% increase = 1 if the current quarter's value of $\sigma\left(\frac{OIDB}{TA}\right)$ *is at least 10% higher than the previous years' (same quarter) value*

The 5% and 10% increase measures are both scaled by annual firm count within the industry to account for the growing size of the industry over time.

Figure 3.3 presents the time-series of industry cash flow volatility as compared to the calculated value for the RRV industry error variable (M/V). A notable pattern in the time-series is the negative correlation between the two series from the start of the sample period, 1979, until around the year 2000, when the series begin switch to a positive correlation. This pattern, when compared against aggregate merger activity presented in Figure 3.4, shows that the bulk of the merger activity during the sample period takes place while industry cash flow volatility is increasing and the RRV industry error measure is decreasing (1979-2000). As we hypothesize, this pattern fits the profile of an increasing volatile industry which results in an increasingly larger discount to (a measure of) "true" value. Empirical testing in section 6 formally tests the hypothesis that increasing uncertainty drives industry merger activity.

We use valuation variables from Rhodes-Kropf et al. (2005) to quantify misvaluation at the industry level. Rhodes-Kropf et al. decompose the market to book (M/B) ratio into two variables. The first variable is a measure of market price to fundamentals (M/V); the second a measure of fundamentals to book value (V/B). As in Rhodes-Kropf et al. (2005) we run industry-level cross-sectional regressions of firm market equity on firm accounting data each year to decompose M/B. In order to do so, we match each firm's fiscal year accounting data from Compustat with CRSP market value of equity at fiscal year-end and run the following regression:

$$\mathbf{m}_{it} = \alpha_{0jt} + \alpha_{1jt}\mathbf{b}_{it} + \alpha_{2jt}\ln(\mathbf{NI})^{+}_{it} + \alpha_{3jt}I_{(<0)}\ln(\mathbf{NI})^{+}_{it} + \alpha_{4jt}\mathbf{LEV}_{it} + \varepsilon_{it} \tag{1}$$

where **m** is market value of firm equity, **b** is book value of firm equity, **NI** is firm net income and **LEV** is firm financial leverage. Market equity $\mathbf{m}_{it}$ and book value of equity $\mathbf{b}_{it}$ are computed in logs (and notated in lowercase) to account for the right skewness in the accounting data. $\mathbf{NI}^{+}$ is the absolute value of net income and $I(<0)\ \ln(\mathbf{NI})^{+}_{it}$ is an indicator function for negative net income observations. Estimating this cross-sectional regression for each industry-year, allows the industry multiples (α_k, k = 0,…, 4) to vary both over time and across industries.

We apply the industry-year multiples and their long-run industry averages from the regression to the firm-level, time-varying accounting information to compute the industry market-to-value (M/V) and long-run value-to-book (V/B) ratios, respectively. V/B measures the component of market valuation that reflects growth opportunities based on long-run industry average multiples. M/V measures the component of market valuation that reflects potential misvaluation based on the deviation of short-run industry multiples from their long-run average values. RRV (2005) argue that the deviation could be interpreted as an “overheated” segment of the market recognized by management of firms within the industry, given private information that was unknown to the market at the time. The authors note that this view does not require that assets be mispriced in an asset-pricing sense.

Figure 3.2 displays the time-series of the calculated RRV M/B decomposition. The figure displays the value of the median annual M/B ratio of the industry, the median annual V/B ratio of the industry and the median annual M/V ratio of the industry. The values are displayed in lognormal format. A notable feature of the RRV time series in Figure 3.2 is that the estimated value of the industry error variable (M/V) is positive and greater than the estimated value of the value to book variable (V/B) from the start of the sample period, 1979, and declines until switching magnitudes and becoming negative in 1991. Similarly, the estimated value of the value to book variable (V/B) is negative and lower than the estimated value of the industry error variable (M/V) from the start of the sample period, 1979, and increases until switching magnitudes and becoming positive in 1991. Subsequent to 1994 the two variables diverge, with the long-run growth options variable (V/B) becoming increasing positive and the industry error variable (M/V) becoming increasingly negative. The two variables begin to converge after 2002 before they both finish negative in 2009 during the financial crisis.

As noted, RRV argue that the V/B ratio reflects long-run growth opportunities while the M/V ratio can be interpreted as short-run market price deviations from "true" value. In this context, the patterns shown in Figure 3.2 may be interpreted as reflecting the shift within the banking industry, beginning around the 1980's, to a more profitable yet risky product mix. This shift is reflected in the increasing level of the V/B ratio as the market forecasts future profit growth in the industry, incorporating in part the anticipated expansion of product markets as Glass-Steagall restrictions are gradually repealed and interstate banking and technology changes force less efficient banks out of the market place (Stiroh and Strahan, 2003). The increasing risk profile of the median bank in the industry is reflected in the divergence of the M/V ratio, the discount to "true value", from the V/B ratio, the "true" value, until 2003 when the two ratios begin to converge again.

In order to test the hypothesis that shifts within the industry to more volatile sources of revenue drove the observed increases in revenue and cash flow volatility over time, we construct variables that measure bank product mix and product revenue contribution to total revenue. To do so we disaggregate bank revenue (at the industry level) into two broad categories: *Interest and Investment Revenue* and *Trading and Fee Revenue*. We follow previous work on bank product mix and risk (notably DeYoung and Roland, 2001) to categorize revenue into buckets that represent traditional vs. newer emerging banking income sources. *Interest and Investment Revenue* is defined as the sum of loan revenue and investment revenue. Loan revenue is the sum of the income (both interest and fee) from the bank loan portfolio. Investment revenue is defined as the income (interest, dividend and capital gains/losses) from the bank's investments not held in trading portfolios. *Trading and Fee Revenue* is essentially all remaining revenue not categorized as *Interest and Investment Revenue* and is defined as the sum of trading, fee-based and deposit revenue. Trading revenue is defined as the income (interest, dividend and capital gains/losses) from the bank's trading portfolios. Deposit revenue is the total of all fees charged to customers for deposit services. Fee-based revenue includes fees from all other products, including trust department income, credit card fees, real estate operations and all other fees and charges not included in other categories. These categories capture 100% of reported bank revenue.

Revenue data is sourced from Compustat. The variable *median fee revenue percentage* is calculated annually as the median industry ratio of firm *Trading and Fee Revenue / Total Revenue*. The variable *median interest revenue percentage* is calculated annually as the median industry ratio of firm *Interest and Investment Revenue / Total Revenue*.

The variable *std. dev. of revenue volatility* captures the volatility of total bank revenue. We measure total revenue annually by firm and use the last 5 years to calculate the measure. We scale total revenue by firm total assets to remove any skewness attributable to large firms. Annual data is used in order to capture the granular breakdown of revenue described above; quarterly Compustat reports do not capture these measures as completely. Revenue volatility is calculated as follows:

$$\sigma\left(\frac{TotalRevenue}{TotalAssets}\right) = standard\ deviation\ of\ \left(\frac{TotalRevenue}{TotalAssets}\right) over\ years\ t = 0, \ldots, -5$$

Table 3.2 reports descriptive statistics for the variables used in regression analysis. All variables are approximately normally distributed with the exception of the *std. dev. of cash flow volatility*. The log transform of this variable is normally distributed and is used, for that reason, in later regression analysis. Table 3.3 presents the correlation of explanatory variables. The M/B ratio and the two RRV variables decomposed from it, M/V and V/B, are all highly correlated. The two RRV variables are also highly correlated with the *ln_std. dev. of cash flow volatility*. In turn, *ln_std. dev. of cash flow volatility* is highly correlated with *median fee revenue percentage* and *median interest revenue*. As a matter of construction, the two revenue percentage variables are inversely related.

Evidence of Neoclassical and Behavioral Factors that Drive Merger Activity

In order to gain an understanding of industry merger activity within the context of the contemporary structure of the industry, we document the entry and exit activity over the sample period 1979 to 2009. Table 3.4 reports the count of banks reported on CRSP for the Fama and French bank code

45. As can been seen, the number of entries to the industry (for purposes of this analysis defined as listing on a public exchange) spikes during the bull markets of the mid 1980's and 1990's, averaging roughly 100 annual new listings during those periods. Entries decrease and exits increase during the recessions of the early 1990's and 2000's. The 1990's are characterized by an expanding industry while the count during the 2000's consistently shrinks. Overall, Table 3.4 depicts an industry with a steadily growing number of participants and significant entry and exit activity. The industry ends in 2009 with more than double the number of public banks (564) than at the start of the sample period in 1979 (212).

Figure 3.4 shows the timeline of merger activity. The predominate pattern is one of increasing merger activity throughout the sample period. Merger count increases steadily throughout the 1990's, averaging roughly 40 mergers a year and peaking at 88 mergers in 2000. Merger activity falls during the early 2000s recession but picks up again during the middle of the decade before falling drastically during the financial crisis. Figure 3.5 shows the annual merger activity by total market value of equity. Beginning in the mid-1990's total deal value increases dramatically, averaging over $50 million per year with a high of $175 million in 2004.

A noticeable trend in the merger time-series data, as seen in Figure 3.4, is the increase in merger activity following the two deregulatory acts studied in this paper. Following the Riegle-Neal act of 1994, average annual merger activity increases to 48 for the five year period following passage (1994 to 1998). As shown in Table 3.5 this marks an 83% increase from the 26.2 average per year for the period 1989 to 1993. A t-test of difference in means for the two series produces a t-statistic of 3.92, significant at the .01% level. Following the Graham-Leach-Bliley act of 1999 the average annual merger activity increases from 48 per year (1994 to 1998) to 64.8 per year (1999 to 2003). The t-statistic for a t-test of a difference in means is 1.90, indicating significance at the 10% level.

These findings are consistent with evidence in the extant literature that industry deregulation spurs merger activity (Mitchell and Mulherin, 1996; Harford, 2005; and Ovtchinnikov, 2010). As a further test of the influence of deregulation and other fundamental shock variables, we next perform univariate tests of both the fundamental shock factors and behavioral factors. Table 3.6 reports the results of OLS analysis of the effect of structural and behavioral explanatory variables, lagged one year (time *t=-1*), on annual industry merger count (time *t=0*). Results of univariate tests of structural variables are consistent with predictions in $H_0$1 as well as evidence from test of the merger time series presented in Table 3.5.

We use an indicator variable to measure the impacts of industry deregulation on merger activity. *Dereg* is an indicator variable that takes on a value of 1 for each annual observation beginning two years before to two years after a deregulatory event, 0 otherwise. Evidence from the extant literature shows that the market efficiently anticipates the passage of deregulatory events and often acts before its passage (Becher, 2009) thus we begin to measure an act's impact two years prior to its passage. Results in Table 3.6 show that both deregulatory indicator variables, *Dereg (1999)* and *Dereg (1994 and 1999),* are positive and statistically significant. Increases in the economic shock variable increase merger count in the subsequent year, although the effect is not significant. The sign, but not the magnitude, of this variable is similar to the effect documented in Mitchell and Mulherin (1996) and Harford (2005).

Results of univariate tests of behavioral variables presented in Table 3.6 are consistent with predictions from hypothesis $H_0$3. The RRV long-term growth variable, median industry V/B ratio, is positive and statistically significant, consistent with the notion that increases in long-run growth opportunities spur merger activity. As predicted in hypotheses $H_0$4, the RRV industry error variable, median industry M/V ratio, is negative and statistically significant. This result can be interpreted as follows: given the behavior of the RRV variables in Figure 3.2, M/V decreasing over time while V/B increases, the increasing misvaluation (negative M/V ratio) increases merger activity.

The univariate analysis thus far has tested the hypotheses that changes in one year lagged explanatory variables drive current year's merger activity. However, it may be the case that several years worth of cumulative change drive merger activity for several subsequent years. In order to explore this possibility, and as a further robustness check, we test the hypothesis that the sum of two prior years (time *t=t-1,t-2*) changes in fundamental and behavioral variables drive changes in merger count for the subsequent three years (time *t=0, t+1,t+2*). The test results presented in Table 3.7 support the tests of a one year lag presented in Table 3.6, and with greater statistical significance. The economic shock variable increases merger count in the subsequent years, although the effect is still not significant in this specification. Both deregulatory indicator variables *Dereg (1999)* and *Dereg (1994 and 1999)* are positive and statistically significant. In this specification, however, the variable that represents both deregulatory acts, *Dereg (1994 and 1999),* is slightly more powerful than the 1999 deregulatory variable alone. The RRV long-term growth variable, V/B ratio, is positive and statistically significant while the industry error variable, M/V ratio, is negative and statistically significant.

Table 3.8 reports the results of multivariate OLS analysis of the effect of structural and behavioral explanatory variables, lagged one year (time *t=-1*), on annual industry merger count (time *t=0*). We test specifications that allow us to run a horse race between fundamental shock variables and behavioral variables. Estimates from Model 1 show that a structural shock variable, *Dereg (1999),* is positively and significantly related to next year merger levels. The behavioral variable, *V/B,* a proxy for long run growth opportunities is also positively and significantly related to next year merger levels. The estimate for the structural shock variable, *Econ Shock Index,* is positive but not significant. Due to the presence of multicollinearity (see reported correlations in Table 3.3) specifications that include the *Ind Error* and *V/B* variables produce inaccurate estimates. Substituting *Ind Error* for *V/B*, Model 2 reports essentially the same magnitude and direction for the two structural shock variables, *Econ Shock Index*, *Dereg (1999)*, while the *Ind Error* variable is negative and significant. Results from both models support results from univariate analyses.

Models 3 and 4 control for the effects of market power and industry efficiency increases. As discussed in the literature review, the bank merger literature documents evidence that industry mergers are, in part, motivated by the desire to increase both cost efficiency and market power. The *Herfindahl-Hirschman* index is a proxy for market power and *Dispersion in ROS* is a gauge of the dispersion of firm cost efficiency across the industry. Introducing these control variables in models 3 and 4 produce coefficients of similar direction and magnitude to that reported in models 1 and 2, however, the structural shock variable *Dereg (1999)* loses significance.

The Influence of Competition, Product Mix and Idiosyncratic Volatility on Merger Activity

In this section, we examine whether increased product market competition and a shift toward more volatile revenue sources in the banking industry explain increases in cash flow volatility, and ultimately, merger activity over time.

Figure 3.6 displays a time-series comparison of product market competition (median industry ROA) and firm revenue volatility. Following Irvine and Pontiff (2008) we use return on assets (ROA) as a proxy for competition. Firms with less competition and more market power will generate higher returns, on average, than those firms with more competition and less market power. Irvine and Pontiff (2008) test the cross section of industries in the Fama French 49 and find that idiosyncratic stock volatility is negatively and significantly related to firm ROA; the ROA time-series declines over the period 1964 – 2003 while idiosyncratic volatility rises over that same period, consistent with the notion than increases in competition increase firm risk. Moreover, they examine deregulated industries and find that the banking industry (among others) experiences increases in idiosyncratic risk after deregulation.

As noted, the measure for idiosyncratic volatility of the banking industry used in this paper, cash flow volatility, also increases over the sample period and begins a rapid increase after 1990 (Figure 3.3). Following the Riegle-Neal act of 1994, the standard deviation of industry cash flow volatility increases to rough 87% for the five year period following passage (1994 to 1998). As shown in Table 3.9 this marks a 10% increase from the 79% average per year for the period 1989 to 1993. A t-test of difference in means for the two series is not significant. However, following the Graham-Leach-Bliley act of 1999 the average annual merger activity increases from 87% (1994 to 1998) to 180% (1999 to 2003). The t-statistic for a t-test of a difference in means is 4.44, indicating significance at the 1% level.

It may be that an increasingly risky industry drives the power of the RRV misvaluation variable to explain merger activity. As discussed, the time-series of industry cash flow volatility and the calculated value for the RRV industry misvaluation variable (M/V) displays a negative correlation from the start of the sample period, 1979, until around the year 2000, when the series begin switch to a positive correlation (Figure 3.3). As we hypothesize, this pattern fits the profile of an increasing risky industry which results in an increasingly larger discount to "true" value. We analyze the validity of this hypothesized relation by examining the time-series relation between industry misvaluation and industry cash flow volatility and shocks. Table 3.10 reports the results of OLS analysis of the effects of log-transformed industry cash flow volatility and proxies for cash flow shocks on industry misvaluation. Model 1 of Table 3.10 reports a significant negative relation between industry cash flow volatility and industry valuation error. The effect of the estimated coefficient may be interpreted such that as industry cash flow volatility increases so too does the level of misvaluation. As shown in Figure 3.2, the level of the industry error variable (M/V) is lower than the "true" value (V/B); thus the level of industry error is being driven further from "true" value as it decreases. Finally, cash flow shock variables are insignificant, indicating that shocks do not drive industry valuation error.

We also examine the volatility of firm revenue as a measure of risk. The percentage of revenue from trading and fee revenue (median industry fee revenue percentage) captures the shift over time to more volatile sources of revenue. As shown in Figure 3.6 the time series of industry median ROA peaks at 2.8% in 1992 and then begins a steady decline until the end of the sample period in 2009. This downward trend suggests increased product market competition brought about by deregulation; the series is negatively correlated with increases in industry revenue volatility. Revenue volatility jumps considerably at the end of the 1990's as the Federal Reserve relaxed restrictions on trading revenue prior to passage of the Gramm-Leach-Bliley Act and commercial banks began to shift their product mix in favor of trading and capital markets products. Revenue volatility again jumps in the mid-2000's as mortgage securitizations and derivate products drove profitability at many banks.

We analyze the validity of our competition and product mix explanation by examining the time-series relation between industry revenue volatility and proxies for competition. Table 3.11 reports the results of OLS analysis of the effect of industry median ROA and industry turnover on industry median revenue volatility. We again follow Irvine and Pontiff (2008) in the use of a second competition variable: turnover. Industry turnover (exit and entry from an industry) may proxy for the market power of the firms within the industry. Model 1 of Table 3.11 reports that contemporaneous industry median ROA has a significantly negative relation with industry median revenue volatility. Model 2 reports a negative but insignificant relation for a one-period lagged ROA. Model 3 reports a negative but insignificant relation for the variable turnover, the opposite of the predicted effect. Adding in controls for structural shocks, Model 4 reports that contemporaneous median ROA maintains a significantly negative relation with industry median revenue volatility while turnover remains insignificant. Taken as a whole, results in Table 3.11 support the notion that increased product market competition significantly increase revenue volatility.

The previous section provides evidence that greater industry competition leads to higher industry volatility. This section examines the relation between industry revenue volatility and firm product mix. Do increases in revenue volatility lead to increases in cash flow volatility? Or, does diversification of product offerings buffer the effects of revenue volatility and produce more stable cash flows? The extant literature provides evidence that deregulation of the industry led to greater product innovation; a change which, in turn, led to a greater reliance on revenue from non-interest income sources. These activities had the effect of increasing risk, financial leverage and earnings volatility (DeYoung and Roland, 2001, Stiroh and Rumble, 2006). As shown in Figure 3.7 the contribution of fee revenue to total revenue for the median bank in the sample grows from roughly 5% at the start of the sample period to greater than 35% at the end of the sample period.

We examine the time-series relation between industry cash flow volatility and variables representing revenue volatility and percentage revenue from trading and fee revenue vs. interest income. Table 3.12 reports the results of OLS analysis. The results in Table 3.12 support the notion that shifts to a greater percentage of revenue from more volatile sources of revenue, proxied by trading and fee revenue, are positively and significantly related to cash flow volatility. Model 1 reports a positive and highly significant relation between one-period lagged fee revenue percentage and industry cash flow volatility, *LN (Cash Flow Vol, St Dev)*. Model 2 reports an identical magnitude and significance but negative relation for one-period lagged interest income revenue, a traditionally less volatile source of revenue. Similarly, Model 3 reports a positive and highly significant relation between one-period lagged industry median revenue volatility and industry cash flow volatility. Univariate competition variable regressions are insignificant. Multivariate regression results in models 7 and 8 support the univariate evidence that increases in fee revenue percentage and industry median revenue volatility are significantly related to industry cash flow volatility.

We have thus far established that industry revenue volatility and fee revenue percentage are significant drivers of industry cash flow volatility and that industry cash flow volatility is significantly related to industry misvaluation error. We next test the hypothesis that these changes in fundamentals subsume the effect of the RRV industry misvaluation error as drivers of industry merger activity. We analyze the validity of this hypothesis by examining the time-series relation between industry merger count and a range of variables tested in previous sections.

Table 3.13 reports the results of multivariate OLS analysis of the effect of the lagged one year (time *t=-1)* variables tested above on annual industry merger count (time *t=0*). Model 1 shows that shocks have a stronger effect on merger activity than does revenue volatility. The structural shock variable *Dereg (1999)* has a positive and significant impact on industry merger activity, while the industry revenue volatility variable has a positive but insignificant impact on merger activity. Adding industry valuation error to the specification in Model 2 renders the influence of the three variables from Model 1 insignificant; while industry valuation error significantly increases merger activity (a negative sign on the coefficient indicates an increase in misvaluation). The specifications in Models 3 and 4 substitute industry fee revenue percentage for revenue volatility. The results in Model 3 demonstrate that source of revenue has a greater effect on industry merger activity than do structural shocks; while the coefficients on all three variables are positive and significant, the coefficient for the fee revenue percentage variable is significant at the 99% level, versus >95% for the structural shock variables. Once again, adding industry valuation error to the specification in Model 4 reduces the influence of the three variables from Model 3. In this specification, however, the structural shock variable, economic shock index, is positively and significantly related to industry merger activity, while the industry valuation error variable also significantly increases merger activity.

Substituting industry cash flow volatility for source of revenue on Models 5 and 6, yields similar results. While the coefficients on all three variables in Model 5 are positive, the coefficients for industry cash flow volatility and *Dereg (1999)* are both significant at the > 95% level. Adding industry valuation error to the specification in Model 6 once again reduces the influence of the three variables from Model 5. However, the structural shock variable, *Dereg (1999)*, is positively and significantly related to industry merger activity, while the industry valuation error variable also significantly increases merger activity. Model 7 provides a complete specification, including the control variables *Herfindahl-Hirschman* index and *Dispersion in ROS*, proxies for market power and dispersion in firm cost efficiency, respectively. Although the model specification likely suffers from multicollinearity issues (See Table 3.11 for details) that reduce the reliability of the coefficient estimates of magnitude and direction, the specification is useful to assess the relative significance of the competing structural and behavioral proxies. Results in Model 7 support the theory that increased reliance on volatile fee revenue creates a more heterogeneous set of riskier banks within the industry which, in turn, leads to increasing takeover activity. The coefficient for industry fee revenue percentage remains positive and significant while coefficient for the industry valuation error variable is insignificant. Furthermore, the significance of the structural shock variables is subsumed by the effect of the industry fee revenue percentage proxy. Finally, the high (adjusted) R^2 value of the regression, (.80) .85, demonstrates the power of the model specification to explain one-period ahead industry merger activity.

Conclusion

We study the U.S. banking industry over the last thirty years in order to provide new evidence on the determinants of aggregate industry merger activity. The U.S. banking industry provides a good laboratory to contrast neoclassical and behavioral hypotheses of merger activity. The industry has undergone significant deregulation over the last thirty years which helped create an increasingly profitable and heterogeneous industry characterized by product innovation and diversification. This, in turn, resulted in higher levels of growth options and widening product margins. In addition to deregulatory and technological changes, the industry was also subject to a significant run-up in average stock prices during the bull market run of the 1990's and, to some extent, during the mid-2000s.

We use measures of economic shock, deregulatory legislative acts, stock misvaluation and industry revenue and cash flow uncertainty to test competing neoclassical and behavioral merger theories. Test results indicate that merger activity is significantly related to both structural industry change and the RRV aggregate stock misvaluation variable. Merger activity increases significantly following the two deregulatory acts examined (1994 and 1999) while showing a weaker positive link to a broader proxy for economic shock. Merger activity is also positively and significantly linked to industry growth options and RRV aggregate stock misvaluation. However, we show that RRV aggregate stock misvaluation increases significantly with increases in industry level cash flow volatility and that cash flow volatility increases with increases in industry revenue volatility and fee revenue percentage. We tie the increase in industry revenue and cash flow volatility to increased industry competition after several deregulatory events. Finally, we show that increases in the percentage of fee revenue (a more volatile source of revenue than interest income) as a percentage of total revenue subsumes the power of behavioral variables and other structural variables to explain subsequent merger activity. Given the evidence that fee revenue percentage significantly drives industry level cash flow volatility we conclude that the deregulation of the banking industry promoted an increased reliance on new and profitable, yet volatile, fee revenue sources that, in turn, created a more heterogeneous set of banks within the industry. This widening dispersion of profitability and risk profiles within the industry ultimately led to increases in industry takeover activity.

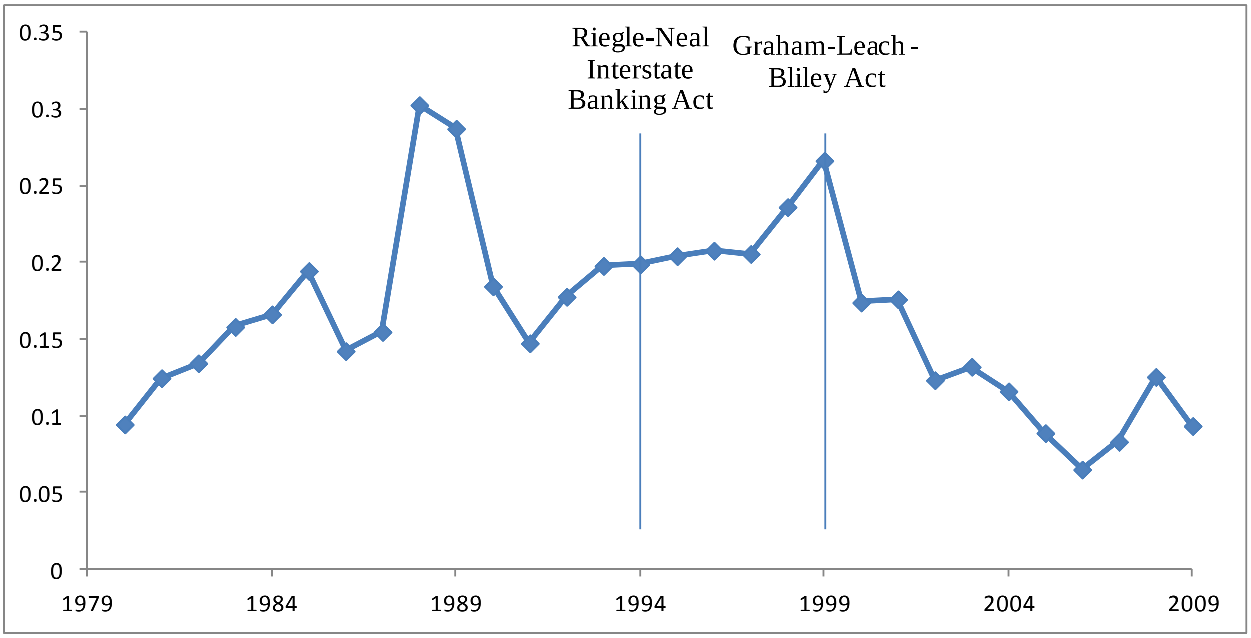

Figure 3.1: Annual time-series comparison of economic shock index values

This table presents a time-series plot of the calculated values of Harford 's (2005) economic shock index. The index is the first principal component of seven economic shock variables; each economic shock variable is measured as the median absolute change in the underlying economic variable, per industry year. The variables are: return on sales (ROS), return on assets (ROA), asset turnover, research and development scaled by assets, capital expenditures scaled by assets, employee growth and sales growth.

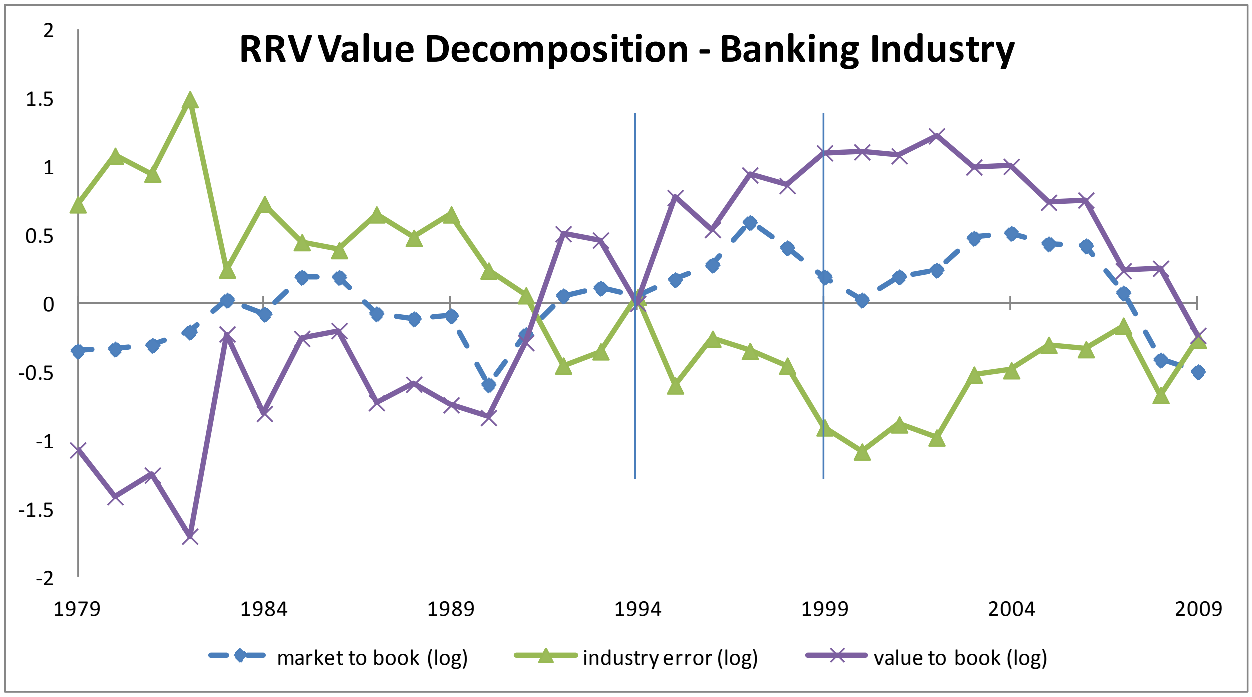

Figure 3.2: Annual time-series of market to book decomposition

Market to book is the ratio of market value of equity to book value of equity. Industry error is defined as a measure of market price to firm fundamentals. Value to book is a measure of firm fundamentals to book value.

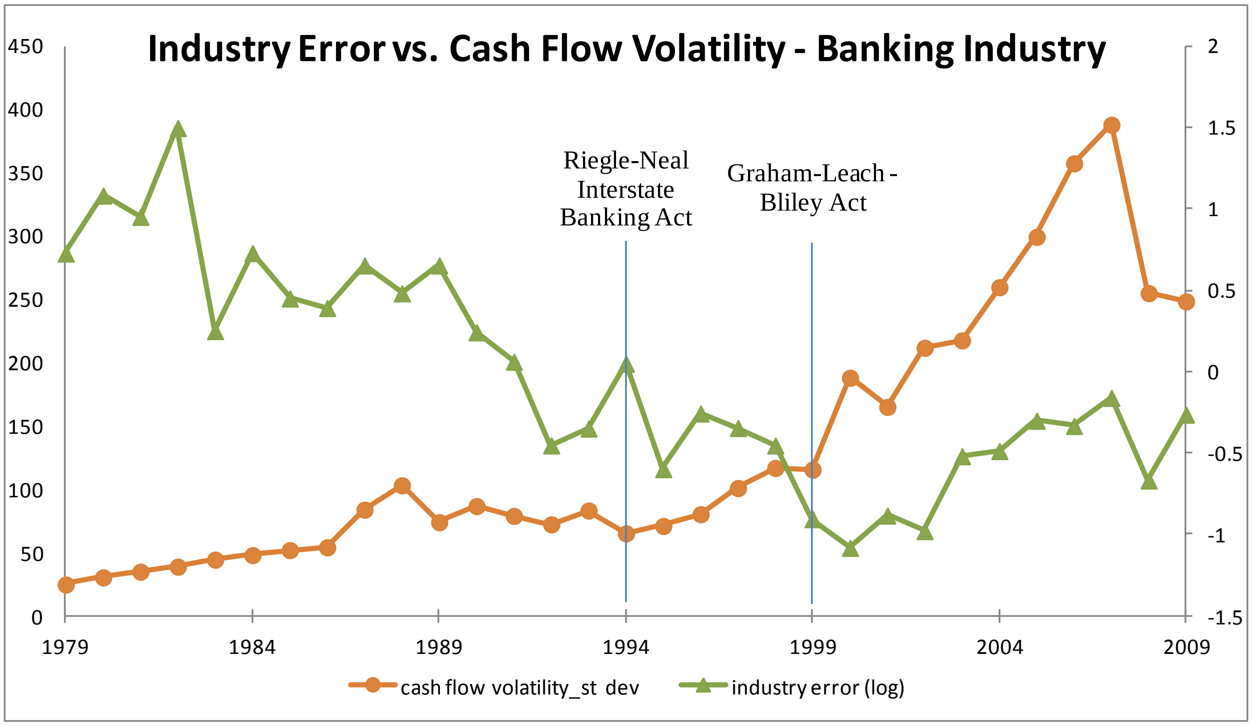

Figure 3.3: Annual time-series comparison of industry error, standard deviation of industry cash flows and merger activity (count)

This table presents a time-series plot of industry valuation error for the banking industry as compared to annual cash flow volatility of the banking industry. Industry valuation error is a proxy for industry level stock misvaluation; the measure is calculated using the Rhodes-Kropf et al. (2005) M/B decomposition. Cash Flow Volatility, a proxy for cash flow uncertainty, is the standard deviation of firms' past twenty periods of quarterly cash flow, measured as the firm's operating income before depreciation (OIBDP), and scaled by quarter-end firm total assets. Cash Flow Volatility_St Dev is the annual cross sectional standard deviation of Cash Flow Volatility across the banking industry.

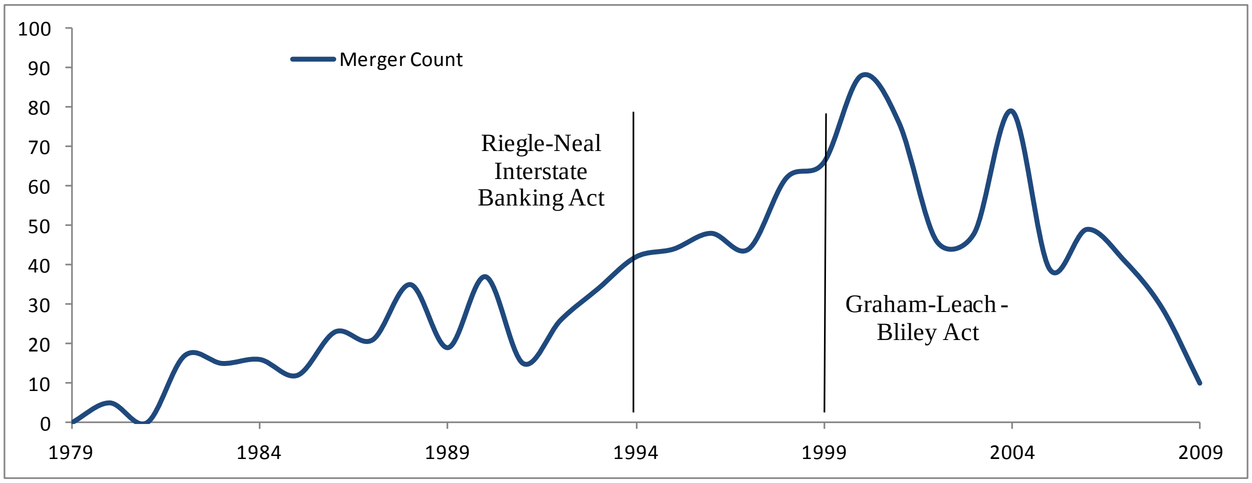

Figure 3.4: Annual time-series of merger activity (count)
This table presents a time-series plot of the number mergers for the sample period.

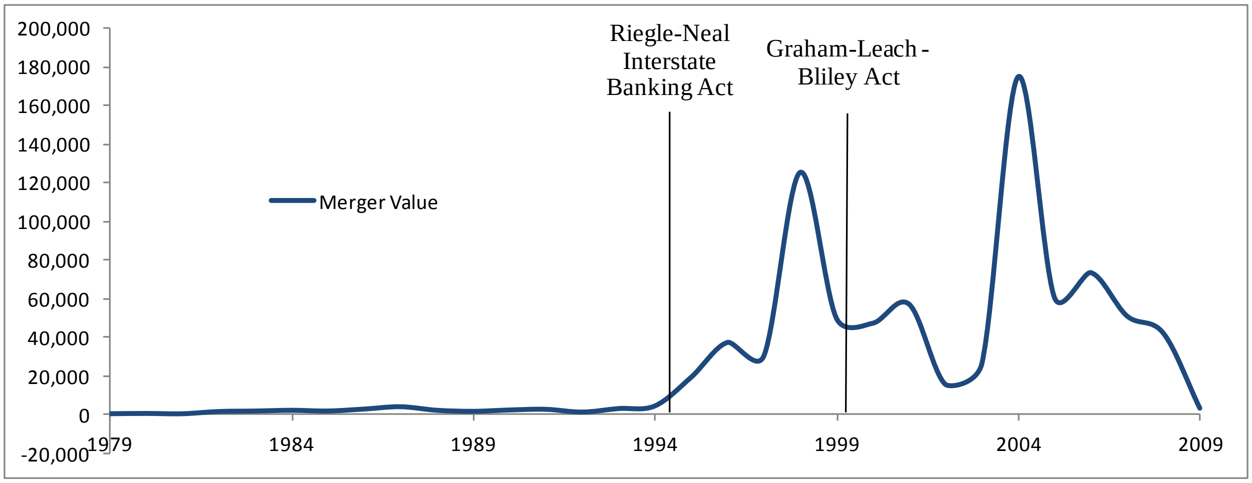

Figure 3.5: Annual time-series of merger value ($ mil)

This table presents a time-series plot of the annual market value of the target firms acquired for the sample period.

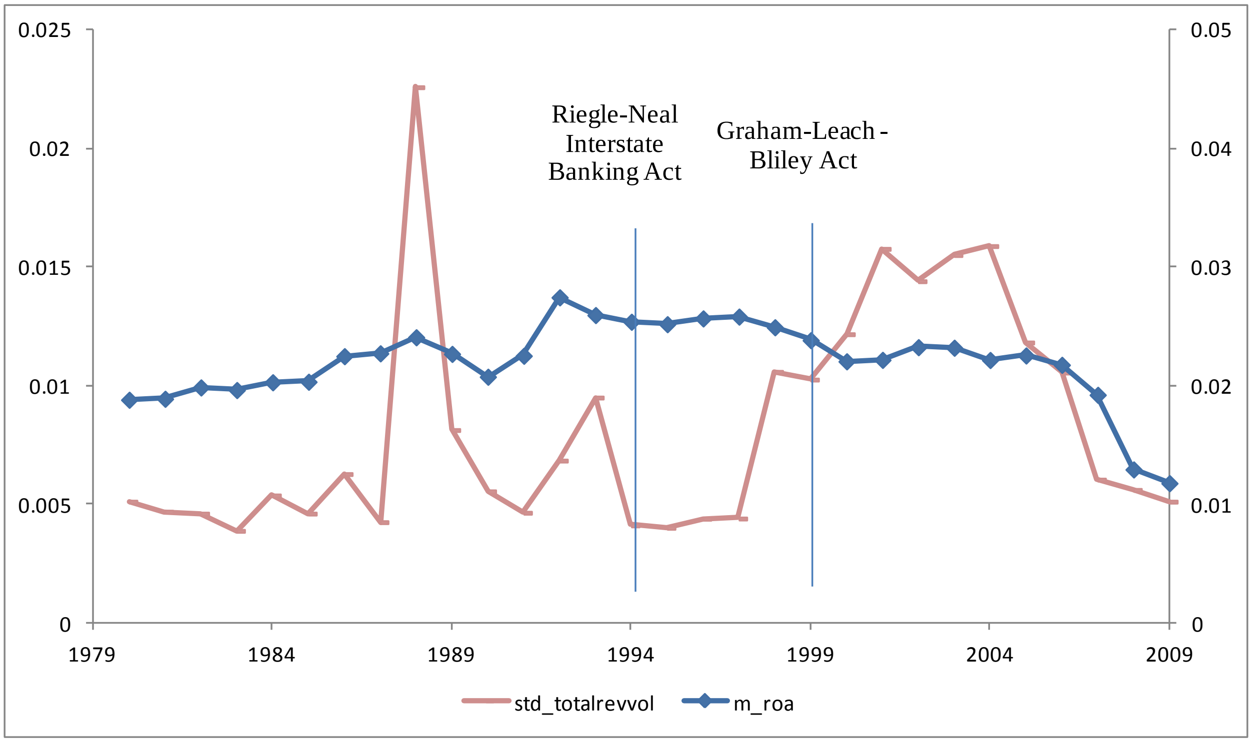

Figure 3.6: Annual time-series comparison of product market competition and bank revenue volatility This table presents a time-series plot of proxies for product market competition and revenue volatility. We use annual median industry return on assets (ROA) as a proxy for competition. Total revenue volatility is calculated annually as the standard deviation of 5 years of firm total revenue scaled by firm total assets. The variable standard deviation industry revenue volatility is the standard deviation of annual industry revenue volatility.

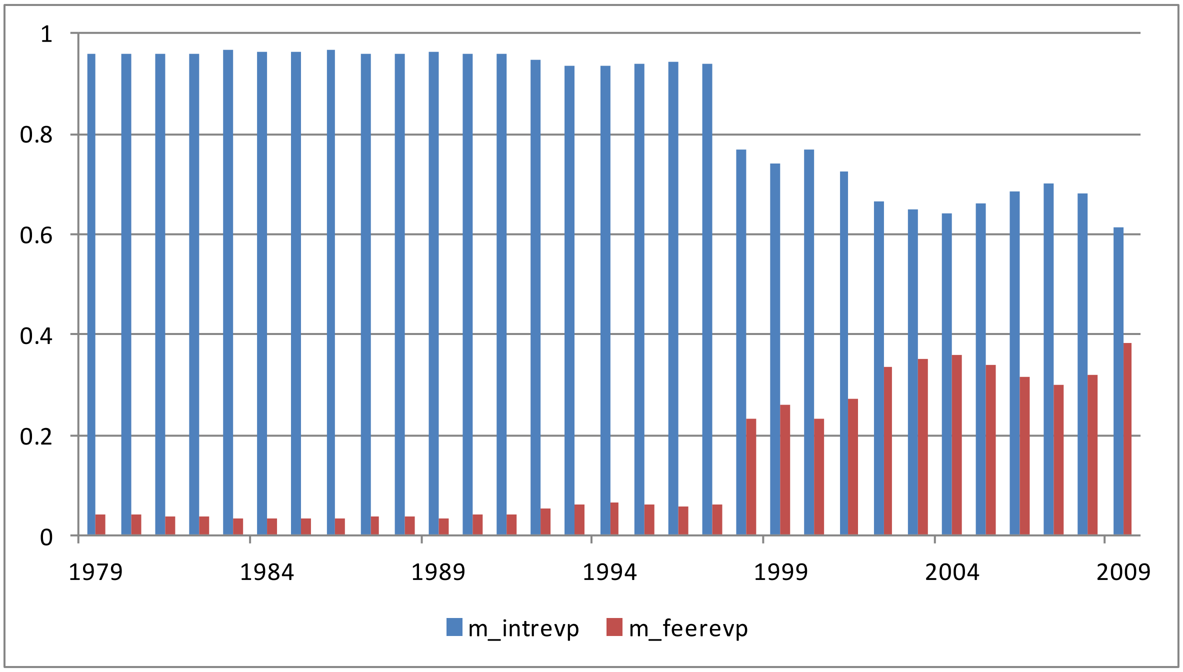

Figure 3.7: Annual time-series of contribution to total revenue
This table presents a time-series chart of percentage to total revenue from interest-income and fee income. The variable m_ intrevp is the percentage of total revenue from interest-income for the median bank in the sample. The variable m_ feerevp is the percentage of total revenue from interest-income for the median bank in the sample.

Table 3.1: Summary of studies on bank mergers and acquisitions

Authors	Time Period	Event Window	Number of Observations	Bidder Return (%)
Wealth Effects				
James and Wier (1987a)	1972 - 1983	(-1,0)	60 acquisitions	1.07
Neely (1987)	1979 - 1985	week 0	26 acquisitions	-1.23
Trifts and Scanlon (1987)	1982 - 1985	week 0	14 mergers	-1.73
Cornett and De (1991)	1982 - 1986	(-1,0)	152 bidders	0.55
Houston and Ryngaert (1994)	1985 - 1991	(-4,+1)	153 mergers	-2.32
Houston and Ryngaert (1997)	1985 - 1992	(-2, +1)	209 mergers	-2.30
Gupta, LeCompte and Misra (1997)	1979 - 1992	(-1,0)	138 acquisitions	-0.75
Becher (2000)	1980 - 1997	(-5,+5)	558 mergers	-1.08
Efficiency Effects				
Jayaratne and Strahan (1998)	1975 - 1992			
Berger, Demsetz, Strahan (1999)			survey	
Calomiris (1999)	1984 - 1999			
Houston, James and Ryngaert (2001)	1985 - 1996	(news leak date - 4 , +1)	64 mergers	-3.47
Amel, Barnes, Panetta and Salleo (2004)	1990 - 2010			
Nail and Parisi (2005)			survey	
Hagendorff, Collins and Keasey (2008)	1996 - 2004	(-1,+1)	204 mergers	-0.50
Stock Valuation Effects				
Esty, Narasimhan, Tufano (1999)	1980 - 1994		477 mergers	
General				
Wheelock and Wilson (2004)	1987 -1999		3,000+ banks	

Table 3.2: Summary statistics of explanatory variables

This table presents summary statistics for the explanatory variables employed in the regression analysis for the period from 1980 to 2009. ECONOMIC SHOCK INDEX is measured each year as the first principal component of the median absolute change in five economic variables: sales/assets, net income/sales, ROA, sales growth, and employee growth. DEREG is a deregulation indicator variable that identifies an 5-year deregulation window spanning from two years before to two years after a deregulatory event. HH INDEX is Herfindahl-Hirschman index of industry concentration, the sum of the squared market shares (sales over total industry sales) of firms in an industry in a given year. DISP ROS is the cross-sectional standard deviation of the return on sales (cash flow/sales). M/B (log) is the average market-to-book equity ratio. Valuation Error (proxy for industry misvaluation) and V/B (proxy for fundamental value-to-book) are computed using the Rhodes-Kropf et al. (2005) M/B decomposition. CASH FLOW VOLATILITY, is the standard deviation of firms' past twenty periods of quarterly cash flow, measured as the firm's operating income before depreciation (OIBDP), and scaled by quarter-end firm total assets. LN CASH FLOW VOLATILITY, ST DEV is the natural log transformation of the annual cross sectional measures of CASH FLOW VOLATILITY across the banking industry. DISP CFLOW SHOCKS is the cross sectional standard deviation of firms' quarterly cash flow shocks, winsorized and scaled by quarter-end share price. MEDIAN ROA is the annual median industry return on assets; used as a proxy for competition. TURNOVER is defined as the number of exits and entries from an industry and is a proxy for the market power of the firms within the industry. MEDIAN INTEREST REVENUE PERCENTAGE is calculated annually as the median industry ratio of firm Interest and Investment Revenue / Total Revenue. MEDIAN FEE REVENUE PERCENTAGE is calculated annually as the median industry ratio of firm Trading and Fee Revenue / Total Revenue. Total revenue volatility is calculated annually as the standard deviation of 5 years of firm total revenue. The variable ST DEV TOTAL REVENUE VOLATILITY is the standard deviation of annual industry revenue volatility.

Summary Statistics	Mean	Median	Min	Max	Std. Dev.	Annual Obs.
ECON SHOCK INDEX	0.17	0.17	0.06	0.07	0.31	29
DEREG (1999)	0.17	-	0.38	-	1.00	29
HH INDEX	0.04	0.04	0.02	0.02	0.09	29
DISP ROS	0.17	0.16	0.03	0.12	0.24	29
MEDIAN_M/B	0.08	0.08	0.29	(0.59)	0.60	29
MEDIAN_IND ERROR, M/V	(0.27)	0.06	2.51	(4.44)	4.06	29
MEDIAN_V/B	0.35	0.11	2.74	(4.14)	4.96	29
CASH FLOW VOLATILITY, ST DEV	130.23	83.88	99.75	30.46	387.84	29
LN (CASH FLOW VOLATILITY, ST	4.61	4.43	0.72	3.42	5.96	29
DISP CFLOW SHOCKS 5%	0.57	0.57	0.08	0.37	0.68	29
DISP CFLOW SHOCKS 10%	0.49	0.50	0.08	0.30	0.63	29
MEDIAN_ROA	0.02	0.02	0.00	0.01	0.03	29
TURNOVER	0.06	0.05	0.03	0.02	0.11	29
MEDIAN_INTEREST REVENUE % t-1	0.01	0.00	0.00	0.02	0.00	29
MEDIAN_FEE REVENUE % t-1	0.01	0.00	0.00	0.01	0.00	29
ST DEV_TOTAL REVENUE VOL t-1	0.01	0.01	0.00	0.02	0.00	29

Table 3.3: Correlations of explanatory variables

This table presents summary statistics for the explanatory variables employed in the regression analysis for the period from 1980 to 2009. Variables are defined in Table 2.

Panel A: Correlations	ECON SHOCK INDEX	DEREG (1999)	HH INDEX	DISP ROS	MEDIAN_M/B	MEDIAN _IND ERROR, M/V	MEDIAN _V/B	CASH FLOW VOL., ST DEV
ECON SHOCK INDEX	1.00							
DEREG (1999)	0.35	1.00						
HH INDEX	-0.61	0.11	1.00					
DISP ROS	0.13	-0.43	-0.32	1.00				
MEDIAN_M/B	-0.03	0.33	0.18	-0.77	1.00			
MEDIAN_IND ERROR, M/V	0.13	-0.51	-0.55	0.66	-0.73	1.00		
MEDIAN_V/B	-0.12	0.51	0.53	-0.69	0.78	-1.00	1.00	
CASH FLOW VOLATILITY, ST DEV	-0.51	0.03	0.83	-0.44	0.39	-0.65	0.64	1.00

Panel B: Correlations, continued	LN (CASH FLOW VOL., ST DEV)	DISP CFLOW SHOCKS 5%	DISP CFLOW SHOCKS 10%	MEDIAN_ ROA	TURNOVER	MEDIAN _INT REV % t-1	MEDIAN _FEE REV % t-1	ST DEV_TOT REV VOL t-1
LN (CASH FLOW VOLATILITY, ST DEV)	1.00							
DISP CFLOW SHOCKS 5%	-0.28	1.00						
DISP CFLOW SHOCKS 10%	-0.40	0.95	1.00					
MEDIAN_ROA	-0.04	0.56	0.50	1.00				
TURNOVER	-0.09	0.00	-0.01	-0.29	1.00			
MEDIAN_INTEREST REVENUE % t-1	-0.89	0.33	0.42	0.16	-0.01	1.00		
MEDIAN_FEE REVENUE % t-1	0.89	-0.33	-0.42	-0.16	0.01	-1.00	1.00	
ST DEV_TOTAL REVENUE VOL t-1	0.54	-0.12	-0.27	0.20	-0.22	-0.56	0.56	1.00

Table 3.4: Time-series count of CRSP banking entry and exit activity

This table reports the time-series distribution of a sample of U.S. public banks, identified from CRSP each year of the 1979 to 2009 sample period. 1,956 banks listed on CRSP are tracked over the sample period using their unique CRSP PERMNO. In addition to the 212 banks listed on CRSP as at the beginning of 1980, 1,744 firms enter the public market (list on CRSP) and 1,434 exit the public market (delist from CRSP) over the sample period. These firms belong to fama french industry code 45, which identifies firms in the (traditional) banking industry. The sample comprises domestic firms, excluding foreign incorporated firms and ADRs.

Year	Beginning	Entry	Exit	Net Change	Ending
1979					212
1980	212	21	16	5	217
1981	217	17	8	9	226
1982	226	17	20	-3	223
1983	223	80	18	62	285
1984	285	51	19	32	317
1985	317	71	17	54	371
1986	371	150	26	124	495
1987	495	135	35	100	595
1988	595	42	50	-8	587
1989	587	31	38	-7	580
1990	580	30	66	-36	544
1991	544	30	41	-11	533
1992	533	65	39	26	559
1993	559	108	34	74	633
1994	633	93	55	38	671
1995	671	102	51	51	722
1996	722	130	52	78	800
1997	800	92	53	39	839
1998	839	116	73	43	882
1999	882	61	82	-21	861
2000	861	34	98	-64	797
2001	797	35	82	-47	750
2002	750	39	62	-23	727
2003	727	37	54	-17	710
2004	710	41	87	-46	664
2005	664	42	52	-10	654
2006	654	34	59	-25	629
2007	629	24	55	-31	598
2008	598	11	45	-34	564
2009	564	5	47	-42	522

Table 3.5: Merger activity before and after deregulation
This table presents yearly averages of industry-level merger activity 5 years before and 5 years after banking deregulatory acts passed in 1994 and 1999. The variable M&A count is annual merger count. t(diff) is the t-statistic of the difference in the means.

	5-Year Averages			
Variable	Before	After	% Increase	t(diff)
Panel A:	*1989 to 1993*	*1994 to 1998*		
M&A count	26.2	48.0	83%	(3.92) ***
Panel A:	*1994 to 1998*	*1999 to 2003*		
M&A count	48.0	64.8	35%	(1.90) *

The symbols*,**, and *** denote statistical significance at the 0.05, 0.01 and 0.001 levels, respectively.

Table 3.6: Univariate regression of annual merger count on lagged explanatory variables

This table presents the results from regressions of annual merger count on lagged explanatory variables for the 1980 to 2009 sample period. ECONOMIC SHOCK INDEX is measured each year as the first principal component of the median absolute change in five economic variables: sales/assets, net income/sales, ROA, sales growth, and employee growth. DEREG is a deregulation indicator variable that identifies an 5-year deregulation window spanning from two years before to two years after a deregulatory event. CASH FLOW VOLATILITY, is the standard deviation of firms' past twenty periods of quarterly cash flow, measured as the firm's operating income before depreciation (OIBDP), and scaled by quarter-end firm total assets. LN CASH FLOW VOLATILITY, ST DEV is the natural log transformation of the annual cross sectional measures of CASH FLOW VOLATILITY across the banking industry. M/B (log) is the average market-to-book equity ratio. Valuation Error (proxy for industry misvaluation) and V/B (proxy for fundamental value-to-book) are computed using the Rhodes-Kropf et al. (2005) M/B decomposition.

Panel A: Dependent Variable = Merger Activity (Count)

Explanatory Variables							
ECON SHOCK INDEXt-1	101.47						
	(1.46)						
DEREG (1999)t-1		36.64					
		(4.35)					
DEREG (1994 and 1999)t-1			27.05				
			(3.86)				
LN CASH FLOW VOL., ST DEV t-1				14.14			
				(2.71)			
M/Bt-1					50.29		
					(4.72)		
IND ERRORt-1						-23.45	
						(5.23)	
V/Bt-1							20.12
							(6.54)
Constant	20.23	30.96	27.95	-27.95	33.26	36.23	34.77
	(1.64)	(8.86)	(6.80)	(1.15)	(10.44)	(12.37)	(13.33)
R-Square	0.07	0.41	0.36	0.21	0.45	0.50	0.61
Adj. R-Square	0.04	0.39	0.33	0.18	0.43	0.49	0.60
Observations	29	30	29	29	29	29	29

Table 3.7: Univariate regression of annual merger count on lagged explanatory variables
This table presents the results from regressions of annual merger count on lagged explanatory variables for the 1980 to 2009 sample period. Count is the sum of period t, t+1 and t+2 values. Explanatory variables are the sum of period t-1 and t-2 values. Variables are defined in Table 2.

Panel B: Dependent Variable = Merger Activity (Count - sum(t, t+1, t+2))						
Explanatory Variables						
ECON SHOCK INDEX(sum(t-1, t-2))	174.78					
	(1.64)					
DEREG (1999)(t-1 or t-2)		95.17				
		(5.41)				
DEREG (1994 and 1999)(t-1 or t-2)			86.73			
			(6.36)			
M/B(sum(t-1, t-2))				66.82		
				(4.11)		
IND ERROR(sum(t-1, t-2))					-35.89	
					(7.38)	
V/B(sum(t-1, t-2))						27.59
						(7.56)
Constant	59.34	99.00	84.27	107.61	118.66	113.68
	(1.52)	(11.72)	(9.50)	(11.87)	(19.41)	(18.69)
R-Square	0.10	0.55	0.63	0.41	0.69	0.70
Adj. R-Square	0.06	0.53	0.61	0.39	0.68	0.69
Observations	26	26	26	26	26	26

Table 3.8: Multivariate regression of annual merger count on lagged explanatory variables

This table presents the results from regressions of annual merger count on lagged explanatory variables for the 1980 to 2009 sample period. Explanatory variables are defined in Table 2. Control variables: HH INDEX is Herfindahl-Hirschman index of industry concentration, the sum of the squared market shares (sales over total industry sales) of firms in an industry in a given year based on data from CRSP/Compustat merged file. DISP ROS is the cross-sectional standard deviation of the return on sales (cash flow/sales).

Dependent Variable = Merger Activity (Count)				
Explanatory Variables	(1)	(2)	(3)	(4)
ECON SHOCK INDEXt-1	61.61	50.48	64.34	66.73
	(1.44)	(1.03)	(1.16)	(1.16)
DEREG (1999)t-1	15.36	19.00	12.44	11.82
	(2.07)	(2.24)	(1.69)	(1.54)
IND ERRORt-1		-17.97		-12.99
		(3.90)		(2.97)
V/Bt-1	16.67		12.23	
	(5.31)		(3.30)	
HH INDEXt-1			-110.19	-124.76
			(0.64)	(0.69)
DISP ROSt-1			-210.75	-287.85
			(2.39)	(3.58)
Constant	22.21	24.72	63.14	77.44
	(3.09)	(3.01)	(3.25)	(4.00)
R-Square	0.73	0.64	0.78	0.77
Adj. R-Square	0.69	0.59	0.74	0.72
Observations	29	29	29	29

Table 3.9: Cash flow volatility before and after deregulation

This table presents yearly averages of inter-firm dispersion in cash flow volatility 5 years before and 5 years after banking deregulatory acts passed in 1994 and 1999. CASH FLOW VOLATILITY is the standard deviation of firms' past twenty periods of quarterly cash flow, measured as the firm's operating income before depreciation (OIBDP), and scaled by quarter-end firm total assets. CASH FLOW VOLATILITY, ST DEV is the standard deviation of CASH FLOW VOLATILITY across the banking industry. t(diff) is the t-statistic of the difference in the means.

	5-Year Averages			
Variable	Before	After	% Increase	t(diff)
Panel A:	*1989 to 1993*	*1994 to 1998*		
CASH FLOW VOLATILITY, ST DEV	79.1	86.9	10%	(0.78)
Panel B:	*1994 to 1998*	*1999 to 2003*		
CASH FLOW VOLATILITY, ST DEV	86.9	179.6	107%	(4.44) ***

The symbols*,**, and *** denote statistical significance at the 0.05, 0.01 and 0.001 levels, respectively.

Table 3.10: Univariate regression of industry valuation error on explanatory variables

This table presents the results from regressions of annual industry valuation error on explanatory variables for the 1980 to 2009 sample period. IND ERROR (a proxy for industry misvaluation) is computed using the Rhodes-Kropf et al. (2005) M/B decomposition. CASH FLOW VOLATILITY, is the standard deviation of firms' past twenty periods of quarterly cash flow, measured as the firm's operating income before depreciation (OIBDP), and scaled by quarter-end firm total assets. LN CASH FLOW VOLATILITY, ST DEV is the natural log transformation of the annual cross sectional measures of CASH FLOW VOLATILITY across the banking industry. CASH FLOW SHOCK, 5% INCREASE = 1 if the current year's value of cash flow volatility is at least 5% higher than the same value four years earlier. CASH FLOW SHOCK, 10% INCREASE = 1 if the current quarter's value of cash flow volatility is at least 10% higher than the same value four years earlier.

Panel A: Dependent Variable = IND ERROR			
Explanatory Variables	(1)	(2)	(3)
LN CASH FLOW VOLATILITY, ST DEV	-0.65		
	(5.15)		
CASH FLOW SHOCK, 5% INCREASE		-0.06	
		(0.04)	
CASH FLOW SHOCK, 10% INCREASE			0.87
			(0.57)
Constant	2.96	-0.01	-0.47
	(5.01)	(0.01)	(0.62)
R-Square	0.50	0.00	0.01
Adj. R-Square	0.48	-0.04	-0.02
Observations	29	29	29

Table 3.11: Regression of revenue volatility on explanatory variables

This table presents the results from regressions of annual merger count on lagged explanatory variables for the 1980 to 2009 sample period. Annual median industry return on assets (ROA) is used as a proxy for competition. Turnover is defined as the number of exits and entries from an industry and is a proxy for the market power of the firms within the industry. Economic Shock Index (Harford (2005)) is measured each year as the first principal component of the median absolute change in five economic variables: sales/assets, net income/sales, ROA, sales growth, and employee growth. DEREG is a deregulation indicator variable that identifies an 5-year deregulation window spanning from two years before to two years after a deregulatory event. Control variables: DISP ROS is the cross-sectional standard deviation of the return on sales (cash flow/sales). To compute DISP ROS I exclude firm-year observations where ROS is greater than 1 or less than -1, in order to remove the influence of extreme values.

Dependent Variable = Median industry-level revenue volatility				
Explanatory Variables	(1)	(2)	(3)	(4)
MEDIAN_ROA	-808,670			-1,030,701
	(3.06)			(2.61)
MEDIAN_ROA t-1		-530,225		
		(1.49)		
TURNOVER			-19,938	-35,260
			(0.56)	(1.25)
DEREG (1999) t-1				3,183
				(1.19)
ECON SHOCK INDEX				-22,719
				(1.15)
DISP ROS				-46,590
				(1.49)
Constant	23,034	17,265	6,364	41,280
	(3.91)	(2.16)	(2.85)	(3.53)
R-Square	0.25	0.08	0.01	0.49
Adj. R-Square	0.22	0.04	-0.02	0.39
Observations	30	29	30	30

Table 3.12: Regression of cash flow volatility on explanatory variables

This table presents the results from regressions of the log transform of the natural log transformation of the annual cross sectional measures (standard deviation) of CASH FLOW VOLATILITY across the banking industry on lagged explanatory variables for the 1980 to 2009 sample period. Explanatory variables are defined in Table 2. Control variables: DISP ROS is the cross-sectional standard deviation of the return on sales (cash flow/sales).

Dependent Variable = LN st. dev. industry-level cash flow volatility								
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MEDIAN_FEE REVENUE % t-1	4.9						5.3	6.4
	(11.60)						(8.93)	(7.76)
MEDIAN_INTEREST REVENUE % t-1		-4.9						
		(11.60)						
ST DEV_TOTAL REVENUE VOL t-1			74.4				-5.9	-8.6
			(3.12)				(0.40)	(0.55)
MEDIAN_ROA				-32.4			25.6	69.0
				(0.83)			(1.40)	(2.33)
MEDIAN_ROA t-1					0.8			
					(0.02)			
TURNOVER						-3.7	-0.1	1.2
						(0.79)	(0.07)	(0.60)
DISP ROS								5.0
								(2.08)
DEREG (1999) t-1								0.1
								(0.47)
ECON SHOCK INDEX								0.6
								(0.41)
Constant	4.0	8.9	4.1	5.4	4.7	4.8	3.4	1.3
	(49.39)	(24.27)	(17.75)	(6.18)	(4.53)	(16.91)	(7.74)	(1.21)
R-Square	0.83	0.83	0.26	0.02	0.00	0.02	0.85	0.88
Adj. R-Square	0.83	0.83	0.24	-0.01	-0.04	-0.01	0.82	0.84
Observations	29	29	29	30	29	30	29	29

Table 3.13: Multivariate regression of annual merger count on lagged explanatory variables

This table presents the results from regressions of annual merger count on lagged explanatory variables for the 1980 to 2009 sample period. Explanatory variables are defined in Table 2. Control variables: HH INDEX is Herfindahl-Hirschman index of industry concentration, the sum of the squared market shares (sales over total industry sales) of firms in an industry in a given year based on data from CRSP/Compustat merged file. DISP ROS is the cross-sectional standard deviation of the return on sales (cash flow/sales).

Panel A: Dependent Variable = Merger Activity (Count)										
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ST DEV_REVENUE VOL t-1	1,069.4	-288.24						-703.6	-1,110.1	-1,123.1
	(1.57)	(0.48)						(1.23)	(2.17)	(2.14)
M_FEE REVENUE % t-1			91.7	6.1			12.0		164.9	57.0
			(3.56)	(0.16)			(0.23)		(3.25)	(2.68)
LN CASH FLOW VOLATILITY, ST DEV t-1					13.6	4.6	-1.3	8.6		1.6
					(3.10)	(0.77)	(0.16)	(1.53)		(0.29)
ECON SHOCK INDEXt-1	15.4	116.9	133.5	113.4	88.4	67.1	115.1	94.0	88.22	87.4
	(0.27)	(2.41)	(2.31)	(2.20)	(1.57)	(1.25)	(2.14)	(1.61)	(1.76)	(1.70)
DEREG (1999)t-1	32.8	10.0	21.7	10.9	27.4	19.7	10.5	9.7	13.2	13.5
	(3.63)	(1.18)	(2.54)	(1.29)	(3.28)	(2.29)	(1.18)	(1.27)	(1.98)	(1.96)
IND ERRORt-1		-6.28		-5.7		-14.3	-5.7	-3.8	-1.6	-1.5
		(4.49)		(2.81)		(2.13)	(2.73)	(2.36)	(0.98)	(0.88)
HH INDEXt-1								-352.389	-890.4	-884.7
								(1.64)	(3.33)	(3.23)
DISP ROSt-1								-255.0	-189.0	-193.1
								(3.09)	(2.59)	(2.54)
Constant	20.0	16.0	-2.6	13.4	-45.1	1.0	18.2	42.5	75.0	69.3
	(1.83)	(1.93)	(0.22)	(1.11)	(1.80)	(0.03)	(0.56)	(1.64)	(5.02)	(2.78)
R-Square	0.47	0.71	0.61	0.71	0.58	0.65	0.71	0.83	0.88	0.88
Adj. R-Square	0.40	0.66	0.57	0.66	0.53	0.59	0.65	0.78	0.84	0.83
Observations	29	29	29	29	29	29	29	29	29	29

CHAPTER 4

REGULATORY FORBEARANCE DURING THE FINANCIAL CRISIS: A MARKET VALUATION APPROACH

Introduction

"The trouble is that the market doesn't believe Bank of America's assets are worth anything close to what Bank of America says they are worth."

Business Insider, August 23, 2011; BAC share price @ $6.30

The sentiment expressed in this statement, while likely more strident than other analyst opinions, was a common refrain during the depths of the financial crisis. The crisis caused severe asset quality deterioration for U.S. banks, first in MBS securities and mortgage loans, and then in commercial and real estate development loan portfolios. The ensuing write-downs, in concert with severe funding problems, pushed many banks to the brink of solvency. Anecdotal evidence, such as the quote above, supports the contention that bank managers, in many instances, were slow to mark down asset values on the balance sheet as capital positions became perilously thin.

Past studies have shown that US financial regulators are inclined to practice capital forbearance during financial crises (Eisenbeis and Horvitz (1994) surveys the literature). Put simply, forbearance allows troubled or insolvent financial institutions to continue operation despite evidence of capital inadequacy (in hope that the institution may return to financial health). The recovery of a troubled institution would not only save the institution itself, the reasoning goes, it may help prevent the further destabilization of an already weakened financial system during a time of crisis.

However, considerable evidence exists to show that regulatory forbearance, in the end, is more costly to the insurance funds that underpin the U.S. banking system than the prompt seizure and resolution of insolvent or severely distressed institutions. In particular, several studies of the savings and loan (S&L) crisis of the 1980's show that regulatory forbearance ultimately cost the US taxpayers tens of billions of dollars (DeGennaro and Thompson, 1996; Kane and Yu, 1996). In response to the failings of the regulatory bodies during the S&L crisis, the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991 revamped the regulatory structure in place to handle bank failures. The Prompt Corrective Action provision (PCA) of FDICIA specifically addresses capital forbearance by allowing examiners to close a bank before it becomes insolvent and the losses become substantial; the overarching goal being to resolve the institution at the least possible long-term cost to the insurance fund.

The recent financial crisis in the US has again tested the regulations in place to ensure the stability of the financial system. Relatively little work has been done to date to study the effects of the regulations during this latest crisis; however, the work that has been done suggests a familiar theme. Huizinga and Laeven (2012) study US banks from 2001 to 2008 and find that banks overstate the value of distressed assets with the intent of bolstering their profitability and levels of regulatory capital. They conclude that bank balance sheets offer "a distorted view of the financial health of the banks and provide suggestive evidence of regulatory forbearance and noncompliance with accounting rules."

This paper examines the valuation of bank loan portfolios during the years 2008 to 2010 in order to examine two related issues. First, do bank financial statements accurately reflect asset value, asset impairment and capital adequacy? Or are market-based valuations more useful in assessing the impact of asset impairment on capital levels? Financial reporting should provide information to help investors, creditors and others about the economic resources of an enterprise, claims to those resources, and changes in them[5]. However, empirical evidence strongly indicates that market prices can provide information that is more accurate, frequent and timely than that acquired from other sources. Second, if market-based estimates of loan portfolio values are more useful than those reported on bank financial statements, do those estimates provide *ex-post* evidence of capital forbearance by supervising bank regulators in failed banks sold at FDIC auction?

[5] Kieso and Weygandt, 1992

I use new and unique data on bank failures from the recent financial crisis to examine these questions. Focusing on the banking industry around the time of the financial crisis provides a natural experiment to test these two broad hypotheses. I find that, while the market discounts the loan portfolios of both failed banks and surviving industry peers heavily during the financial crisis, the market values of failed bank lowers are consistently and significantly lower; reflecting the lower quality/higher risk of their portfolios. I also find evidence that both bank groups understate asset impairment on the balance sheet and consequently overstate regulatory capital. An examination of failed banks *ex-post* shows that market value-adjusted capital ratios are more efficient in diagnosing distress than book value ratios. Moreover, market value-adjusted capital ratios provide evidence of regulatory forbearance for several quarters prior to seizure. I provide estimates of savings to the FDIC deposit insurance fund that might have accrued had the banks been seized in a prompt manner.

The paper proceeds as follows: Section 2 briefly reviews the literature and establishes the framework for testing the hypotheses, Section 3 outlines the empirical approach to testing and describes the data used in the empirical analysis, Section 4 presents empirical analysis of market value-adjusted loan and capital, Section 5 presents regression analysis of FDIC estimated losses as a result of bank failures, Section 6 presents estimates of possible savings from prompt corrective action, and Section 7 concludes.

Literature review and hypothesis development

Because capital forbearance occurs with greater frequency during crises the extant literature documenting forbearance in the U.S. banking system is comprised primarily of studies of forbearance during the S&L crisis of the 1980s and early 1990s. DeGennaro and Thompson (1996) compare the estimated costs of the prompt resolution of 372 distressed thrifts in 1980 to their actual resolution costs during the subsequent decade. They estimate that delays in closing the thrifts cost $51 billion in today's dollars. Kane and Yu (1996) analysis cash flow data from the Federal Home Loan Bank reporting system find during the 1980s and conclude that each year of forbearance for market value insolvent thrifts cost $16 billion in today's dollars.

Both of these studies provide support for the notion that flat-rate deposit insurance creates a moral-hazard problem in that managers of distressed banks have incentives to pursue a riskier, high growth strategy to recover from economic distress. Regulatory forbearance strengthens this incentive. Gupta and Misra (1999) survey the literature as part of an analysis of the crisis. They characterize forbearance as a "mechanism that enabled regulators to postpone the day of reckoning into the indefinite future, at great cost to the nation's taxpayers" and endorse a structured early intervention and resolution approach; one that was codified, in large part, by the FDICIA. Eisenbeis and Wall (2002) analyze the effectiveness of the FDICIA and conclude that PCA considerably reduces the risk of large losses to the deposit insurance fund by resolving distressed banks before losses become substantial. Moreover, they endorse "FDICIA's focus on preventing failed banks from imposing a high cost to the deposit insurance fund rather than on limiting the number of failures".

More recent work has examined instances of forbearances in countries experiencing economic distress. Brown and Dinc (2009) study bank failures in twenty one emerging market countries in the 1990s and find that a government is less likely to take over or close a failing bank if the banking system is weak. They also find that this "Too-Many-to-Fail" effect is stronger for larger banks and when there is a large government budget deficit. Edwards (2011) compares the Prompt Corrective Action provision of the FDICIA with newly drafted Early Remediation System (ERS) of the Dodd-Frank Act. The author notes the incidence of forbearance during the recent financial crisis and opines that the subjective early intervention criteria of ERS will be prone to regulatory forbearance: with ERS "we are reliant on market discipline to check regulatory forbearance even though it can cause the same systemic consequences that the Dodd-Frank Act failed to address."

An emerging strand of literature has examined the effects of the financial crisis on the market values of assets held by banks. As highlighted, Huizinga and Laeven (2012) find that banks overstate the value of distressed assets during 2007 and 2008 with the intent of bolstering their profitability and levels of regulatory capital. However, Calomoris and Nissim (2012) study the changes in the market valuation of banking activities around the financial crisis and attribute the majority of the drop in market-to-book ratios of banks to factors other than unrecognized loan and securities losses. Several studies find that the market values of real-estate related assets held by banks dropped significantly relative to historic cost (Bhat, et al., 2011; Kolasinski, 2011 and Diamond and Rajan, 2011). Goh et al. (2009) analyze the market pricing of bank assets and find that assets with greater information asymmetry and lower liquidity are priced lower relative to assets with an active secondary market. Importantly, this pricing differential increased over the course of 2008, consistent with increasing market concerns about illiquidity and information risk associated with those assets.

The widespread failure of banks during the financial crisis, along with the government's bailout of large banks via the Troubled Asset Relief Program, has resulted in a heightened focus on both the capital structure of regulated banks and the resolution process of insolvent institutions. Many economists have supported the mandatory conversion of bank debt into bank equity as an efficient solution; this process has been referred to as "speed bankruptcy", "Super Chapter 11 and "debt-to-equity conversion" (Stiglitz, 1999; Zingales and Hart; 2010 and Jones, 2010). The PCA provision of FDICIA effectively eliminates recapitalization of distressed banks as the preferred method for dealing with financial crises and, instead, utilizes asset redistribution through a change of corporate control. This paper has implications for the cost and incidence of the industry-wide use of this method to deal with financial crises.

Testable predictions for the effects of market valuation on bank assets and the incidence of regulatory forbearance, synthesized from the discussions above, are as follows:

H_O1: Loan portfolio values reported in bank financial statements properly reflect impairment levels

H_A1: Stock market prices more accurately reflect the level of impairment in non-traded loan instruments than do loan portfolio values reported in bank financial statements

H_O2: Stock market based valuation does not indicate capital forbearance, ex-post, in banks seized by supervising regulators during the period 2008– 2010

H_A2: Capital levels of failed banks, adjusted for stock market-based valuation of loan portfolios, exhibit indications of capital forbearance by supervising regulators during the period 2008 – 2010

Empirical methodology

Using information found in the SEC filings of the public acquirers of failed banks I collect valuation data about the loan portfolios of failed banks purchased at FDIC auction. All of the transactions used in this study were accounted for as a business acquisition as defined by the *Business Combinations* topic (ASC 805). Following the requirements set forth in ASC 805, the assets and liabilities acquired were recorded at their fair values on the date of the acquisition. Fair values were determined based on the requirements of FASB ASC Topic 820, *Fair Value Measurements*. A majority of the transaction-based valuations collected have been audited and opined on by a CPA firm.

Because there is no active secondary market for the majority of bank loan types I derive an estimate of the market value of each failed bank's loan portfolio from the bank's stock price. To do this I employ the options valuation technique developed by Black and Scholes (1973) and applied specifically to bank risk-based insurance by Merton (1977). Ronn and Verna (1986) and Giammarino, Schwartz and Zechner (1989), most prominently, adopt Merton's technique to value bank loan portfolios using the bank's equity price and risk. I use the auction date fair value data to validate the derived historical loan market values. I compare the transaction-based acquisition fair value to the financial statement values (as of the date of the takeover date) to determine if there are significant differences. I also compile a time series of derived market values vs. financial book value of the bank's loan portfolios over time to determine if market- based pricing provides additional information about the value and impairment of the loan portfolio. It may be the case that the market discounts the portfolios of the industry as a whole in bad times. To examine this possibility I perform the same real options valuation for the entirety of the SIC code 6020 – commercial banks and financial institutions (net of the banks that failed through 2010).

Black and Scholes (1973) note that it is possible to value numerous assets using an option-pricing approach. They specifically highlight that one may value a bank's assets in this way if one were to treat the bank's equity as a call option on the bank's assets. In an option-pricing context, stockholders of a publicly-traded bank have the option to "repurchase" the bank's assets from the liability holders (the depositors, in the case of a bank) by paying the depositors the required interest and or/principal amounts owed. If the assets are worth less than the liabilities, the stockholder's have the option to forfeit the assets to the depositors and walk away from the bank, forfeiting the assets in settlement of the debt in the process. The payoff to this option is thus:

$$E = \max(0, V - B) \tag{1}$$

where E is the value of bank equity V is the total market value of bank assets and B is the value of bank liabilities. In this way, the market value of a bank's equity can be viewed as a derivative of the bank's assets, of which loans make up a majority of the value and for which there is often no readily available market price.

Of course, the duration of the liabilities is likely to vary, making the "repurchase" option at expiration of the option difficult to model. Merton (1977) argues that the annual audit of a public bank may effectively serve as an expiration date; if the bank is found insolvent by auditors and seized the stockholder's are wiped out. Thus, for valuation purposes, one year may be used for the length of time to option maturity. As noted previously, however, regulators may also be inclined to practice capital forbearance. For purposes of this model, that means that the bank may not be seized when the asset/liability is strictly 1.0; regulators may seize the bank only when the asset/liability is well under 1.0, such as .97, .95 or lower. The adjustment for forbearance can be represented in the payoff equation by ρ:

$$E = \max(0, V - \rho B) \tag{2}$$

In the context of the Black Scholes model, with the same assumptions, the equation may be represented as:

$$E = VN(x) - \rho BN\left(x - \sigma_v\sqrt{T}\right) \tag{3}$$

$$x = (\ln(V/\rho B) + \sigma_v{}^2T/2))/\left(\sigma_v\sqrt{T}\right) \tag{4}$$

and:

$$\sigma_E = (V/E)(\partial E/\partial V)\sigma_v \tag{5}$$

where N is the cumulative standard normal distribution function, T is the time to maturity (or next audit) and σ_v is the instantaneous standard deviation of dV/V.

Given that one can observe the market value of equity (E) and the standard deviation of equity returns (σ_E), it remains to solve for the two unknowns in the above equations: V, the total market value of bank assets and σ_v, the standard deviation of the rate of change of the total market value of bank assets (V). I refer the reader to Ronn and Verna (1986) for a more complete discussion of the theoretical underpinnings of the model.

I use the software program MATLAB's F-solve non-linear optimization routine to solve for the two unknown variables, V and σ_v. The market value of equity (E) and the standard deviation of equity returns (σ_E) are from CRSP. The book value asset and liability data is from Compustat. Loan and securities data used in regression is from Call reports, as is data on regulatory capital. Estimated loss data is from FDIC purchase and assumption (P&A) legal agreements. The book value and fair value of assets sold at auction is hand collected from acquirer 8k, 10Q and 10K SEC statements.

I lean on prior studies (Ronn and Verna,1986; Giammarino, et al., 1989 and Liu, et al., 2006), for guidance in setting the value of the forbearance adjustment variable ρ = .95. While subsequent analysis shows that the actual forbearance ratio may vary considerably above or below that value, a value of .95 not only helps facilitate comparison with prior studies, it produces market valuations consistent with the stylized facts for the mortgage and real estate related bank assets that make up a majority of the loan portfolios in this industry as well as the empirical valuation estimates in Huizinga and Laeven (2012). While the market values derived using this technique are sensitive to this assumption, unreported sensitivity analysis shows that setting ρ = .95 produces valuations most consistent with fair values determined by acquirers at the time of sale, the valuations in Huizinga and Laeven (2012) and the stylized facts of the asset class as a whole.

To compile the sample I assemble the population of all banks sold at FDIC P&A auctions from 2008 to 2010 from the FDIC's Historical Banking Failures and Assistance Transactions on-line database. For each bank sold via a whole bank P&A, I determine if the winning bidder is publicly traded and contained in the CRSP database. If so, I manually search the SEC EDGAR database for disclosure of the transaction by the winning bank. If substantially all of the assets and liabilities of the failed bank are sold via the whole bank P&A, I am able to match the fair value asset data to historical data for the failed bank in Compustat and Call reports. As reported in Figure 4.1, there are 28 such publicly traded banks. In total, my sample contains 49 publicly traded banks (including the 28 banks in Figure 4.1) that were seized and sold via auction from 2008 to 2010 with the requisite data in both CRSP and Compustat.

Summary statistics of the primary variables of interest are presented in Table 4.1. Panel A presents statistics for the commercial banking industry. The industry is proxied by the banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks that overlap SIC code 6020 have been removed from this sample. Real estate loans, on average, make up roughly 54% of the total assets of banks in the industry. Commercial and industrial loans make up roughly 10% of total assets, while total securities make up roughly 18% of total assets. The securities portfolios are dominated by Available for Sale (AFS) securities, which are required to be carried at market value. AFS securities make up roughly 16% of total assets while Held to Maturity (HTM) securities account for only 1%, on average. The industry mean total assets is $3.2 billion with the largest bank in the sample at $55.5 billion and the smallest, $46.6 million. Thus, this SIC code is comprised of small to medium size banks; of which lending makes up the primary source of revenue.

Panel B presents statistics for the failed bank sample and for variables used in subsequent regression analysis. Real estate loans for this sample of banks make up roughly 65% of the total assets, while commercial and industrial loans make up roughly 7% of total assets. AFS and HTM securities account for only 9% and 1%, on average. It appears the failed banks are characterized by a higher exposure to real estate lending, with less of a reliance on security income than the industry peer group. The mean total assets for the failed bank group are $2.4 billion while the largest bank in the sample worth

$25.5 billion and the smallest, $184.2 million. Similar to their industry peer group, the failed bank group is comprised of small to medium size banks; of which lending makes up the primary source of revenue.

<u>Empirical market valuation of bank loan portfolios</u>

This section provides the results of real options analysis used to obtain the market value of loan portfolios implied by the banks' stock prices. Test results show that, for many failed banks, there is a significant difference between the auction date book value of the loan portfolios as reported on the failed bank's books and the fair value of the portfolio as recorded on the acquirer's books. Table 4.6 shows that, on average, the loan portfolios of failed banks sold at FDIC auction are written down over 30% when marked to fair value. Table 4.2 shows that, for a subsegment of publicly traded banks for which detailed valuation data is available, market implied valuations are significantly lower than the values reported on the company's balance sheets immediately prior to, and during, the financial crisis. Market values drop below book value a full 2 years (8 quarters), on average, before seizure date (quarter 1); reaching a discount of 12% a full six months before auction date. This finding is consistent with a stylized fact of prior banking crises; the distressed status of the bank appears to be associated with a substantial deterioration in asset values.

Using the asset valuation model calibrated on the set of banks with available fair value information in Figure 4.1, I next examine a broader set of publicly traded banks; some of which do not have fair value disclosures available. Figure 4.2 reports on substantially all publicly traded banks seized and subsequently sold at auction in the period 2008 to 2010. Table 4.3 reports that at seizure date (quarter 1), the market to book ratio of the loan portfolios were 80%, on average. The difference between book and estimated market value is statistically significant. These steep discounts help produce a median market value asset/liability ratio of .92 while a corresponding median book value asset/liability ratio of 1.02 indicates the banks are solvent for financial reporting purposes. Moreover, these estimates also show that, on average, these failed banks were insolvent on a market value basis one full year (quarter 5) before seizure. The median book value asset/liability ratio on that same date is a relatively stable 1.07.

Figure 4.3 displays the same comparative analysis for the commercial banking industry, SIC code 6020, net of failed banks. Loan valuation data for the industry is consistent with the stylized facts we know of for the mortgage and real estate related assets that make up a majority of the loan portfolios in this industry; namely that they garner a premium (9% to 11%) during the height of the real estate bubble in 2004 to 2006 and begin to dip significantly below book value in Q1 2008. Table 4.4 reports that the difference between book and estimated market value is statistically significant before and after the start of the financial crisis. Values dip considerably in Q4 of 2008 after the failures of Lehman Brothers, Washington Mutual, Wachovia and others revealed new information to the market about the true impairment of these assets. The blended discounts of the failed and solvent bank loan portfolios in Figures 4.1 and 4.2 are roughly consistent with the discount of 14% on real estate loans in 2008 reported by Huizinga and Laeven (2012). Notably, the median market value asset/liability ratio of these *ex-post* solvent banks are greater than 1 in all quarters, the lowest average ratio is 1.02 in Q1 2009 while the median book value asset/liability ratio remains about 1.10 throughout the time-series.

Figure 4.4 presents a comparative analysis of the market valuations of the solvent (industry) vs. failed bank loan portfolios. The estimated market to book ratio of both the solvent commercial banking industry and the failed banks follows a pattern similar to that observed in Figure 4.3. The ratios are greater than 1 during the real estate bubble years of 2004 to 2006 and fall to less than 1 during the year 2007. However, the estimated market to book ratio of the commercial banking industry is higher in almost all quarters displayed: Q1 2004 to Q4 2009. The flip flop of relative values is likely a small sample issue as only 5 banks make up the failed bank group in Q1 2010. The differences are statistically significant in roughly half of the quarters reported (Table 4.5). Thus, it appears that the market recognizes either the lower asset quality of, or perhaps the elevated levels of risk inherent within, the real estate-dominated loan portfolios

The evidence presented to this point gives some support to the notion that market estimates of asset impairment were not incorporated into the financial reporting of either failed or solvent banks during the financial crisis. In the case of the *ex-post* failed bank group, two important facts deserve highlighting. First, the market appears able to recognize the lower quality/higher risk assets *ex-ante*. Second, the lower average market value asset/liability ratio of the *ex-post* failed bank group indicates that the capital buffers of these banks were likely lower than their industry peers. These two observations provide evidence that suggests supervising regulations may have enabled bank managers to forestall asset write-downs in order to preserve regulatory capital and stave off seizure. I analyze the impact of market valuations on bank capital in this section.

Table 4.7 presents a comparison of the median asset / liability ratios (a/l ratio) of the solvent industry bank group and the *ex-post* failed bank group. The industry group in Panel A is displayed chronologically while the failed bank group in Panel B is displayed relative to the auction date. The median book value a/l ratio of the failed bank group, an average of roughly 1.08, is similar to the median book value a/l ratio of the industry group, an average of roughly 1.10, for most of the period presented. The failed bank ratio then drops in the 3rd and then 2nd quarters preceding auction to 1.03. While the median market value a/l ratio of the industry group remains above 1.0 (dropping to a low of 1.02 in Q3 2009), the median market value a/l ratio of the failed bank group drops below 1.0 a full six quarters before the auction date; ending at .96 in Q2.

Panels A and B next present a sort based on the market value a/l ratio. The first group is comprised of those banks with a market value a/l ratio of less than 1.0 and the second those with a ratio equal to or greater than 1.0. Panel A shows that a non-trivial percentage of the solvent industry banks have a market value a/l ratio of less than 1.0 during the time period presented. Depending on the quarter, 10 to 35% of the solvent industry banks have a market value a/l ratio of less than 1.0; with a median ratio of either .98 or .97 in all quarters reported. The majority of solvent industry banks have a market value a/l ratio comfortably greater than 1.0, however. Conversely, Panel B reports that 2 quarters before auction date almost all of the failed bank group has a market value a/l ratio of less than 1.0; the median ratio is .96. The book value a/l ratio of this group is noticeably lower than that of the industry group in the less than 1.0 group; 1.03 vs. 1.08. The median loan market/book ratio is roughly similar for both bank groups. These characteristics illustrate a motive for delaying accounting recognition of impairment; the *ex-post* failed bank group is thinly capitalized, on average, while the *ex-post* solvent group is better capitalized.

To this point I have presented evidence on possible capital forbearance based on standard financial ratios. The decision to seize a troubled bank, however, is made not on financial reporting numbers, but on regulatory capital levels. Banks are classified into categories of capitalization, based primarily upon two regulatory capital ratios: the total risk-based capital ratio and the leverage ratio. In general, a bank is considered to have a stable capital base if it has a total risk-based capital ratio greater than 8%, and a leverage ratio greater than 4%. A bank is categorized as "significantly undercapitalized" if it has a total risk-based capital ratio less than 6% or a leverage ratio less than 3%. A bank is categorized as "critically undercapitalized" if it has a leverage ratio less than 2%. If a bank is, on average, critically undercapitalized for 270 days it must be seized, by regulation, unless certain conditions are met and regulators make a determination that the bank is "viable" and not expected to fail.

Table 4.8 presents a comparison of the regulatory capital ratios of the solvent industry bank group and the *ex-post* failed bank group. Due to data restrictions, the industry group reported in this table is smaller than the group reported in previous analysis; roughly 30 banks were dropped because of insufficient data. The industry group in Panel A is again displayed chronologically while the failed bank group in Panel B is displayed relative to the auction date. The actual capital ratios of the banks, obtained from regulatory Call reports and based on book values, are reported in the first section. The median book value capital levels of the solvent industry group fall within the "well capitalized" category in each quarter presented. The median market value-adjusted leverage ratio characterizes the solvent industry group as a relatively stable "well capitalized" to "undercapitalized" in all quarters but one, Q1 2009, in which the group is classified as "significantly undercapitalized", on average.

By definition, we expect the *ex-post* failed bank group presented in Panel B to be characterized by much lower regulatory ratios. Two full years before auction, in Q9, this group has a median leverage ratio similar to its industry peers, however it's median tier one and total risk-based ratios are over one full percentage point lower than its industry peers, meaning that the risk based assets number in the denominator of the ratio is larger, on average, than the industry. This finding supports the notion that the *ex-post* failed bank group holds loan that are of lower quality, and thus riskier, than its industry peers and is consistent with the evidence in Figure 4.4 that the market discounts the loans of the failed bank group more heavily.

Beginning over a year before auction date, the book and market regulatory capital ratios of the failed bank group begin to fall significantly. In fact, 5 quarters before auction date the median market-adjusted leverage ratio falls to 1.98%, putting the average bank in this group in the "critically undercapitalized" category. However, the median book total risk-based and leverage ratios of the banks in this quarter are 10.63% and 7.46%, meaning that the average bank in this group is still "well capitalized" from a regulatory supervision standpoint. A rating of "well capitalized" means no regulatory restrictions are required on bank activity nor is enhanced monitoring required of supervising regulators.

For the next three successive quarters the median market-adjusted leverage ratio of the failed bank group is less than 2%, which by regulation should trigger the seizure of the banks (in Q3). In reality, the banks are not seized for another six months, on average. In normal economic times with a small number of failures this apparent forbearance may not be costly, but in times of crisis, with unstable asset prices and low levels of market liquidity, this may prove to be very costly. Section 6 examines the cost of this delay.

It is worthwhile to note that, as of Q1, the defacto seizure date, the median book total risk-based and leverage ratios of the average failed banks is 5.44% and 3.03%, on average; which characterizes them as "significantly undercapitalized" but not "critically undercapitalized". The fact that supervising regulators did, in fact, seize the banks supports the notion that financial reporting data based on book values does not appropriately represent the impairment and risk levels of banks during the sample period examined in this paper.

Regression analysis of estimated FDIC losses

Regression analysis of estimated losses on failed bank assets is reported in Table 4.9. The dependent variable is the intrinsic loss estimate which is the FDIC's estimate of future credit losses for each loan portfolio covered by shared loss agreements of failed banks sold at auction. The sample is the same sample of publicly traded failed banks from 2008 to 2010 reported in Figure 4.2. Each bank in the sample was sold with shared loss assets and so each observation contains an intrinsic loss estimate. As reported in Model 1, the percentage of real estate loans significantly increases the estimated credit losses imbedded in the loan portfolio. Commercial and industrial loans have no significant effect on predicted losses. These results are similar to the results reported by Huizinga and Laeven (2012) who find that the level of real estate loans significantly drive decreases in bank market values and significantly increases loan charge offs, while the level of non real estate loans have no effect on market value decreases. The level of total assets significantly drives estimated losses in all models presented in Table 4.9.

The specification in Model 3 adds the difference between book and market value of loan values as a proxy for loan portfolio credit losses. Although the direction is positive as expected, the estimate is statistically insignificant, indicating that market value adjustments may not accurately model future estimated credit losses. Other unreported market value-based proxies similarly lack significant predictive power. One item to note is that the negative effect of Held to Maturity (HTM) securities becomes significant in Models 3 and 5. This effect is somewhat inconsistent with Huizinga and Laeven (2012) who find some evidence that HTM MBS securities drive decreases in bank market values.

Models 5 and 6 introduces region and time fixed effects. The fixed effects do not significantly alter the direction or significance of the estimated coefficients in Models 1 through 4. Of note is the positive and statistically significant effect of the Northeast region. This can be attributed to two large bank deals in Puerto Rico in which very large estimated loss were part of the loss share deals given by the FDIC. Furthermore, the Georgia region, which has experienced a large number of community bank failures, is positive and marginally significant. The estimated coefficients on the region indicator variables are fairly consistent with the notion that regional economic forces drive many of the bank failures and large credit losses; the exposure to real estate development in the Georgia banking industry being a prime example.

I next run the same specifications above substituting as the dependent variable the ratio of FDIC estimated credit losses as a percentage of total loans. In unreported results, all of the variables maintain the same sign as those reported in Table 4.9, however all but the HTM securities variables lose significance. The ratio of HTM securities to total assets retains a negative estimated coefficient, significant at the 1% level in all specifications. However, the ratio of real estate loans to total assets and total assets variable lose the statistical power to explain the estimated loss in the cross section of failed banks. The ratio of market value loan adjustment to total loans, while positive as expected, is statistically insignificant as in the regressions on the level of estimated loss above.

Estimated savings to FDIC deposit insurance fund

This section estimates potential savings from prompt corrective action by regulators. The estimates simulate the savings if the banks were seized one, two or several quarters prior to the actual seizure date. I calculate the estimates based upon a sample of 188 of the 218 failed banks that were sold as whole banks with loss share guarantees from 2008 to 2010. Rigorous enforcement of the regulatory capital standards under the PCA directive of FDICIA would also mean that additional "healthy" banks would be seized, however. I simulate the cost of action by applying the appropriate capital standard to the market value adjusted leverage ratios of the solvent industry group. Given that these estimates are based upon a sample of banks, and consider only the direct costs to the FDIC from whole bank sales, the analysis is essentially a partial-equilibrium approach. I do not consider the economy-wide impact of bank failures, nor the cost.

Potential savings come from two sources: 1) future credit losses are presumed to be lower the sooner the bank is seized and sold – preventing further asset quality deterioration. I use FDIC Estimated Loss amounts gathered from Purchase and Assumption agreements to measure the predicted credit losses at time of auction. 2) Cash paid by the FDIC to winning bidders will be lowered or possibly eliminated by reducing the asset discount bids received at auction due to enhanced portfolio credit quality; and larger book capital positions means higher net asset values purchased by the winning bidders.

FDICIA effectively stipulates that a bank must be placed in receivership if its leverage ratio is smaller than 2.0%, on average, for over 270 days. I apply this capital standard to the market value adjusted leverage ratios of the solvent industry group. On this basis, 35 of the roughly 100 banks that make up this group annually over the sample period would be seized during the period 2008 to 2010. I approximate the cost to the FDIC if all 35 were sold at auction using the pricing formula above and modeling the asset discounts as the difference between book and market value of the loan portfolio. I forecast future credit losses by applying the coefficients in regression model (1) presented in Table 4.9 to the balance sheet of each bank as of the date of simulated failure.

Table 4.10 reports estimates of potential savings. The estimates apply the market to book loan portfolio and overall asset to liability ratios generated from the public bank sample reported in Figure 4.2. As reported in Table 4.10, the average failed bank in the period 2008 to 2010 was insolvent on a market value basis for over a year before it was seized. At that point the assets amounted to 92% of the book value of liabilities. The market value of the loan portfolio as seizure was 80% of book value, on average.

By acting just one quarter sooner, on average, the FDIC stands to save over $16 billion of the $74 billion that the 332 bank failures from 2008 through 2010 are estimated to cost the Deposit Insurance Fund. The additional bank failures would cost the FDIC almost $3 billion, most of which comes from estimated future credit losses. Because these banks have healthier balance sheets than the failed bank sample at the time of simulated failure, auction costs are essentially break-even. The total savings is $13.7 billion. This conservative estimate is in line with the estimated costs of forbearance during the S&L crisis of the 1980's calculated by a number of studies. DeGennaro and Thompson (1996) estimate that delays in closing 372 thrifts cost $51 billion in today's dollars. Kane and Yu (1996) find that each year of forbearance for market value insolvent thrifts cost $16 billion in today's dollars.

Conclusion

This paper examines the effect of market valuation on the loan portfolios and regulatory capital levels of U.S. banks during the financial crisis. I use unique data on bank asset values, gathered from SEC merger documents, to provide a benchmark for asset fair values for a sample of US banks during the financial crisis.

Using a sample of banks from 2008 to 2010, I find that bank financial statements consistently underreport the level of impairment in loan portfolios implied by market prices. Loan portfolio discounts average 9% during 2009 and run as high as 20% for failed bank portfolios. Notably, test results show that the market recognizes the lower quality / higher risk of the real estate-dominated loan portfolios of the failed banks *ex-ante*. The evidence in this study suggests that many banks were slow to reflect on their balance sheets the level of impairment caused by the financial crisis. This was especially true of the group of failed banks studied in this paper; over half of the group had estimated credit losses greater than 30% of the value of their loan portfolio when they failed, with some as high as 50%.

I also use the market value estimates of loan impairment to adjust the capital ratios of the banks in the sample; the resulting ratios indicate significant capital forbearance in the *ex-post* failed bank group. Median ratios show a six month delay in the seizure required by FDICIA. Moreover, these same banks are not critically undercapitalized, on average, when seized. A conservative estimate of the costs of forbearance to the deposit insurance fund from 2008 to 2010 is roughly $14 billion.

The results of this study provide further support for the use of market data in the CAMELS supervisory assessment. The rating guidelines currently stress the sensitivity of bank assets to market prices or interest rates in the Sensitivity to Market Risk section of the ratings guidelines. However, this analysis clearly shows the usefulness of the market price of the banks' own stock as an indicator of the banks' financial health. The power of the stock market to incorporate the impact of forward-looking projections into an estimate of a firm's value today would be a valuable early-warning indicator in times of financial crisis.

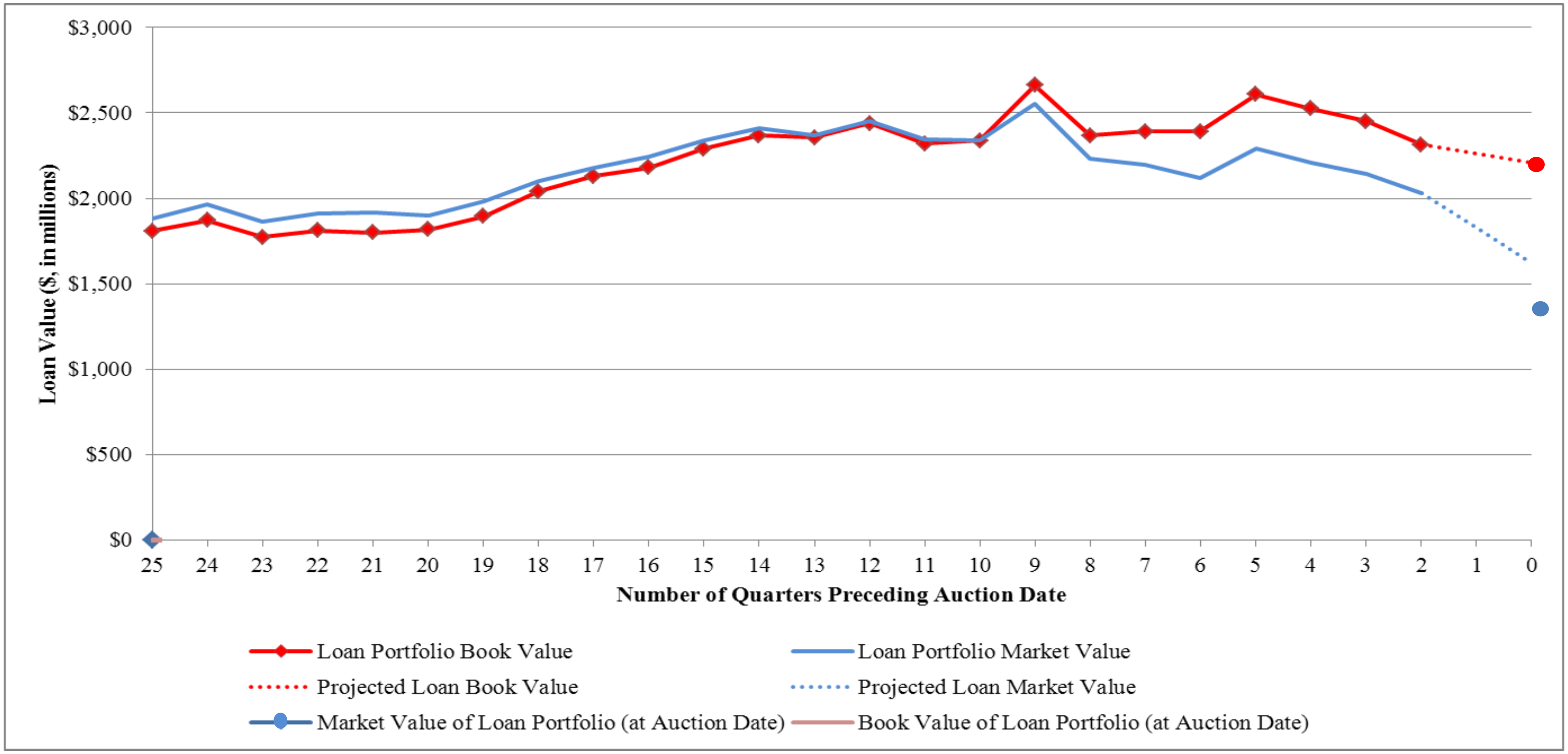

Figure 4.1: Quarterly time-series comparison of average market value and average book value of failed bank loan portfolios sold in whole bank form at FDIC auction

This figure presents a time-series plot of the average book value of the loan portfolios of failed banks as compared to the average market value of the loan portfolios of the same failed banks. Loan portfolio book value is the mean of the book value of total loans of failed banks in the sample. Balance sheet data is from Compustat. Observations are quarterly. Loan portfolio market value is the mean of the market value of total loans of the failed banks as derived from the bank's daily stock prices using a real options methodology. Book and market values of loan portfolios at auction date are the mean values of the failed bank portfolios as reported and valued by the acquirers. Values are sourced from acquirer 8-K, 10-Q and 10-K SEC filings. Projected loan portfolio book and market values are the interpolated values from the last available quarterly financial reports prior to seizure (and last quarter end stock prices prior to delisting) and the book and market values reported at auction. The sample is comprised of publicly traded banks seized during the period 2008 to 2010 for which detailed valuation is publicly available and for banks in which essentially all assets and liabilities were sold to acquirers at FDIC auction.

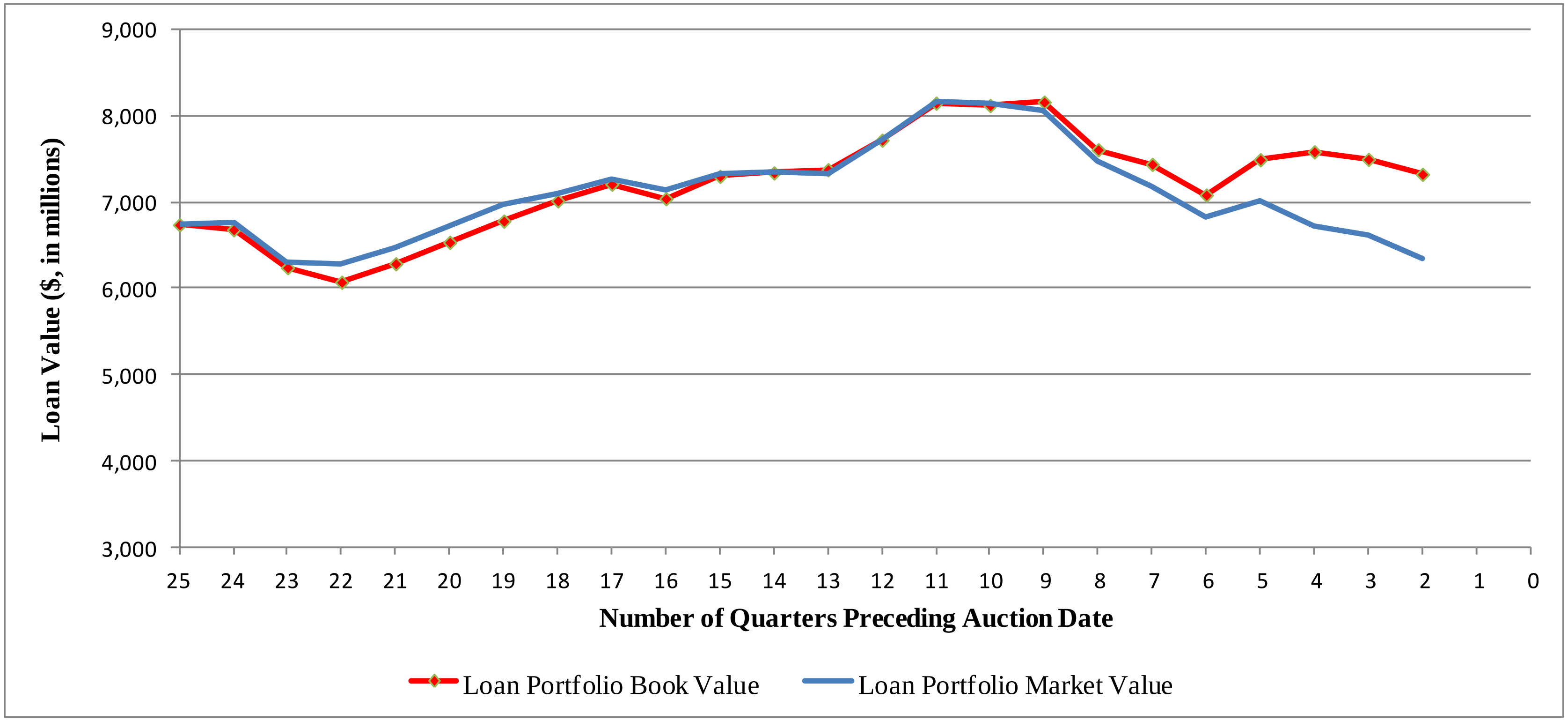

Figure 4.2: Quarterly time-series comparison of average market value and average book value of failed bank loan portfolios

This figure presents a time-series plot of the average book value of the loan portfolios of failed banks as compared to the average market value of the loan portfolios of the same failed banks. Loan portfolio book value is the mean of the book value of total loans of failed banks in the sample. Balance sheet data is from Compustat. Observations are quarterly. Loan portfolio market value is the mean of the market value of total loans of the failed banks as derived from the bank's daily stock prices using a real options methodology. Book value asset/liability ratios are calculated from quarterly Compustat data. Market value asset/liability ratios are calculated from quarterly Compustat data and adjusted for the effects of market valuation. % < 1.0 indicates the percentage of banks for the sample period with a asset/liability ratio below 1.0. Ratios for periods 0 and 1 are calculated based on interpolated run-rates derived from the sample presented in Figure1. The sample is comprised of publicly traded banks seized during the period 2008 to 2010. Reported p-values are values from Wilcoxon signed rank sum tests.

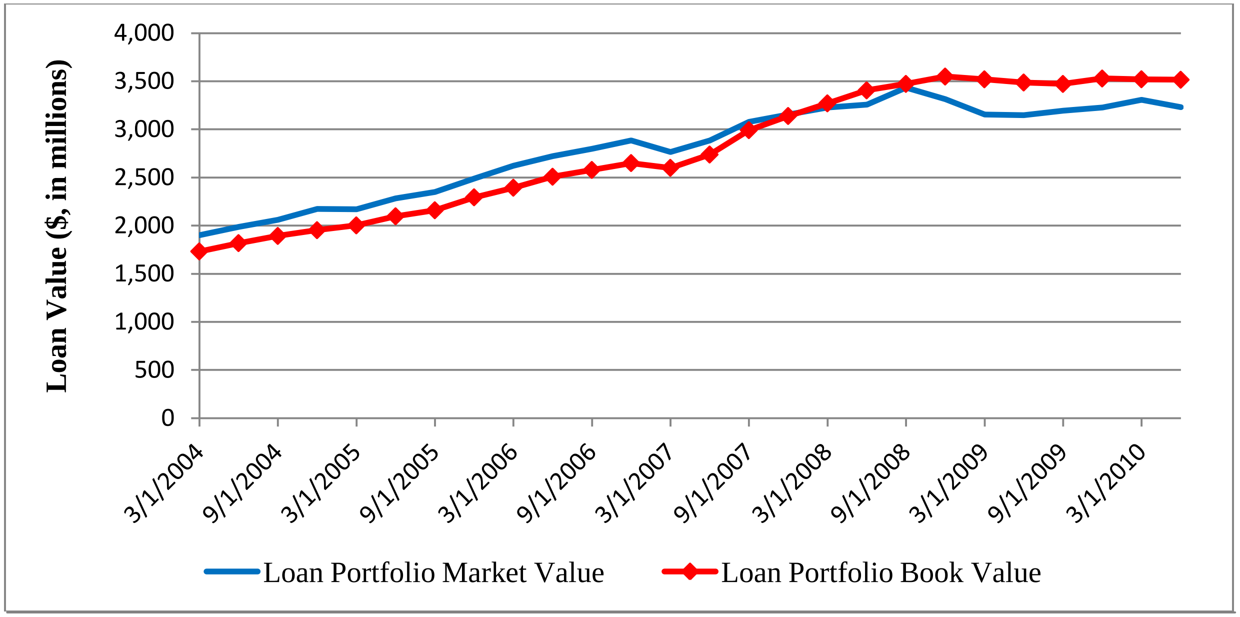

Figure 4.3: Quarterly time-series comparison of average market value and average book value of the commercial banking industry
This figure presents a time-series plot of the average book value of the loan portfolios of the solvent banks within the commercial banking industry as compared to the average market value of the loan portfolios of the same banks. The industry is proxied by the sample of banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks presented in Figure 2 that overlap SIC code 6020 have been removed from this sample. Loan portfolio book value is the mean of the book value of total loans of the banks in the sample. Balance sheet data is from Compustat. Observations are quarterly. Loan portfolio market value is the mean of the market value of total loans as derived from the bank's daily stock prices using a real options methodology. Book value asset/liability ratios are calculated from quarterly Compustat data. Market value asset/liability ratios are calculated from quarterly Compustat data and adjusted for the effects of market valuation. % < 1.0 indicates the percentage of banks for the sample period with a asset/liability ratio below 1.0. Reported p-values are values from Wilcoxon signed rank sum tests.

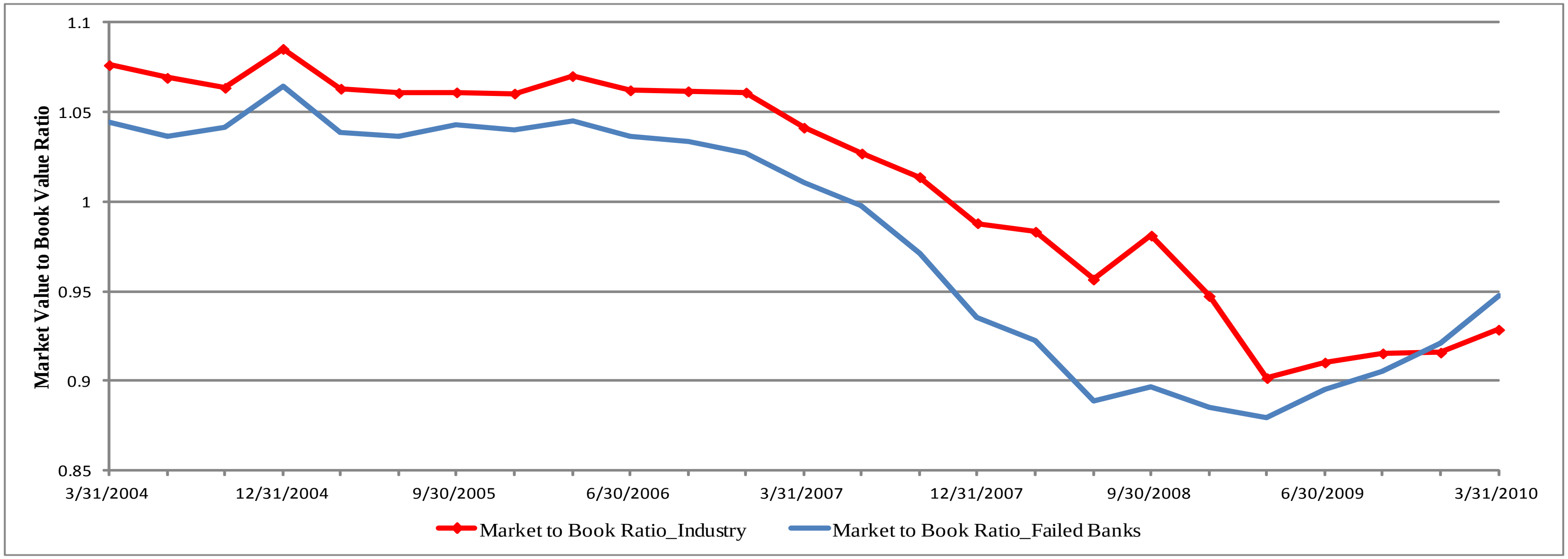

Figure 4.4: Quarterly time-series comparison of loan portfolio market to book values of solvent and failed banks
This figure presents a time-series plot of the average market to book ratio of the loan portfolios of the solvent banks within the commercial banking industry as compared to the average market to book ratio of the loan portfolios of failed banks. The industry is proxied by the sample of banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks presented in Figure 2 that overlap SIC code 6020 have been removed from this sample. Observations are quarterly. Loan portfolio market value is derived from the bank's daily stock prices using a real options methodology. Loan portfolio book value is from quarterly Compustat data. Reported p-values are values from Wilcoxon signed rank sum tests.

Table 4.1: Summary statistics of the primary variables of interest for 2008 to 2010

This table presents summary statistics for the primary variables examined in this paper. Panel A presents statistics for the commercial banking industry from 2008 to 2010. The industry is proxied by the sample of banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks presented in Figure 2 that overlap SIC code 6020 have been removed from this sample. Panel B presents the statistics for the explanatory variables employed in the regression analysis of failed bank losses for the period from 2008 to 2010. Real estate loans is the ratio of real estate loans to total assets. Commercial and industrial loans is the ratio of commercial and industrial loans to total assets. AFS securities is the ratio of available for sale securities to total assets. HTM securities is the ratio of held to maturity securities to total assets. Securities is the ratio of total securities to total assets. Total assets is the lognormal transform of total assets. Intrinsic Loss is the lognormal transform of the losses estimated for each failed banks shared loss covered loan portfolio.

Panel A: Industry	Mean	Median	Min	Max	Std. Dev.	# of Banks
Real estate loans	0.53	0.55	0.04	0.90	0.15	101
Commercial and industrial loans	0.11	0.09	0.00	0.83	0.09	101
AFS securities	0.17	0.15	0.00	0.64	0.10	101
HTM securities	0.02	0.00	0.00	0.37	0.04	101
Securities	0.19	0.16	0.00	0.64	0.11	101
Total loans, ratio	0.68	0.70	0.15	0.98	0.12	101
Total loans	2,226,300	1,063,792	45,050	40,737,392	4,264,329	101
Total assets	3,270,935	1,653,171	46,588	55,566,801	6,023,575	101

Panel B: Failed Banks	Mean	Median	Min	Max	Std. Dev.	# of Banks
Real estate loans	0.65	0.66	0.45	0.86	0.11	38
Commercial and industrial loans	0.07	0.06	0.01	0.22	0.04	38
AFS securities	0.09	0.08	0.00	0.30	0.07	38
HTM securities	0.01	0.00	0.00	0.20	0.03	38
Securities	0.10	0.10	0.00	0.30	0.07	38
Total loans, ratio	0.71	0.72	0.51	0.89	0.10	38
Total loans	1,635,734	603,836	104,215	16,233,255	2,977,519	38
Total assets	2,380,379	949,428	184,184	25,455,112	4,566,093	38
Estimated credit losses	608,263	225,500	22,000	5,000,000	1,090,574	38
LN(total loans)	13.56	13.31	11.55	16.60	1.11	38
LN(real estate loans)	13.47	13.20	11.49	16.52	1.09	38
LN(total assets)	13.92	13.76	12.12	17.05	1.10	38
LN(est. credit losses)	12.47	12.33	10.00	15.42	1.23	38

Table 4.2: Quarterly time-series comparison of average market value and average book value of failed bank loan portfolios sold in whole bank form at FDIC auction

This table presents a time-series comparison of the average book value of the loan portfolios of failed banks as compared to the average market value of the loan portfolios of the same failed banks. Variables are defined in Figure 1. The sample is comprised of publicly traded banks seized during the period 2008 to 2010 for which detailed valuation is publicly available and for banks in which essentially all assets and liabilities were sold to acquirers at FDIC auction. Reported p-values are values from Wilcoxon signed rank sum tests.

	Number of Quarters Prior to Auction Date											
	13	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**
Book Value	2,356	2,438	2,321	2,339	2,663	2,367	2,391	2,390	2,610	2,524	2,450	2,315
Market Value	2,368	2,453	2,347	2,342	2,553	2,231	2,196	2,121	2,289	2,206	2,144	2,030
Difference	(11)	(15)	(26)	(3)	110	136	194	269	320	318	306	285
(p-value)	(.542)	(.779)	(.927)	(.338)	(.016)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
M / B Ratio	1.00	1.01	1.01	1.00	0.96	0.94	0.92	0.89	0.88	0.87	0.88	0.88
# of Obs.	27	27	25	26	27	27	27	27	28	28	28	28
	25	**24**	**23**	**22**	**21**	**20**	**19**	**18**	**17**	**16**	**15**	**14**
Book Value	1,809	1,871	1,773	1,811	1,799	1,817	1,896	2,039	2,130	2,181	2,292	2,366
Market Value	1,884	1,965	1,865	1,911	1,917	1,899	1,982	2,101	2,178	2,244	2,336	2,411
Difference	(74)	(94)	(92)	(100)	(118)	(82)	(87)	(62)	(48)	(62)	(45)	(45)
(p-value)	(.294)	(.09)	(.134)	(.035)	(.05)	(.052)	(.06)	(.239)	(.239)	(.082)	(.215)	(.245)
M / B Ratio	1.04	1.05	1.05	1.05	1.07	1.05	1.05	1.03	1.02	1.03	1.02	1.02
# of Obs.	20	20	22	23	24	25	25	25	25	26	26	26

Table 4.3: Quarterly time-series comparison of average market value and average book value of failed bank loan portfolios

This table presents a time-series comparison of the average book value of the loan portfolios of failed banks as compared to the average market value of the loan portfolios of the same failed banks. Variables are defined in Figure 2. The sample is comprised of publicly traded banks seized during the period 2008 to 2010. Reported p-values are values from Wilcoxon signed rank sum tests.

	Number of Quarters Prior to Auction Date											
	12	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**0**
Book Value	7,723	8,125	8,165	7,612	7,442	7,085	7,496	7,588	7,500	7,326	7,168	7,021
Market Value	7,736	8,144	8,058	7,481	7,191	6,835	7,011	6,715	6,626	6,335	5,763	5,526
Difference	(13)	(19)	107	131	251	250	485	873	874	992	1,405	1,495
(p-value)	(.688)	(.378)	(.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
M / B Ratio	1.00	1.00	0.99	0.98	0.97	0.96	0.94	0.88	0.88	0.86	0.80	0.79
# of Obs.	44	44	44	45	45	47	49	49	49	49	49	49
	25	**23**	**22**	**21**	**20**	**19**	**18**	**17**	**16**	**15**	**14**	**13**
Book Value	6,740	6,243	6,073	6,288	6,537	6,783	7,018	7,212	7,043	7,303	7,343	7,380
Market Value	6,733	6,309	6,276	6,461	6,716	6,963	7,098	7,270	7,143	7,326	7,360	7,323
Difference	8	(66)	(203)	(173)	(179)	(180)	(80)	(58)	(100)	(23)	(17)	57
(p-value)	(.419)	(.093)	(.008)	(.001)	(.001)	(.002)	(.012)	(.017)	(.004)	(.02)	(.096)	(.304)
M / B Ratio	1.00	1.01	1.03	1.03	1.03	1.03	1.01	1.01	1.01	1.00	1.00	0.99
# of Obs.	44	44	44	44	44	44	44	44	44	44	44	44

Table 4.3: Quarterly time-series comparison of average market value and average book value of failed bank loan portfolios, continued

This table presents a time-series comparison of the average book value of the loan portfolios of failed banks as compared to the average market value of the loan portfolios of the same failed banks. Variables are defined in Figure 2. The sample is comprised of publicly traded banks seized during the period 2008 to2010.

	Number of Quarters Prior to Auction Date									
	9	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**0**
Book Value										
Median	1.09	1.09	1.09	1.08	1.07	1.07	1.05	1.03	1.02	1.00
High	1.20	1.21	1.19	1.17	1.16	1.16	1.15	1.15	1.20	1.26
Low	1.05	1.05	1.04	1.03	1.02	1.01	0.98	0.97	0.84	0.72
% < 1.0	0%	0%	0%	0%	0%	0%	6%	21%	43%	53%
Market Value										
Median	1.05	1.05	1.02	1.00	0.98	0.97	0.96	0.96	0.92	0.91
High	1.27	1.17	1.17	1.15	1.14	1.12	1.07	1.06	1.07	1.13
Low	0.98	0.97	0.96	0.96	0.95	0.95	0.95	0.95	0.79	0.68
% < 1.0	7%	16%	27%	47%	67%	80%	88%	96%	90%	82%
# of Obs.	44	45	45	47	49	49	49	49	49	49

Table 4.4: Quarterly time-series comparison of average market value and average book value of the commercial banking industry

This table presents a time-series comparison of the average book value of the loan portfolios of the solvent banks within the commercial banking industry as compared to the average market value of the loan portfolios of the same banks. The industry is proxied by the sample of banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks presented in Figure 2 that overlap SIC code 6020 have been removed from this sample. Variables are defined in Figure 2. Reported p-values are values from Wilcoxon signed rank sum tests.

	6/30/07	9/30/07	12/31/07	3/31/08	6/30/08	9/30/08	12/31/08	3/31/09	6/30/09	9/30/09	12/31/09	3/31/10	6/30/10
Book Value	2,739	2,992	3,139	3,270	3,405	3,472	3,549	3,520	3,487	3,472	3,529	3,521	3,515
Market Value	2,885	3,078	3,152	3,228	3,258	3,433	3,314	3,153	3,148	3,192	3,226	3,307	3,231
Difference	(146)	(86)	(13)	42	147	40	235	367	339	280	303	214	285
(p-value)	(<.001)	(.082)	(.024)	(.015)	(<.001)	(.042)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
M / B Ratio	1.05	1.03	1.00	0.99	0.96	0.99	0.93	0.90	0.90	0.92	0.91	0.94	0.92
# of Obs.	111	108	106	104	102	102	102	102	101	101	100	99	99
	3/31/04	6/30/04	9/30/04	12/31/04	3/31/05	6/30/05	9/30/05	12/31/05	3/31/06	6/30/06	9/30/06	12/31/06	3/31/07
Book Value	1,732	1,819	1,893	1,953	2,003	2,097	2,160	2,295	2,394	2,508	2,579	2,650	2,600
Market Value	1,900	1,987	2,061	2,173	2,171	2,281	2,348	2,490	2,624	2,721	2,799	2,884	2,766
Difference	(167)	(169)	(168)	(220)	(168)	(184)	(189)	(196)	(230)	(213)	(220)	(234)	(165)
(p-value)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
M / B Ratio	1.10	1.09	1.09	1.11	1.08	1.09	1.09	1.09	1.10	1.08	1.09	1.09	1.06
# of Obs.	146	139	135	135	135	132	130	127	124	123	121	116	114

Table 4.4: Quarterly time-series comparison of average market value and average book value of the commercial banking industry, continued
This table presents a time-series comparison of the average book value of the loan portfolios of the solvent banks within the commercial banking industry as compared to the average market value of the loan portfolios of the same banks. The industry is proxied by the sample of banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks presented in Figure 2 that overlap SIC code 6020 have been removed from this sample. Variables are defined in Figure 2. % < 1.0 indicates the percentage of banks for the sample period with a asset/liability ratio below 1.0. Reported p-values are values from Wilcoxon signed rank sum tests.

	6/30/07	9/30/07	12/31/07	3/31/08	6/30/08	9/30/08	12/31/08	3/31/09	6/30/09	9/30/09	12/31/09	3/31/10	6/30/10
Book Value													
Median	1.10	1.10	1.10	1.10	1.10	1.09	1.10	1.10	1.10	1.10	1.10	1.11	1.11
High	1.22	1.23	1.23	1.18	1.18	1.18	1.21	1.20	1.19	1.21	1.20	1.20	1.18
Low	1.06	1.06	1.05	1.05	1.05	1.03	1.04	1.03	1.03	1.02	1.02	1.01	0.99
% < 1.0	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
Market Value													
Median	1.12	1.11	1.09	1.09	1.05	1.07	1.05	1.02	1.03	1.03	1.03	1.05	1.04
High	1.26	1.27	1.23	1.26	1.29	1.33	1.35	1.31	1.34	1.33	1.34	1.31	1.29
Low	1.01	1.00	0.98	0.98	0.97	0.96	0.95	0.95	0.96	0.96	0.95	0.95	0.95
% < 1.0	0%	0%	2%	4%	12%	11%	19%	36%	35%	32%	33%	27%	25%
# of Obs.	111	108	106	104	102	102	102	102	101	101	100	99	99
	3/31/04	6/30/04	9/30/04	12/31/04	3/31/05	6/30/05	9/30/05	12/31/05	3/31/06	6/30/06	9/30/06	12/31/06	3/31/07
Book Value													
Median	1.09	1.09	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.09	1.10	1.10	1.10
High	1.22	1.20	1.21	1.22	1.21	1.22	1.22	1.20	1.20	1.20	1.21	1.22	1.22
Low	1.06	1.04	1.05	1.05	1.05	1.05	1.05	1.06	1.06	1.06	1.06	1.06	1.07
% < 1.0	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Market Value													
Median	1.14	1.14	1.14	1.15	1.14	1.13	1.14	1.13	1.14	1.13	1.14	1.14	1.13
High	1.29	1.30	1.33	1.35	1.30	1.30	1.31	1.29	1.34	1.29	1.29	1.34	1.29
Low	1.03	1.03	1.02	1.01	1.01	1.02	1.02	1.01	1.01	1.00	1.01	1.01	1.01
% < 1.0	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
# of Obs.	146	139	135	135	135	132	130	127	124	123	121	116	114

Table 4.5: Quarterly time-series comparison of loan portfolio market to book values of solvent and failed banks

This table presents a time-series plot of the average market to book ratio of the loan portfolios of the solvent banks within the commercial banking industry as compared to the average market to book ratio of the loan portfolios of failed banks. The industry is proxied by the sample of banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks presented in Figure 2 that overlap SIC code 6020 have been removed from this sample. Observations are quarterly. Loan portfolio market value is derived from the bank's daily stock prices using a real options methodology. Loan portfolio book value is from quarterly Compustat data. Reported p-values are values from Wilcoxon signed rank sum tests.

	3/31/04	**6/30/04**	**9/30/04**	**12/31/04**	**3/31/05**	**6/30/05**	**9/30/05**	**12/31/05**	**3/31/06**	**6/30/06**	**9/30/06**	**12/31/06**
Industry	1.08	1.07	1.06	1.09	1.06	1.06	1.06	1.06	1.07	1.06	1.06	1.06
Failed Banks	1.04	1.04	1.04	1.06	1.04	1.04	1.04	1.04	1.05	1.04	1.03	1.03
Difference	0.032	0.033	0.022	0.021	0.024	0.024	0.018	0.021	0.025	0.025	0.028	0.034
(p-value)	(.011)	(.005)	(.052)	(.09)	(.032)	(.048)	(.23)	(.098)	(.052)	(.06)	(.032)	(.003)
	6/30/07	**9/30/07**	**12/31/07**	**3/31/08**	**6/30/08**	**9/30/08**	**12/31/08**	**3/31/09**	**6/30/09**	**9/30/09**	**12/31/09**	**3/31/10**
Industry	1.03	1.01	0.99	0.98	0.96	0.98	0.95	0.90	0.91	0.92	0.92	0.93
Failed Banks	1.00	0.97	0.94	0.92	0.89	0.90	0.89	0.88	0.90	0.90	0.92	0.95
Difference	0.029	0.043	0.053	0.061	0.068	0.084	0.062	0.022	0.015	0.010	(0.005)	(0.019)
(p-value)	(.003)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.294)	(.657)	(.988)	(.329)	n/a

Table 4.6: Loan valuation sample statistics

This table reports target firm loan characteristics for transactions over the period 2008-2010. The subsample comprises 102 transactions for which detailed deal valuation data is available. Data are reported for whole bank P&A auctions. Data is from acquirer 8K, 10Q or 10K filings. Book Value Loans is book value of total loans of the failed bank as of the purchase date. Fair Value Adjustment Loans is the adjustment to book value used to properly record loans of the failed bank at fair value as of the purchase date. Fair Value Loans is fair value of total loans of the failed bank as of the purchase date.

	Target Bank						
Variables	**N**		**Mean**	**Median**	**Standard Dev.**	**Max**	**Min**
Book Value Loans ($ thous)	81	$	1,023,636	324,285	2,362,987	14,328,000	32,472
Fair Value Adjustment Loans ($ thous)	82	$	(348,206)	(96,717)	961,249	(5,424)	(6,163,904)
Fair Value Loans ($ thous)	97	$	594,724	196,673	1,384,658	9,776,000	131

Table 4.7: Time-series comparison of asset / liabilities ratio of solvent and failed banks

This table presents a time-series comparison of the average asset to liability ratio of the solvent banks within the commercial banking industry as compared to the average asset to liability ratio of failed banks from the period 2008 to 2010. The industry is proxied by the sample of banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks presented in Figure 2 that overlap SIC code 6020 have been removed from this sample. Balance sheet data is from Compustat. Book value asset/liability ratios are calculated from quarterly Compustat data. Market value asset/liability ratios are calculated from quarterly Compustat data and adjusted for the effects of market valuation. Observations are quarterly. Loan portfolio market value is the mean of the market value of total loans as derived from the bank's daily stock prices using a real options methodology. Loan portfolio book value is the mean of the book value of total loans of the banks in the sample.

Panel A: Industry	**9/30/08**	**12/31/08**	**3/31/09**	**6/30/09**	**9/30/09**	**12/31/09**	**3/31/10**	**6/30/10**
Asset / Liability Ratio								
Book Value	1.09	1.10	1.10	1.10	1.10	1.10	1.11	1.11
Market Value	1.07	1.05	1.02	1.03	1.03	1.03	1.05	1.04
Market Value A/L < 1.0								
N	10	16	32	34	28	30	24	24
Book Value	1.08	1.08	1.09	1.09	1.09	1.08	1.08	1.08
Market Value	0.98	0.98	0.98	0.98	0.98	0.98	0.97	0.97
Market Value A/L >= 1.0								
N	92	86	70	67	73	70	75	75
Book Value	1.10	1.10	1.11	1.11	1.11	1.11	1.11	1.11
Market Value	1.08	1.07	1.04	1.06	1.05	1.06	1.07	1.06
N	102	102	102	101	101	100	99	99

	Number of Quarter Before Auction							
Panel B: Failed Banks	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**
Asset / Liability Ratio								
Book Value	1.09	1.09	1.09	1.08	1.07	1.07	1.05	1.03
Market Value	1.05	1.04	1.02	1.00	0.98	0.97	0.96	0.96
Market Value A/L < 1.0								
N	3	7	9	18	32	39	42	45
Book Value	1.11	1.06	1.07	1.07	1.07	1.06	1.04	1.03
Market Value	0.98	0.98	0.98	0.97	0.97	0.97	0.96	0.96
Market Value A/L >= 1.0								
N	41	37	36	29	17	10	7	4
Book Value	1.09	1.10	1.09	1.08	1.08	1.09	1.06	1.04
Market Value	1.06	1.05	1.04	1.03	1.04	1.03	1.02	1.00
N	44	44	45	47	49	49	49	49

Table 4.8: Time-series comparison of regulatory capital ratios of solvent and failed banks

This table presents a time-series comparison of the regulatory capital ratios of the solvent banks within the commercial banking industry as compared to the regulatory capital ratios of failed banks from the period 2008 to 2010. The industry is proxied by the sample of banks that comprise SIC code 6020 - commercial banks and financial institutions. Any failed banks presented in Figure 2 that overlap SIC code 6020 have been removed from this sample. Capital ratio data is from Call reports. Market value leverage ratios are calculated from quarterly Compustat and Call report data and adjusted for the effects of market valuation. Observations are quarterly. Market valuation is derived from the bank's daily stock prices using a real options methodology.

Panel A: Industry	**6/30/08**	**9/30/08**	**12/31/08**	**3/31/09**	**6/30/09**	**9/30/09**	**12/31/09**	**3/31/10**	**6/30/10**
Book Value									
Tier One Risk-Adjusted Capital	11.34%	11.22%	11.20%	11.76%	11.98%	12.11%	11.74%	12.17%	12.39%
Tier Two Risk-Adjusted Capital	1.34%	1.43%	1.44%	1.48%	1.47%	1.49%	1.51%	1.50%	1.49%
Total Risk-Adjusted Capital	12.67%	12.64%	12.64%	13.24%	13.45%	13.60%	13.24%	13.67%	13.88%
Tier One Leverage	8.59%	8.51%	8.55%	8.76%	8.69%	8.73%	8.42%	8.56%	8.68%
Market Value									
Tier One Leverage	6.07%	7.33%	4.96%	2.50%	3.14%	3.39%	3.35%	4.53%	4.05%
N	64	67	69	70	70	71	72	73	72

	Number of Quarter Before Auction								
Panel B: Failed Banks	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Book Value									
Tier One Risk-Adjusted Capital	10.17%	10.12%	9.83%	9.43%	9.34%	9.01%	8.29%	5.88%	3.83%
Tier Two Risk-Adjusted Capital	1.15%	1.18%	1.25%	1.26%	1.26%	1.27%	1.27%	1.29%	1.28%
Total Risk-Adjusted Capital	11.42%	11.25%	11.05%	10.78%	10.63%	10.39%	9.71%	7.34%	5.44%
Tier One Leverage	8.42%	8.53%	8.25%	8.03%	7.46%	7.21%	6.47%	4.70%	3.03%
Market Value									
Tier One Leverage	6.07%	5.61%	3.90%	3.53%	1.98%	1.96%	1.95%	2.58%	0.41%
N	47	47	47	47	48	49	49	49	49

Table 4.9: Regression of estimated losses on explanatory variables

This table presents the results from regressions of FDIC estimated Intrinsic Loss amounts on explanatory variables for publicly traded failed banks seized and auctioned during the 2008 to 2010 sample period. Intrinsic Loss is the lognormal transform of the losses estimated for each failed banks shared loss covered loan portfolio. Real estate loans is the ratio of real estate loans to total assets. Commercial and industrial loans is the ratio of commercial and industrial loans to total assets. AFS securities is the ratio of available for sale securities to total assets. HTM securities is the ratio of held to maturity securities to total assets. Securities is the ratio of total securities to total assets. Market value of estimated losses is the estimated credit losses embedded in firm loan portfolios as estimated by market value discount amounts. Total assets is the lognormal transform of total assets. Regions are from the Bureau of labor Statistics, Census regions. Bank HQs are from the FDIC. T-stats are reported in parentheses. Standard errors are adjusted for date and region clusters.

Dependent Variable = LN estimated credit losses						
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Real estate loans	2.2	2.0	2.0	1.8	2.3	2.1
	(2.56)	(2.38)	(2.43)	(2.42)	(3.10)	(2.94)
Commercial and industrial loans	0.0	0.1	-0.1	0.0	0.5	0.7
	(0.02)	(0.05)	(0.06)	(0.01)	0.2	(0.25)
AFS securities	0.1		-0.7		-1.0	
	(0.08)		(0.44)		(0.55)	
HTM securities	-2.6		-3.3		-3.5	
	(1.07)		(2.97)		(1.86)	
Securities		-0.4		-1.2		-1.9
		(0.30)		(0.82)		(1.22)
Market value estimate of estimated losses			0.2	0.2	0.1	0.1
			(1.03)	(1.04)	(0.34)	(0.41)
Total assets	1.1	1.1	0.9	0.9	1.0	1.0
	(14.46)	(14.40)	(4.29)	(4.08)	(3.70)	(3.60)
Georgia region					0.4	0.4
					(1.73)	(1.86)
Washington region					-0.1	-0.1
					(0.14)	(0.20)
California region					0.2	0.1
					(0.87)	(0.44)
West region					0.1	0.1
					(0.68)	(0.54)
Midwest region					0.2	0.2
					(0.56)	(0.20)
Northeast region					0.8	0.9
					(4.76)	(6.22)
Constant	-4.0	-3.7	-3.3	-3.0	-4.2	-3.9
	(3.52)	(3.34)	(3.11)	(3.03)	(2.85)	(2.69)
Time fixed effects	N	N	N	N	Y	Y
R-squared	0.89	0.89	0.89	0.89	0.92	0.92
Observations	38	38	38	38	38	38

Table 4.10: Savings to FDIC Deposit Insurance Fund from robust capital adequacy enforcement

This table reports estimates of the savings to the FDIC Deposit Insurance fund from prompt seizure of troubled or insolvent banks. The sample is comprised of 188 of the 218 banks sold with loss share coverage during the period 2008 to 2010. Date 0 is the actual seizure date of each bank in the sample. Average asset/liability ratios are the ratios derived from the public sample in Figure 2. Average market/book ratio of bank loan portfolios are the ratios derived from the public sample in Figure 2. Estimated credit savings is the potential savings from seizing and selling the bank 1 quarter prior to the actual seizure date; savings accrue from better credit quality of the loan portfolio. Auction price savings accrue from lower asset discounts received at auction and stronger book capital amounts. Cost of additional bank failures is the sum of auction costs and estimated credit loss from industry bank failures as a result of enforcing capital adequacy regulations. Total savings is the total of credit and auction savings and costs from additional bank failures.

	Number of Quarters Prior to Seizure Date			
	0	1	2	3
Average Asset/Liability Ratio				
Book Value	1.02	1.03	1.05	1.07
Market value	0.92	0.96	0.96	0.97
Average Market/Book Ratio, Loan Portfolio	0.80	0.86	0.88	0.88
Estimated Credit Loss Savings ($, thous)	n/a	7,606,314	17,978,836	19,772,989
Auction Price Savings ($, thous)	n/a	8,798,344	12,113,681	13,107,441
Cost of Additional Bank Failures	n/a	(2,700,875)	(1,530,706)	(1,732,695)
Total Savings ($, thous)	n/a	13,703,782	28,561,812	31,147,735

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Appendix A

Variable Definitions

Variables	Description
Price	Realized sales price for target bank
Measures of Asset Quality	
Noncurrent assets plus other real estate owned	Noncurrent assets as a percent of total assets. Noncurrent assets are defined as assets that are past due 90 days or more plus assets placed in nonaccrual status plus other real estate owned. Quarterly measure.
Fair value adjustment purchased loans	Adjustment to book value of purchased loan pools in order to record loans at fair value based on the current market price at time of purchase
Core deposit intangible	Premium paid to acquire the core deposits of an institution. The premium is the amount paid in excess of the dollar amount of the deposits. The value of the core deposit intangible is calculated as the difference between the costs of the core deposits as compared to the most favorable market alternative.
Measures of Earnings	
Return on assets	Net income after taxes and extraordinary items (annualized) as a percent of average total assets. Quarterly measure.
Cost of funding earning assets	Annualized total interest expense on deposits and other borrowed money as a percent of average earning assets. Quarterly measure.

Variables	Description
Measure of Size	
LN(number of branches sold)	Log of number of bank branches sold to acquirer
Measures of IndustryDistress	
# Banks failed following quarter	Count of the number of institutions seized in the quarter following the announcement of failure. Quarterly measure.
Median industry leverage ratio	Industry median tier 1 (core) capital as a percent of average total assets minus ineligible intangibles. Tier 1 (core) capital includes: common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. Quarterly measure.
Measures of Liquidity	
Change in industry median liquid assets(t) / asset(t-1)	Reflects the change in industry median liquid assets, defined as noninterest-bearing cash balances + interest-bearing cash balances + non-MBS and non-ABS held-to-maturity securities + non-MBS and non-ABS available-for-sale securities + fed funds sold + securities purchased under agreements to resell, divided by the previous year's median total assets at the quarter end preceding the announcement of failure. Quarterly measure.
(Change in industry commitments + loans(t)) / asset(t-1)	Reflects the change in industry median illiquid assets, defined as loans + undrawn commitments divided by total assets at the quarter end preceding the announcement of failure. Quarterly measure.
(Acquirer commitments + loans) / asset(t-1)	Sum of the acquirer's loans + undrawn commitments divided by total assets at the quarter end preceding the announcement of failure. Quarterly measure.

Variables	Description
LN(Acquirer core deposits)	Natural log of acquirer's total domestic demand, savings and time deposits under $100,000 at the quarter end preceding the announcement of failure.
LN(Acquirer liquid assets)	Natural log of acquirer's liquid assets, as defined above, at the quarter end preceding the announcement of failure.
Measure of Industry Outsider	
Outsider Dummy	Dummy variable equal to one if a winning bidder is an industry outsider and zero otherwise