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Essays on Bank Acquisitions and Systemic Risk

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ESSAYS ON BANK ACQUISITIONS AND SYSTEMIC RISK

by

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Abstract

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Adviser: Professor Gayle DeLong

This dissertation consists of two chapters on bank acquisitions and systemic risk.

Chapter 1 This chapter explores whether bank acquisitions are associated with systemic risk-shifting. Acquisitions can form larger and more diversified firms and, as such, increase the correlation of the acquirer's investment with other banks and subsequently the probability of their joint failure. This can be beneficial for the acquirer due to (implicit) government "too-many-to-fail" guarantees. I find that bank acquisitions on average lead to an increase in acquires' systemic risk, which is in turn associated with an increase in firm value for non-distressed acquisitions. Interestingly, congruent with the concept of "availability" in behavioral finance, this usually favorable market reaction to acquisition-induced increase in acquirers' systemic risk turns into a significantly unfavorable one during crisis periods as investors perceive a higher probability for tail events. I then, classify acquisitions into activity diversifying and focusing to explore whether diversification is the mechanism for systemic risk-shifting. I find that diversifying acquisitions that lead to an increase in the systemic risk contribution of acquirers are associated with higher acquisition announcement abnormal return for acquirers' shareholders. Additionally, I find that diversifying acquisitions with relatively well-performing acquirers exhibit higher degrees of systemic risk-shifting, regardless of value creation. Overall, I put forward a potential incentive for diversifying acquisitions, namely, systemic risk-shifting. These findings can bring value to banking supervisors by

identifying acquisitions with more likelihood of threatening financial stability.

Chapter 2 This chapter explores the source of systemic risk in financial institutions. I utilize an aggregate measure of systemic risk and show that the operational risk component drives systemic risk exposure and impacts future macroeconomic conditions. The operational risk component of aggregate systemic risk forecasts economic downturns up to 12 months into the future while the non-operational component has no predictive power. Operational risk is measured as the residual risk remaining after accounting for market and credit risk in equity returns.

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Contents

List of Tables

List of Figures

Chapter 1

Bank acquisitions: Do acquirers gain private benefit at public cost?

1.1 Introduction

In this study we examine whether bank acquisitions are associated with an increase in acquirers (systemic) risk and whether an increase in (systemic) risk is correlated with value creation for acquirers shareholders. This is in line with the concept of systemic risk-shifting. M&A activities can result in a more concentrated banking system, composed of a smaller number of larger and more diversified firms. The dark side of diversification has long been a topic of discussion in the academic literature (see, e.g., Stiroh and Rumble, 2006; Beine, Cosma, and Vermeulen, 2010; van Oordt, 2014). Many studies have argued that diversification of risks at financial institutions, although beneficial on its own, can increase similarities among firms and expose them to the same risks. This in turn can increase the likelihood of systemic crisis and contribute to the fragility of the financial system (see, e.g., Berger, Demsetz, and Strahan, 1999; DeNicoló and Kwast, 2002; Wagner, 2008; Wagner, 2010). Consolidation of financial industry can change the financial network architecture and consequently increase the likelihood of systemic failures due to contagion of counterparty risk (see, e.g., Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2015). Therefore, diversification is not always optimal and does not necessarily help the safety and soundness of the financial system.

An increased debt capacity and risk reduction benefit of acquisitions may create an incentive for acquirers to take on more risk (see e.g., Lewellen, 1971[1]; Shleifer and Vishny, 1992[2]; DeNicoló, Bartholomew, Zaman, and Zephirin, 2004[3]), however, the impact of consolidations on fragility of financial system is argued to hold even if acquirers do not engage in riskier activities.

Although dark for the financial system, acquisitions and the resulting diversification can be beneficial to some individual firms, as acquisitions increase the extent of diversification and subsequently similarity of consolidated firms. Similarity can in turn increase the likelihood of joint survival and joint failure of the banks which is valuable due to existence of a (implicit) regulatory "safety net" and "too-big-to-fail" or "too-many-to-fail" guarantees that give rise to risk-shifting incentives (see e.g., Acharya, 2009). This does not necessarily imply that the consolidated institutions will engage in any activity that is systemically more risky. Even in absence of an increase in systemic risk, the fact that the acquisition results in concentration of systemic risk in one institution may create a perception for the investors that the consolidated institution would be more complex and difficult to resolve, therefore, there is a higher chance for government interventions in case of default.

Since a bank can kill two birds with one stone through diversification (i.e., reduce its non-systemic risk or increase expected return while increasing its systemic risk), the natural question that follows is *Do banks use diversification as a risk-shifting mechanism, particularly*

[1]Lewellen (1971) argues that the more conglomerate the consolidation, the greater the expansion of the partners debt-carrying ability pursuant to merger because diversification reduces earnings variability.

[2]Shleifer and Vishny (1992) argue that conglomerates may have a higher debt capacity as they can avoid fire-sales in bad times that are ex ante a significant private cost of leverage.

[3]In their study of the effects of consolidation on the risk-taking incentives of individual financial firms, DeNicoló et al. (2004) find that factors creating incentives for firms to take on more risk, appear to have outweighed the risk reduction potentially achievable through diversification.

in the systemic dimension?

In this paper, we contribute to the aforementioned literature by studying whether the acquisitions, that may lead to fragility of financial system and be costly to the taxpayers, is associated with any private gains for acquirers shareholders. This analysis involves exploring the effect of acquisition on risk and the relationship between acquisition-induced changes in the acquirer's risk and firm value. First, we revisit the prior literature finding that M&As reduce non-systemic risk but increase systemic risk of the consolidated firm (see e.g., Berger, 2000; Weiß, Neumann, and Bostandzic, 2014; Berger, Demsetz, and Strahan, 1999). Therefore, we study changes in acquirers' risk from two angles: non-systemic and systemic. The former refers to the sum of idiosyncratic and systematic risk, while the latter to correlation of returns with the financial sector in the tail. Second, we investigate whether the impact of systemic risk-shifting on firm value is different during crisis versus non-crisis periods. This can occur due to the fact that our measure of value creation involves the market perception of the fundamental value and, as such, it brings investors' sentiments into the equation. We also explore the change in systemic risk of combined entities, however since this limits the sample to those acquisitions with a publicly-traded target and this sample seems to have a different characteristics than the entire population, we dont find a significant increase in systemic risk of combined entities. Although, for that sample we find that the systemic risk of acquirers alone are higher than the acquirers and targets combined prior to acquisition.

Third, we classify acquisitions of banking firms according to activity and geography similarity (focusing) or dissimilarity (diversifying). We show that diversifying acquisitions are the ones that create value for acquirers shareholders through systemic risk-shifting. Hence, we put forward a crucial incentive for bidders to engage in diversifying acquisitions, namely, systemic risk-shifting (see e.g., Acharya, 2009; Wagner, 2010). Forth, we study whether diversifying versus focusing acquisitions are more likely to engage in and exhibit higher degree of systemic risk-shifting.

We focus on M&As within the USA involving deals announced and completed between 1986 and 2015. Non-systemic risk is estimated using the same methodology as in Amihud, DeLong, and Saunders (2002) to calculate what they deem "Total Relative Risk" (TTR), which is meant to include both idiosyncratic and systematic risks. We measure systemic risk-shifting as an increase in market adjusted systemic-risk of the bidder resulting from acquisition. In order to measure systemic risk we use Acharya, Pedersen, Philippon, and Richardson (2016)'s Marginal Expected Shortfall (MES). In our study, systemic risk-shifting exists when the Market Adjusted MES (MAES) is positive as a result of acquisition. As in the literature, we measure value creation for acquirers' shareholders using a Cumulative Abnormal Return (CAR) measure. We follow DeLong (2001) to classify acquisitions of banking firms according to activity and geography similarity (focusing) or dissimilarity (diversifying).[4]

We find that acquirers' systemic risk increases as the result of acquisition, although their non-systemic risk does not significantly change. Our analysis indicate that the observed increase in acquirers' systemic risk is not the result of absorbing target's systemic risk. We also find that (ex-ante) the market reacts favorably to an increase in systemic risk in non-crisis periods. Our results suggest that risk-shifting, particularly in the systemic dimension, is a source of value creation for acquiring banks' shareholders or, in other words, acquirers take private benefit at public cost.

This finding does not generally apply to distressed acquisitions. Interestingly, we find that market (ex-ante) reaction to an increase in systemic risk for acquisitions announced during adverse macro conditions (or crisis periods) is significantly unfavorable. This is in line with the concept of "availability" in behavioral finance, which promotes the idea that the

[4]This methodology examines the past movement of stock returns to determine whether partners engage in different types of risks and are therefore involved in different types of activities. This methodology is particularly relevant for studying the impact of systemic risk-shifting.

realization of a tail event during crisis periods affects investors' perception of the probability of such events and make them particularly risk averse (see Tversky and Kahneman, 1973).

Our results suggest that only diversifying (as opposed to focusing) acquisitions lead to an increase in acquirers' systemic risk contribution create value for acquirers' shareholders.[5] Furthermore, we find that systemic risk-shifting creates statistically and economically significant value for acquirers' shareholders only for diversifying acquisitions. Our results also suggest that the value of systemic risk-shifting for acquirers' shareholders has increased after the recent financial crisis. Taken all together, our findings could be particularly helpful to banking supervisors by narrowing down their focus on acquisitions that have a higher likelihood of threatening financial stability.

The remainder of this paper is organized as follows. In Section 1.2, we develop the hypotheses. Section 1.3 presents the methodology for constructing measures of: systemic risk, non-systemic risk and abnormal returns. It also presents the methodology for classifying acquisitions into diversifying and focusing. Section 1.4 describes the M&A and equity return data used in the empirical study. Empirical results are given in Section 1.5, and robustness checks are given in Section 1.6. Section 1.7 concludes. Variable definitions and theories from the literature are presented at the end of the chapter.

1.2 Hypothesis

As stated in the Introduction, consolidation of individual financial institutions can be detrimental to the financial stability in at least two ways. First, consolidation can change the financial network architecture, i.e., increase similarity of the nodes and density of interconnections and consequently increase the likelihood of systemic failures due to contagion of counterparty risk. DeNicoló and Kwast (2002) show that consolidation in the financial

[5] Although MES is arguably a measure of systemic risk exposure, for our purposes we do not distinguish between exposure and contribution.

sector is associated with an increase in inter-dependencies of large and complex banking organizations. In their theoretical frameworks, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) and Battiston, Gatti, Gallegati, Greenwald, and Stiglitz (2012) show that diversification can lead to either financial stability or fragility depending on factors such as structure and heterogeneity of firms' financial robustness or on the magnitude of negative shocks. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) argue that dense interconnections, corresponding to a more diversified pattern of interbank liabilities, can serve as a mechanism for the propagation of shocks. Second, M&As can increase the acquirers' incentive to take on more risk by expanding the acquirers' debt capacity (see, e.g., Lewellen, 1971).

M&As, however, can be beneficial to some individual firms due to increasing the likelihood of government forbearance in case of default. Furthermore, M&As can lead to either decrease in (non-systemic) risk of consolidated institution as a result of diversification or to a higher expected return if the acquirer chose to increase risk in pursuit of higher expected returns. Berger, Demsetz, and Strahan (1999) find that in many cases, consolidating institutions chose to move along the risk-expected return frontier and take most of the benefits of diversification gains as higher returns by shifting their portfolios toward higher risk-higher expected return investments.

Given these benefits (i.e., reduce non-systemic risk (or alternatively increase expected return) while increasing systemic risk (or externalizing the risk)), we investigate whether acquisitions lead to (systemic) risk-shifting and hypothesize that:

($\mathbf{H}_1$): Bank acquisitions can lead to systemic risk-shifting.

One may argue that an increase in acquirers' systemic risk is the result of absorbing target's systemic risk and therefore, acquisitions do not impose additional costs to the economy. To investigate this possibility, we consider the systemic risk of acquirer and target combined before the acquisition and compare it to the risk of consolidated entity after the acquisition.

We investigate the following hypothesis:

($\mathbf{H}_2$): The consolidated entity will be riskier than the two banks separately.

We expect that the impact of systemic risk-shifting on firm value is different during crisis versus non-crisis periods. In particular, we expect that the investors require higher compensation for taking the tail risk during a crisis period. Hence, we hypothesize that:

($\mathbf{H}_3$): Investors do not perceive systemic risk-shifting as favorably during crisis periods. More generally, the relationship between acquirers' value gain and systemic risk-shifting may not hold for distressed acquisitions as other factors can impact the firm value in those cases.

We tackle these hypotheses in two steps. First, we examine the change in acquirers' risk as a result of acquisition. More specifically, we use a difference-in-difference framework to estimate the change in (non-systemic and systemic) risks of a bidding bank before and after an acquisition relative to a financial sector index. Second, we explore the relationship between changes in risk of the acquirer and (abnormal) return for the acquirer's shareholders upon acquisition announcement. We also examine whether the market reacts to an increase in acquirers systemic differently during adverse versus normal economic conditions and more generally in the presence of distressed acquisitions.

Next, given that we hypothesized systemic risk-shifting in acquisitions is achieved through increased similarities among institutions, we expect to observe more systemic risk-shifting in diversifying acquisitions versus the focusing ones. Several studies have examined the value of diversifying versus focusing mergers based on bidder's abnormal stock return upon merger announcement. These studies found that focusing mergers consistently created positive value for bidders throughout 1960s to 1990s, while diversifying mergers destroyed value (see, e.g., Hubbard and Palia, 1999). DeLong (2001) confirms these findings and further shows that the loss in value for diversifying bidders is not the result of a wealth-transfer from bidders to targets.

The natural question that follows is, given that diversifying mergers are destroying value, what incentives do bidders have to engage in such value-destroying mergers? Several studies cite "managerial benefits" as the reason for overpaying and subsequently destroying shareholders' wealth through diversifying mergers (see, e.g., Amihud and Lev, 1981; Donaldson and Lorsch, 1983; Morck, Shleifer, and Vishny, 1990; Cornett, Hovakimian, Palia, and Tehranian, 2003). While diversifying mergers may be on average value-destroying, not all diversifying mergers lead to value destruction. We focus on value-creating diversifying M&As and investigate the following hypotheses:

($\mathbf{H}_4$): Systemic risk-shifting is an incentive for diversifying acquisitions and leads to value creation for acquirers' shareholders.

($\mathbf{H}_5$): Acquisition-induced systemic risk-shifting is higher for diversifying versus focusing acquisitions as a function of bidder pre-merger performance.

We test our fourth hypothesis by conducting three specific exercises. First, we examine whether all diversifying acquisitions lead to value destruction. If they do not, we then assess whether diversifying acquisitions create value through systemic risk-shifting. Second, we investigate whether value creation through systemic risk-shifting is only associated with diversifying acquisitions. Last, since a great deal of government interventions and bailouts took place during the recent financial crisis and the potential value of systemic risk-shifting is linked to such government forbearance, we test whether the value of systemic risk-shifting increased after the recent financial crisis (as a consequence of those bailouts).

In our fifth hypothesis, we explore whether the degree of acquisition-induced systemic risk-shifting is higher for diversifying versus focusing acquisitions regardless of the effect on acquirers' shareholders wealth. We study this relationship as a function of bidder's pre-merger performance because other motives for diversifying acquisitions, such as managerial benefits, are often associated with bidders' poor performance prior to acquisition, while we expect systemic risk-shifting motive to be associated with better performing bidders. To test this hypothesis, we also control for a set of bidders' and targets' characteristics.

1.3 Methodology

To conduct our empirical analysis, we construct risk measures that capture non-systemic and systemic risk of the acquiring bank, as well as a measure that captures the market reaction to the acquisition announcement. Finally, we lay out the methodology to classify acquisitions into diversifying and focusing.

1.3.1 Systemic risk measure

As in Weiß, Neumann, and Bostandzic (2014), we quantify changes in systemic risk due to acquisition by estimating changes in bidding banks' Marginal Expected Shortfall (MES). The MES measure was first proposed by Acharya, Pedersen, Philippon, and Richardson (2016) in a 2010 version of the paper as a measure of systemic risk contribution. MES is calculated as the average return of a bank during the x% worst days for the market (i.e., its losses in the tail of the system's loss distribution).

In order to control for other factors that could potentially impact systemic risk of acquirers, we utilize a difference-in-difference framework. Similar to Weiß et al. (2014), we construct a market adjusted MES measure (MAES) and estimate the changes in MES due to bank mergers relative to the Expected Shortfall (ES) of a financial sector index. We define the financial sector index return as the weighted average return of all common stocks issued by financial firms with SIC codes in the range of [6000,6800] that are reported in CRSP, where the weight is the market capitalization of the firm. The changes in market adjusted systemic risk indicate the extent to which the bidding banks experience disproportionately larger increases (or decreases) in their contribution to systemic risk than other firms in the financial sector.

In our empirical study, we estimate the differences between the bidding banks' pre- and post- acquisition MAES as follows. First, we define a day t to belong to the pre-acquisition period if it falls into the interval [-180,-11] relative to the acquisition announcement. Similarly, we consider a day t to belong to the post-acquisition period if it falls into the interval [+11,+180] relative to the acquisition completion.[6] The MAES is estimated as the difference between bidder's MES and financial sector's ES within the same time period. MAES of bidder i is calculated as

$$MAES_i^{5\%} = MES_i^{5\%} - ES_{Index}^{5\%} \tag{1.1}$$

where 5% indicates that MES is calculated using the average return of a bidder during the 5% worst days of a financial sector index.

From equation (1.1), the difference in MAES of bidder i pre- and post- acquisition is given by

$$\Delta MAES_i^{5\%} = MAES_{i,[+11,+180]}^{5\%} - MAES_{i,[-180,-11]}^{5\%} \tag{1.2}$$

where $\text{MAES}_{i,[-180,-11]}^{5\%}$ and $\text{MAES}_{i,[+11,+180]}^{5\%}$ correspond to pre- and post-acquisition MAES respectively. The [-180,-11] interval is relative to acquisition announcement, and [+11,+180] interval is relative to acquisition completion.

[6] We follow the financial literature in the choice of the estimation window length to make our results more comparable (see, e.g., Amihud, DeLong, and Saunders, 2002).

1.3.2 Non-systemic risk measure

As in Amihud et al. (2002), we calculate the acquirer's Non-Systemic Risk (NSR)[7] as the variance of the acquiring bank stock return relative to that of a financial sector index before and after the acquisition. We define the NSR of acquirer i as

$$NSR_i = Var(R_i)/Var(R_Index) \tag{1.3}$$

where R_i is the daily stock return of acquirer i, and Index is a financial sector index as defined in Section 1.3.1. We then calculate the change in NSR$_i$ as follows:

$$\Delta NSR_i = NSR_{i,[+11,+180]} - NSR_{i,[-180,-11]} \tag{1.4}$$

where NSR$_{i,[-180,-11]}$ and NSR$_{i,[+11,+180]}$ correspond to pre- and post- acquisition NSR respectively. As in the previous subsection, the [-180,-11] interval is relative to acquisition announcement, and [+11,+180] interval is relative to acquisition completion.

1.3.3 Market reaction measure

In order to gauge market reaction to acquisition announcement, or acquisition value creation for acquiring bank's shareholders, we estimate bidders' abnormal returns upon the announcement of acquisition. It is important to note that despite the pervasive use of this measure as the typical acquisition value creation measure, the acquirer's stock returns upon acquisition announcement are only partly driven by how much value is fundamentally created because the acquisition announcement also induces investors to reevaluate the acquirer's stock in light of the decision to merge, which might also bring investors' sentiments into the equation

[7] This is refered to as "Total Relative Risk" in Amihud et al. (2002). To emphasize the distinction with systemic risk, we refer to this as non-systemic risk. We ensured that non-systemic risk is orthognal to systemic risk by regressing it on systemic risk and estimating its correlation with the residual.

(Bhagat, Dong, Hirshleifer, and Noah, 2005; Savor and Li, 2009).

This measure relies heavily on stock market responses, and, thus, investor choices unrelated to acquisition value may still influence its measurement. The distinction between acquisition value creation and investors' evaluation of it becomes important later in the paper when we find macroeconomic conditions can impact investors' perception of acquisition's value.

We use the standard event study methodology in the finance literature (see, e.g., DeLong, 2001; Brown and Warner, 1985) with the market model:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{Mt}) \tag{1.5}$$

where AR_{it} and R_{it} are the abnormal return and the return on stock i at time t respectively, and R_{Mt} represents the return on the market at time t. We estimate the intercept and slope coefficients, α and β, using daily returns collected 300 to 51 trading days before the acquisition announcement. The market return is the value-weighted index of returns including dividends from CRSP database. Cumulative Abnormal Returns (CAR) of bank i are computed from 10 days before the acquisition announcement to 1 day following the announcement:

$$CAR_i = \sum_{t=-10}^{1} AR_{it} \tag{1.6}$$

where AR_{it} is defined in equation (1.5) and t represents days with respect to the acquisition announcement.

1.3.4 Classification of M&As into Diversifying versus Focusing

In order to classify the acquisitions into activity diversifying and focusing, we use the cluster analysis methodology outlined in DeLong (2001). We first classify the acquisitions based on their geography diversification. Acquisitions with in-state acquirers are considered as "geography focusing" and those with out-of-state acquirers, as "geography diversifying." It is important to classify the acquisitions by geography before classifying them by activity because the latter classification is based on stock returns, which may have embedded some geography diversification patterns.

Next, we classify the acquisitions into activity diversifying and focusing. We use Ward's method of cluster analysis to classify acquisitions based on a vector of monthly stock returns for the last 12 months before the acquisition announcement.[8,9] We choose to stop the cluster formation when within-group variation explains about 75% of the total variation. Once firms are clustered based on similarity of their stock returns, merging partners that fall into the same cluster are considered as "activity focusing", while those that fall into different clusters are "activity diversifying".

Finally, we sort the acquisitions into four groups using the previous classifications: Geography Focusing and Activity Focusing (GFAF), Geography Focusing and Activity Diversifying (GFAD), Geography Diversifying and Activity Focusing (GDAF), and Geography Diversifying and Activity Diversifying (GDAD).

Alternatively, we use Ward's method to classify acquisitions without controlling first for geography. This allows us to classify acquisitions into two categories "diversifying" and "focusing" without prescribing the source of such diversification (i.e., activity versus geog-

[8] Ward's method seeks to minimize the ratio of within-group variation to between-group variation. That is, the squared Euclidean distances between the centroids of the various clusters. One gauge for determining when to stop the process is to examine the amount of total variation, which is the sum of squared Euclidean distances from each observation to the central mean, that a formation of clusters explains.

[9] As argued in the literature, stock returns reflect the pricing of various types of risk to which a firm exposes itself, and therefore provide a measure of the similarity between two firms.

raphy). In that sense, this classification is more flexible and its purpose will become clear in Section 1.5.4.

1.4 Data

We use the SNL Mergers and Acquisitions (M&A) datasets to build the sample of merging financial institutions. We consider a subset of M&As involving deals announced and completed between 1986 and 2015 and require both buyer and seller to be located in the United States. We define a acquisition as one firm obtaining more than 50% of the voting shares of the target firm, or adding to a lower percentage in order to reach more than 50%. This purchase results in the de-listing of the stock of the target firm. We only include mergers where both bidding and target firms are financial institution with SIC codes in the range [6000,6800].

As in Weiß et al. (2014), we exclude deals with an underlying deal value of less than 10 million U.S. dollars and also those with missing deal value. By using only large acquisitions, our sample allows us to detect risk implications and valuation consequences more readily than a sample including smaller transactions. Additionally, to avoid the distorting effects of confounding events, we require an interval of 360 days between the completion of a deal and the announcement of another transaction by the same acquirer. Since acquisition's abnormal return could be related to the transfer of wealth from taxpayers to merging entities in the cases that U.S. Federal Deposit Insurance Corporation assists a acquisition, we omit these mergers from our analysis to prevent confounding effects. The resulting sample is comprised of 780 acquisitions.

There are 573 unique acquirers associated with these 780 acquisitions in our sample. 427 of these acquirers appear only once in the sample while there are repeated acquistions associated with the rest. Specifically, 101 acquirers have 2 acquisitions and 55 acquirers have more than 2 (but less than 5) acquisitions in our sample. Thirty three have 3, 8 have 4 and 4 have 5 acquisitions.[10]

Table 1.1: Descriptive statistics.

This table reports summary statistics for CAR and characteristics of deal, acquirer and target. All variables are defined in the Appendix. Deal value is stated in billions, while CAR, bidder and target pre-acquisition performances are in percentages.

	Observations	mean	p10	p25	p75	p90	sd	min	max
CAR	780	-0.41	-8.06	-3.84	2.57	6.91	6.19	-21.16	38.01
$\Delta MAES$	780	0.04	-1.49	-0.75	0.84	1.74	1.66	-16.30	9.73
ΔNSR	780	-0.03	-4.39	-1.65	1.18	3.37	9.41	-57.22	157.60
Deal value	780	0.23	0.01	0.02	0.10	0.27	1.24	0.01	23.40
Relative size	780	0.01	0.00	0.00	0.01	0.02	0.07	0.00	1.23
Bidder pre-merger performance	780	-4.40	-30.75	-19.19	7.07	23.98	26.91	-71.66	274.03
Bidder assets	723	14.50	12.77	13.38	15.33	16.74	1.58	9.77	21.50
Bidder market-to-book	723	1.85	0.86	1.15	2.12	2.82	1.58	-0.34	26.47
Bidder non-interest income	575	1.73	0.29	0.55	1.34	1.97	7.27	-5.38	130.50
Target pre-merger performance	199	-8.44	-36.94	-24.21	6.94	23.48	25.15	-75.01	118.95
Target assets	618	12.53	11.15	11.69	13.25	14.16	1.39	6.99	18.64

We use monthly and daily stock return data from CRSP and CRSP/Compustat merged databases. Financial accounting data and other acquisition characteristics are obtained from the SNL database. Descriptive statistics of the data in the final sample are given in Table 1.1, and the total number and value of acquisitions announced in each year of our sample are depicted in Figure 1.1.

The deal value of acquisitions in our sample ranges from 10 million to 23.4 billion dollars, while target assets (book value) ranges from 1 million to 124 billion (the upper bound corresponds to the acquisition of Phoenix Companies, Inc. with Kayne Anderson Rudnick Investment Management, LLC in 2005). Bidders' CAR upon acquisition announcement is negative on average, ranging between roughly -21 to 38 percent. Both bidders' and targets' pre-acquisition performance are on average less than the industry's index. However, as

[10]Future research could separate out banks that existed for the entire sample period.

expected, targets' pre-acquisition performance are, on average, worse than bidders.

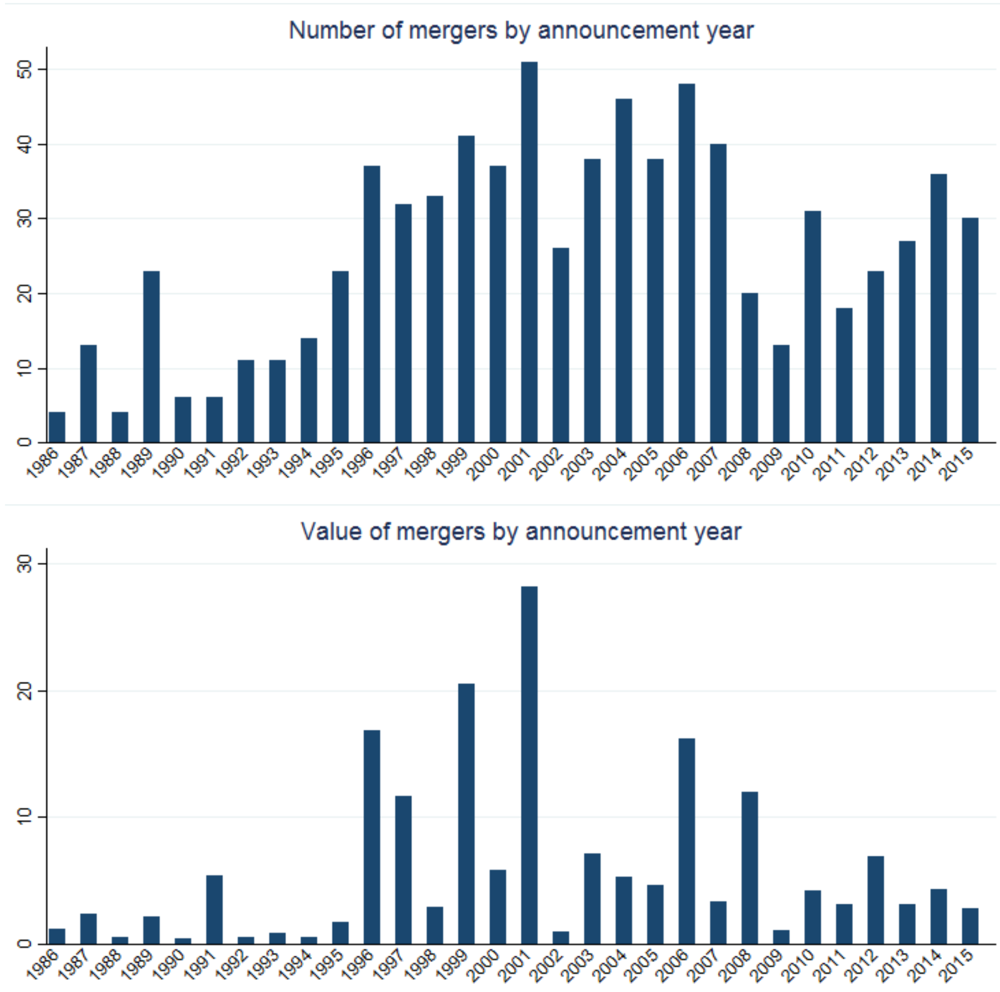

Figure 1.1: Acquisitions count and value.

Acquisitions announced and completed between 1986 and 2015. The year reported corresponds to the acquisition announcement year. Deal values are reported in billions of dollars.

The top graph in Figure 1.1 shows that acquisition activity in the financial sector has substantially increased since mid 80s peaking in 2006 right before the financial crisis. Bank acquisitions slowed down after the crisis, but there has been growth since 2013 raising the number of acquisitions to near pre-crisis levels. There are important differences observed in M&A activities pre and post the 2008 financial crisis. Prior to the crisis, deals were funded mostly by cash. In contrast, after the crisis, the majority of the deals had some stock component in response to increases in capital requirements by regulators. Furthermore, some industry experts sustain that firms are now more strategic in their acquisitions and try to stay away from those that would take them to additional regulations (i.e., crossing the 10B or 50B thresholds after which they would be subject to the Dodd-Frank Act). While regulatory requirements seem to be stricter for bank acquisitions relative to prior years, we continue to observe an increase in M&A activity.

The bottom graph in Figure 1.1 shows much higher acquisition value during crisis periods such as 1990, 2001 and 2008. This is expected as acquisition of large firms due to their distress is more likely under adverse macroeconomic conditions. Table 1.2 presents the summary statistics for the acquisitions that were announced during crisis and those that were announced during non-crisis periods, separately. Although bidders pre-acquisition performance is only slightly different in crisis, targets pre-acquisition performance are substantially lower. We also observe that during crisis periods, acquisitions lead to higher reduction in acquirers' non-systemic (ΔNSR) and systemic ($\Delta MAES$) risks. Those acquisitions are also, in general, more value-enhancing relative to the ones announced during non-crisis periods. We will elaborate more on this observation in Section 1.5.

Table 1.2: Descriptive statistics, crisis vs. non-crisis periods.

This table reports summary statistics for crisis (top panel) versus non-crisis (bottom panel) periods.

	Observations	mean	p10	p25	p75	p90	sd	min	max
CAR	135	0.16	-9.99	-3.82	3.79	8.54	7.52	-14.08	36.12
$\Delta MAES$	135	-0.34	-2.88	-1.24	0.87	2.11	2.58	-16.30	5.78
ΔNSR	135	-0.25	-3.98	-1.79	0.36	2.35	5.01	-13.04	30.72
Deal value	135	0.35	0.01	0.03	0.11	0.20	2.16	0.01	23.40
Relative size	135	0.02	0.00	0.00	0.01	0.01	0.12	0.00	1.23
Bidder pre-merger performance	135	-4.06	-35.10	-19.65	11.91	26.04	23.45	-65.18	72.20
Bidder assets	127	14.77	12.88	13.64	15.62	17.20	1.72	10.14	19.54
Bidder market-to-book	127	2.05	0.81	1.07	2.23	2.78	2.05	0.38	15.36
Bidder non-interest income	94	1.44	0.40	0.52	1.24	1.81	2.96	0.12	22.95
Target pre-merger performance	32	-11.86	-41.67	-28.74	5.65	24.98	25.82	-52.20	48.37
Target assets	96	12.62	11.40	11.84	13.44	14.07	1.39	7.48	18.64

	Observations	mean	p10	p25	p75	p90	sd	min	max
CAR	645	-0.53	-7.87	-3.88	2.42	6.52	5.87	-21.16	38.01
$\Delta MAES$	645	0.11	-1.40	-0.64	0.84	1.68	1.38	-8.01	9.73
ΔNSR	645	0.02	-4.55	-1.61	1.30	3.56	10.09	-57.22	157.60
Deal value	645	0.20	0.01	0.02	0.10	0.27	0.94	0.01	12.31
Relative size	645	0.01	0.00	0.00	0.01	0.02	0.06	0.00	0.77
Bidder pre-merger performance	645	-4.47	-30.19	-19.17	5.89	23.91	27.60	-71.66	274.03
Bidder assets	596	14.45	12.76	13.36	15.30	16.61	1.55	9.77	21.50
Bidder market-to-book	596	1.81	0.88	1.15	2.11	2.82	1.46	-0.34	26.47
Bidder non-interest income	481	1.79	0.28	0.56	1.35	1.97	7.84	-5.38	130.50
Target pre-merger performance	167	-7.78	-35.75	-22.56	6.94	20.29	25.05	-75.01	118.95
Target assets	522	12.51	11.14	11.63	13.23	14.16	1.39	6.99	17.88

1.4.1 Crisis periods and distressed acquisitions

In this study, we investigate whether an increase in acquirers systemic risk is associated with value gain for acquirers shareholders. This is obviously not the only source of value gain for bank acquisitions. Therefore, it is important to control for other sources of value creation to the extent possible. As outlined in previous studies, bank acquisitions can create value by reducing costs and/or increasing revenues. Cost reductions can be achieved in many ways, such as improving efficiency, eliminating redundant managerial positions, closing overlapping bank branches, and consolidating back office functions. The opportunities for restructuring and efficiency gains are potentially more in case of poor-performing or distressed targets. So, in our study it is important to control for distressed acquisitions.

We identify distressed acquisitions in two different ways: acquisitions with relatively poor-performing targets and acquisitions announced during a crisis period. Government-assisted acquisitions would be a third type of distressed acquisitions; however, these acquisitions are systematically excluded from the sample when we drop acquisitions with missing deal value. This is not a concern since these acquisitions are motivated by special circumstances and we would have excluded them anyway from our study.[11]

First, we control for acquisitions with relatively poor performing targets. We classify the sample based on targets' pre-acquisition performance, taking its 25^{th} percentile over our entire time period as the cutoff.[12] We then define a dummy variable "low" equal to 1 if target's pre-acquisition performance is below 25^{th} percentile and 0 otherwise. Second, we account for acquisitions announced during crisis periods by including a crisis dummy equal to 1 for acquisitions announced during the years 1990, 2001, 2007-2008, and 2011, and 0 otherwise. Distress during crisis periods could be mostly driven by adverse macroeconomic conditions.

The crisis periods in our analysis correspond to those identified by the National Bureau of Economic Research (NBER) plus the year 2011 to account for spillover effects into the U.S. financial sector due to the European sovereign debt crisis.[13] In fact, the FDIC report

[11]Based on FDIC Resolution Handbook, "A failing institution is absorbed into an acquiring institution that receives FDIC assistance. In 1950, the FDIC was authorized by section 13(e) of the Federal Deposit Insurance Act (FDI Act) of 1950 to implement assisted mergers. In 1982, when the FDI Act was amended, the merger authority, as amended, was written into section 13(c) of the FDI Act. Such transactions allow the FDIC to take direct action to reduce or avert a loss to the deposit insurance fund and to arrange the merger of a troubled institution with a healthy FDIC insured institution without closing the failing institution. Assisted mergers were the Federal Savings and Loan Insurance Corporations preferred resolution method."

[12]We use the 25^{th} percentile as a cutoff for simplicity. Other more sophisticated approaches could be based on clustering techniques.

[13]NBER identified downturns in our analysis time period includes: 1990Q3-1991Q1, 2001Q2-2001Q4 and 2008Q1-2009Q2.

indicates more than 800 troubled banks in 2011. As a robustness check to adding 2011 to the periods identified by the NBER, in Section 1.6 we also run the analysis excluding that year from the crisis periods and find the results to be robust to this alternative choice. Admittedly, the early 2000s crisis is not a banking one and thus did not result in many bank failures. However, we still see indications of distress in banks and other financial institutions' portfolios as a result of the dotcom bubble burst in conjunction with other events during 2001 (e.g., terrorist attack of 9/11, and wars of Afghanistan and Iraq), which affected the broader economic and business environments (see Jones and Critchfield, 2005). Therefore, we keep the NBER classification for this year.

1.4.2 Diversifying and focusing mergers

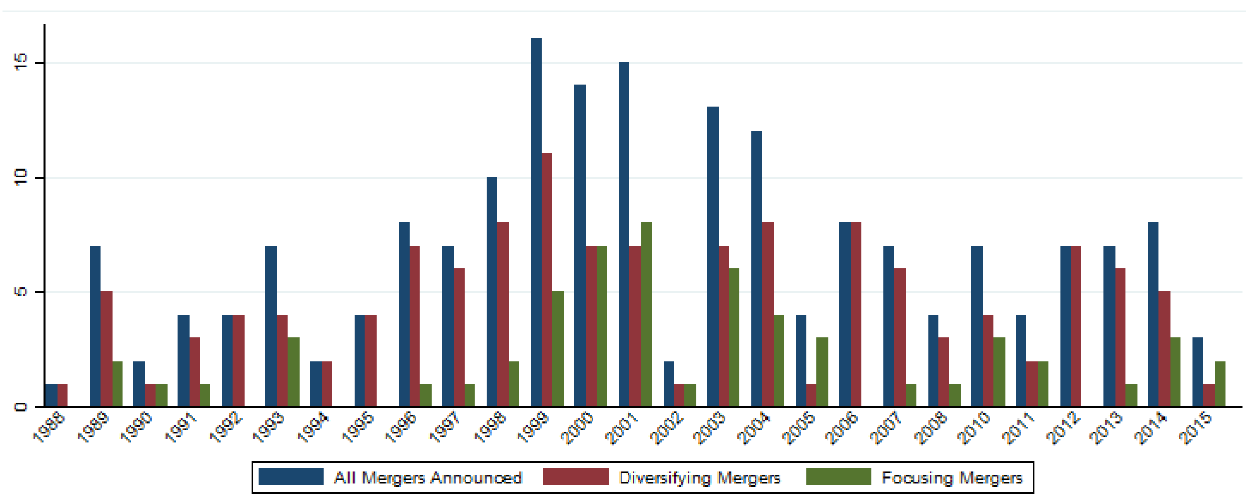

Figure 1.2: Acquisitions count and value

Acquisitions announced and completed between 1988 and 2015. The year reported corresponds to the acquisition announcement year.

In the second part of our analysis we categorize the acquisitions into diversifying and focusing based on the correlation of bidder and target equity return. This substantially reduce our sample size to those acquisitions with publicly-traded acquirer and target. Descriptive statistics of this sample are given in Table 1.3, and the total number of acquisitions announced in each year is depicted in Figure 1.2. This sample contains more M&As around the dotcom bubble burst of early 2000s. The deal value of acquisitions in this sample ranges from 10 million to 10.67 billion dollars, while target assets (book value) ranges from 74 million to 80 billion dollars (the upper bound corresponds to the acquisition of Hudson City Bancrop, Inc. by M&T Bank Corporation that was announced in 2012 and completed by 2015). Homogeneity of targets' size in our sample is partly driven by the fact that we require targets to be publicly-traded. Bidders' CAR upon acquisition announcement is negative on average, ranging between roughly -21 to 12 percent. Both bidders' and targets' pre-merger performance are on average less than the industry's index. Interestingly, MAES of bidders as the result of acquisition is negative on average; however, it ranges from about -5.6 to 3.2 percent.

Table 1.3: Descriptive statistics of the sample with public target.

This table reports summary statistics for CAR and characteristics of deal, acquirer and target. All variables are defined in the Appendix. Deal value is stated in billions, while CAR, bidder and target pre-merger performances are in percentages.

	Observations	mean	p10	p25	p75	p90	sd	min	max
CAR	193	-2.13	-9.92	-5.44	1.79	4.69	5.77	-21.16	12.63
$\Delta MAES$	193	-0.11	-1.46	-0.82	0.64	1.42	1.25	-5.56	3.24
ΔNSR	193	0.25	-3.29	-1.30	0.84	2.30	6.18	-22.28	48.88
Deal value	193	0.37	0.02	0.04	0.20	0.48	1.32	0.01	10.67
Relative size	193	0.02	0.00	0.00	0.01	0.03	0.08	0.00	0.63
Bidder pre-merger performance	193	-8.10	-30.87	-19.98	2.65	15.74	18.20	-46.75	55.86
Bidder assets	188	14.74	12.86	13.70	15.76	16.82	1.46	11.21	18.21
Bidder market-to-book	188	1.67	0.85	1.09	2.10	2.62	0.80	0.42	5.98
Bidder non-interest income	180	1.10	0.24	0.53	1.45	1.90	1.32	-0.20	15.12
Target pre-merger performance	192	-8.59	-36.15	-23.51	5.06	23.48	25.17	-75.01	118.95
Target assets	193	13.29	11.93	12.44	13.85	14.82	1.25	10.70	17.59

1.5 Empirical Analysis

In this section, we jointly study hypotheses (H1), (H2) and (H3) in sections 1.5.1, 1.5.2 and 1.5.3. First, we look at the change in acquirer's non-systemic and systemic risk as the result of acquisition in a univariate framework. Second, we explore the relationship between changes in risk and acquirer's value upon acquisition announcement. Then, we investigate hypotheses (H4) and (H5) on the limited sample in sections 1.5.4 and 1.5.5.

1.5.1 Effect of bank acquisitions on acquirers' risk

We first examine the change in acquiring banks' systemic risk as a result of acquisition relative to a financial sector index. This test is based on the market adjusted expected shortfall measure (MAES) defined in equation (1.1) of Section 1.3. We perform a t-test for the means of MAES, pre- and post- acquisition, and for the change in MAES resulting from acquisition (ΔMAES) as defined in equation (1.2) of Section 1.3. The null hypothesis is that the mean is equal to zero. Table 1.5 presents the results.

We start by looking at the entire sample and find no significant change in MAES. Next, we split the sample into crisis and non-crisis periods to accommodate for potentially different motives for bank acquisitions in crisis periods. For non-crisis periods we find that ΔMAES is positive and significant, indicating that bank acquisitions indeed lead to a significant increase in the MAES of bidders. This effect, however, disappears during the crisis periods. Our results are different from those of Weiß et al. (2014). They find that the change in systemic risk contribution of bidders is not significantly different from their non-merging competitors. Their conclusion could be driven by not separating the analysis in crisis and non-crisis periods.

We next examine the change in bidders' non-systemic risk as the result of acquisition using the methodology outlined in Section 1.3.2 for NSR and ΔNSR. In Table 1.6 we conduct an analogous exercise to the one carried out for systemic risk. The results suggest that, in general, bank acquisitions do not lead to any statistically significant change in acquirers' NSR. In summary, we find that bank acquisitions lead to an increase in acquiring banks' systemic risk (during non-crisis periods) while their individual risk does not significantly change.

Table 1.7 presents the same analysis controling for all distressed acquisitions. We observe similar results in that bank acquisitions lead to an increase in acquiring banks' systemic risk (for non-distressed acquisitions) while their individual risk does not significantly change.

Univariate analysis of acquirers' risk

In this section, we perform univariate analysis and examine the change in bidders' systemic and non-systemic risk by some of bidder and deal characteristics. Table 1.8 presents the analysis by tertiles of deal value. Panel A includes non-distressed and panel B distressed acquisitions. Interestingly, the acquisition-induced change in acquirers' systemic risk is statistically significant for medium deal values, but the change is in opposite directions for distressed vs. non-distressed acquisitions. This could be an evidence that becoming too-big-to-fail is not the only driver of an increase in acquirers' systemic risk. The change in acquirers' non-systemic risk is statistically insignificant for non-distressed acquisitions across all tertiles of deal value, however it is significantly negative for distressed acquisitions with high and medium deal values.

Table 1.8 presents the change in bidders' systemic and non-systemic risk by tertiles of bidders' total assets. Change in systemic risk is consistent with observations by tertiles of deal value in that the bidders with medium assets seems to have higher and statistically significant increase in systemic risk relative to those with low and high total assets. Decrease in non-systemic risk, however, seems to be higher in magnitude and statistically significant for acquirers with low total assets. This is consistent with the intuition that smaller firms benefit more from diversification. Although, this is not the case for distressed acquisitions. The results indicate that large and medium acquirers benefit more from a distressed acquisition in terms of reducing their (non-systemic) risk.

Table 1.10 presents the acquisition-induced change in acquirers' systemic and non-systemic risk by tertiles of bidders' pre-merger performance. The results indicate that for non-distressed acquisitions, an increase in systemic risk is mostly associated with high bidder performance while a significant decrease in non-systemic risk is observed for low-performing bidders.

Overall, the analysis in this section indicates that an increase in systemic risk is associated with medium deal value and medium acquirer's total assets, but high bidder's performance. Higher diversification benefit in terms of reducing non-systemic risk is observed for bidders with low total assets and low performance. Note that the observations for non-distressed acquisitions do not generally hold for distressed ones.

1.5.2 Systemic risk of acquirer and target combined

In the previous section, we found that systemic risk of acquirers on average increased after an acquisition, although, their non-systemic risk does not significantly change. In this section, we consider the systemic risk of acquirers and targets combined before the acquisition and compare it to the risk of consolidated entity after the acquisition to test whether an increase in acquirers' systemic risk is the result of absorbing the targets systemic risk. If the systemic risk of the consolidated entity is less than the combined risk of acquirer and target before the acquisition, one could perhaps conclude that acquisitions do not impose more costs to the economy. As mentioned earlier, Weiß, Neumann, and Bostandzic (2014) find an increase in systemic risk of acquiring banks', combined banks' and overall financial system as the result of M&As. We investigate the following hypothesis:

(H_3): The consolidated entity will be riskier than the two banks separately.

To assess this hypothesis, we compare weighted average of acquirer's and target's MAES before acquisition announcement to MAES of consolidated entity after acquisition completion. Weighted MAES of acquirer and target before acquisition is determined by adding market value of acquirer and target and computing daily percent returns as follows.

$$Return_{A+T,t} = Ln[1 + ((MV_{A,t} + MV_{T,t})(MV_{A,t-1} + MV_{T,t-1}))/(MV_{A,t-1} + MV_{T,t-1})] \tag{1.7}$$

Where A is the acquirer, T is the target and MV is the market value of equity.

One caveat to this analysis is that the sample size is drastically reduced (to 199 acquisitions) as estimating this measure requires both acquirer and target to be publicly-traded firms. Furthermore, this limited sample of acquisitions might not be a random sample and could have different characteristics compared to the rest of acquisitions in our sample.

Table 1.11 presents the results. Pre-acquisition MAES is the weighted MAES of acquirer and target, whereas, post-acquisition MAES is the MAES of combined entity. ΔMAES is the difference of the two. Consistent with previous results, we find that the combined systemic risk of acquirer and target increases for acquisitions announced in non-crisis periods, although the difference is not statistically significant. As pointed out earlier, this could be due to different characteristics of this limited sample. To investigate this further, we perform three analysis as follows.

First, in panel B, we look at the MAES of acquirers (only) for the same sample. The results show that this sample is indeed different from the entire population as we observe a (statistically insignificant) decrease in systemic risk of acquirers unlike the overall results in Table 1.5.[14] Interestingly, we observe that the increase in systemic risk is even higher

[14]Since we observe that the acquisitions envolving a pulbic target seem to behave differently, as a robustness

on average when the combined systemic risk of target and acquirer is considered. So it is unlikely that the increase in acquirers' systemic risk is the result of absorbing the target's systemic risk.

Second, I divide this limited sample of 199 acquisitions according to whether the target was distressed or not. Panel A of Table 1.12 presents the MAES of acquirers and targets combined with this categorization. The MAES for acquisitions of a non-distressed target is positive and larger than those acquisitions announced in a non-crisis period, however still statistically insignificant.

The results presented in the first analysis is in line with the empirical results presented in Weiß et al. (2014). in that they also find a larger change in systemic risk of combined entity relative to acquirer only. However, while they find a significant increase in combined entitys systemic risk over 1991-2009, our results in first and second analysis indicates an overall decrease in systemic risk. In order to investigate the driver of this difference, we first conduct the same analysis limiting the sample to acquisitions announced and completed from 1991-2009 to be comparable. Panel B of Table 1.12 presents the results. MAES is positive for overall sample and statistically significant for acquisitions with non-distressed targets. Weiß et al. (2014) also exclude serial acquirers from their main analysis. We do the same and run the analysis again. Panel C of Table 1.12 presents the results which are similar to Panel B. One remaining major difference is that we do the analysis using market-adjusted change in MES, while Weiß et al. (2014) do not consider market adjustment in their analysis of combined entity. Panel D of Table 1.12, presents the change in systemic risk of combined entity without market adjustment. The MES is significantly positive for all acquisitions in line with the results presented in Weiß et al. (2014).

Third, in order to investigate whether this limited sample is different from the rest,

check, we will remove them from our sample and test whether the results hold. This will likely strengthen our results.

we compare the MAES and NSR of acquirers in two sub-samples of acquisitions with a public target (i.e. the limited sample) and those with a non-public target. The results are presented in Tables 1.13 and 1.14. For acquisitions announced in a non-crisis period, MAES of those with a public target is negative, whereas MAES of those with a non-public target is significantly positive. NSR is also different across two sub-samples. It is positive for acquirers of a public target, while it is negative for the rest of the sample. Note NSR is statistically insignificant in both sub-samples. This conclusion holds for all as well as non-crisis sub-samples. Overall, this analysis suggests that acquisitions with a public target have different characteristics than those with a non-public target.

1.5.3 Market reaction to systemic risk-shifting

Market reaction (CAR)

We start by computing CAR for each acquirer, as outlined in Section 1.5.3, to investigate whether acquirer's shareholders benefit from acquisition-induced changes in acquirer's risk. Table 1.15 presents the mean of CAR for different time periods and target pre-acquisition performance. We find that CAR is on average negative and statistically significant, except for the crisis periods. This is in line with the results of a number of studies on bank acquisitions (see, e.g., Hawawini and Swary, 1990; Houston and Ryngaert, 1994).

Interestingly, the acquisitions announced during crisis periods, in general, create more value for the acquirers' shareholders. This is consistent with the notion that acquisition gains must outweigh presumably high capital reallocation costs during crisis periods. During crisis periods, acquirers can benefit from acquiring assets at distressed prices. A lower number of potential bidders and higher number of potential targets during crisis periods may also lead to higher acquisition value for the acquirers' shareholders (see James and Wier, 1987).

Consistent with our results in Table 1.15, [15] Beltratti and Paladino (2013) find that abnormal returns for bank acquirers are zero on average after announcements.

We also consider categorizing the sample along targets' pre-acquisition performance due to the reasons outlined in section 1.4.1. We choose the 25th percentile of targets' pre-acquisition performance as threshold and denote the two groups as *"Poor Target Perf."* and *"Good Target Perf."* Table 1.15 shows that in the case of poor performing targets the value destroyed is much larger and statistically significant (except for the crisis periods), whereas for good performing targets we cannot reject the null that CAR is different from zero.

Control variables

In our analysis, we control for acquirer, target and deal characteristics that the literature has identified to be important to the announcement outcome. Namely, relative size of target to bidder, bidder pre-acquisition performance, geographic diversification, market-to-book ratio, bidder assets, target assets, bidder non-interest income, and deal type. The definition of control variables is outlined in the Appendix.

We control for relative size of the target to bidder as previous studies have found it is positively related to CAR (see, e.g., James and Wier, 1987; DeLong, 2001). There is also evidence of a significant relationship between acquisition diversification and value creation in the literature. For instance, DeLong (2001) finds that diversifying acquisitions (both geographic and functional) tend to create less value for acquirers' shareholders relative to focusing acquisitions. Hence, we also control for this source of value creation by defining a categorical variable for geographic expansion, which is set to 0 for "In market", 1 for "Partial overlap" and 2 for "Market expansion."

Another acquirer's pre-acquisition characteristics that could influence acquisition's value

[15] The acquirers' CAR associated with acquisitions during a crisis period is positive (although statistically insignificant), whereas, for those acquisitions during other periods is significantly negative.

creation is market-to-book ratio. We account for acquirer's market-to-book ratio to control for the bank's investment opportunity set (see Baker and Wurgler, 2002). Higher market-to-book could either motivate the bank to engage in too-risky acquisitions, or prevent them from increasing risk because the more valuable banks possess fewer incentives to act rashly (see Keeley, 1990).

In order to account for the possibility that the market could have anticipated the increase in systemic risk as the result of acquisition ex-ante, we look into acquisition characteristics that could have indicated acquisition-related increase in systemic risk at the time of deal announcement. In the academic literature, higher non-interest income (i.e., non-core activities like investment banking and trading) has been associated with a higher contribution to systemic risk relative to traditional banking (i.e., deposit taking and lending) (see, e.g., Brunnermeier, Dong, and Palia, 2012; Shleifer and Vishny, 2010; Dittmar and Thakor, 2007). Therefore, the deal type could signal systemic risk implications of the acquisition at the time of the deal announcement. The types of acquisitions in our sample can be categorized into five main groups of companies: "bank and thrift," "specialty finance," "financial technology," "securities and investment," and "insurance." If the market indeed reacts positively to an increase in systemic risk contribution in benign periods, one would expect CAR to be higher for "securities and investment" deals relative to other types of acquisitions.

Main results

In order to empirically assess the relationship between systemic risk-shifting and acquirer's value, we first need to disentangle the impact of other sources of acquisition value creation. For instance, acquisitions that involve a distressed target, suffering from clear deficiencies, could gain value through restructuring and turnaround of the target. Koetter et al. (2007) argue that not accounting for distressed mergers in bank acquisition studies might lead to biased conclusions.

Furthermore, there is evidence in the literature supporting the notion that even "non government-assisted" acquisitions during crisis could be motivated by distress or higher probability of failure. Dunn, Intintoli, and McNutt (2015) find that targets are valued lower and are less efficient relative to their acquirers during crisis versus normal times. Perhaps more importantly, investors' risk aversion or heightened uncertainty (see Beltratti and Paladino, 2013) during crisis periods might lead to different valuations of mergers. In particular, we expect this risk aversion or uncertainty to be more evident in case of acquisition-induced changes in systemic risk.

In order to account for both distressed acquisitions and also investors' differential valuation during crisis periods, we proceed in two ways in our model specification. We first consider overall distressed acquisitions and construct a dummy variable equal to 1 if a acquisition is announced in a crisis period or target's pre-acquisition performance is below the 25^{th} percentile, and 0 otherwise. This "distress" dummy is basically equal to the summation of the dummies "crisis" and "Low." Then, in a second exercise, we disentangle between these two sources of distress to allow for the possibility that alternative sources of distress can interact differently with changes in risk and, thus, impact CAR in different manners.

In our sample of 780 acquisitions, about 80% (i.e., 606 acquisitions) are non-distressed. 135 acquisitions were announced in a crisis period and 50 acquisitions involve a relatively low-performing target. So, only 11 acquisitions are common between "Low" and "crisis" dummy variables.

The main results are presented in Table 1.16 and Table 1.17. In the first table, we use the *distress* dummy, which accounts for both crisis periods and relatively low pre-acquisition performance; while in the second table we disaggregate the sources of distress by means of the dummies, *crisis* and *low*. Since some control variables have many missing observations we add them in three steps. Specification (1) is the baseline that includes all the 780 acquisitions, specification (2) incorporates additional bidder characteristics and the geographic diversification dummy, and specification (3) adds bidder non-interest income and target assets. Specification (4) adds to specification (2) the deal type categorical variable discussed in Section 1.5.3. We consider specification (2) as our main specification since it gives a good compromise between additional control variables and sample size.

We find two sets of important results that relate to hypotheses **(H1)** and **(H2)** respectively.[16] First, in both tables the coefficient of ΔMAES is positive and significant at a 1% level in specifications (2) and (4), and at a 5% level in specification (3). Therefore, an increase in systemic risk of bidders as a result of acquisition is positively correlated with an increase in firm value (CAR). This supports our first hypothesis that acquisitions in general can lead to systemic risk shifting. At the same time, we find no evidence of a statistically significant relationship between CAR and acquisition-induced change in acquirer's individual risk (ΔNSR). Second, for distressed acquisitions we do not observe the same relationship between CAR and change in systemic risk. In Table 1.16, the interaction term between the *distress* dummy and ΔMAES is negative and significant at a 5% level, after controlling for other factors such as geographic diversification, bidder assets and target assets. In fact, the significantly negative relationship confirms that one should control for distressed acquisitions in this study.

As mentioned earlier, our "distress" measure includes the acquisitions with either low performing target or the ones that are announced during crisis periods. Therefore, in order to further explore what are the underlying drivers of opposite market reactions to an increase in systemic risk, in Table 1.17 we replace the "distress" dummy by it's components (i.e., "low" and "crisis" dummies). Interestingly, we find that although investors value the increase in

[16] As explained earlier, we categorize the acquisitions based on targets' pre-acquisition performance. However, since this measure is only available when the target is a publicly traded company, our estimation sample is substantially reduced if we discard acquisitions with private targets. In order to take advantage of the entire sample, we assume that private targets' pre-acquisition performance are at the median. This leads to the higher number of observations in our main analysis. However, we perform two robustness checks in Table 1.26 to ensure this does not drive our results.

systemic risk and react positively to those acquisitions in normal times, market reaction to such acquisitions announced during crisis is significantly unfavorable. This result could be attributed to the fact that investors place lower probability on tail risk in benign periods, relative to crisis periods when the tail risk is just materialized. This is in line with the concept of "availability," pioneered by Tversky and Kahneman (1973) which states that the easier it is for us to recall instances in which something has happened, the more likely we will assume it is. This will be discussed in further details in Section 1.5.3.

For acquisitions with low performing targets we do not observe the same relationship between CAR and change in systemic risk. Although the effect is bigger in magnitude (almost twice the coefficient of the interaction term with the "crisis" dummy, except for specification (1)), it is not statistically significant. This implies that acquisitions with poor performing targets do not create value through systemic risk-shifiting and can be attributed to other opportunities for value creation in those cases. As outlined in previous studies, bank acquisitions can increase value by reducing costs and/or increasing revenues. Cost reductions can be achieved in many ways, such as improving efficiency, eliminating redundant managerial positions, closing overlapping bank branches, and consolidating back office functions. The opportunities for restructuring and efficiency gains are potentially more in case of poor performing targets. This result provides evidence in support of our second hypothesis.

In addition to our main results, it is worth mentioning a couple of interesting observations based on the geographic diversification dummy and the deal type categorical variable. Geographic diversification has been the prevalent force underlying the acquisition movement since 1980s. As the restrictions on intrastate and interstate banking were removed, many banks expanded their operations.[17] Consistent with an efficiency rationale for acquisition value creation, our results confirm the findings of DeLong (2001) and Akkus, Cookson, and

[17] The lifting of restrictions was followed by the approval of Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, which in June 1995 allowed nationwide interstate banking through holding company banks and as of September 30, 1997, allowed interstate branch banking.

Hortacsu (2015) that acquisition value is greater when it is more focused in nature and when there is a greater overlap between acquirer and target markets.

Regarding deal type, our results in specification (4) of both tables indicate significantly higher CAR for "securities and investment" deals, whereas the relationship with other types of acquisitions are not statistically significant in Table 1.17 and are only significant at a 10% level in Table 1.16 (except for financial technology deal, which is not significant in either table). As mentioned earlier, these types of activities are associated with higher systemic risk contribution and, as such, this result provides evidence supporting our main finding that the market rewards acquisition-induced increase in systemic risk. Furthermore, since non-interest income is associated with systemic risk contribution, accounting for bidders' non-interest-income before the acquisition can to some extent control for the bidders' pre-acquisition systemic risk contribution. Although the relationship is positive in specification (3), it is not statistically significant.

Acquisitions during a crisis period

As discussed earlier, we expect the acquisitions announced during a crisis period to exhibit different characteristics. They generally involve acquirers that are sufficiently strong, despite a global liquidity drought, to take advantage of forced sales from weaker competitors (see Beltratti and Paladino, 2013). In previous section, we found that market reaction to acquisitions announced during a crisis is negatively correlated with ΔMAES. This could be attributed to the concept of "availability," however could also be explained by alternative hypotheses.

One explanation could be that the relation between ΔMAES and CAR during a crisis period is driven by other endogeneous factors that are influenced by a crisis. For example, heightened uncertainty in a crisis could be relatively more for larger or diversifying acquisitions that are at the same time associated with a higher ΔMAES. Beltratti and Paladino

(2013) find that during a crisis period, abnormal returns for bank acquirers are zero on average after announcements due to opacity of target's asset value. However, cumulative abnormal returns are positive after the date of completion as the acquisition due diligence to certify the value of target is completed and conclusions are announced. This is another main difference of an acquisition in a crisis vs. non-crisis times that might impact our results, *i.e. the acquisition value creation is not reflected at the time of announcement, but later on as the acquisition is completed.* Hence, the negative market reaction to an increase in systemic risk contribution could be the result of hightened opacity that is expected to be even higher for larger or diversifying acquisitions during a crisis period.

In general, signaling incentives can develop in any situation in which bidders benefit from uninformed outsiders perceiving high values after the takeover. In other words, acquirer's profit does not only depend on its actual value of the target, but also on uninformed outsiders' perception of the value. Such signaling incentives are widespread and could arise from bidders' financing needs, use of collars in equity payments, managerial myopia, and exposure to liquidity shocks (see Liu, 2012). Due to higher uncertainty in crisis periods, the bidders have higher incentive to use signaling strategies. Degree of signaling incentive could be correlated with the factors influencing ΔMAES and therefore lead to negative correlation of abnormal return with ΔMAES.

To further investigate these hypotheses, we can do as follows. First, we can estimate the abnormal returns around the completions of acquisitions announced in a crisis and see how investors react to an increase in ΔMAES. Second, we can include a measure of target opacity to control for this important determinant of abnormal returns during the crisis periods and potential endogeneities arising from it.

Table 1.18 presents the results for the sample of acquisitions announced during a crisis period. This leads to drastic reduction in sample size and in contrast to our main results in Table 1.17, we do not observe a statistically significant unfavorable reaction to an increase in ΔMAES. There are a few interesting observations. First, in regression (3), relative size is statistically and economically significant. This is consistent with our prior that relatively larger deals impose much higher risk and uncertainty during a crisis period versus other times. Second, the bidder non-interest income is associated with a higher abnormal return. Third, securities & investment deals are associated with higher abnormal return, consistent with our finding for the overall sample.

Table 1.19 presents the results for the sample limited to acquisitions announced during 2001 only. ΔMAES is significantly negative for this sample. This could be driven by the fact that 2001 is not a banking crisis. As a future research direction, I will look into what factors during this specific crisis are contributing to different results from other crisis periods.

Too-big-to-fail motive

As discussed earlier, M&As can lead to an increase in acquirers' systemic risk contribution due to becoming larger and more interconnected. An increase in size and interconnections can create value for acquirers' shareholders as market percieves higher probability of using governments too-big-to-fail (TBTF) subsidies in case of default. Therefore, larger banks tend to pose greater risks on the system, independent of any changes in their non-systemic (individual bank) risks. Brewer and Jagtiani (2013) and other studies find that banking organizations were willing to pay an added premium for mergers that would put them over the asset sizes that are commonly viewed as the threshold for being TBTF. In this section, we investigate whether the value created for acquirers' shareholders through an increase in systemic risk is driven by becoming TBTF.

Since TBTF is not officially defined by law or regulatory policy, its impact relies upon judgments of regulators and the market perception. We control for TBTF impact in 3 different ways as follows.

First, we control for the change in size of the merged institution ($\Delta Size$) defined as the change in the book value of total assets of the merged entity one quarter after deal completion relative to acquirer's book value of total assets one quarter before the acquisition announcement.

Second, we define TBTF_1 dummy variable to be equal to 1 if as the result of acquisition, the acquirer moves up to the top size quartile (based on book value of total assests) after the deal completion from any other size quartile prior to acquisition announcement and 0 otherwise. This approach results in 50 acquisitions with TBTF motive versus 495 other acquisitions for which we have the total assets in the dataset.

Third, we follow Brewer and Jagtiani (2013) to set the TBTF threshold. They find that a TBTF threshold of $100 billion in total assets was perceived by the market as an important criterion for becoming TBTF during the period of the 1990s and early 2000s. It also provides a good dividing line for separating organizations with a national scope from regional organizations. We define TBTF_2 to be equal to 1 if the acquisition results in an institution with more than $100 billion in total assets and 0 otherwise. This results in only 9 TBTF acquisitions in our sample.

Table 1.20 presents the results. Regression (1) indicates that neither the coefficient of $\Delta Size$ nor its interaction with $\Delta MAES$ are statistically significant, while our main results are robust (i.e., the coefficient of $\Delta MAES$ is positive while the coefficient of its interaction with *Distress* dummy is negative and both are statistically significant). In regression (2), the coefficient of TBTF_1 is signifiantly negative and its interaction with $\Delta MAES$ is statistically insignificant. Regression (3)'s result is consistent with the literature in that becoming TBTF leads to a premium in market valuation of the acquisition, however its interaction with $\Delta MAES$ is negative and statistically insignificant. In all cases, while we control for TBTF motive, our main results hold and we do not find any evidence that our results are driven by the merged entity becoming TBTF. Hence, we conclude that the value creation through acquisition-induced increase in systemic risk is not limited to the cases where acquirers become TBTF.

1.5.4 The value of diversifying acquisitions

Distribution of acquisitions value

As noted in Section 1.2, given our hypothesis that systemic risk-shifting in an acquisition is achieved through increased correlation of institution with other firms in financial sector, we expect to observe more systemic risk-shifting in diversifying acquisitions versus the focusing ones. In this section, we test this hypothesis. Given that extant literature has characterized diversifying M&As as value destroying, we start our analysis by investigating whether all diversifying acquisitions lead to value destruction. First, in Table, 1.21 we look at the means and p-values of CAR, along with other descriptive statistics, for all acquisitions in our sample. These are classified in four possible groups according to activity and geography diversification. As explained in the methodology section, we first group the acquisitions into geography focusing and diversifying, and then consider the activity dimension using cluster analysis. It is worth noting that we perform our cluster analysis before applying any data filter. Specifically, we perform cluster analysis for all acquisitions where 12 months stock returns prior to announcement are available for both buyer and target. This initial sample includes 1128 acquisitions. After applying the filters outlined in the data section, we are left with 193 acquisitions.[18]

Table 1.21 suggests that CAR is, in general, significantly negative. Acquisitions with both dimensions of diversification (activity and geography) are more value destroying, whereas for activity and geography focusing acquisitions we cannot reject the null that acquisition value is different from zero. The latter is also the case for geography diversifying and activity focusing acquisitions, although it could be driven by the small sample size in this category.

[18] Requiring an interval of 360 days between the completion of a deal and the announcement of another transaction by the same acquirer is one of the main limiting filters.

If we only classify acquisitions in diversifying and focusing without controlling for geography, as in Table 1.22, we see that value destruction is on average much higher for diversifying than for focusing acquisitions. This broader classification allows us to avoid the aforementioned small sample size issue in a given acquisition group.

Overall, the results in the previous tables are in line with the literature, which supports that diversifying acquisitions are on average value destroying. However, if we look at other descriptive statistics in these tables, we see that dispersion is relatively high in all categories, the range is large, and all maximum values are positive. This suggests that not all diversifying acquisitions are value destroying. In order to further investigate these observations, in Figure 1.3, we take a closer look at the distribution of CAR for diversifying versus focusing acquisitions, rather than average values. As in Table 1.22, we classify acquisitions using cluster analysis without first controlling by geography in order to look at diversification more broadly. Although diversifying acquisitions on average destroy value, there is a considerable proportion (36% of diversifying acquisitions) that actually creates value for acquirers' shareholders. Our focus in this paper is to better understand the source of value creation for diversifying acquisitions. More specifically, we investigate whether diversifying acquisitions create value through systemic risk-shifting.

Main results

The main results are presented in Table 1.23. We test whether diversifying acquisitions gain value through systemic risk-shifting. We use measures of activity and geography diversification separately and jointly. Specifications (1)-(3) account for both activity and geography diversification using three dummy variables as well as their interactions with acquisition-induced change in acquirers' systemic risk contribution (ΔMAES). We are in the benchmark case of geography & activity focusing acquisitions (GFAF) when all three dummy variables are equal to 0. Before adding ΔMAES into the analysis, we provide a baseline case in specification (1) and check that our results are broadly aligned with the literature. The results in (1) indicate that the return on GDAD acquisitions is lower than that of GFAF acquisitions, although not statistically significant.

In specification (2) we incorporate ΔMAES into the analysis, and control for crisis periods by adding a level and an interaction term with ΔMAES. The latter is included to account for the fact that the market reaction to changes in systemic risk for acquisitions announced during adverse macroeconomic conditions may differ from normal times. As expected, the coefficient of this interaction is negative, although not significant.

Our main finding is provided in specification (3) and is centered around the interaction terms between the diversification dummies and ΔMAES. A positive and statistically significant coefficient on a given interaction term indicates that the type of acquisition (e.g., GDAD) creates value (i.e., CAR>0) through increasing systemic risk contribution (i.e., ΔMAES>0). We find that GFAD and GDAF acquisitions that engage in systemic risk-shifting have an overall positive impact on shareholders' value, leading to about 1.097ppt ($-0.642+1.739$) and 2.114ppt ($-1.171+3.285$) higher abnormal return relative to GFAF acquisitions respectively. Statistically, these values are higher since only the interaction terms are significant (at a 10% and 5% level respectively). The value created by GDAD acquisitions through systemic risk-shifting is also positive and significant at a 1% level (p-value=0.010). These results suggest that diversifying acquisitions in some capacity, either activity or geography, create value for acquirers' shareholders through systemic risk-shifting.

Based on our previous conclusions, in specifications (4)-(6) we classify the acquisitions in diversifying and focusing without first controlling for geography. We define the dummy *Div* equal to 1 if acquisitions are diversifying and equal to 0 if focusing, and the dummy *Geo_div* equal to 1 for "in-state" buyer (diversifying) and 0 otherwise (focusing). Specification (4) is analogous to (3) but without explicitly controlling for geography; while specification (5) separately controls for geography. The interaction of the diversification dummy and ΔMAES in specification (4) is positive and significant at 1% level, indicating that diversifying acquisitions that are associated with an increase in bidders' systemic risk have an overall positive impact on acquisition's value. The magnitude of the overall impact on CAR for acquisitions that engage in systemic risk-shifting is about 1.104ppt ($-1.069 + 2.173$), which is also economically significant (since the level is not significant this value is statistically higher, 2.173ppt). Because the diversification dummy is arguably capturing both activity and geography, in specification (5) we separately control for geography to further investigate whether activity and/or geography matter for systemic risk-shifting. We find that the interaction term between the geography dummy and ΔMAES is not significant, which is not surprising given that *Div* is capturing both activity and geography diversification.

Next, we address whether only diversifying acquisitions create value through systemic risk-shifting or whether this is also the case for focusing acquisitions. From specification (3), we find that the interaction terms for GFAD and GDAF with ΔMAES are negative and significant, suggesting that focusing acquisitions with some dimension of diversification create value. However, if we look at purely focusing acquisitions, which are the baselines for specifications (3) (GFAF) and (4) (Foc = 1-Div), we find that only diversifying acquisitions create value through systemic risk-shifting.[19]

Finally, in specification (6) we explore our third research question by testing whether the value of systemic risk-shifting through acquisition has increased after the recent financial crisis. The difference between pre- and post-crisis periods is reflected in the coefficient of the triple interaction term Div∗ΔMAES∗post-crisis, where $post - crisis$ is a dummy variable equal to 1 for periods after 2009 (i.e., 2010-2015) and 0 otherwise. This coefficient is positive

[19] An interesting observation is that on the one hand, in specification (3) of Table 1.23, GDAF group has the highest coefficient of interaction with ΔMAES among others. On the other hand, in specification (4) of Table 1.16, we observe a premium for "Securities & Investments" deals. These observations may imply that our results are driven by Securities & Investment firms that acquire other firms with similar activity, but in a different geographical region. We checked the deal type within the sample of 199 acquisitions with publicly-traded targets and found only 1 such a deal. The results are robust to excluding that one deal. Therefore, we rule out the possibility that our results are driven by such cases.

and statistically significant at the 10% level. Although the result is not statistically strong, it provides some evidence that the value of systemic risk-shifting through acquisition has increased since the recent financial crisis.

1.5.5 Systemic risk-shifting in diversifying acquisitions

In this section, we focus on our fifth hypothesis $(\mathbf{H}_5)$ and move away from value creation. As explained in the introduction, prior literature has found that managerial benefits can be an incentive for diversifying acquisitions and those benefits are more applicable to bidders with poor pre-merger performance. In the previous section, we found that systemic risk-shifting is another incentive for diversifying acquisitions. Motivated by these two observations, in this section we investigate the relationship between acquisition diversification and systemic risk-shifting, as a function of bidder's pre-merger performance.

We estimate the following model:

$$\begin{aligned}\Delta\mathrm{MAES}_i = \gamma_0 + \gamma_1 Div \times (Bidder\, pre-merger\, performance)_i \\ + \gamma_2(Bidder\ characteristics)_i + \gamma_3(Target\ characteristics)_i + \epsilon_i \end{aligned} \tag{1.8}$$

where i indexes acquisitions. The main coefficient of interest corresponds to the interaction term between the *Div* dummy and bidder pre-merger performance.

We expect to see a positive coefficient. Our prior is that among diversifying acquisitions, those with higher bidder pre-merger performance are associated with higher levels of systemic risk-shifting. This is founded on the idea that poorly performing bidders engage in diversifying acquisitions for managerial benefits while well-performing bidders engage in diversifying acquisition for systemic risk-shifting motive.

The model is estimated using both OLS and quantile regression at the 75th percentile. Quantile regression is used to focus on acquisitions that lead to more systemic risk-shifting (i.e., higher values of ΔMAES). The results are presented in Table 1.24. As expected, in specifications (3) and (6), the coefficient of the interaction term between the *Div* dummy and bidder pre-merger performance is positive and significant at a 5% and 1% level respectively. This result suggests that systemic risk-shifting is higher as a function of bidder's pre-merger performance for diversifying versus focusing acquisitions (in line with our prior). Furthermore, this means that diversifying acquisitions with relatively well-performing bidders are associated with higher systemic risk-shifting.

Our analysis also supports the following conclusions. First, bidders with higher non-interest income seem to engage more in systemic risk-shifting via acquisitions (significant at a 1% level). This is consistent with the literature, which finds that higher non-interest income (i.e., non-core activities like investment banking and trading) is associated with a higher contribution to systemic risk relative to traditional banking (i.e., deposit taking and lending) (see, e.g., Brunnermeier, Dong, and Palia, 2012; Shleifer and Vishny, 2010; Dittmar and Thakor, 2007). Second, both analyses show an inverse relationship between target's pre-merger performance and systemic risk-shifting (significant at a 10% and 1% level respectively). This could be attributed to other oppertunities for value creation in acquisitions with under-performing targets (e.g., bidders can create value by improving the management and efficiency of the target).

Next, we perform a similar analysis using a logistic regression to explore likelihood in addition to degree of systemic risk-shifting. We define a dummy variable *Increase_75* equal to 1 if ΔMAES is above the 75th percentile and 0 otherwise. As in the quantile regression analysis, the reason for choosing the 75th percentile is to focus on acquisitions that lead to more systemic risk-shifting (i.e. higher values of ΔMAES). We estimate the following model:

$$ln\left(\frac{Pr(Increase)_i}{1 - Pr(Increase)_i}\right) = \lambda_0 + \lambda_1 Div \times (Bidder\, pre - merger\, performance)_i$$
$$+ \lambda_2(Bidder\ characteristics)_i + \lambda_3(Target\ characteristics)_i + \epsilon_i \tag{1.9}$$

where i indexes acquisitions.

The results are presented in Table 1.25. Specification (4) supports our finding from quantile regression, although the result is weaker (significant at a 10% level). In addition, specification (4) also supports the finding that bidders with higher non-interest income are more likely to increase bidders' contribution to systemic risk as the result of acquisition (odd ratio > 1 and significant at a 10% level).

1.6 Robustness checks

As stated earlier, target pre-acquisition performance is available for only a subset of our sample, so in order to determine "distressed" acquisitions based on targets' pre-merger performance, we imputed the median for the missing values. In this section, we perform two robustness tests to gain comfort in our proposed solution to address this data limitation. First, in specifications (1)-(4) of Table 1.26 we perform the same analysis as in Table 1.17 without accounting for poor-performing targets (i.e., we do not use the dummy "low" in our analysis). Our conclusions are robust to excluding the dummy "low" and its interaction with $\Delta MAES$. Namely, the market reacts significantly positive to an increase in systemic risk contribution (H_1), unless the acquisition is announced during a crisis period (H_2). Second, we run the same specification as in Table 1.17 model (2) but limiting the sample to acquisitions that have a non-missing value for target's pre-merger performance. The results are presented in specification (5) of Table 1.26. As anticipated, the sample size drops significantly to 172 observations because the target pre-merger performance measure is available only for publicly-traded targets. The main results are still robust and significant at 10% level. The lower level of signficance can be due to the smaller sample size or the characteristics of this restricted subsample.

Next, rather than controlling for targets' pre-merger performance by using a dummy variable, we restrict the sample to those acquisitions with "good" targets (i.e., where target's pre-acquisition performance is above the 25^{th} percentile). This allows us to study the relationship of changes in systemic risk and CAR in crisis versus non-crisis periods in a relatively large sample while avoiding imputing values for missing pre-merger performance. Furthermore, by restricting to relatively well performing targets we are also able to focus exclusively on economic conditions as the source of distress. Results are presented in Table 1.27. For comparison purposes, the first specification also includes private targets for which pre-merger performance measure is not available and hence imputed at the median. The results are robust in all specifications, indicating that an increase in bidders' systemic risk contribution is associated with a favorable market reaction resulting in an increase in bidders' market value.

Another potentially influential choice in our analysis is the threshold for targets' pre-merger performance to identify "distressed" acquisitions (i.e., 25^{th} percentile). In this section we test if our results are robust to alternative thresholds. We consider 10^{th} and 50^{th} percentiles as alternative thresholds and specify "low" and "distress" dummy variables based on those alternative choices. Table 1.28 presents our analysis using the 10^{th} percentile threshold. Our main results are still robust; however, the interaction term between changes in systemic risk and the dummy variable "low" is now significant for all the specifications ((1),(2), and (4) at 10% and (3) at 5% level). This is not surprising since by reducing the threshold from the 25^{th} to the 10^{th} percentile we are focusing on targets with really poor performance in relative terms. Results for the 50^{th} percentile are given in the appendix in Table 1.29 and are also robust.

Next, we investigate the choice of the crisis periods. As mentioned earlier, the crisis periods in our analysis correspond to those identified by the NBER plus the year 2011 to account for spillover effects of European sovereign debt crisis into the U.S. financial sector. Since 2011 is not a crisis specific to US and our analysis is focused on acquisitions of US institutions, we check if our results are robust to excluding 2011 from the crisis periods. The results are presented in Table 1.30. Notice that the sample size remains the same since this change only affects the definition of the "crisis" dummy. Table 1.30 suggests that our results are robust to the exclusion of 2011 as a crisis period.

As mentioned in Section 1.4, there are 573 unique acquirers in our sample. 427 of these acquirers appear only once while there are more acquistions associated with the rest. To ensure those repeat acquirers are not impacting our results, we perform the main analysis excluding repeat acquirers. As observed in Table 1.31, the main results are robust to excluding those observations.

We next assess the robustness of our results in Section 1.5.4 and 1.5.5 by weighing against alternative measures of activity and geography diversification. We use a second method to measure activity (and geography) relatedness of merging partners based on the correlation coefficient of their stock returns. As with the "Div" measure, because this measure is also built upon stock returns correlations it will capture some geography relatedness as well. Following Morck et al. (1990), we examine the correlation coefficients of monthly stock returns of the partners over three years prior to the acquisition announcement, and require at least 24 non-missing monthly returns for this calculation. We take the 50th percentile of the correlation coefficients as the cutoff for classifying acquisitions into focusing (above the 50th percentile) and diversifying (at or below the 50th percentile).

Table 1.32 presents the robustness results for Section 1.5.4. Specifications (1)-(2) are analogous to (4)-(5) in Table 1.23, but use instead the correlation measure for diversification. Specification (3) is also analogous to specification (5) but, in addition to the correlation measure, it uses a different geography diversification measure based on market overlap. *Market_overlap* is a categorical variable equal to 0 for "In market", 1 for "Partial overlap" and 2 for "Market expansion." Overall, we find that our results are consistent with Table 1.23. Particularly, diversifying acquisitions that are associated with an increase in MAES have a positive impact on acquirers' shareholders wealth (significant at a 5% level in specifications (1) and (3), and at a 1% level in specification (2), where we separately control for geography diversification).

Finally, specifications (4)-(5) only have measures of geography diversification to further test whether value creation is driven by geography as opposed to activity focus or diversification. The results highlight that geography diversification on its own, measured based on market overlap does not lead to creating value through systemic risk-shifting. In contrast, when measured as "in or out of state buyer" the opposite conclusion holds (significant at a 5% level). The latter result, in conjunction with the conclusions from specification (2) suggest that geography diversification may play a role in systemic risk-shifting. Based on these results, in specification (6) we only include a measure of activity diversification by adding the dummies "GFAD + GDAD" (activity diversifying) and "GFAF + GDAF" (activity focusing). The interaction term with ΔMAES is signifcant at a 10% level, which means the results are consistent with Table 1.23 although weaker than when using the "*Div*" measure. This is not surprising because "*Div*" is a more flexible measure that does not impose a prior classification by geography before grouping acquisitions into activity diversifying and focusing and may be partially capturing the role of geography diversification in systemic risk-shifting.

Table 1.33 presents the robustness results for Section 1.5.5. Our findings are generally robust for "Bidder non-interest income," which is significant at a 1% level in specifications

(3) and (6); and "Target pre-merger performance," which is significant at a 10% and 1% level in specifications (3) and (6) respectively. The relation between the alternative diversification measure and ΔMAES is not statistically significant. As evidenced by Table 1.32, the results are weaker with this alternative diversification measure. This is not too surprising since the correlation between "Div" and "$Correlation\_50$" is relatively low (0.15 approx.). This may suggest that "$Correlation\_50$" is too simplistic and may not capture well diversifying patterns.

1.7 Conclusion

In this paper, we explore whether acquirers shareholders gain from acquisitions through systemic risk-shifting. We find that in general, acquisitions coincide with an increase in systemic risk[20] of acquirers (relative to their non-merging counterparts) while their non-systemic risk does not statistically change. We also find that the market (ex-ante) reacts positively to an increase in acquirers' market-adjusted systemic risk leading to a value gain for acquirers. This result suggests that risk-shifting, particularly in the systemic dimension, is a source of value creation for acquirers. In other words, acquirers take private benefit at public cost. This finding does not generally apply to distressed acquisitions.

Interestingly, we find that the market reacts negatively to an increase in acquirers' market adjusted systemic risk when acquisition is announced during crisis periods. This is congruent with the notion of availability in behavioral finance that the easier it is for us to recall instances in which something has happened, the more likely we will assume it is. During crisis periods, realization of tail risk can lead to investors' higher risk aversion and unfavorable reaction to systemic risk-taking.

Prior literature have identified two channels through which bank consolidation may lead

[20]However, we do not observe an increase in systemic risk contribution for the acquisitions announced during crisis periods.

to overall fragility of financial system. First, consolidation can lead to forming larger and more diversified institutions, which can change the financial network architecture and consequently increase the likelihood of systemic failures. In particular, an increase in similarity of the institutions and density of their interconnections makes it more likely for the shocks to be transmitted across the system. Second, according to empirical findings, consolidation seems to increase the incentives of individual financial firms to take on more risk, such that it appears to outweigh the potential risk-reduction achievable through diversification.

We argue that if acquisitions contribute to instability of financial system due to forming more diversified institutions, we should see more negative impact from diversifying acquisitions relative to focusing ones. Our results suggest that only diversifying (as opposed to focusing) acquisitions create value by engaging in systemic risk-shifting. We find this is particularly the case when the acquisition is not driven by managerial incentives (i.e., when bidder pre-merger performance is relatively poor). Systemic risk-shifting is, however, not limited to a specific dimension of diversification. Indeed, it can be achieved through either activity or geography expansion.

Furthermore, since systemic risk-shifting is driven by implicit or explicit government guarantees in "too-big-to-fail" or "too-many-to-fail" cases, we study whether the extensive bailouts in recent financial crisis have increased the market value of such guarantees for financial institutions. We find empirical evidence that supports this notion.

Overall, our findings imply that there are circumstances in which acquirers' shareholders gain private benefit at the expense of the economy. Our findings suggest the existence of a new source of value gain in bank acquisitions, namely systemic risk-shifting, which due to its systemic nature could have important implications for financial stability and may call for higher regulatory attention in certain types of M&A activity.

Table 1.4: Definitions of variables used in the empirical study.

Variable	Definition
CAR	Cumulative Abnormal Returns (CAR) of an acquirer is computed over [-10,+1] relative to the acquisition announcement. The coefficients of the market model are estimated using daily returns over 300 to 51 trading days before the acquisition announcement.
Crisis	Is a dummy variable equal to 1 for acquisitions announced during the years 1990, 2001, 2007-2008, and 2011, and 0 otherwise.
Geo_div	Is a categorical variable for geographic diversification, which is set to 0 for "In market", 1 for "Partial overlap" and 2 for "Market expansion."
Increase	Is a dummy variable equal to 1 if $\Delta MAES$ is positive and 0 otherwise.
Low	Is a dummy variable equal to 1 if target's pre-merger performance is below 25^{th} percentile and 0 otherwise.
Distress	Is a dummy variable equal to 1 if acquisition is announced in a crisis period or target's pre-merger performance is below 25^{th} percentile and 0 otherwise.
MES	Is the average return on an individual bank's stock on the days the bank sector index experienced its 5% worst outcomes.
ΔMAES	MAES is the Market Adjusted Expected Shortfall defined as the difference between the acquirer's MES and the financial sector's ES. ΔMAES is the difference between post- and pre-merger MAES, where the pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and the post-merger period is the interval [+11,+180] relative to the acquisition completion.
ΔNSR	Individual Risk (NSR), as defined in Amihud et al. (2002), is the variance of daily stock returns of acquiring bank relative to that of a financial sector index. ΔNSR is the difference between post- and pre-merger NSR, where the pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and the post-merger period is the interval [+11,+180] relative to the acquisition completion.
Relative size	Ratio of deal value to market value of the acquirer's equity 10 days before the deal announcement.
Bidder/Target characteristics	
Assets	Natural logarithm of a bank's total assets at fiscal year end prior to the acquisition.
Non-interest income	Banks' (long term) non-interest income standardized by their average assets.
Pre-merger performance	Return of a target (bidder) 300 to 51 days before the acquisition announcement minus the return on the financial sector index for the same period.
Market-to-book	Market value of common equity 10 days before announcement divided by book value of common equity.

Variable	Definition
Diversification Variables	
Div	Is a dummy variable equal to 1 for "Diversifying" acquisitions and 0 for "focusing", without controlling first for geography.
Activity Div	Is a dummy variable equal to 1 for "Diversifying" acquisitions and 0 for "focusing", when controlling first for geography.
Geo_div	Is a dummy variable equal to 1 for "Not In-state" buyer and 0 otherwise.
Market_overlap	Is a categorical variable for geography diversification, which is set to 0 for "In market", 1 for "Partial overlap" and 2 for "Market expansion."
GDAD	Geography Diversifying and Activity Diversifying
GDAF	Geography Diversifying and Activity Focusing
GFAF	Geography Focusing and Activity Focusing
GFAD	Geography Focusing and Activity Diversifying
CAR	Cumulative Abnormal Return (CAR) of an acquirer is computed over [-10,+1] relative to the acquisition announcement. The betas and alphas (of market model) are estimated using daily returns from 300 to 51 trading days before the acquisition announcement.
Crisis	Is a dummy variable equal to 1 for acquisitions announced during the years 1990, 2001, 2007-2008, and 2011, and 0 otherwise.
MES	Is the average return on an individual bank's stock on the days the bank sector index experienced its 5% worst outcomes.
ΔMAES	MAES is the Market Adjusted Expected Shortfall defined as the difference between the acquirer's MES and the financial sector's ES. ΔMAES is the difference between post- and pre-merger MAES, where the pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and the post-merger period is the interval [+11,+180] relative to the acquisition completion.
Relative size	Ratio of deal value to market value of the acquirer's equity 10 days before the deal announcement.
Bidder/Target characteristics	
Assets	Natural logarithm of a bank's total assets at fiscal year end prior to the acquisition.
Non-interest income	Banks' (long term) non-interest income standardized by their average assets.
Pre-merger performance	Return of a target (bidder) 300 to 51 days before the acquisition announcement minus the return on the financial sector index for the same period.
Market-to-book	Market value of common equity 10 days before announcement divided by book value of equity.

Table 1.5: Change in market adjusted systemic risk.

This table presents pre- and post- acquisition levels as well as changes in the acquirer's Market Adjusted Marginal Expected Shortfall (MAES). We use MES as a measure of systemic risk contribution calculated based on the average return of a bank during the 5% worst days of a financial sector index. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index: $\text{MAES}_i^{5\%} = \text{MES}_i^{5\%} - \text{ES}_{Index}^{5\%}$. $\Delta\text{MAES}_i^{5\%} = \text{MAES}_{i,[+11,+180]}^{5\%} - \text{MAES}_{i,[-180,-11]}^{5\%}$. The pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and the post-acquisition period is the interval [+11,+180] relative to the acquisition completion. Means and p-values are presented for the full sample, and for the non-crisis and crisis subsamples. The crisis years are 1990, 2001, 2007-2008, and 2011.

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Periods	780	-0.308	0.000	-0.273	0.000	0.035	0.553
Non-Crisis Periods	645	-0.341	0.000	-0.228	0.000	0.114	0.036
Crisis Periods	135	-0.148	0.296	-0.488	0.067	-0.341	0.128

Table 1.6: Change in bidders' non-systemic relative risk.

This table presents pre- and post- acquisition levels as well as changes in the acquirer's Non-Systemic Relative Risk (NSR). $NSR_i = Var(R_i)/Var(Index)$, where R_i is the daily return of acquirer i and Index is a financial market index. We calculate the change in NSR for acquirer i as $\Delta NSR_i = NSR_{i,[+11,+180]} - NSR_{i,[-180,-11]}$. Pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-acquisition period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011.

		pre-merger NSR		post-merger NSR		ΔNSR	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Periods	780	5.198	0.000	5.171	0.000	-0.027	0.937
Non-Crisis Periods	645	5.491	0.000	5.510	0.000	0.020	0.961
Crisis Periods	135	3.799	0.000	3.550	0.000	-0.249	0.565

Table 1.7: Change in bidders' risk for non-distressed vs. distressed acquisitions.

Panel A: Systemic risk

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Acquisitions	780	-0.308	0.000	-0.273	0.000	0.035	0.553
Non-distressed	606	-0.310	0.000	-0.182	0.001	0.128	0.023
Distressed	174	-0.299	0.016	-0.587	0.006	-0.288	0.109

Panel B: Non-systemic risk

		pre-merger NSR		post-merger NSR		Δ NSR	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Acquisitions	780	5.198	0.000	5.171	0.000	-0.027	0.937
Non-distressed	606	5.529	0.000	5.569	0.000	0.040	0.923
Distressed	174	4.043	0.000	3.783	0.000	-0.260	0.554

Table 1.8: Change in bidders' risk by tertile of deal value.

Panel A: Non-distressed acquisitions

		Δ MAES		Δ NSR	
	Obs	Mean	P-value	Mean	P-value
Low deal value	202	0.050	0.622	-0.873	0.304
Medium deal value	202	0.206	0.020	0.269	0.506
High deal value	202	0.128	0.214	0.724	0.377

Panel B: Distressed acquisitions

		Δ MAES		Δ NSR	
	Obs	Mean	P-value	Mean	P-value
Low deal value	58	-0.511	0.213	1.210	0.239
Medium deal value	58	-0.437	0.094	-1.348	0.074
High deal value	58	0.084	0.724	-0.641	0.044

Table 1.9: Change in bidders' risk by tertile of bidders' total assets.

Panel A: Non-distressed acquisitions

		Δ MAES		Δ NSR	
	Obs	Mean	P-value	Mean	P-value
Low total assets	187	0.116	0.270	-1.172	0.087
Medium total assets	186	0.225	0.012	-0.470	0.151
High total assets	186	0.112	0.270	1.064	0.228

Panel B: Distressed acquisitions

		Δ MAES		Δ NSR	
	Obs	Mean	P-value	Mean	P-value
Low total assets	55	-1.252	0.004	-0.091	0.937
Medium total assets	55	-0.124	0.601	-0.704	0.329
High total assets	54	0.491	0.043	-0.391	0.109

Table 1.10: Change in bidders' risk by tertile of bidders' performance.

Panel A: Non-distressed acquisitions

		Δ MAES		Δ NSR	
	Obs	Mean	P-value	Mean	P-value
Low bidder performance	202	-0.041	0.637	-1.321	0.012
Medium bidder performance	202	0.082	0.381	0.563	0.462
High bidder performance	202	0.343	0.002	0.878	0.290

Panel B: Distressed acquisitions

		Δ MAES		Δ NSR	
	Obs	Mean	P-value	Mean	P-value
Low bidder performance	58	-0.055	0.875	0.823	0.333
Medium bidder performance	58	-0.696	0.019	-0.569	0.516
High bidder performance	58	-0.112	0.696	-1.033	0.041

Table 1.11: Change in market adjusted systemic risk of acquirers and targets combined.

This table presents pre-acquisition Market Adjusted Marginal Expected Shortfall (MAES) of acquirers and targets combined versus post-acquisition MAES of combined entity and the change in MAES as the result of a acquisition. We use MES as a measure of systemic risk contribution calculated based on the average return of a bank during the 5% worst days of a financial sector index. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index: $\text{MAES}_i^{5\%} = \text{MES}_i^{5\%} - \text{ES}_{Index}^{5\%}$. $\Delta\text{MAES}_i^{5\%} = \text{MAES}_{i,[+11,+180]}^{5\%} - \text{MAES}_{i,[-180,-11]}^{5\%}$. The pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and the post-acquisition period is the interval [+11,+180] relative to the acquisition completion. Means and p-values are presented for the full sample, and for the non-crisis and crisis subsamples. The crisis years are 1990, 2001, 2007-2008, and 2011.

Panel A: Systemic risk of acquirers and targets combined

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Periods	199	-0.348	0.000	-0.387	0.000	-0.039	0.660
Non-Crisis Periods	167	-0.382	0.000	-0.354	0.000	0.028	0.761
Crisis Periods	32	-0.170	0.533	-0.562	0.069	-0.393	0.158

Panel B: Systemic risk of acquirers for the limited sample

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Periods	199	-0.311	0.001	-0.387	0.000	-0.077	0.384
Non-Crisis Periods	167	-0.345	0.000	-0.354	0.000	-0.009	0.923
Crisis Periods	32	-0.131	0.637	-0.562	0.069	-0.431	0.136

Table 1.12: Change in combined entity's systemic risk for non-distressed vs. distressed acquisitions.

Panel A: Acquisitions during 1986-2015

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Acquisitions	199	-0.348	0.000	-0.387	0.000	-0.039	0.660
Non-distressed	128	-0.259	0.005	-0.178	0.056	0.080	0.423
Distressed	71	-0.509	0.007	-0.764	0.000	-0.255	0.145

Panel B: Acquisitions during 1991-2009

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Acquisitions	147	-0.565	0.000	-0.515	0.000	0.050	0.603
Non-distressed	91	-0.426	0.000	-0.241	0.026	0.185	0.104
Distressed	56	-0.790	0.000	-0.960	0.000	-0.169	0.325

Panel C: Acquisitions during 1991-2009 excluding repeat acquirers

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Acquisitions	127	-0.660	0.000	-0.598	0.000	0.061	0.537
Non-distressed	79	-0.487	0.000	-0.310	0.007	0.176	0.162
Distressed	48	-0.944	0.000	-1.073	0.000	-0.128	0.424

Panel D: Acquisitions during 1991-2009 excluding repeat acquirers- MES is not market-adjusted

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Acquisitions	127	1.133	0.000	1.450	0.000	0.318	0.023
Non-distressed	79	1.092	0.000	1.166	0.000	0.074	0.562
Distressed	48	1.199	0.000	1.919	0.000	0.719	0.019

Table 1.13: Change in market adjusted systemic risk of acquisitions with public targets vs. those with non-public targets.

This table presents pre- and post- acquisition levels as well as changes in the acquirer's Market Adjusted Marginal Expected Shortfall (MAES). We use MES as a measure of systemic risk contribution calculated based on the average return of a bank during the 5% worst days of a financial sector index. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index: $\text{MAES}_i^{5\%} = \text{MES}_i^{5\%} - \text{ES}_{Index}^{5\%}$. $\Delta\text{MAES}_i^{5\%} = \text{MAES}_{i,[+11,+180]}^{5\%} - \text{MAES}_{i,[-180,-11]}^{5\%}$. The pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and the post-acquisition period is the interval [+11,+180] relative to the acquisition completion. Means and p-values are presented for the full sample, and for the non-crisis and crisis subsamples. The crisis years are 1990, 2001, 2007-2008, and 2011.

Panel A: Acquisitions with **public targets**

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Periods	199	-0.311	0.001	-0.387	0.000	-0.077	0.384
Non-Crisis Periods	167	-0.345	0.000	-0.354	0.000	-0.009	0.923
Crisis Periods	32	-0.131	0.637	-0.562	0.069	-0.431	0.136

Panel B: Acquisitions with **non-public targets**

		pre-merger MAES		post-merger MAES		Δ MAES	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Periods	581	-0.307	0.000	-0.233	0.004	0.073	0.320
Non-Crisis Periods	478	-0.340	0.000	-0.183	0.007	0.157	0.018
Crisis Periods	103	-0.153	0.355	-0.465	0.167	-0.312	0.265

Table 1.14: Change in bidders' non-systemic relative risk of acquisitions with public targets vs. those with non-public targets.

This table presents pre- and post- acquisition levels as well as changes in the acquirer's Non-Systemic Relative Risk (NSR). $NSR_i = Var(R_i)/Var(Index)$, where R_i is the daily return of acquirer i and Index is a financial market index. We calculate the change in NSR for acquirer i as $\Delta NSR_i = NSR_{i,[+11,+180]} - NSR_{i,[-180,-11]}$. Pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-acquisition period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011.

Panel A: Acquisitions with **public targets**

		pre-merger NSR		post-merger NSR		Δ NSR	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Periods	199	4.414	0.000	4.552	0.000	0.138	0.755
Non-Crisis Periods	167	4.716	0.000	5.019	0.000	0.304	0.557
Crisis Periods	32	2.843	0.000	2.116	0.000	-0.727	0.164

Panel B: Acquisitions with **non-public targets**

		pre-merger NSR		post-merger NSR		Δ NSR	
	Obs	Mean	P-value	Mean	P-value	Mean	P-value
All Periods	581	5.466	0.000	5.383	0.000	-0.083	0.845
Non-Crisis Periods	478	5.761	0.000	5.682	0.000	-0.080	0.875
Crisis Periods	103	4.096	0.000	3.996	0.000	-0.100	0.853

Table 1.15: Market reaction to bank acquisitions.

This table presents the market reaction to acquisition announcement estimated as the CAR (Cumulative Abnormal Return) computed from 10 days before the acquisition announcement to 1 day following the announcement. The crisis years are 1990, 2001, 2007-2008 and 2011.

	All Mergers			Poor Target Perf.			Good Target Perf.		
	Obs	Mean	P-value	Obs	Mean	P-value	Obs	Mean	P-value
All Periods	780	-0.411	0.064	50	-3.954	0.000	730	-0.168	0.456
Non-Crisis Periods	645	-0.532	0.022	39	-4.146	0.000	606	-0.299	0.204
Crisis Periods	135	0.165	0.799	11	-3.271	0.193	124	0.469	0.484

Table 1.16: Market reaction to changes in systemic risk.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. "Distress" is 1 if acquisition is announced in a crisis period or target's pre-acquisition performance is below the 25^{th} percentile and 0 otherwise. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-acquisition period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011.

	(1)	(2)	(3)	(4)
Distress	-0.562	-1.124*	-1.431**	-1.303**
	(0.372)	(0.084)	(0.035)	(0.044)
$\Delta MAES$	0.406**	0.563***	0.424**	0.558***
	(0.016)	(0.007)	(0.046)	(0.008)
Distress*$\Delta MAES$	-0.584*	-0.672**	-0.660**	-0.719**
	(0.063)	(0.039)	(0.027)	(0.023)
ΔNSR	-0.0137	-0.0271	-0.00552	-0.0294
	(0.423)	(0.258)	(0.819)	(0.207)
Relative size	-3.512	-5.189	-2.828	-4.590
	(0.379)	(0.403)	(0.742)	(0.439)
Bidder pre-merger performance	-0.0265***	-0.0352***	-0.0383***	-0.0358***
	(0.005)	(0.002)	(0.008)	(0.001)
Geo diversification		-0.321	-0.700**	-0.383
		(0.215)	(0.015)	(0.144)
Bidder assets		0.0254	0.206	-0.105
		(0.867)	(0.320)	(0.486)
Bidder market-to-book		0.109	-0.297	-0.114
		(0.346)	(0.443)	(0.403)
Bidder non-interest income			0.0263	
			(0.359)	
Target assets			-0.587**	
			(0.018)	
Specialty Finance deal				1.977*
				(0.056)
Financial Technology deal				2.115
				(0.238)
Securities & Investments deal				4.380***
				(0.005)
Insurance deal				1.240*
				(0.088)
Constant	-0.403*	-0.663	4.730	1.169
	(0.082)	(0.767)	(0.216)	(0.597)
Observations	780	645	490	639
Adjusted R2	0.015	0.027	0.048	0.054

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.17: Market reaction to changes in systemic risk by source of distress.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with pre-acquisition perfromance below the 25^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-acquisition period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011.

	(1)	(2)	(3)	(4)
Crisis	0.792	0.261	0.00761	-0.101
	(0.261)	(0.717)	(0.992)	(0.888)
Low	-4.224***	-4.445***	-3.624***	-3.956***
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta MAES$	0.446***	0.608***	0.487**	0.602***
	(0.008)	(0.004)	(0.024)	(0.005)
Crisis*$\Delta MAES$	-0.608*	-0.632*	-0.608**	-0.684**
	(0.059)	(0.054)	(0.045)	(0.033)
Low*$\Delta MAES$	-0.695	-1.372	-1.265	-1.334
	(0.386)	(0.207)	(0.239)	(0.219)
ΔNSR	-0.0148	-0.0293	-0.00838	-0.0310
	(0.377)	(0.226)	(0.729)	(0.188)
Relative size	-3.332	-3.462	-1.600	-3.255
	(0.354)	(0.541)	(0.843)	(0.561)
Bidder pre-merger performance	-0.0306***	-0.0402***	-0.0442***	-0.0398***
	(0.002)	(0.000)	(0.002)	(0.000)
Geo diversification		-0.328	-0.661**	-0.384
		(0.199)	(0.019)	(0.138)
Bidder assets		-0.0437	0.126	-0.144
		(0.769)	(0.537)	(0.338)
Bidder market-to-book		0.0747	-0.242	-0.116
		(0.507)	(0.522)	(0.400)
Bidder non-interest income			0.0178	
			(0.538)	
Target assets			-0.540**	
			(0.026)	
Specialty Finance deal				1.692
				(0.112)
Financial Technology deal				1.834
				(0.314)
Securities & Investments deal				3.856**
				(0.014)
Insurance deal				1.046
				(0.144)
Constant	-0.423*	0.352	5.100	1.747
	(0.067)	(0.873)	(0.173)	(0.425)
Observations	780	645	490	639
Adjusted R2	0.042	0.054	0.070	0.072

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.18: Market reaction to changes in systemic risk in crisis periods.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with pre-acquisition perfromance below the 25^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-acquisition period is the interval [+11,+180] relative to the acquisition completion. The sample is limited to acquisitions announced in a crisis, i.e., years 1990, 2001, 2007-2008, and 2011.

	(1)	(2)	(3)	(4)
$\Delta MAES$	-0.1000	-0.0996	-0.0898	-0.216
	(0.717)	(0.718)	(0.718)	(0.421)
Low	-4.086*	-4.084*	-2.886	-2.939
	(0.098)	(0.098)	(0.262)	(0.232)
Relative size	0.00120		-229.6***	0.0285
	(1.000)		(0.003)	(0.995)
Bidder pre-merger performance	-0.0519	-0.0519	-0.0464	-0.0548
	(0.133)	(0.133)	(0.272)	(0.117)
Bidder assets	-0.493	-0.499	-0.0869	-0.612
	(0.342)	(0.335)	(0.861)	(0.260)
Bidder market-to-book	-0.0960	-0.0982	-0.204	-0.459
	(0.739)	(0.732)	(0.874)	(0.196)
Deal value		0.0129		
		(0.937)		
Bidder non-interest income			1.451***	
			(0.000)	
Target assets			0.260	
			(0.715)	
Specialty Finance deal				6.716
				(0.206)
Financial Technology deal				-2.364
				(0.636)
Securities & Investments deal				4.957*
				(0.074)
Insurance deal				1.742
				(0.389)
Constant	7.550	7.637	-2.567	8.602
	(0.346)	(0.339)	(0.845)	(0.279)
Observations	127	127	83	127
Adjusted R2	0.018	0.018	0.284	0.066

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.19: Market reaction to changes in systemic risk of acquisitions announced in 2001.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with pre-acquisition perfromance below the 25^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-acquisition period is the interval [+11,+180] relative to the acquisition completion. The sample is limited to acquisitions announced in 2001.

	(1)	(2)	(3)	(4)
$\Delta MAES$	-3.168**	-3.168**	-1.918**	-2.873**
	(0.019)	(0.019)	(0.016)	(0.014)
Low	-3.212	-3.219	-2.961	-2.114
	(0.225)	(0.223)	(0.353)	(0.460)
Relative size	7.922*		-1160.5*	4.581
	(0.082)		(0.065)	(0.188)
Bidder pre-merger performance	-0.0458	-0.0458	-0.0102	-0.0326
	(0.260)	(0.259)	(0.831)	(0.491)
Bidder assets	-1.544*	-1.537*	0.0658	-1.640*
	(0.092)	(0.092)	(0.960)	(0.065)
Bidder market-to-book	-0.784*	-0.783*	0.183	-0.807
	(0.068)	(0.068)	(0.950)	(0.211)
Deal value		0.412*		
		(0.080)		
Bidder non-interest income			1.534***	
			(0.000)	
Target assets			2.162	
			(0.246)	
Specialty Finance deal				7.438
				(0.536)
Securities & Investments deal				2.150
				(0.761)
Insurance deal				5.327**
				(0.017)
Constant	24.33*	24.25*	-24.05	24.85*
	(0.093)	(0.093)	(0.318)	(0.061)
Observations	46	46	36	46
Adjusted R2	0.283	0.283	0.555	0.291

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.20: Robustness to controling for TBTF motive.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. *TBTF_1* is equal to 1 if the acquirer moves up to the top quartile of total assests after the deal completion and 0 otherwise. *TBTF_2* is equal to 1 if the acquirer's total assets after acquisition is more than $100 billion and 0 otherwise. "Distress" is 1 if acquisition is announced in a crisis period or target's pre-merger performance is below the 25^{th} percentile and 0 otherwise. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-acquisition period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-acquisition period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011.

	(1)	(2)	(3)
Distress	-1.558**	-1.542**	-1.581**
	(0.020)	(0.019)	(0.016)
$\Delta MAES$	0.528**	0.509**	0.462**
	(0.021)	(0.019)	(0.032)
Distress*$\Delta MAES$	-0.860***	-0.835***	-0.836***
	(0.005)	(0.006)	(0.007)
Δ Size	0.0000715		
	(0.377)		
$\Delta Size * \Delta MAES$	-0.000110		
	(0.409)		
Geo Diversification	-0.707**	-0.728**	-0.666**
	(0.014)	(0.011)	(0.020)
ΔNSR	-0.0208	-0.0274	-0.0216
	(0.640)	(0.533)	(0.628)
Bidder pre-merger performance	-0.0424***	-0.0428***	-0.0416***
	(0.003)	(0.003)	(0.004)
Bidder assets	0.161	0.126	0.212
	(0.481)	(0.546)	(0.319)
Bidder market-to-book	-0.0524	0.0110	0.0374
	(0.887)	(0.977)	(0.917)
Bidder non-interest income	-0.366	-0.231	-0.365
	(0.182)	(0.379)	(0.186)
Target assets	-0.819***	-0.455*	-0.749***
	(0.001)	(0.071)	(0.001)
Relative size		-3.958	-5.382
		(0.660)	(0.456)
TBTF_1		-2.256**	
		(0.011)	
TBTF_1* $\Delta MAES$		-0.703	
		(0.291)	
TBTF_2			6.711***
			(0.000)
TBTF_2* $\Delta MAES$			-1.026
			(0.225)
Constant	8.031**	4.099	6.341*
	(0.035)	(0.276)	(0.074)
Observations	471	471	478
Adjusted R2	0.063	0.073	0.082

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.21: Acquisition value (CAR) by activity and geography diversification.

This table presents the market reaction to acquisition announcement estimated as the CAR (Cumulative Abnormal Return) computed from 10 days before the acquisition announcement to 1 day following the announcement. Acquisitions are grouped by both geography and activity diversification.

	N	mean	p-value	sd	min	max
All acquisitions	193	-2.135	0.000	5.77	-21.16	12.63
Geography & activity focus	25	-1.923	0.140	6.30	-12.38	11.31
Geography focus & activity div.	102	-1.774	0.002	5.56	-21.16	12.63
Geography div. & activity focus	8	-2.048	0.292	5.08	-11.90	3.07
Geography & activity div.	58	-2.872	0.001	6.06	-20.68	11.43

Figure 1.3: Distribution of CAR for diversifying versus focusing acquisitions.

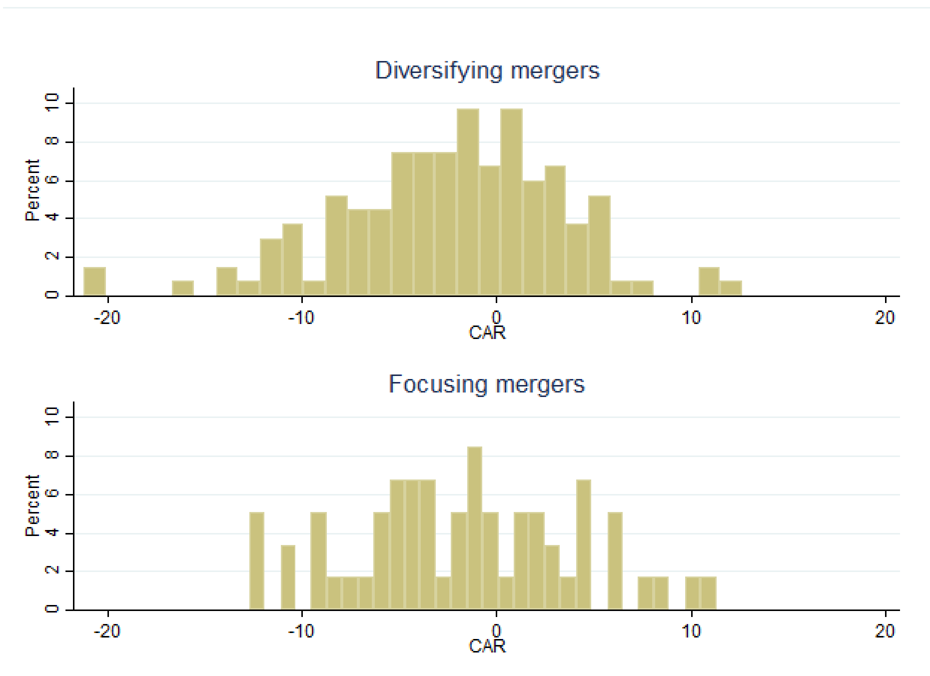

Table 1.22: Acquisition value (CAR) by diversification without controlling for geography.

This table presents the market reaction to acquisition announcement estimated as the CAR (Cumulative Abnormal Return) computed from 10 days before the acquisition announcement to 1 day following the announcement. Acquisitions are grouped by diversification without controlling for geography.

	N	mean	p-value	sd	min	max
All acquisitions	193	-2.135	0.000	5.77	-21.16	12.63
Focusing	59	-1.676	0.029	5.75	-12.70	11.31
Diversifying	134	-2.337	0.000	5.79	-21.16	12.63

Table 1.23: Value of diversifying acquisitions.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011. Post-crisis refers to 2010-2015. In specifications (1)-(4): GFAF (Geography and activity focus), GFAD (Geography focus and activity diversification), GDAF (Geography diversification and activity focus) and GDAD (Geography and activity diversification). In specifications (5)-(7): "Div" is a dummy variable for diversification without controlling for geography, and "Geo_div" is a dummy variable equal to 1 for "Not In-state" buyer and 0 otherwise.

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta MAES$		0.482	-1.116*	-1.036	-1.299*	-1.063
		(0.333)	(0.091)	(0.109)	(0.052)	(0.150)
Crisis*$\Delta MAES$		-1.452	-1.313	-1.649**	-1.415	
		(0.113)	(0.165)	(0.026)	(0.101)	
Crisis		-0.865	-1.010	-0.859	-0.901	
		(0.545)	(0.502)	(0.539)	(0.531)	
GFAD	-0.642	-0.522	-0.642			
	(0.655)	(0.722)	(0.651)			
GDAF	-0.466	-0.550	-1.171			
	(0.873)	(0.848)	(0.693)			
GDAD	-1.417	-1.118	-1.202			
	(0.377)	(0.490)	(0.445)			
GFAD*$\Delta MAES$			1.739*			
			(0.062)			
GDAF*$\Delta MAES$			3.285**			
			(0.037)			
GDAD*$\Delta MAES$			2.871**			
			(0.010)			
Div				-1.069	-0.919	-0.533
				(0.238)	(0.327)	(0.582)
Div * $\Delta MAES$				2.173***	2.057***	1.511*
				(0.005)	(0.008)	(0.089)
Geo_div					-0.295	
					(0.771)	
Geo_div*$\Delta MAES$					1.394	
					(0.157)	
Div*$\Delta MAES$*post-2009						3.042*
						(0.089)
post-2009						0.887
						(0.672)
Div*post-2009						-2.113
						(0.385)
$\Delta MAES$*post-2009						-2.114
						(0.179)
Relative size	-15.49	-15.86	-17.78*	-15.89*	-17.15*	-15.20
	(0.104)	(0.100)	(0.072)	(0.090)	(0.077)	(0.102)
Bidder pre-merger performance	-0.0590*	-0.0614*	-0.0644**	-0.0685**	-0.0704**	-0.0682**
	(0.074)	(0.055)	(0.039)	(0.025)	(0.022)	(0.027)
Bidder assets	0.175	0.167	0.214	0.157	0.253	0.151
	(0.601)	(0.622)	(0.533)	(0.627)	(0.462)	(0.652)
Bidder market-to-book	0.162	0.0931	0.137	0.0164	-0.00843	-0.0105
	(0.794)	(0.882)	(0.825)	(0.979)	(0.989)	(0.987)
Bidder non-interest income	0.0348	-0.0110	0.182	-0.00899	0.0974	0.00333
	(0.822)	(0.951)	(0.245)	(0.962)	(0.616)	(0.982)
Target pre-merger performance	0.0392*	0.0398*	0.0452**	0.0443**	0.0455**	0.0471**
	(0.076)	(0.076)	(0.043)	(0.046)	(0.035)	(0.024)
Constant	-4.126	-3.949	-4.654	-3.555	-4.968	-3.681
	(0.412)	(0.441)	(0.361)	(0.468)	(0.332)	(0.458)
Other controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	179	179	179	179	179	179
Adjusted R2	0.032	0.033	0.056	0.083	0.085	0.069

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.24: Analysis of ΔMAES - OLS & Quantile regressions

The dependent variable is ΔMAES. The quantile regressions are at the 75th percentile. The analysis uses acquisitions announced and completed between 1986 and 2015. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. "Div" is a dummy variable for diversification.

	OLS Regression			Quintile Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Div	-0.323	-0.373*	-0.110	-0.193	-0.241	0.223
	(0.115)	(0.087)	(0.654)	(0.332)	(0.332)	(0.353)
Div * Bidder pre-merger performance			0.0279**			0.0339***
			(0.031)			(0.004)
Bidder pre-merger performance	0.00252	0.00712	-0.0124	-0.00291	0.00180	-0.0186**
	(0.696)	(0.376)	(0.244)	(0.632)	(0.809)	(0.043)
Relative size	-0.463	-0.857	-1.053	-2.499	-1.719	-2.573
	(0.538)	(0.329)	(0.242)	(0.207)	(0.503)	(0.194)
Bidder assets	-0.00885	-0.00619	0.0180	-0.0150	-0.0254	0.0217
	(0.898)	(0.936)	(0.807)	(0.846)	(0.788)	(0.767)
Bidder market-to-book	0.200	-0.0764	-0.107	0.324*	-0.0392	-0.0761
	(0.113)	(0.649)	(0.540)	(0.063)	(0.883)	(0.635)
Bidder non-interest income	0.356***	0.368***	0.370***	0.430***	0.429	0.388***
	(0.006)	(0.005)	(0.002)	(0.000)	(0.151)	(0.000)
Bidder maturity mismatch	-0.0328	-0.273	-0.317	0.203	0.136	-0.193
	(0.975)	(0.805)	(0.766)	(0.802)	(0.931)	(0.788)
Target pre-merger performance		-0.00918*	-0.00883*		-0.0128***	-0.0177***
		(0.075)	(0.071)		(0.010)	(0.001)
Target market-to-book		0.512**	0.552**		0.577**	0.655**
		(0.038)	(0.031)		(0.033)	(0.013)
Target maturity mismatch		1.647	1.509		0.0855	0.267
		(0.122)	(0.125)		(0.954)	(0.795)
Observations	158	140	140	158	140	140
Adjusted R2	0.0454	0.0662	0.0940			

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.25: Analysis of ΔMAES - Logistic regression

The dependent variable is *Increase_75*, a dummy variable equal to 1 if ΔMAES is greater than 75th percentile and 0 otherwise. The analysis uses acquisitions announced and completed between 1986 and 2015. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. “Div” is a measure of diversification. Odd ratios reported.

	(1)	(2)	(3)	(4)
Div	0.901	1.477	0.883	1.508
	(0.812)	(0.505)	(0.791)	(0.499)
Div * Bidder pre-merger performance		1.039		1.051*
		(0.140)		(0.072)
Bidder pre-merger performance	0.996	0.967	1.008	0.972
	(0.737)	(0.153)	(0.593)	(0.260)
Relative size	0.252	0.169	0.262	0.176
	(0.627)	(0.537)	(0.653)	(0.564)
Bidder assets	0.765	0.767	0.825	0.846
	(0.114)	(0.128)	(0.293)	(0.385)
Bidder market-to-book	1.897**	1.930**	1.197	1.193
	(0.023)	(0.022)	(0.652)	(0.668)
Bidder non-interest income	1.581*	1.624*	1.699*	1.734*
	(0.074)	(0.070)	(0.063)	(0.064)
Bidder maturity mismatch	0.791	0.749	0.759	0.760
	(0.925)	(0.911)	(0.919)	(0.923)
Target pre-merger performance			0.982	0.984
			(0.114)	(0.162)
Target market-to-book			1.796	1.821
			(0.283)	(0.270)
Target maturity mismatch			0.297	0.203
			(0.689)	(0.624)
Observations	158	158	140	140

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.26: Robustness to imputing missing values in targets' pre-acquisition performance measure

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with pre-merger perfromance below the 25^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011.

	(1)	(2)	(3)	(4)	(5)
Crisis	0.719	0.135	-0.208	-0.239	-0.582
	(0.314)	(0.853)	(0.797)	(0.744)	(0.655)
$\Delta MAES$	0.430***	0.565***	0.432**	0.561***	0.774*
	(0.010)	(0.007)	(0.049)	(0.009)	(0.106)
Crisis*$\Delta MAES$	-0.607*	-0.630*	-0.612**	-0.689**	-1.227
	(0.061)	(0.056)	(0.045)	(0.032)	(0.148)
ΔNSR	-0.0138	-0.0267	-0.00551	-0.0292	-0.00687
	(0.417)	(0.274)	(0.825)	(0.218)	(0.919)
Relative size	-3.922	-5.338	-2.839	-4.848	-1.941
	(0.332)	(0.408)	(0.754)	(0.437)	(0.766)
Bidder pre-merger performance	-0.0262***	-0.0338***	-0.0349**	-0.0341***	-0.0899***
	(0.006)	(0.002)	(0.014)	(0.002)	(0.000)
Geo Diversification		-0.342	-0.689**	-0.405	-1.339**
		(0.188)	(0.016)	(0.123)	(0.015)
Bidder assets		0.0000930	0.189	-0.122	0.00827
		(1.000)	(0.364)	(0.417)	(0.980)
Bidder market-to-book		0.0912	-0.298	-0.125	-0.613
		(0.427)	(0.448)	(0.366)	(0.336)
Bidder non-interest income			0.0350		
			(0.188)		
Target assets			-0.616**		
			(0.014)		
Specialty Finance deal				1.976*	
				(0.058)	
Financial Technology deal				2.231	
				(0.218)	
Securities & Investments deal				4.251***	
				(0.007)	
Insurance deal				1.286*	
				(0.078)	
Low					-3.371***
					(0.002)
Low*$\Delta MAES$					-1.380
					(0.237)
Constant	-0.644***	-0.513	5.055	1.211	0.304
	(0.005)	(0.816)	(0.186)	(0.580)	(0.951)
Observations	780	645	490	639	172
Adjusted R2	0.017	0.021	0.038	0.046	0.112

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.27: Robustness to excluding poor-performing targets

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015, where targets' pre-merger performance is above 25^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011.

	(1)	(2)	(3)	(4)
Crisis	0.800	0.207	0.00950	-0.177
	(0.278)	(0.784)	(0.991)	(0.816)
$\Delta MAES$	0.416**	0.585***	0.446**	0.577***
	(0.013)	(0.005)	(0.036)	(0.007)
Crisis*$\Delta MAES$	-0.540*	-0.591*	-0.538*	-0.638**
	(0.095)	(0.071)	(0.070)	(0.046)
ΔNSR	-0.0147	-0.0296	-0.00716	-0.0314
	(0.399)	(0.232)	(0.772)	(0.192)
Relative size	-1.665	-0.983	0.538	-0.934
	(0.628)	(0.868)	(0.954)	(0.876)
Bidder pre-merger performance	-0.0308***	-0.0415***	-0.0489***	-0.0412***
	(0.002)	(0.000)	(0.001)	(0.000)
Geo Diversification		-0.239	-0.574**	-0.294
		(0.363)	(0.048)	(0.269)
Bidder assets		-0.0255	0.124	-0.137
		(0.867)	(0.557)	(0.373)
Bidder market-to-book		0.104	-0.129	-0.0815
		(0.365)	(0.736)	(0.558)
Bidder non-interest income			0.0179	
			(0.509)	
Target assets			-0.512**	
			(0.040)	
Specialty Finance deal				1.703
				(0.109)
Financial Technology deal				1.799
				(0.324)
Securities & Investments deal				3.748**
				(0.017)
Insurance deal				1.188*
				(0.094)
Constant	-0.443*	-0.0901	4.465	1.460
	(0.055)	(0.968)	(0.262)	(0.515)
Exclude poor performing targets?	Yes	Yes	Yes	Yes
Observations	730	600	446	594
Adjusted R2	0.020	0.027	0.039	0.046

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.28: Robustness to alternative threshold for identifying poor-performing targets (10^{th} percentile)

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with pre-merger performance below the 10^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011.

	(1)	(2)	(3)	(4)
Crisis	0.781	0.196	-0.102	-0.170
	(0.266)	(0.782)	(0.895)	(0.811)
Low	-5.092***	-4.950***	-3.879***	-4.479***
	(0.000)	(0.000)	(0.002)	(0.000)
$\Delta MAES$	0.466***	0.615***	0.499**	0.610***
	(0.006)	(0.004)	(0.026)	(0.005)
Crisis*$\Delta MAES$	-0.611*	-0.643**	-0.629**	-0.698**
	(0.056)	(0.049)	(0.036)	(0.029)
Low*$\Delta MAES$	-2.056*	-2.301*	-2.282**	-2.227*
	(0.091)	(0.060)	(0.048)	(0.072)
ΔNSR	-0.0145	-0.0274	-0.00632	-0.0295
	(0.384)	(0.253)	(0.794)	(0.208)
Relative size	-3.948	-5.221	-3.509	-4.800
	(0.327)	(0.418)	(0.703)	(0.442)
Bidder pre-merger performance	-0.0296***	-0.0389***	-0.0431***	-0.0388***
	(0.002)	(0.001)	(0.003)	(0.000)
Geo Diversification		-0.311	-0.660**	-0.374
		(0.228)	(0.021)	(0.153)
Bidder assets		-0.00823	0.185	-0.121
		(0.956)	(0.366)	(0.417)
Bidder market-to-book		0.0966	-0.228	-0.106
		(0.402)	(0.554)	(0.444)
Bidder non-interest income			0.0237	
			(0.388)	
Target assets			-0.581**	
			(0.020)	
Specialty Finance deal				1.816*
				(0.086)
Financial Technology deal				2.006
				(0.271)
Securities & Investments deal				4.043**
				(0.010)
Insurance deal				1.211*
				(0.089)
Constant	-0.548**	-0.333	4.620	1.255
	(0.017)	(0.879)	(0.220)	(0.563)
Observations	780	645	490	639
Adjusted R2	0.035	0.044	0.060	0.065

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.29: Robustness to alternative threshold for identifying poor-performing targets (50th percentile)

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with below 25^{th} percentile of pre-merger performance MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011. All specifications control for bidder assets and market-to-book ratio.

	(1)	(2)	(3)	(4)
Crisis	0.825	0.265	0.00907	-0.0858
	(0.240)	(0.712)	(0.991)	(0.905)
Low	-3.323***	-3.366***	-2.573***	-2.839***
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta MAES$	0.485***	0.674***	0.561**	0.667***
	(0.005)	(0.002)	(0.011)	(0.002)
Crisis*$\Delta MAES$	-0.627*	-0.675**	-0.656**	-0.722**
	(0.051)	(0.038)	(0.030)	(0.024)
Low*$\Delta MAES$	-0.799	-1.361**	-1.253*	-1.333**
	(0.144)	(0.045)	(0.067)	(0.049)
ΔNSR	-0.0148	-0.0330	-0.0151	-0.0341
	(0.364)	(0.163)	(0.524)	(0.144)
Relative size	-2.808	-2.843	-2.695	-2.874
	(0.404)	(0.594)	(0.728)	(0.590)
Bidder pre-merger performance	-0.0315***	-0.0412***	-0.0446***	-0.0403***
	(0.001)	(0.000)	(0.001)	(0.000)
Geo Diversification		-0.378	-0.695**	-0.422
		(0.138)	(0.013)	(0.102)
Bidder assets		0.0143	0.153	-0.0800
		(0.924)	(0.454)	(0.597)
Bidder market-to-book		0.0725	-0.214	-0.102
		(0.517)	(0.567)	(0.456)
Bidder non-interest income			0.0274	
			(0.279)	
Target assets			-0.372	
			(0.135)	
Specialty Finance deal				1.447
				(0.176)
Financial Technology deal				1.674
				(0.360)
Securities & Investments deal				3.599**
				(0.021)
Insurance deal				0.842
				(0.246)
Observations	780	645	490	639
Adjusted R2	0.048	0.062	0.072	0.075

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.30: Robustness to excluding 2011 as a crisis period.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with pre-merger performance below the 25^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, and 2007-2008.

	(1)	(2)	(3)	(4)
Crisis	0.232	-0.230	-0.265	-0.502
	(0.756)	(0.765)	(0.736)	(0.511)
Low	-4.177***	-4.378***	-3.555***	-3.892***
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta MAES$	0.413**	0.580***	0.481**	0.578***
	(0.013)	(0.005)	(0.024)	(0.006)
Crisis*$\Delta MAES$	-0.587*	-0.627*	-0.635**	-0.685**
	(0.072)	(0.055)	(0.032)	(0.031)
Low*$\Delta MAES$	-0.746	-1.443	-1.333	-1.397
	(0.372)	(0.199)	(0.227)	(0.212)
ΔNSR	-0.0141	-0.0280	-0.00818	-0.0298
	(0.406)	(0.245)	(0.734)	(0.203)
Relative size	-3.231	-3.632	-1.674	-3.392
	(0.371)	(0.520)	(0.835)	(0.542)
Bidder pre-merger performance	-0.0303***	-0.0402***	-0.0437***	-0.0399***
	(0.002)	(0.000)	(0.002)	(0.000)
Geo Diversification		-0.332	-0.678**	-0.388
		(0.194)	(0.016)	(0.135)
Bidder assets		-0.0283	0.153	-0.134
		(0.848)	(0.450)	(0.370)
Bidder market-to-book		0.0833	-0.263	-0.111
		(0.460)	(0.488)	(0.421)
Bidder non-interest income			0.0190	
			(0.511)	
Target assets			-0.552**	
			(0.023)	
Specialty Finance deal				1.678
				(0.108)
Financial Technology deal				1.838
				(0.311)
Securities & Investments deal				3.930**
				(0.012)
Insurance deal				1.019
				(0.155)
Constant	-0.318	0.205	4.961	1.658
	(0.166)	(0.925)	(0.181)	(0.448)
Observations	780	645	490	639
Adjusted R2	0.039	0.054	0.070	0.073

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.31: Market reaction to changes in systemic risk - excluding repeat acquirers

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with pre-merger perfromance below the 25^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011. All specifications control for bidder assets and market-to-book ratio.

	(1)	(2)	(3)	(4)
Distress	-0.229	-0.982	-1.212	-1.294*
	(0.757)	(0.203)	(0.101)	(0.090)
$\Delta MAES$	0.509***	0.749***	0.632**	0.748***
	(0.008)	(0.003)	(0.016)	(0.004)
Distress*$\Delta MAES$	-0.520	-0.687*	-0.795**	-0.752**
	(0.132)	(0.067)	(0.015)	(0.033)
ΔIR	-0.0238	-0.0447*	-0.0272	-0.0464*
	(0.169)	(0.090)	(0.296)	(0.077)
Relative size	-2.253	-4.208	-6.697	-5.597
	(0.540)	(0.536)	(0.393)	(0.334)
Bidder pre-merger performance	-0.0325***	-0.0418***	-0.0386**	-0.0416***
	(0.002)	(0.001)	(0.012)	(0.000)
Geo Diversification		-0.353	-0.684**	-0.373
		(0.259)	(0.040)	(0.234)
Bidder assets		0.125	0.225	-0.00371
		(0.528)	(0.445)	(0.984)
Bidder market-to-book		-0.00898	-0.589	-0.289*
		(0.931)	(0.221)	(0.063)
Bidder non-interest income			0.0381	
			(0.195)	
Target assets			-0.308	
			(0.382)	
Specialty Finance deal				1.613
				(0.200)
Financial Technology deal				2.350
				(0.418)
Securities & Investments deal				6.160***
				(0.006)
Insurance deal				1.440*
				(0.098)
Constant	-0.399	-1.739	1.536	0.0750
	(0.150)	(0.541)	(0.748)	(0.978)
Observations	572	450	345	446
Adjusted R2	0.022	0.038	0.046	0.080

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.32: Value of diversifying acquisitions - Robustness to alternative diversification measures.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. *Correlation_50* is a dummy variable equal to 1 if correlation of bidder and target monthly stock return over 36 months before acquisition announcement is less than 50th percentile (diversifying acquisition) and 0 otherwise. *Market_overlap* is a categorical variable for geography diversification, which is set to 0 for "In market", 1 for "Partial overlap" and 2 for "Market expansion." *Geo_div* is a dummy variable equal to 1 for "Not In-state" buyer and 0 otherwise. "Activity Div" is a dummy for activity diversification.

	Correlation Measure			Geography Div.		Activity Div.
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta MAES$	-0.820	-1.448**	-1.493**	-0.206	-0.578	-0.685
	(0.176)	(0.026)	(0.031)	(0.757)	(0.467)	(0.297)
Crisis	0.116	0.260	0.0403	0.0443	-0.161	-0.936
	(0.939)	(0.864)	(0.979)	(0.976)	(0.914)	(0.523)
Crisis*$\Delta MAES$	-1.462*	-1.110	-1.417	-0.568	-0.704	-1.590*
	(0.100)	(0.226)	(0.127)	(0.591)	(0.500)	(0.063)
Correlation_50	-0.427	-0.329	-0.398			
	(0.678)	(0.745)	(0.694)			
Correlation_50*$\Delta MAES$	2.127**	2.346***	2.095**			
	(0.015)	(0.004)	(0.025)			
Target pre-merger performance	0.0658***	0.0650***	0.0573***	0.0649***	0.0561**	0.0442*
	(0.002)	(0.002)	(0.009)	(0.002)	(0.010)	(0.053)
Geo_div		0.0261		0.0307		
		(0.979)		(0.975)		
Geo_div*$\Delta MAES$		2.268**		1.977**		
		(0.015)		(0.039)		
Market_overlap			-0.887		-0.704	
			(0.195)		(0.270)	
Market_overlap*$\Delta MAES$			0.748		0.869	
			(0.181)		(0.147)	
Activity Div						-0.677
						(0.583)
Activity Div * $\Delta MAES$						1.664*
						(0.055)
Relative size	-15.80*	-18.58*	-16.22*	-17.55*	-15.67*	-16.95*
	(0.096)	(0.063)	(0.098)	(0.072)	(0.099)	(0.074)
Bidder pre-merger performance	-0.0868***	-0.0898***	-0.0966***	-0.0884***	-0.0935***	-0.0601**
	(0.006)	(0.004)	(0.003)	(0.004)	(0.002)	(0.047)
Bidder assets	0.156	0.251	0.321	0.265	0.313	0.0713
	(0.694)	(0.539)	(0.446)	(0.458)	(0.394)	(0.826)
Bidder market-to-book	0.315	0.331	0.183	0.158	0.0187	0.169
	(0.652)	(0.634)	(0.793)	(0.823)	(0.979)	(0.784)
Bidder non-interest income	0.278	0.533	0.573	0.146	0.324	0.0629
	(0.509)	(0.216)	(0.185)	(0.727)	(0.455)	(0.660)
Bidder maturity mismatch	4.285	3.438	3.249	3.616	3.870	
	(0.336)	(0.439)	(0.481)	(0.420)	(0.394)	
Constant	-5.105	-6.746	-6.802	-6.439	-6.526	-2.667
	(0.414)	(0.286)	(0.298)	(0.233)	(0.247)	(0.586)
Observations	149	149	143	157	151	179
Adjusted R2	0.181	0.207	0.219	0.152	0.166	0.118

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.33: Analysis of ΔMAES - OLS & Quantile regressions using a correlation-based diversification measure.

The dependent variable is ΔMAES. The analysis is performed using OLS and quantile regression at the 75th percentile. Acquisitions are announced and completed between 1986 and 2015. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion.

	OLS Regression			Quintile Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Correlation_50	-0.262	-0.331	-0.275	-0.319	-0.223	-0.273
	(0.211)	(0.147)	(0.291)	(0.231)	(0.284)	(0.265)
Correlation_50 * Bidder pre-merger performance			0.00684			-0.00615
			(0.600)			(0.573)
Geo_div	-0.132	-0.0779	-0.0800	-0.116	0.0141	-0.212
	(0.539)	(0.740)	(0.735)	(0.707)	(0.946)	(0.360)
Bidder pre-merger performance	0.000199	0.00560	0.00118	-0.00221	-0.00422	0.00282
	(0.976)	(0.498)	(0.900)	(0.744)	(0.508)	(0.752)
Relative size	-0.615	-1.350	-1.189	-2.671	-2.823*	-2.547
	(0.481)	(0.168)	(0.251)	(0.301)	(0.070)	(0.250)
Bidder assets	-0.0490	-0.0745	-0.0718	-0.0144	-0.0796	-0.0757
	(0.535)	(0.409)	(0.427)	(0.865)	(0.223)	(0.288)
Bidder market-to-book	0.237*	-0.00580	-0.00318	0.316*	0.180	0.119
	(0.079)	(0.972)	(0.985)	(0.091)	(0.384)	(0.568)
Bidder non-interest income	0.355***	0.366***	0.372***	0.375***	0.384**	0.363***
	(0.004)	(0.002)	(0.002)	(0.000)	(0.012)	(0.000)
Bidder maturity mismatch	0.0279	0.0247	-0.00157	0.139	-0.277	-0.201
	(0.980)	(0.983)	(0.999)	(0.897)	(0.846)	(0.889)
Target pre-merger performance		-0.0109**	-0.0105*		-0.0135***	-0.0134***
		(0.050)	(0.061)		(0.000)	(0.005)
Target market-to-book		0.472*	0.457*		0.443*	0.500**
		(0.052)	(0.060)		(0.052)	(0.034)
Target maturity mismatch		2.148*	2.099*		1.028	1.487
		(0.055)	(0.059)		(0.380)	(0.264)
Observations	149	134	134	149	134	134
Adjusted R2	0.0380	0.0663	0.0609			

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.34: Market reaction to changes in systemic risk by source of distress

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. Low refers to targets with pre-merger perfromance below the 25^{th} percentile. MAES is defined as the difference between MES of the acquirer and Expected Shortfall (ES) of a financial sector index. Pre-merger period is defined as the interval [-180,-11] relative to the acquisition announcement, and post-merger period is the interval [+11,+180] relative to the acquisition completion. The crisis years are 1990, 2001, 2007-2008, and 2011. All specifications control for bidder assets and market-to-book ratio.

	(1)	(2)	(3)	(4)
Crisis	0.888	0.366	0.171	0.0140
	(0.202)	(0.605)	(0.826)	(0.984)
Low	-4.128***	-4.281***	-3.489***	-3.817***
	(0.000)	(0.000)	(0.001)	(0.000)
$\Delta MAES$	0.155	0.240	0.111	0.203
	(0.301)	(0.156)	(0.470)	(0.222)
ΔNSR	-0.00995	-0.0127	0.00940	-0.0127
	(0.630)	(0.615)	(0.705)	(0.602)
Relative size	-3.682	-3.957	-1.973	-3.755
	(0.311)	(0.492)	(0.811)	(0.511)
Bidder pre-merger performance	-0.0294***	-0.0390***	-0.0422***	-0.0385***
	(0.002)	(0.001)	(0.002)	(0.000)
Geo Diversification		-0.356	-0.684**	-0.409
		(0.171)	(0.016)	(0.120)
Bidder assets		-0.0838	0.0844	-0.182
		(0.572)	(0.677)	(0.224)
Bidder market-to-book		0.0891	-0.197	-0.0940
		(0.444)	(0.603)	(0.506)
Bidder non-interest income			0.0328	
			(0.162)	
Target assets			-0.542**	
			(0.025)	
Specialty Finance deal				1.621
				(0.136)
Financial Technology deal				1.773
				(0.331)
Securities & Investments deal				3.745**
				(0.017)
Insurance deal				1.008
				(0.165)
Constant	-0.381*	1.000	5.748	2.377
	(0.099)	(0.650)	(0.122)	(0.279)
Observations	780	645	490	639
Adjusted R2	0.037	0.046	0.060	0.063

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures 1.4 and 1.5 show the distribution of ΔMAES for diversifying and focusing acquisitions, and for all acquisitions respectively. It is clear from these graphs that the distributions sufficiently cover both positive and negative values of ΔMAES making the inferences econometrically robust.

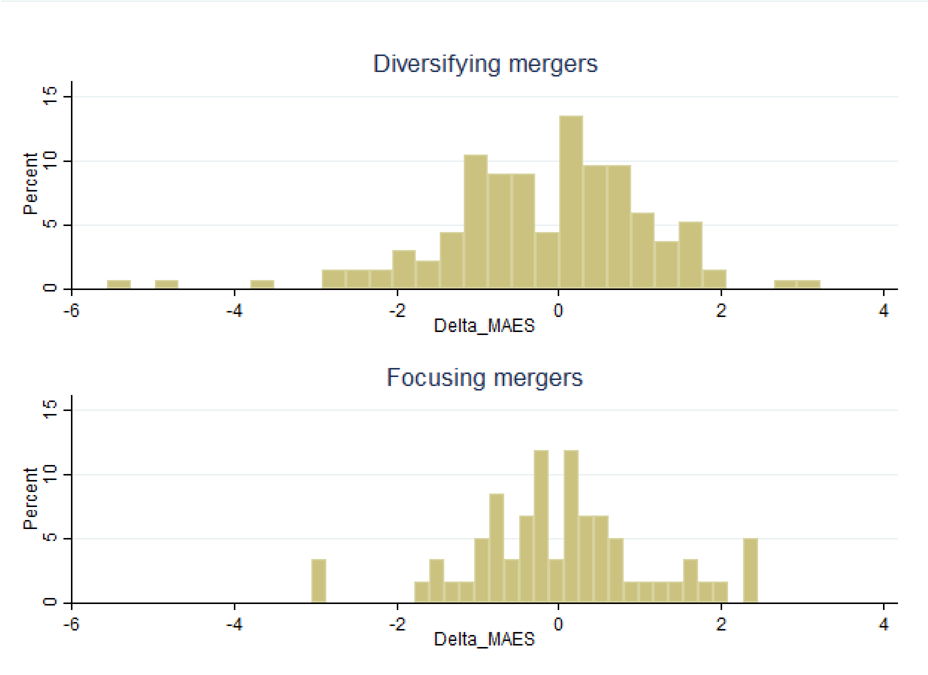

Figure 1.4: ΔMAES for diversifying and focusing acquisitions

This graph shows the distribution of ΔMAES across diversifying and focusing acquisitions.

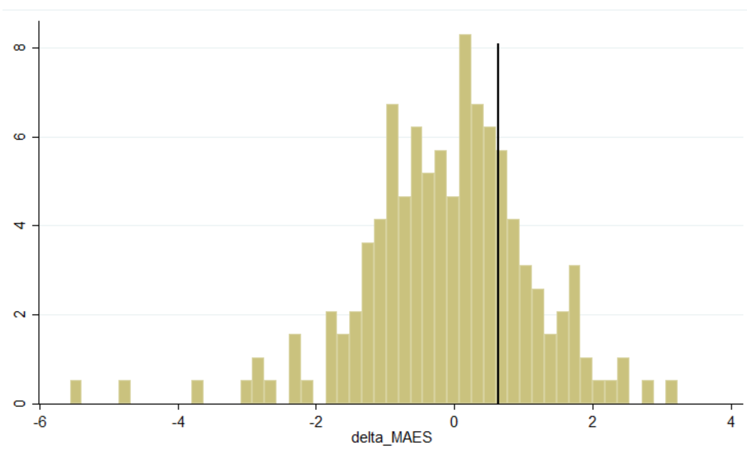

Figure 1.5: ΔMAES for all acquisitions.

This graph shows the distribution of ΔMAES for all acquisitions in our sample. The vertical line marks the 75th percentile of the distribution.

Table 1.35: Value of diversifying acquisitions.

The dependent variable is CAR. The analysis uses acquisitions announced and completed between 1986 and 2015. In specifications (1)-(2): GFAF (Geography and activity focus), GFAD (Geography focus and activity diversification), GDAF (Geography diversification and activity focus) and GDAD (Geography and activity diversification). In specification (3), "Div" is a dummy variable for diversification without controlling for geography. In specification (4): "Activity Div" is a dummy variable for activity diversification constructed from the four dummies in specifications (1)-(2).

	(1)	(2)	(3)
GFAD	-0.706		
	(0.352)		
GDAF	1.057		
	(0.359)		
GDAD	-0.513		
	(0.502)		
Relative size	-5.354***	-4.960***	-5.275***
	(0.000)	(0.001)	(0.001)
Bidder pre-merger performance	-0.0107	-0.0103	-0.0110
	(0.381)	(0.398)	(0.373)
Bidder assets	0.256*	0.286**	0.293**
	(0.055)	(0.021)	(0.018)
Bidder market-to-book	-0.0846	-0.0687	-0.0945
	(0.694)	(0.744)	(0.659)
Bidder non-interest income	-0.0610	-0.0487	-0.0556
	(0.101)	(0.170)	(0.126)
Target pre-merger performance	0.0121	0.0132	0.0122
	(0.142)	(0.102)	(0.140)
Div		-0.774*	
		(0.084)	
Activity Div			-1.013*
			(0.087)
Constant	-5.114**	-5.560***	-5.290***
	(0.017)	(0.005)	(0.009)
Observations	863	869	863
Adjusted R2	0.015	0.015	0.016

p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table 1.36: Description of related literature

Theory & Description
Bank consolidation & financial stability (systemic risk)
Berger, Demsetz, and Strahan (1999) The potential effects of consolidation on risk of individual institutions and financial stability are highlighted as following: 1. M&As may either increase or decrease the risk of institutions, largely depending upon whether any diversification gains are offset by the institutions' pursuit of additional risks. Their results suggest that in many cases, consolidating institutions chose to move along the risk-expected return frontier and take most of the benefits of diversification gains as higher returns by shifting their portfolios toward higher risk-higher expected return investments. 2. M&As lead to larger institutions with larger systemic consequences of the failures such as spreading problems to more counterparties, particularly for those heavily involving in clearing and settlement functions. Larger institutions may also tend to fund themselves in ways that increase their reliance on intraday credit, which could increase the demand for intraday credit and increase systemic exposures. 3. Consolidation may also impose costs on the financial system by expanding the financial safety net. some institutions may try to increase the value of their access to the government's financial safety net (including deposit insurance, discount window access, payments system guarantees) through consolidation. If financial market participants perceive very large organizations to be "too big to fail" (i.e., that explicit or implicit government guarantees will protect debtholders or shareholders of these organizations) there may be incentives to increase size through consolidation in order to lower the cost of funding and increase the value of shares.
DeNicoló and Kwast (2002) They estimate firm inter-dependencies by correlations of stock returns, and relate this measure to the consolidation activities in financial sector. They conclude that consolidation at their sample LCBOs appears to have contributed to LCBOs inter-dependencies.
Wagner (2008) Presents a model where diversification, even though beneficial by itself, can reduce welfare because it may encourage banks to take on more risks. He argues this negative side effect of diversification, however, can be completely avoided by regulation that does not give capital reliefs for more diversified banks.
Wagner (2010) Shows that the diversification of risks at financial institutions makes systemic crises more likely by increasing the institutions similarities and exposing them to the same risks. When systemic crises induce costs beyond individual banking failures (for example, because they cause premature liquidation of assets in the economy), efficient diversification has to trade-off a lower overall probability of banking failure with a higher probability of systemic failures. He argues that a bank merger can produce the same outcome as full diversification and a merger between banks which have reached their optimal degree of diversification is always welfare reducing.
Weiß, Neumann, and Bostandzic (2014) They study the systemic risk effects of bank mergers using the marginal expected shortfall as well as the lower tail dependence to capture the merger-related change in an acquirer's contribution to systemic risk. They find evidence of a significant increase in the merging banks', the combined banks' as well as their competitors' contribution to systemic risk following mergers, thus confirming the "concentration-fragility" hypothesis.

Theory & Description
Battiston, Gatti, Gallegati, Greenwald, and Stiglitz (2012) Using a theoretical framework they find that the diversification of credit risk across many borrowers has ambiguous effects on systemic risk in the presence of mechanisms of loss amplifications such as in the presence of potential runs among the short-term lenders of the agents in the network. In particular, network structure and heterogeneity of levels of financial robustness across agents should be carefully taken into account when trying to devise policies that enhance the resilience of the financial system.
Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) They find that diversification can contribute to both financial stability and fragility depending on magnitude of negative shock. As long as the magnitude of negative shocks affecting financial institutions are sufficiently small, a more densely connected financial network (corresponding to a more diversified pattern of interbank liabilities) enhances financial stability. However, beyond a certain point, dense interconnections serve as a mechanism for the propagation of shocks, leading to a more fragile financial system.
Positive effects of diversification & consolidation
Berger (2000) Finds that integration in financial services industry appears to bring about larger revenue efficiency gains than cost efficiency gains, and most of the gains appear to be linked to benefits from risk diversification.
Boot and Thakor (2000) They find that as interbank competition increases, banks make more relationship loans, but each has lower added value for borrowers. Capital market competition reduces relationship lending (and bank lending shrinks), but each relationship loan has greater added value for borrowers. In both cases, welfare increases for some borrowers but not necessarily for all.
Diamond (1984) Develops a theory of financial intermediation based on minimizing the cost of monitoring information and analyses the determinants of delegated monitoring costs. In his model a financial intermediary has a net cost advantage relative to direct lending and borrowing. Diversification within the intermediary is key to the possible net advantage of intermediation and serves to reduce these costs, even in a risk neutral economy.
? and Rochet and Tirole (1996) Present some evidences suggesting that the monitoring of banks by other banks may be an efficient mechanism for controlling systemic risk, and this task may be easier and less costly after consolidation .
Systemic risk-shifting
Acharya (2009) In a theoretical model of systemic risk shows that the limited liability of banks and the presence of a negative externality of one bank's failure on the health of other banks give rise to a systemic risk-shifting incentive where all banks undertake correlated investments, thereby increasing economy-wide aggregate risk. The idea is that the banks have incentive to take correlated investments in order to increase the probability of joint survival and therefore joint failure due to regulatory (implicit) "too-many-to-fail" guarantees, as bankers anticipate greater forbearance upon joint failure than in individual failure.

Theory & Description

Value of Diversifying vs. Focusing M&As

Servaes (1996)
Studies the trend of mergers from 1960s to 1980s and observes that the diversification trend of the late 1960s and early 1970s revereses toward corporate focus in 1980s. He finds that there was a large diversification discount during the 1960s, but this discount declined to zero during the 1970s.

DeLong (2001)
Shows that mergers that focus both activity and geography enhance stockholder value by 3.0% while the other types do not create value. She further demonstrates that the loss in value for diversifying bidders is not the result of a wealth-transfer from bidders to targets.

Diversification & Internal Capital Market

Hubbard and Palia (1999)
Examine mergers during the 1960s and find the highest bidder returns when financially "unconstrained" buyers acquire "constrained" targets. They conclude that diversifying mergers could create value by forming an effective internal capital market to overcome the information deficiencies of the less-developed capital markets, thereby lowering the cost of capital.

Bhide (1990)
Argues that because of economic, technological, and regulatory changes during the 1970s and 1980s, information asymmetries have become less of an issue in corporate financing and that the disadvantages of diversification have started to outweigh the benefits (i.e., the internal capital market).

Diversification & Debt Capacity

Lewellen (1971)
Focuses on financial efficiencies of corporate mergers rather than operational efficiencies. He argues the more conglomerate the character of the consolidation (i.e., the milder the extent of earnings interdependence present) the greater the expansion of the partners'debt-carrying ability pursuant to merger. So conglomerates can sustain higher levels of debt because corporate diversification reduces earnings variability. If the tax shields of debt increase firm value, this argument predicts that conglomerate firms are more valuable than companies operating in a single industry.

Shleifer and Vishny (1992)
Argue that conglomerates may have a higher debt capacity because in bad states of the world they can sell assets in those industries that suffer the least from liquidity problems. In other words, diversified firms can avoid fire-sales in bad times, that are ex ante a significant private cost of leverage.

Diversification & Economies of Scope

Teece (1980)
Argues that diversification leads to economics of scope. He examines elements of an efficiency-based theory of the multiproduct firm. And suggests that if economies of scope are based upon the common and recurrent use of proprietary knowhow or the common and recurrent use of a specialized and indivisible physical asset, then multiproduct enterprise (diversification) is an efficient way of organizing economic activity.

Geographic Diversification

Berger and DeYoung (2001, 2006)
found that the greatly increased geographic footprints of U.S. bank holding companies due to industry consolidation resulted in managerial difficulties that reduced operational efficiency. However, they also found that technological advancement has gradually reduced the importance of these inefficiencies over time. Because geographic expansion inevitably leads to multi-market contact, there is some concern that competitive rivalry may diminish as banking companies enter each others home markets, and allow the home bank to dominate and drive prices, i.e., mutual forebearance.

Theory & Description

Diversification & Managerial Benefit

Jensen (1986)
Suggests that companies diversify to increase the private benefits of managers. His theory explains why "diversification" programs are more likely to generate losses than takeovers or expansion in the same line of business (i.e., focusing) or liquidation-motivated takeovers.

- Managers have incentive to cause their firms to grow beyond the optimal size. Growth increases managers' power by increasing the resources under their control. It is also associated with increases in managers'compensation, because changes in compensation are positively related to the growth in sales.
- Product and factor market disciplinary forces are often weaker in new activities and activities that involve substantial economic rents or quasi rents.

Amihud and Lev (1981)
Hypothesize that managers, as opposed to investors, engage in diversifying conglomerate mergers to decrease their largely undiversifiable "employment risk" (i.e., risk of losing job, professional reputation, etc). Such risk reduction activities are considered as managerial perquisites in the context of the agency cost model. Their empirical results suggest that "managerial" incentives are driving conglomerate merger.

Shleifer and Vishny (1989)
Argue that pursuit of entrenchment often leads managers to expand existing lines of business excessively. They suggest that managers have an incentive to diversify into areas where they have a comparative management advantage since diversifying into those industries will make their skills more indispensable to the firm.

Morck, Shleifer, and Vishny (1990)
Find that the returns to bidding shareholders are lower when their firm diversifies (diversifying vs. focusing mergers are defined based on 4-digit SIC code or correlation coefficients being above the median for the sample). They find that bad managers are also bad acquirers, consistent with the notion that poor performance drives managers to try something new. They conclude that managerial objectives may drive acquisitions that reduce bidding firms' values.

Cornett, Hovakimian, Palia, and Tehranian (2003)
Find bank mergers that increased the product line focus (as well as the geographic focus) of the acquiring bank resulted in significantly higher stock market reactions. They examines whether shareholder value-maximizing corporate governance mechanisms assist in reducing the managerial incentive to enter value-destroying bank acquisitions and find that corporate governance variables (such as CEO share and option ownership and a smaller board size) in the bidding bank are less effective in diversifying acquisitions than in focusing acquisitions.

Hendershott et al. (2002)
Study the market reaction to the Gramm-Leach-Bliley Act of 1999, and conclude that benefits from diversification into new product lines are more likely to accrue to non-bank financial firms than to banking firms. They find that insurance firms and investment banks experienced positive market reactions to the new law, whereas the stock prices of commercial banking companies were left statistically unaffected.

Jensen and Ruback (1983)
Argue that the gains created by corporate takeovers do not appear to come from the creation of market power. And suggest it is difficult to find managerial actions related to corporate control that harm stockholders; the exceptions are those actions that eliminate an actual or potential bidder, for example, through the use of targeted large block repurchases or standstill agreements.

Chapter 2

Source of systemic risk: Operations

2.1 Introduction

During times of financial crisis, losses tend to spread across financial institutions, threatening the global financial system as a whole. The comovement of financial markets is accentuated during times of crisis, thereby giving rise to systemic risk. Since the 2007-2008 global financial crisis, regulators and academicians alike have focused on measuring systemic risk, which is the spillover effect of risk exposures that spread contagiously to other institutions, potentially infecting the entire financial sector. Micro-level measures of systemic risk (e.g., MES by Acharya, Pedersen, Philippon, and Richardson, 2016; CoVar by Tobias and Brunnermeier, 2015) calculate the pair-wise exposure of financial institutions on all other institutions. These measures of systemic risk can be used by regulators to identify systemically important financial institutions, thereby internalizing the externality by levying systemic risk premiums (possibly contingent capital requirements).

The importance of systemic risk extends beyond the financial sector as excessive aggregate systemic risk taking is shown to forecast macroeconomic declines (see Allen, Bali, and Tang, 2012). Given its importance, I investigate the source of systemic risk. That is, I delve beneath the varying measurements of systemic risk to understand where systemic risk is generated within financial institutions. I decompose total systemic risk into its underlying risk sources and examine which source of systemic risk leads to the externalities that are most damaging to the state of the macroeconomy. I find that operations are the source of the systemic risk. That is, if regulators have concern about systemic risk taking in the financial sector, they should focus on operational risk as the breeding ground for the systemic risk that is most damaging to real economic conditions. In this paper, I decompose the measure of aggregate systemic risk-taking of financial sector from Allen et al. (2012) into market risk, credit risk and operational risk components. I find that only the operational risk component of this measure can forecast future macroeconomic downturns, whereas the non-operational component have no predictive ability.

The analysis can be understood in the context of the most recent financial crisis. Some experts claim that the ongoing global macroeconomic decline stemmed directly from credit risk exposure in the form of imprudent subprime mortgage lending that was securitized without accountability (e.g., Bhattacharyya and Purnanandam, 2011). While not discounting the importance of credit risk in initiating the financial crisis, other experts claim that it was the resulting financial market illiquidity and fire-sale mentality that triggered falling asset prices throughout financial markets (see Shleifer and Vishny, 2010). Thus, market risk could have triggered macroeconomic declines worldwide. Still other experts claim that the operational problems in registering and documenting mortgages created "limbo loans" without clear ownership claims to the underlying property collateral backing the mortgages (see Allen, Peristiani, and Tang, 2015). These limbo loans act as an impediment to aggregate lending activity, thereby depressing macroeconomic activity. In this paper, I test whether any or all three of these risk sources, operating separately or in unison, can explain macroeconomic declines.

I decompose systemic risk into credit risk, market risk and operational risk components using the methodology of Allen and Bali (2007) to measure operational risk as the residual risk after accounting for market and credit risk exposures. I devise empirical risk measures. For credit risk, I utilize monthly volatility in the AAA-BBB credit spread. For market risk, I utilize monthly shocks to interest rate, exchange rates and stock price indices. This is a comprehensive measure of operational risk based on equity returns that includes model estimation error, fraud, dishonesty, strategic errors, reputational losses, as well as day-to-day operational flaws. I validate this measure using fraudulent accounting restatements.

All risk measures are estimated for each individual financial institution using a monthly time series of equity returns over its lagged value and the specified risk factors. Since I found that credit risk and market risk have no explanatory power taken individually, I then combine them into a single measure of non-operational risk to be contrasted with the operational risk component. That is, I decompose the measure of aggregate systemic risk taking of the entire financial sector (hereinafter CATFIN) into the operational and non operational components (OpCATFIN and NonOpCATFIN respectively). I test the predictive power of each of these components for future economic downturns as well as their use as an early warning system. Only OpCATFIN has predictive power, forecasting economic downturns 12 months into the future.

The paper is organized as follows. The estimation of operational and non-operational risks is presented in Section 2.4. In Section 2.5, the aggregate systemic risk measure CATFIN is estimated and decomposed into OpCATFIN and NonOpCATFIN. Section 2.7 presents the main empirical results, testing the predictive ability of OpCATFIN and NonOpCATFIN for future economic downturns. Then, I develop an early warning system based on OpCATFIN. Furthermore, I show the underlying mechanism through which OpCATFIN is transmitted to the real economy. Section 2.9 concludes.

2.2 Related literature

This paper is related to several strands of literature. Some of these studies focus on defining and measuring operational risk. Jarrow (2008) formally defines and provides an economic and mathematical characterization of operational risk. He characterizes operational risk as either related to the firms operating technology or the agency costs. Allen and Bali (2007) use equity returns to estimate operational risk. This study is closely related to the literature that aim to understand the nature of operational risk and its association with the broader economy. Using supervisory data from large U.S. bank holding companies (BHCs), Mihov, Curti, and Abdymomunov (2017) document a significant association between BHCs' operational losses and the U.S. macroeconomic environment. They find that in adverse conditions, BHCs face higher and more volatile operational losses. The frequency of loss events increases. So does average severity, driven by large individual loss events. Using a copula framework, Abdymomunov and Ergen (2017) find that occurrences of large losses are positively correlated across banks. They do not, however, directly test the systemic risk implications of operational risk events.

The main contribution of this paper is to the growing literature that examines the nature of systemic risk (see, e.g., Bhattacharyya and Purnanandam, 2011; Shleifer and Vishny, 2010; Acharya, 2009). Brunnermeier, Dong, and Palia (2012) examine the bank-level determinants of systemic risk. Cummins, Wei, and Xie (2007) explore intra and inter-sector spillover effects of operational risk events. McConnell (2013) describes an example of systemic operational risk.

2.3 Is operational risk the source of systemic risk?

The financial system has been shaken by a number of operational failures over the past decades. Due to their crucial role as "delegated monitors" (see Diamond, 1984) and partly due to the opacity of their business (see Morgan, 2002), financial institutions are even more vulnerable to losses resulting from operational failures which undermine public trust and confidence. According to Chernobai, Rachev, and Fabozzi (2008), more than 100 operational losses exceeding $100 million in value each and a number of losses exceeding $1 billion, have impacted financial firms globally since the end of 1980s. Operational risk is also the source of approximately 50% of all hedge-fund failures. Some of these operational failures have triggered a more wide-spread systemic risk impacting other firms in the financial sector and the overall economy.

This section outlines two channels through which operational risk in financial institutions may lead to an increase in aggregate systemic risk of the financial sector. The first channel is the so-called "information" channel that relies upon the information revealed about the similar operational risks in other financial firms after an operation risk event. The second channel is the "contagion" channel.

- ***Information channel***

Operational risk events may have significant informational externalities or spillover effects on other financial institutions. An operational risk event may make customers and investors wary of similar risks in other firms even in the absence of such risks and hence makes them worse off. Opacity of financial sector can exacerbate this spillover channel.

Extant research reveals that operational loss events have a strong, statistically significant negative impact on the announcing firms equity returns (see Cummins, Lewis, and Wei, 2006; Perry and de Fontnouvelle, 2005). Interestingly, these studies find that the market value loss is significantly higher than the amount of the operational loss, implying that these operational loss events may convey adverse information about future cash flows of those firms. Similar to the information channel of bankruptcy impact (see, e.g., Lang and Stulz, 1992), an operational risk event may reveal negative information about potentially similar faulty operations in other financial firms and, consequently, increases the markets expectation of such operational losses which are not yet discovered or materialized.

- ***Contagion channel***

Operational losses at a financial firm may have a negative impact on the counterparties in the form of credit risk. Some studies have reported a positive correlation between operational risk and non-operational risks such as credit risk. Chernobai, Jorion, and Yu (2011) identify firm-specific determinants of operational risk that implies a positive correlation between credit risk and operational risk. For example, they find that the firms suffering from operational risk events tend to be younger and more complex and particularly, have higher financial distress risk as measured by a wide range of firm characteristics including equity volatility, Tier 1 capital, market-to-book ratio, cash holdings and the Merton (1974) distance-to-default.

In their study of corporate losses, Duffie, Eckner, Horel, and Saita (2009) find that the probability of extreme default losses on portfolios of U.S. corporate debt is much greater than would be estimated under the assumption that default correlation is only due to exposure to (ex-ante) observable risk factors. They find strong evidence for the presence of common latent factors, even when controlling for observable factors that provide the most accurate model of firm-level probabilities of default. These latent factors are most often the correlated operational risks across financial institutions. An example of an important factor leading to 2008 financial crisis is the degree to which borrowers and mortgage brokers provided proper documentation of borrowers credit qualities. In other words, failing to request and assess the proper documentation of borrowers credit qualities, i.e. a common operational failure, has led to build up of systemic risk in financial institutions.

Another instance of systemic operational risk is evident in defaults of Enron and WorldCom. Fraudulent accounting practices at Enron led to one of the largest bankruptcies in U.S. history in 2001.[1] Duffie et al. (2009) argue that these events may have revealed faulty accounting practices that could have been in use at other firms, and thus may have had an impact on the conditional default probabilities of other firms and therefore on overall U.S. corporate debt portfolio losses. This is in line with the empirical findings of Cummins et al. (2007), whcih find that operational risk events cause strong negative intra and inter-sector spillover effects (i.e., the stock prices of non-announcing firms respond negatively to operational loss announcements) that is information-based rather than purely contagious.[2]

McConnell (2013) describes the LIBOR scandal and argues that it is an example of systemic operational risk, in particular people risk. Allen and Bali (2007) find evidence[3] that operational risk events are more likely to be the cause of large unexpected catastrophic losses, although when they occur, the losses are smaller than those resulting from a combination of market risk, credit risk or other risk events.

Motivated by all these findings in the extant literature, I investigate whether operational risk is the source of systemic risk.

[1]This led to substantial losses and accusation of several other financial institutions including Merill Lynch, NatWest, Citibank, JPMorgan Chase and Salomon Smith Barney, among others.

[2]In their study of the near-collapse of Long-Term Capital Management (LTCM), Kabir and Hassan (2005) find that commercial and investment banks with exposure to LTCM lost significant market value around the event. Smaller S&L institutions and bigger insurance companies were also affected by the crisis, implying a form of contagion effect in the financial sector.

[3]They find that operational risk loss levels are lower than overall catastrophic loss levels. Moreover, the area under the lower tail of the operational risk distribution was higher than the area under the lower tail of the return distribution for extremely low returns (equity returns below 12%), thereby suggesting that operational risk events are more likely to be the cause of extremely large declines in returns than other risk events.

2.4 Operational risk measure

2.4.1 Methodology

Defining and estimating operational risk of financial firms is a very controversial topic. The definitions range from very narrow to extremely broad classifications. As of December 2017, the Basel Committee defines operational risk as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events." This definition includes legal risk, but excludes strategic, reputational and systemic risk, as well as all indirect losses or opportunity costs.

In this study, in order to explore the source of systemic risk, I need a more comprehensive measure of operational risk including not only high frequency/low intensity events, but more importantly low frequency/high intensity events. Hence, I adopt Allen and Bali (2007)'s definition of operational risk as a residual measure. After all the identifiable sources of risk (i.e., credit and market risk including term structure risk, exchange rate risk, equity risk, etc.) are accounted for, the remainder is defined as operational risk. This yields a comprehensive measure of operational risk that includes model estimation error, fraud, dishonesty, strategic errors, reputational losses as well as day-to-day operational flaws.

This top-down[4] measure of operational risk relies on equity returns to measure the impact of operational loss events on overall firm value, rather than just accounting for the cost. Other studies reveal that operational loss events have a strong, statistically significant negative stock price impact on announcing firms (see, e.g., Perry and de Fontnouvelle, 2005). Interestingly, they find that the market value of the losses significantly exceeds the amount of operational loss, implying that such losses convey adverse information about future cash

[4]Allen, Boudoukh and Saunders (2004) note that whereas bottom-up models may be appropriate for the purposes of risk diagnostics and design of internal managerial controls, top-down models may be effective in estimating economic capital requirements.

flows of announcing firms.

I estimate the following model using OLS regression for each financial institution using a monthly time series of equity returns over the period of 1970-2013 for all firms in the sample with at least 50 consecutive monthly equity returns.

$$r_t = \alpha_{0,t} + \alpha_{1,t}\Delta x_{1,t} + ... + \alpha_{17,t}\Delta x_{17,t} + \beta_t r_{t-1} + \sum_{i=1}^{4} \gamma_{i,t} FF_{it} + \sum_{i=1}^{3} \pi_{i,t} R_{it} + \epsilon_t \qquad (2.1)$$

Where:

- r_t and r_{t-1} are the monthly current and lagged equity returns of each of the financial firms in our sample over the period t = Jan 1970 through May 2013;
- δx_{it}, (i = 1, 2, . . . , 17), is the first order difference of the 17 variables used to estimate credit and market risks;
- FF_{it} represents the three Fama-French (1993) factors (overall excess return on the market, SMB, and HML) and the momentum factor (UMD);
- R_{it} represents the average monthly return for each industry sector: depository institutions, insurance companies and securities firms. The equity returns on each of the three industry sectors are determined by dividing the sample of financial firms into three groups: depository institutions (SIC codes 60XX, 66XX and 6712), insurance companies (SIC codes 63XX and 64XX) and securities firms (all other 6XXX-level SIC codes).
- The 17 δx_{it} variables are taken from the macro variables defined in Table 2.1 and are grouped by risk sources as follows.

Overall Credit Risk Measure:

- $R_{AAA} - R_{BBB}$ = the spread between the AAA and the BBB corporate bond yield

Firm Specific Credit Risk Measures:

- Market value of equity/Book value of assets = 1 leverage ratio
- Net income/sales
- Log of book value of total assets

Interest Rate Risk Measures:

- R_3MTB=3 month US Treasury bill rates
- R_10YTB=10 year US Treasury bond rates
- INTGSTDEM193N=Treasury Bills rates for Germany
- INTGSBDEM193N=Government Bonds rates for Germany
- INTGSTJPM193N=Treasury Bills rates for Japan
- INTGSBJPM193N =Government Bonds rates for Japan
- INTGSTGBM193N=Treasury Bills rates for UK
- INTGSBGBM193N=Government Bonds rates for UK

Exchange Rate Risk Measures:

- Exgeus=Deutschemark/US dollar exchange rate[5]
- Exukus=British pound/US dollar exchange rate
- Exjpus=Japanese yen/US dollar exchange rate

Market Risk Measures:[6]

- Equity Index Japan
- S&P 500 Index

The non-operational risk for each financial institution is then calculated as the total monthly return minus the operational risk.

2.4.2 Validating the operational risk measure

Estimating operational risk as a residual measure, Allen and Bali (2007) show that approximately 18% of financial institutions returns represent compensation for operational risk. This result is similar to the estimates obtained using different empirical methodologies by Kuritzkes (2002) and deFontnouvelle, Dejesus-Rueff, Jordan, and Rosengren (2006). To further validate this operational risk measure, I use accounting restatement announcements due to irregularity or fraud reported by the U.S. General Accounting Office (GAO, 2006) and explore whether it can capture this major operational incidence.

During the time period of 1997 to 2006, the restatement data matched 118 firm-month observations in my sample. I use propensity score matching to determine a control group based on three variables: size (defined as the log of total market capitalization), industry (3 groups of depository, insurance and securities firms) and also the total excess return of the firm during the past year. I then check whether the operational risk of the firms that were required to make accounting restatement is significantly different from the operational risk of the control group. The results are presented in Table 2.4 and show that the operational risk of those firms are indeed higher than the control groups 1 month before the restatement announcement (i.e., when market can anticipate it) and not significantly different afterwards.

Therefore, the results provide evidence that the accounting irregularity/fraud impacts the equity price before the restatement announcement and stock price falls to adjust for the compensation investors require for the higher operational risk. This is in line with the findings of Hribar, Jenkins, and Wang (2009). They show that institutional investors act as though they partially anticipate potential accounting irregularities and adjust their holdings downward prior to the restatement announcement.[7]

2.5 Aggregate systemic risk measure

CATFIN is estimated as the catastrophic VaR of the entire financial sector. That is, in each month, I estimate CATFIN as the VaR of financial firms excess return at 99% confidence level using two parametric distributions (i.e. Skewed Generalized Error Distribution (SGED) and and Generalized Pareto Distribution(GPD)) and the nonparametric method.[8]. CATFIN is estimated as the average of these three VaR measures. Then, the operational and non-operational components of CATFIN are estimated using the same methodology replacing total equity returns by its operational and non-operational risk components as estimated in Section 2.4. Figure 1 depicts these three measures over the sample period.

2.6 Data

I construct the sample of financial firms using CRSP/Compustat merged database. I include all common stocks traded on either NYSE, AMEX or Nasdaq that have primary SIC codes of 6XXX over the time period from Jan 1970 to May 2013. I obtain monthly data (including dividends) from CRSP/Compustat and require that a firm's market capitalization is available at the beginning of each month and monthly stock return. I also adjust stock returns for delisting in order to avoid survivorship bias.

Missing data in Compustat reduced the final number of observations to 292,922 (and 2003 firms), predominately because of missing values for assets, net income and sales as well

[7]One caveat to this validation might be that we do not control for market and credit risk when comparing the operational risk of the treatment and control group. Further extension of this analysis could use some measures of credit or market risk in propensity score matching or alternatively, one can control for these other sources of risk to ensure that differences are driven only by operational risk.

[8]For a description of methodology, please refer to Allen et al. (2012)

as the lack of 50 months of continuous monthly returns, all required for the estimation of operational risk.

In order to estimate the operational risk, I obtain data on all the general risk categories that financial firms are exposed to, such as overall credit, firm-specific and market risks (equity indexes risk, foreign exchange rate risk, term structure risk) and Fama-French plus momentum risk factors. Data and the data sources used are listed in Table 2.1 and descriptive statistics are reported in Table 2.2.

To validate the operational risk measure, I use accounting restatement data. Restatement announcements data are obtained from the U.S. General Accounting Office (GAO, 2006) report, which contains accounting restatements announced in the period of January, 1997 to June, 2006. It contains about 2686 restatement announcements of firms that are required to restate their financial statements because of material accounting irregularity and/or frauds.[9] The GAO database is comprised of the name, ticker symbol, and exchange of the restating firm, the restatement announcement date, the number of shares outstanding, the initiator of the restatement, and the reason(s) for the restatement. The difference of this database from the Compustat accounting restatement is that GAO database generally excludes restatements involving stock splits, changes in accounting principles, and other announced restatements that were not made to correct errors in the application of accounting principles.[10]

[9]The GAO states that they are focused on "financial restatements resulting from accounting irregularities, including so-called aggressive accounting practices, intentional and unintentional misuse of facts applied to financial statements, oversight or misinterpretation of accounting rules, and fraud. As a general rule, they exclude restatements resulting from accounting policy changes because they did not necessarily reveal previously undisclosed, economically meaningful data to market participants."

[10]Using the Lexis-Nexis "Power Search" command and the "US Newspapers and Wires" database, they performed keyword searches using variations of "restate" as well as the terms "adjust," "amend," and "revise"- all within 50 words of "financial statement" or "earning." They excluded restatement announcements that resulted from normal corporate activity or simple presentation issues unless they determined that there was some irregularity involved.

2.7 Main empirical results

In this section, using OpCATFIN, I investigate whether operational risk is the source of systemic risk and therefore drives CATFIN's predictive power.

2.7.1 Predictive ability of OpCATFIN for economic downturns

First, I test the predictive power of CATFIN, reproduced from Allen et al. (2012), in forecasting future economic downturns. Second, I replace CATFIN by its operational component to see if it is in fact the driver of the predictive power. I use Chicago Fed National Activity Index (CFNAI) as the macroeconomic variable. "CFNAI is a monthly index designed to gauge overall economic activity and related inflationary pressure. The CFNAI is a weighted average of 85 monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.[11]"

I estimate the following n-month ahead multivariate predictive regression of CFNAI on CATFIN, and control for a all macroeconomic and financial variables outlined in Table 11 as well as 12 lags of dependent variable:

$$CFNAI_{t+n} = \alpha + \lambda CATFIN_t + \beta X_t + \sum_{i=1}^{12} CFNAI_{t-i+1} + \epsilon_{t+n} \tag{2.2}$$

where X_t includes the macroeconomic and financial market control variables as defined in Table 11.

The results are presented in Table 2.5. All CATFIN coefficients are negative and highly significant after controlling for a wide set of factors, thereby predicting the CFNAI index

[11] The reference is https://www.chicagofed.org/publications/cfnai/index

up to twelve months into the future. The adjusted R^2 values from the predictive regressions are economically significant and in the range of 54% to 24% for 1-month to 12-month ahead regressions.[12]

Next, I replace CATFIN in Equation 2.2 by OpCATFIN to investigate whether this component has any predictive power on future macroeconomic downturns. I estimate the following n-months ahead multivariate predictive regression of CFNAI on OpCATFIN controlling for macroeconomic and financial variables and also 12 lags of the dependent variable:

$$CFNAI_{t+n} = \alpha + \lambda OpCATFIN_t + \beta X_t + \sum_{i=1}^{12} CFNAI_{t-i+1} + \epsilon_{t+n} \tag{2.3}$$

where X_t denotes a vector of control variables in month t.

The results are presented in Table 2.6. The coefficients of OpCATFIN are all negative and significant at 10%, 5% and 1% level for 1 to 11 months ahead regressions. Therefore, OpCATFIN can predict future economic downturns. The adjusted R2 reported in this table are at the same level as those in 2.6. As a robustness check, I also include NonOpCATFIN in the regression. The results are reported in Table 2.9. Both coefficients of OpCATFIN and NonOpCATFIN are negative, however only the coefficient of OpCATFIN is statistically significant in most of the regressions. Among the control variables, term spread, FIN_Beta, SIZE and LEV turn out to be significant predictors of future economic downturns. However, the statistical significance of these macroeconomic and financial variables depend on the horizon.

One could argue that operational risk and non-operational risk are correlated. Some studies have reported a positive correlation between operational risk and non-operational risks such as credit risk. Chernobai et al. (2011) identify firm-specific determinants of oper-

[12] Allen et al. (2012) show that this predictive power is special to aggressive risk taking of financial sector and CATFIN constructed based on all other firms doesn't have any predictive power for future economic downturns.

ational risk that implies a positive correlation between credit risk and operational risk. For example, they find that the firms suffering from operational risk events tend to be younger and more complex[13] and particularly, have a higher financial distress risk as measured by a wide range of firm characteristics including equity volatility, Tier 1 capital, market-to-book ratio, cash holdings and the Merton (1974) distance-to-default.

2.7.2 Developing warning system

If operational risk is the real source of systemic risk, we should be able to develop a warning system similar to the one developed in Allen et al. (2012). This would aid financial firms and regulators to reliably predict the risk-taking events which have the potential of triggering systemic instability in the financial sector and cause real economic downturns.

To develop such a warning system, we need to find out a threshold for OpCATFIN. According to The Federal Reserve Bank of Chicago, 3-month moving average of CFNAI (CFNAI_MA3) of -0.7 or less is an indication of the economic contraction. Following the methodology used in Allen et al. (2012), I calculate the median OpCATFIN for those months when CFNAI_MA3 is less than -0.7. I take this median as the threshold and then construct two new variables based on that. $OpCATFIN_t^{plus}$ equals to OpCATFIN in month t if it is greater than the median and zero otherwise; $OpCATFIN_t^{minus}$ equals OpCATFIN in month t if it is less than or equal to the median, and zero otherwise. Once these variables are generated, I estimate the following regression:

$$CFNAI_{t+n} = \alpha + \lambda_1 OpCATFIN_t^{plus} + \lambda_2 OpCATFIN_t^{minus} + \beta X_t + \sum_{i=1}^{12} CFNAI_{t-i+1} + \epsilon_{t+n} \tag{2.4}$$

Table 2.7 presents the results. $OpCATFIN^{plus}$ is the only variable that significantly pre-

[13] measured by the number of segments reported in Compustat

dicts lower economic activity 2 to 12 months in advance, whereas other variables do not have a statistically significant predictive power for all horizons. The coefficient of $OpCATFIN^{minus}$ becomes significant in the 9 to 12 months ahead regressions. These results indicate that when the (operational) risk of financial firms exceeds a certain threshold, it can predict future economic downturns. However, when the risk is below the critical value, it is not likely to generate an epidemic that affect entire macroeconomic system.

Although $OpCATFIN_t^{plus}$ can predict economic downturns in advance, the main question is whether the operational risk can be caught soon enough for any preemptive measures by regulators. In some cases the systemic operational risk build-up in the financial institutions can be very wide-spread (e.g., as in the case of subprime mortgage lending), however, these risks will be known to the market (or the firms themselves) and consequently reflected in equity returns only after a relatively large operational loss event. Subsequently, this event can impact other firms directly (contagion-based) or indirectly (information-based) and manifest itself through their equity returns (see Cummins et al., 2007).

2.8 How operational risk affects future economic downturns

Kashyap and Stein (2000) argue that an important mechanism for transmission of shocks from the financial sector into the macroeconomy is aggregate bank lending. To further validate OpCATFIN as the driver of systemic risk, I test whether OpCATFIN predicts bank lending activity. I obtain aggregate lending measures for commercial and industrial loans, real estate loans, consumer loans and total loans and leases from Call Report data and regress them separately on OpCATFIN controlling for the same macroeconomic and financial variables and 12 lags of the corresponding dependent variable.

The results are presented in Table 2.8. I find that OpCATFIN forecasts total bank lending up to 12 months in advance. Interestingly, the adjusted R^2 is highest for commercial and industrial lending.

2.9 Conclusion

In this paper, I delve beneath the varying measurements of systemic risk to understand where systemic risk originates within financial institutions. I decompose an aggregate systemic risk measure (CATFIN) into its underlying risk sources and examine which one leads to the externalities that are most damaging to the state of the macroeconomy. I find that operations are the source of systemic risk and only the operational risk component of CATFIN can forecast future macroeconomic downturns, whereas the non-operational components of CATFIN have no predictive ability.

Operational risk is measured as the residual risk after accounting for market and credit risk exposures. This yields a comprehensive measure of operational risk that includes model estimation error, fraud, dishonesty, strategic errors, reputational losses, as well as day-to-day operational flaws. I validate this measure using fraudulent accounting restatements.

I develop a warning system based on OpCATFIN, setting the threshold on median OpCATFIN during the months when 3 month moving average of CFNAI is below -0.7. I then show that the values of OpCATFIN beyond this threshold will significantly lead to real economic downturn. The findings in this paper have regulatory implications. That is, when examining systemic risk in the financial sector, regulators should focus on operational risk as the breeding ground for the systemic risk.

Table 2.1: Data on Risk Factors

Variable Name	Variable Description	Data Source	# of Obs.	Data Range
Overall Credit Risk Measure:				
R_{AAA}	AAA corporate bond yield	FRED		1973-2013
R_{BBB}	BBB corporate bond yield	FRED		1973-2013
Firm Specific Credit Risk Measures:				
MV of equity/BV of Assets	1 leverage ratio	Compustat		1973-2013
Net Income/Sales		Compustat		1973-2013
Ln(Total Assets)		Compustat		1973-2013
Interest Rate Risk Measures:				
R_3MTB	3 month US Tbill rates	FRED		1973-2013
R_10YTB	10 year US Tbond rates	FRED		1973-2013
INTGSTDEM193N	TBills rates for Germany	FRED		1973-2013
INTGSBDEM193N	Gov. Bonds rates for Germany	FRED		1973-2013
INTGSTJPM193N	TBills rates for Japan	FRED		1973-2013
INTGSBJPM193N	Gov. Bonds rates for Japan	FRED		1973-2013
INTGSTGBM193N	TBills rates for UK	FRED		1973-2013
INTGSBGBM193N	Gov. Bonds rates for UK	FRED		1973-2013
Exchange Rate Risk Measures:				
Exgeus	DEM/USD exchange rate	WRDS FX File		1973-2013
Exukus	GBP/USD exchange rate	WRDS FX File		1973-2013
Exjpus	JPY/USD exchange rate	WRDS FX File		1973-2013
Market Risk Measures:				
EquityIndex_Canada		Compustat Global		1979-2013
EquityIndex_France		Compustat Global		1990-2013
EquityIndex_Japan		Compustat Global		1973-2013
EquityIndex_UK		Compustat Global		1980-2013
EquityIndex_Germany		Compustat Global		1987-2013
S&P 500 Index		Compustat Global		1973-2013

Table 2.2: Descriptive statistics.

The first panel reports summary statistics for firm-level variables and second panel reports macro-economic and financial risk factors.

	Observations	mean	p10	p25	p75	p90	sd	min	max
Op_risk	178538	-0.00	-0.04	-0.02	0.01	0.03	0.04	-0.82	1.92
NonOp_risk	178538	0.01	-0.10	-0.04	0.06	0.12	0.12	-1.28	6.42
Equity MV/Assets BV	178538	341.45	42.05	78.32	271.40	735.04	744.33	0.12	28828.29
Net Income/Sales	178538	-0.57	-0.04	0.05	0.15	0.21	91.94	-20083.00	192.20
Ln(Assets)	178538	7.53	4.93	6.28	8.82	10.24	2.14	-0.92	15.01

	Observations	mean	p10	p25	p75	p90	sd	min	max
Baa_spread	485	1.12	0.66	0.79	1.31	1.71	0.47	0.55	3.38
Tbill_3m_US	485	5.25	0.17	3.02	7.22	9.09	3.36	0.01	16.30
Tbond_10y_US	485	6.95	3.56	4.72	8.45	11.38	2.91	1.53	15.32
Tbill_Germany	386	4.89	2.50	3.25	5.99	8.25	2.16	1.65	12.05
Tbond_Germany	485	6.09	3.21	4.22	7.92	8.85	2.23	1.20	10.70
Tbill_Japan	485	2.51	0.01	0.15	4.91	5.68	2.37	0.00	6.82
Tbond_Japan	485	4.30	1.16	1.47	6.95	8.75	2.95	0.53	10.30
Tbill_UK	485	7.47	0.57	4.77	10.80	12.96	4.05	0.22	16.18
Tbond_UK	485	8.49	3.88	4.89	11.34	13.87	3.84	1.65	17.18
DEM/USD	485	1.91	1.45	1.55	2.25	2.58	0.45	1.24	3.30
GBP/USD	485	0.59	0.46	0.53	0.64	0.69	0.09	0.39	0.91
JPY/USD	485	159.30	93.00	108.32	224.18	266.68	68.02	76.64	305.67
EquityIndex_Canada	409	6421.21	2234.51	3275.36	9324.80	12433.50	3862.25	1363.33	14714.70
EquityIndex_France	280	3499.69	1860.65	2119.15	4395.86	5485.25	1319.96	1499.00	6625.42
EquityIndex_Japan	485	13645.26	4989.09	7994.05	17887.71	23290.96	7311.68	3594.55	38915.87
EquityIndex_UK	354	4063.05	1668.80	2420.20	5679.60	6222.50	1710.34	1010.10	6930.20
EquityIndex_Germany	307	4204.37	1545.12	2057.28	6004.33	7096.79	2132.80	936.00	8348.84
S&P500_Index	485	635.12	99.93	150.55	1133.58	1362.93	500.42	63.54	1630.74

Table 2.3: Descriptive statistics of control variables.

	Observations	mean	p10	p25	p75	p90	sd	min	max
CATFIN	484	0.29	0.17	0.22	0.34	0.41	0.10	0.11	0.69
OpCATFIN	435	0.12	0.06	0.08	0.14	0.19	0.05	0.03	0.38
NonOpCATFIN	435	-0.22	-0.33	-0.26	-0.15	-0.12	0.09	-0.63	-0.04
MKT_RET	485	0.00	-0.05	-0.02	0.04	0.06	0.05	-0.23	0.16
FIN_RET	485	0.01	-0.06	-0.03	0.04	0.07	0.06	-0.23	0.21
CORR	485	0.40	0.23	0.29	0.49	0.57	0.13	0.14	0.66
SIZE	485	13.52	12.42	12.59	14.62	14.90	1.02	11.90	15.18
LEV	485	0.92	0.91	0.92	0.93	0.93	0.01	0.88	0.95
FIN_BETA	472	0.85	0.49	0.71	1.00	1.13	0.23	0.34	1.32
FIN_SKEW	485	0.02	-0.65	-0.32	0.38	0.71	0.59	-2.19	2.11
FIN_VOL	485	0.05	0.02	0.03	0.05	0.08	0.04	0.02	0.29
MKT_VOL	485	0.04	0.02	0.03	0.05	0.07	0.02	0.01	0.24

Table 2.4: Validation of operational risk measure

The dependent variable is the restatement dummy. It is equal to 1 if the restatement announcement is going to occur at month t, and zero otherwise. Propensity score matching is based on size (ln of total market capitalization of the firm), industry(whether the financial firm is a depository, insurance or securities firm) and the total equity return over the past one year. The results show that the difference between the operational risk of the treatment and control groups is significant only in the month before the announcemnt and not significantly different afterwards.

	(t-2)	(t-1)	(t)	(t+1)
Restatement	0.00182	-0.0128***	0.00543	0.00409
	(0.43)	(-3.07)	(1.30)	(0.98)
Constant	-0.00158***	-0.00157***	-0.00158***	-0.00158***
	(-15.27)	(-15.19)	(-15.29)	(-15.29)
Observations	173831	173831	173831	173831
Adjusted R2	-0.000	0.000	0.000	-0.000

t-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Predictive ability of $CATFIN$ for future economic downturns

This table reports the coefficient estimates from the predictive regressions: $CFNAI_{t+n} = \alpha + \lambda CATFIN_t + \beta X_t + \sum_{i=1}^{12} CFNAI_{t-i+1} + \epsilon_{t+n}$ where CFNAI is a measure of macroeconomic conditions. T-statistics based on Newey and West (1987) are reported in parentheses. The slope coefficients on 12 lags of the dependent variable are suppressed.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CATFIN	-1.649***	-2.235***	-2.080***	-2.193***	-2.339***	-2.165***	-2.096***	-2.106***	-2.671***	-3.405***	-2.718***	-2.698***
	(-3.18)	(-3.78)	(-2.94)	(-2.91)	(-3.10)	(-2.65)	(-2.77)	(-2.67)	(-3.80)	(-5.17)	(-3.74)	(-3.51)
DEF	-15.29	-14.80	-10.93	-10.76	-7.831	-8.802	-3.734	-8.135	-22.68	-29.47	-24.53	-16.30
	(-1.00)	(-0.77)	(-0.47)	(-0.42)	(-0.31)	(-0.35)	(-0.16)	(-0.36)	(-1.02)	(-1.35)	(-1.12)	(-0.78)
TERM	8.861**	10.39**	13.64***	15.28***	16.04***	16.49***	15.77**	17.58***	16.69**	16.01**	15.17**	10.91
	(2.51)	(2.51)	(2.75)	(2.69)	(2.79)	(2.75)	(2.55)	(2.59)	(2.36)	(2.28)	(2.12)	(1.60)
RREL	-8.921	-12.80*	-11.43	-9.015	-4.655	-6.140	-4.914	-0.288	-4.265	-6.682	-7.897	-12.29
	(-1.27)	(-1.87)	(-1.57)	(-1.10)	(-0.52)	(-0.64)	(-0.47)	(-0.03)	(-0.38)	(-0.59)	(-0.71)	(-1.17)
FIN_RET	-0.0176	0.395	-0.386	1.175	0.699	1.598	0.826	0.205	-0.596	-0.582	-0.579	-0.996
	(-0.01)	(0.26)	(-0.24)	(0.83)	(0.39)	(0.85)	(0.60)	(0.14)	(-0.41)	(-0.47)	(-0.49)	(-0.77)
FIN_VOL	-0.593	1.584	-3.168	-2.866	-4.672	-2.727	-4.052	-3.968	-0.924	3.679	3.379	4.253
	(-0.14)	(0.40)	(-0.48)	(-0.45)	(-0.69)	(-0.54)	(-0.80)	(-0.97)	(-0.23)	(1.11)	(0.95)	(1.31)
FIN_SKEW	-0.0489	-0.130**	-0.0512	-0.182**	-0.0475	-0.0293	-0.0689	-0.0263	0.0507	-0.0208	0.0561	0.111
	(-1.05)	(-2.38)	(-0.67)	(-2.33)	(-0.66)	(-0.45)	(-1.01)	(-0.42)	(0.70)	(-0.29)	(0.76)	(1.63)
FIN_BETA	0.0843	-0.224	-0.605	-0.920*	-1.097*	-1.415**	-1.529**	-1.536**	-1.596**	-1.503**	-1.587**	-1.546**
	(0.30)	(-0.60)	(-1.32)	(-1.68)	(-1.88)	(-2.12)	(-2.30)	(-2.08)	(-2.23)	(-2.12)	(-2.30)	(-2.13)
MKT_RET	-0.0452	1.668	1.854	-0.306	1.498	0.153	0.566	0.910	1.003	0.696	0.0100	-0.678
	(-0.04)	(0.88)	(0.89)	(-0.16)	(0.78)	(0.08)	(0.33)	(0.51)	(0.57)	(0.43)	(0.01)	(-0.50)
MKT_VOL	-4.697	-4.722	2.252	2.805	7.455	6.605	10.45	9.711	8.914	5.093	2.570	1.815
	(-0.72)	(-0.89)	(0.29)	(0.35)	(0.91)	(1.00)	(1.59)	(1.65)	(1.53)	(1.07)	(0.58)	(0.44)
CORR	0.545	0.738	1.072*	1.288**	1.074*	1.366*	1.196	1.062	1.224	1.202	1.255	0.779
	(1.15)	(1.42)	(1.83)	(2.14)	(1.69)	(1.96)	(1.65)	(1.29)	(1.51)	(1.46)	(1.55)	(0.97)
SIZE	0.0215	-0.100	-0.235	-0.361**	-0.481***	-0.607***	-0.717***	-0.754***	-0.844***	-0.848***	-0.857***	-0.891***
	(0.24)	(-0.84)	(-1.64)	(-2.24)	(-2.96)	(-3.08)	(-3.65)	(-3.38)	(-3.85)	(-3.75)	(-4.07)	(-3.93)
LEV	1.425	-3.238	-15.30	-24.06**	-30.73**	-38.59***	-46.95***	-47.11***	-48.85***	-42.38***	-43.32***	-42.30***
	(0.25)	(-0.43)	(-1.47)	(-2.06)	(-2.39)	(-2.77)	(-3.16)	(-3.01)	(-3.30)	(-3.42)	(-3.85)	(-3.70)
Constant	-1.217	4.924	17.85	27.79**	35.69**	44.70***	53.90***	54.66***	57.70***	51.95***	52.89***	52.53***
	(-0.19)	(0.58)	(1.58)	(2.19)	(2.58)	(2.92)	(3.35)	(3.17)	(3.52)	(3.61)	(4.06)	(3.90)
Observations	457	456	455	454	453	452	451	450	449	449	449	449
Adjusted R2	0.537	0.489	0.382	0.330	0.323	0.300	0.300	0.275	0.273	0.271	0.241	0.240

t-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Predictive ability of $OpCATFIN$ for future economic downturns

This table reports the coefficient estimates from the predictive regressions: $CFNAI_{t+n} = \alpha + \lambda OpCATFIN_t + \beta X_t + \sum_{i=1}^{12} CFNAI_{t-i+1} + \epsilon_{t+n}$ where CFNAI is a measure of macroeconomic conditions. T-statistics based on Newey and West (1987) are reported in parentheses. The slope coefficients on 12 lags of the dependent variable are suppressed.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OpCATFIN	-1.317**	-1.901***	-2.356***	-2.073**	-2.438**	-1.820*	-2.711**	-2.285**	-2.275**	-1.956*	-2.277**	-1.623
	(-2.07)	(-2.74)	(-2.85)	(-2.43)	(-2.51)	(-1.86)	(-2.55)	(-2.43)	(-2.31)	(-1.88)	(-2.11)	(-1.39)
DEF	-17.44	-14.30	-17.11	-15.05	-12.63	-7.420	-5.024	-4.072	-10.19	-3.744	2.061	19.20
	(-1.38)	(-1.01)	(-1.11)	(-0.80)	(-0.59)	(-0.33)	(-0.23)	(-0.19)	(-0.47)	(-0.18)	(0.09)	(0.93)
TERM	6.896*	7.705*	9.918**	10.39*	11.83**	12.52**	14.03**	16.69**	17.17**	15.81**	16.54**	11.62*
	(1.89)	(1.82)	(2.18)	(1.94)	(2.16)	(2.10)	(2.23)	(2.37)	(2.33)	(2.26)	(2.22)	(1.68)
RREL	-9.849	-14.60*	-14.23*	-13.29	-7.121	-6.953	-3.876	2.478	-0.0998	-3.899	-3.390	-8.905
	(-1.28)	(-1.92)	(-1.79)	(-1.53)	(-0.75)	(-0.67)	(-0.34)	(0.22)	(-0.01)	(-0.33)	(-0.29)	(-0.81)
FIN_RET	1.620	2.636*	1.577	2.971**	1.583	2.082	1.247	0.387	0.819	1.556	0.973	1.062
	(1.54)	(1.76)	(1.01)	(2.04)	(0.90)	(1.04)	(0.87)	(0.23)	(0.46)	(0.99)	(0.74)	(0.83)
FIN_VOL	-2.194	0.154	-3.176	-1.796	-3.054	-1.307	-2.740	-3.806	-2.421	1.098	1.168	2.953
	(-0.50)	(0.04)	(-0.47)	(-0.26)	(-0.42)	(-0.24)	(-0.51)	(-0.90)	(-0.57)	(0.31)	(0.31)	(0.87)
FIN_SKEW	-0.0800*	-0.151***	-0.0746	-0.192***	-0.0328	-0.0401	-0.109	-0.0740	-0.0360	-0.112	-0.0168	0.0222
	(-1.71)	(-3.05)	(-1.13)	(-2.86)	(-0.51)	(-0.63)	(-1.48)	(-1.03)	(-0.49)	(-1.56)	(-0.24)	(0.33)
FIN_BETA	-0.148	-0.572	-0.959**	-1.302**	-1.472***	-1.693**	-1.864***	-1.777**	-1.944***	-2.129***	-2.350***	-2.557***
	(-0.50)	(-1.43)	(-2.10)	(-2.36)	(-2.61)	(-2.49)	(-2.87)	(-2.41)	(-2.63)	(-2.63)	(-2.91)	(-3.02)
MKT_RET	0.707	1.264	1.922	-0.251	1.878	0.975	1.723	2.517	2.175	1.699	1.248	0.220
	(0.55)	(0.70)	(0.94)	(-0.13)	(0.96)	(0.50)	(1.02)	(1.50)	(1.25)	(1.00)	(0.69)	(0.16)
MKT_VOL	-1.941	-3.937	2.718	1.663	3.938	2.654	6.187	5.929	5.504	1.756	-0.477	-1.635
	(-0.34)	(-0.79)	(0.36)	(0.20)	(0.44)	(0.37)	(0.89)	(1.04)	(1.01)	(0.39)	(-0.10)	(-0.40)
CORR	0.664	0.910	1.176*	1.378**	1.090*	1.198*	0.976	0.684	0.852	0.974	0.893	0.612
	(1.35)	(1.61)	(1.85)	(2.18)	(1.70)	(1.75)	(1.40)	(0.86)	(1.07)	(1.22)	(1.16)	(0.82)
SIZE	-0.0508	-0.172	-0.329**	-0.437**	-0.519***	-0.584***	-0.687***	-0.676***	-0.750***	-0.809***	-0.869***	-0.942***
	(-0.53)	(-1.33)	(-2.08)	(-2.42)	(-2.82)	(-2.71)	(-3.28)	(-2.95)	(-3.26)	(-3.22)	(-3.53)	(-3.65)
LEV	-5.948	-11.95	-23.60**	-30.47***	-33.15***	-36.38***	-43.44***	-41.36***	-44.43***	-46.78***	-50.26***	-54.54***
	(-0.94)	(-1.52)	(-2.34)	(-2.73)	(-2.91)	(-2.92)	(-3.54)	(-3.18)	(-3.33)	(-3.36)	(-3.58)	(-3.73)
Constant	6.407	13.82	26.82**	34.74***	38.53***	42.36***	50.46***	48.38***	52.30***	55.27***	59.55***	64.56***
	(0.91)	(1.53)	(2.34)	(2.72)	(2.96)	(2.92)	(3.56)	(3.18)	(3.39)	(3.39)	(3.64)	(3.77)
Observations	421	420	419	418	417	416	415	414	413	413	413	413
Adjusted R2	0.524	0.473	0.383	0.331	0.301	0.271	0.278	0.237	0.230	0.234	0.231	0.245

t-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: The warning system

This table reports the coefficient estimates from the predictive regressions: $CFNAI_{t+n} = \alpha + \lambda_1 OpCATFIN_t^{plus} + \lambda_2 OpCATFIN_t^{minus} + \beta X_t + \sum_{i=1}^{12} CFNAI_{t-i+1} + \epsilon_{t+n}$ where CFNAI is a measure of macroeconomic conditions. T-statistics based on Newey and West (1987) are reported in parentheses. The slope coefficients on 12 lags of the dependent variable are suppressed.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$OpCATFIN^{plus}$	-0.592	-1.497*	-2.005**	-1.967**	-2.473***	-2.072**	-3.032***	-2.901***	-2.836***	-2.778***	-3.518***	-3.561***
	(-0.82)	(-1.84)	(-2.21)	(-2.12)	(-2.82)	(-2.34)	(-3.37)	(-3.39)	(-3.37)	(-3.58)	(-4.40)	(-3.59)
$OpCATFIN^{minus}$	-1.002	-2.715	-3.674	-3.156	-4.340*	-3.105	-4.804*	-5.171**	-4.754**	-6.354***	-7.528***	-9.081***
	(-0.52)	(-1.31)	(-1.62)	(-1.43)	(-1.72)	(-1.28)	(-1.93)	(-2.22)	(-1.99)	(-3.00)	(-3.50)	(-3.73)
DEF	-6.362	-1.437	1.210	0.148	5.896	2.397	6.812	5.567	-6.243	-0.582	0.351	14.82
	(-0.38)	(-0.07)	(0.06)	(0.01)	(0.26)	(0.11)	(0.33)	(0.26)	(-0.29)	(-0.03)	(0.02)	(0.74)
TERM	8.737**	10.80**	14.07***	16.18***	17.13***	18.19***	17.96***	19.30***	18.89***	16.50**	16.66**	10.76*
	(2.36)	(2.51)	(2.83)	(2.80)	(2.85)	(2.96)	(2.81)	(2.82)	(2.69)	(2.42)	(2.41)	(1.67)
RREL	-8.273	-11.00	-9.449	-6.804	-1.782	-3.159	-1.038	3.360	-0.0739	-2.950	-3.197	-8.384
	(-1.13)	(-1.52)	(-1.25)	(-0.81)	(-0.20)	(-0.32)	(-0.10)	(0.32)	(-0.01)	(-0.26)	(-0.29)	(-0.81)
FIN_RET	0.777	1.593	0.713	2.347*	2.024	2.906	2.160	1.557	1.071	1.415	1.215	0.704
	(0.63)	(1.01)	(0.46)	(1.68)	(1.18)	(1.48)	(1.56)	(0.97)	(0.65)	(0.97)	(0.97)	(0.53)
FIN_VOL	-2.893	-1.517	-5.731	-5.702	-7.576	-5.641	-6.526	-6.566*	-4.548	-1.119	-0.280	0.681
	(-0.68)	(-0.37)	(-0.91)	(-0.91)	(-1.15)	(-1.10)	(-1.33)	(-1.68)	(-1.12)	(-0.33)	(-0.08)	(0.21)
FIN_SKEW	-0.0671	-0.158***	-0.0792	-0.212***	-0.0848	-0.0657	-0.107	-0.0626	0.00716	-0.0689	0.0111	0.0723
	(-1.46)	(-2.97)	(-1.10)	(-2.79)	(-1.19)	(-1.00)	(-1.52)	(-0.90)	(0.09)	(-0.89)	(0.15)	(1.01)
FIN_BETA	-0.0113	-0.409	-0.857*	-1.169**	-1.401**	-1.666**	-1.898***	-1.864**	-1.920***	-1.794**	-1.941***	-1.878**
	(-0.04)	(-1.13)	(-1.92)	(-2.21)	(-2.46)	(-2.49)	(-2.79)	(-2.45)	(-2.62)	(-2.44)	(-2.72)	(-2.58)
MKT_RET	0.471	2.320	2.532	0.404	2.216	0.749	1.183	1.482	1.709	1.556	0.626	-0.0350
	(0.40)	(1.26)	(1.27)	(0.22)	(1.18)	(0.37)	(0.70)	(0.81)	(0.94)	(0.91)	(0.36)	(-0.02)
MKT_VOL	-4.605	-5.127	1.702	2.325	6.479	5.600	8.961	8.171	7.261	3.395	0.192	-0.505
	(-0.72)	(-0.97)	(0.23)	(0.30)	(0.82)	(0.89)	(1.48)	(1.58)	(1.40)	(0.79)	(0.05)	(-0.13)
CORR	0.633	0.812	1.137*	1.364**	1.116*	1.401**	1.187	1.048	1.220	1.193	1.162	0.678
	(1.31)	(1.50)	(1.90)	(2.24)	(1.75)	(2.00)	(1.63)	(1.28)	(1.52)	(1.50)	(1.50)	(0.91)
SIZE	0.0554	-0.0529	-0.213	-0.335**	-0.449***	-0.564***	-0.696***	-0.719***	-0.777***	-0.735***	-0.769***	-0.800***
	(0.53)	(-0.42)	(-1.41)	(-2.00)	(-2.67)	(-2.80)	(-3.37)	(-3.14)	(-3.47)	(-3.19)	(-3.48)	(-3.53)
LEV	-0.838	-5.974	-19.45**	-28.08**	-34.01***	-39.90***	-48.77***	-48.98***	-49.08***	-42.57***	-42.48***	-43.25***
	(-0.14)	(-0.84)	(-2.01)	(-2.54)	(-2.75)	(-2.90)	(-3.31)	(-3.13)	(-3.28)	(-3.23)	(-3.44)	(-3.61)
Constant	0.0655	6.490	21.22**	30.95**	38.15***	45.15***	55.39***	55.94***	56.88***	50.22***	50.90***	52.15***
	(0.01)	(0.80)	(1.97)	(2.53)	(2.83)	(2.96)	(3.42)	(3.21)	(3.41)	(3.31)	(3.55)	(3.69)
Observations	458	457	456	455	454	453	452	451	450	450	450	450
Adjusted R2	0.524	0.473	0.372	0.319	0.316	0.291	0.306	0.280	0.262	0.246	0.247	0.261

t-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Predictive ability of $OpCATFIN$ for aggregate lending

This table reports the coefficient estimates from the predictive regressions: $Y_{t+n} = \alpha + \lambda CATFIN_t + \beta X_t + \sum_{i=1}^{12} Y_{t-i+1} + \epsilon_{t+n}$ where Y_{t+n} is one of the four variables for the n-month-ahead aggregate lending activity: total loans and leases (LOANS), commercial and industrial loans (BUS), real estate loans (REAL), consumer loans (CSM). Newey andWests (1987) t -statistics are reported in parentheses. The sample period is from April 1976 to May 2013.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LOANS	-0.0456*	-0.0895***	-0.0960***	-0.104***	-0.0932**	-0.112***	-0.110***	-0.106***	-0.0900***	-0.0959***	-0.0993***	-0.0791**
	(-1.85)	(-3.25)	(-2.76)	(-2.69)	(-2.38)	(-3.11)	(-3.20)	(-3.13)	(-3.16)	(-3.67)	(-3.92)	(-2.43)
Observations	433	432	431	430	429	428	427	426	425	424	423	422
Adjusted R2	0.422	0.212	0.238	0.243	0.242	0.255	0.270	0.274	0.282	0.277	0.291	0.303

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
BUS	-0.0104	-0.0152*	-0.0180**	-0.0192**	-0.0229***	-0.0260***	-0.0303***	-0.0316***	-0.0294***	-0.0297***	-0.0327***	-0.0395***
	(-1.61)	(-1.84)	(-2.24)	(-2.47)	(-2.95)	(-3.07)	(-3.24)	(-3.28)	(-3.39)	(-3.53)	(-3.51)	(-3.86)
Observations	433	432	431	430	429	428	427	426	425	424	423	422
Adjusted R2	0.688	0.576	0.573	0.573	0.569	0.561	0.553	0.547	0.544	0.549	0.529	0.517

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
REAL	-0.0245	-0.0415**	-0.0435**	-0.0531**	-0.0565**	-0.0644***	-0.0632***	-0.0614***	-0.0509***	-0.0559***	-0.0609***	-0.0449*
	(-1.37)	(-2.09)	(-2.46)	(-2.35)	(-2.22)	(-3.09)	(-3.10)	(-3.04)	(-2.64)	(-2.93)	(-3.50)	(-1.90)
Observations	433	432	431	430	429	428	427	426	425	424	423	422
Adjusted R2	0.444	0.232	0.234	0.238	0.229	0.208	0.191	0.203	0.220	0.238	0.241	0.246

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CSM	-0.0474***	-0.0450***	-0.0417***	-0.0381***	-0.0391***	-0.0396***	-0.0396***	-0.0360***	-0.0289***	-0.0255***	-0.0256***	-0.0322***
	(-4.09)	(-4.07)	(-4.18)	(-4.29)	(-4.58)	(-4.45)	(-4.23)	(-4.07)	(-3.93)	(-3.84)	(-3.54)	(-3.99)
Observations	433	432	431	430	429	428	427	426	425	424	423	422
Adjusted R2	0.327	0.339	0.366	0.385	0.402	0.437	0.474	0.492	0.497	0.506	0.488	0.476

t-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Predictive ability of $OpCATFIN$ & $NonOpCATFIN$ for future economic downturns

This table reports the coefficient estimates from the predictive regressions: $CFNAI_{t+n} = \alpha + \lambda_1 OpCATFIN_t + \lambda_2 NonOpCATFIN_t + \beta X_t + \sum_{i=1}^{12} CFNAI_{t-i+1} + \epsilon_{t+n}$ where CFNAI is a measure of macroeconomic conditions. T-statistics based on Newey and West (1987) are reported in parentheses. The slope coefficients on 12 lags of the dependent variable are suppressed.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OpCATFIN	-1.089	-1.477**	-2.151***	-1.665**	-2.228**	-1.564	-2.372**	-1.713*	-1.787*	-0.795	-1.700*	-0.967
	(-1.60)	(-2.05)	(-2.65)	(-2.01)	(-2.31)	(-1.61)	(-2.36)	(-1.87)	(-1.91)	(-0.85)	(-1.73)	(-0.87)
NonOpCATFIN	0.566	1.056	0.507	1.012	0.511	0.619	0.802	1.403	1.219	2.844***	1.404	1.626*
	(0.92)	(1.46)	(0.63)	(1.26)	(0.59)	(0.67)	(0.91)	(1.47)	(1.34)	(3.42)	(1.64)	(1.91)
DEF	-19.50	-18.14	-18.95	-18.71	-14.47	-9.655	-7.866	-9.259	-14.74	-14.16	-3.051	13.16
	(-1.52)	(-1.22)	(-1.16)	(-0.95)	(-0.67)	(-0.42)	(-0.34)	(-0.42)	(-0.65)	(-0.65)	(-0.13)	(0.63)
TERM	6.949*	7.817*	9.968**	10.50*	11.88**	12.58**	14.11**	16.86**	17.35**	16.14**	16.69**	11.84*
	(1.89)	(1.82)	(2.17)	(1.94)	(2.15)	(2.10)	(2.22)	(2.37)	(2.33)	(2.26)	(2.22)	(1.69)
RREL	-9.941	-14.75*	-14.30*	-13.41	-7.200	-7.039	-3.988	2.345	-0.185	-4.204	-3.551	-9.033
	(-1.29)	(-1.93)	(-1.80)	(-1.53)	(-0.75)	(-0.68)	(-0.35)	(0.21)	(-0.02)	(-0.35)	(-0.30)	(-0.81)
FIN_RET	1.247	1.939	1.241	2.298	1.242	1.668	0.710	-0.570	-0.00529	-0.369	0.0212	-0.0323
	(1.12)	(1.25)	(0.76)	(1.45)	(0.72)	(0.92)	(0.52)	(-0.40)	(-0.00)	(-0.27)	(0.02)	(-0.02)
FIN_VOL	-1.403	1.634	-2.459	-0.371	-2.348	-0.446	-1.623	-1.834	-0.703	5.088	3.137	5.239
	(-0.32)	(0.39)	(-0.36)	(-0.06)	(-0.33)	(-0.08)	(-0.31)	(-0.47)	(-0.17)	(1.53)	(0.83)	(1.60)
FIN_SKEW	-0.0765	-0.144***	-0.0712	-0.185***	-0.0286	-0.0354	-0.103	-0.0626	-0.0267	-0.0882	-0.00510	0.0355
	(-1.64)	(-2.96)	(-1.09)	(-2.78)	(-0.46)	(-0.57)	(-1.43)	(-0.90)	(-0.36)	(-1.29)	(-0.07)	(0.53)
FIN_BETA	-0.136	-0.549	-0.949**	-1.281**	-1.460***	-1.680**	-1.846***	-1.749**	-1.920***	-2.071***	-2.321***	-2.524***
	(-0.46)	(-1.40)	(-2.08)	(-2.34)	(-2.60)	(-2.50)	(-2.88)	(-2.43)	(-2.65)	(-2.65)	(-2.92)	(-3.04)
MKT_RET	0.606	1.078	1.834	-0.425	1.790	0.872	1.587	2.304	1.990	1.253	1.033	-0.0312
	(0.46)	(0.59)	(0.89)	(-0.22)	(0.90)	(0.44)	(0.92)	(1.36)	(1.13)	(0.77)	(0.56)	(-0.02)
MKT_VOL	-1.994	-4.038	2.664	1.562	3.902	2.604	6.117	5.805	5.389	1.504	-0.598	-1.782
	(-0.35)	(-0.81)	(0.35)	(0.18)	(0.43)	(0.37)	(0.88)	(1.01)	(1.00)	(0.34)	(-0.13)	(-0.45)
CORR	0.615	0.817	1.131*	1.286**	1.045	1.142*	0.904	0.553	0.735	0.712	0.765	0.459
	(1.21)	(1.42)	(1.77)	(1.98)	(1.60)	(1.66)	(1.29)	(0.69)	(0.93)	(0.89)	(0.98)	(0.61)
SIZE	-0.0590	-0.188	-0.337**	-0.451**	-0.526***	-0.593***	-0.698***	-0.695***	-0.767***	-0.849***	-0.889***	-0.965***
	(-0.63)	(-1.46)	(-2.14)	(-2.51)	(-2.86)	(-2.72)	(-3.34)	(-3.04)	(-3.35)	(-3.47)	(-3.67)	(-3.79)
LEV	-5.925	-11.84	-23.51**	-30.26***	-33.13***	-36.29***	-43.30***	-40.85***	-43.82***	-45.96***	-49.90***	-53.92***
	(-0.95)	(-1.51)	(-2.33)	(-2.71)	(-2.91)	(-2.92)	(-3.54)	(-3.18)	(-3.32)	(-3.36)	(-3.58)	(-3.74)
Constant	6.590	14.10	26.93**	34.91***	38.69***	42.50***	50.61***	48.41***	52.17***	55.54***	59.72***	64.55***
	(0.94)	(1.57)	(2.36)	(2.73)	(2.97)	(2.92)	(3.58)	(3.21)	(3.41)	(3.48)	(3.69)	(3.83)
Observations	421	420	419	418	417	416	415	414	413	413	413	413
Adjusted R2	0.524	0.476	0.382	0.333	0.300	0.270	0.278	0.241	0.233	0.258	0.235	0.252

t-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: The warning system

This table reports the coefficient estimates from the predictive regressions: $CFNAI_{t+n} = \alpha + \lambda_1 CATFIN_t^{plus} + \lambda_2 CATFIN_t^{minus} + \beta X_t + \sum_{i=1}^{12} CFNAI_{t-i+1} + \epsilon_{t+n}$ where CFNAI is a measure of macroeconomic conditions. T-statistics based on Newey and West (1987) are reported in parentheses. The slope coefficients on 12 lags of the dependent variable are suppressed.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CATFIN^{plus}$	-1.599***	-1.986***	-1.899**	-1.954**	-1.840**	-1.771**	-1.745**	-1.630**	-2.494***	-3.281***	-2.876***	-2.732***
	(-2.87)	(-3.21)	(-2.53)	(-2.41)	(-2.31)	(-2.13)	(-2.14)	(-2.06)	(-3.54)	(-4.66)	(-3.66)	(-3.34)
$CATFIN^{minus}$	-1.507**	-1.530*	-1.573	-1.527	-0.952	-1.078	-1.120	-0.781	-2.174**	-3.062***	-3.157***	-2.792***
	(-2.03)	(-1.94)	(-1.63)	(-1.38)	(-0.93)	(-1.03)	(-1.03)	(-0.78)	(-2.39)	(-3.20)	(-3.04)	(-2.64)
DEF	-15.75	-17.06	-12.57	-12.87	-12.16	-12.15	-6.775	-12.27	-24.26	-30.55	-23.15	-16.00
	(-1.00)	(-0.89)	(-0.54)	(-0.51)	(-0.49)	(-0.49)	(-0.30)	(-0.52)	(-1.06)	(-1.38)	(-1.07)	(-0.77)
TERM	8.757**	9.855**	13.27***	14.81**	15.08***	15.76***	15.08**	16.64**	16.35**	15.77**	15.48**	10.97
	(2.48)	(2.38)	(2.68)	(2.58)	(2.65)	(2.64)	(2.48)	(2.48)	(2.35)	(2.24)	(2.17)	(1.64)
RREL	-8.993	-13.17*	-11.68	-9.331	-5.284	-6.621	-5.368	-0.906	-4.483	-6.840	-7.696	-12.26
	(-1.28)	(-1.94)	(-1.61)	(-1.14)	(-0.59)	(-0.69)	(-0.52)	(-0.09)	(-0.41)	(-0.61)	(-0.69)	(-1.17)
FIN_RET	-0.00924	0.438	-0.356	1.214	0.782	1.667	0.886	0.286	-0.567	-0.562	-0.604	-1.003
	(-0.01)	(0.28)	(-0.23)	(0.86)	(0.43)	(0.90)	(0.64)	(0.20)	(-0.39)	(-0.45)	(-0.50)	(-0.76)
FIN_VOL	-0.558	1.778	-3.044	-2.715	-4.321	-2.464	-3.793	-3.616	-0.784	3.769	3.261	4.226
	(-0.13)	(0.45)	(-0.47)	(-0.43)	(-0.65)	(-0.50)	(-0.76)	(-0.91)	(-0.19)	(1.15)	(0.92)	(1.32)
FIN_SKEW	-0.0488	-0.129**	-0.0510	-0.182**	-0.0482	-0.0306	-0.0697	-0.0274	0.0500	-0.0211	0.0565	0.112
	(-1.05)	(-2.38)	(-0.67)	(-2.34)	(-0.68)	(-0.47)	(-1.01)	(-0.43)	(0.68)	(-0.30)	(0.77)	(1.62)
FIN_BETA	0.0805	-0.245	-0.618	-0.937*	-1.137*	-1.444**	-1.559**	-1.576**	-1.611**	-1.513**	-1.574**	-1.543**
	(0.29)	(-0.66)	(-1.35)	(-1.71)	(-1.96)	(-2.17)	(-2.34)	(-2.14)	(-2.25)	(-2.12)	(-2.25)	(-2.10)
MKT_RET	-0.0479	1.656	1.846	-0.312	1.484	0.145	0.554	0.895	0.999	0.693	0.0109	-0.677
	(-0.04)	(0.88)	(0.89)	(-0.16)	(0.78)	(0.07)	(0.32)	(0.51)	(0.57)	(0.43)	(0.01)	(-0.50)
MKT_VOL	-4.720	-4.855	2.173	2.708	7.219	6.424	10.27	9.467*	8.817	5.031	2.650	1.833
	(-0.73)	(-0.92)	(0.28)	(0.34)	(0.89)	(0.99)	(1.60)	(1.66)	(1.54)	(1.07)	(0.59)	(0.45)
CORR	0.560	0.814	1.126*	1.356**	1.214*	1.476**	1.295*	1.197	1.273	1.237	1.210	0.770
	(1.16)	(1.56)	(1.91)	(2.20)	(1.90)	(2.06)	(1.75)	(1.44)	(1.54)	(1.46)	(1.45)	(0.94)
SIZE	0.0220	-0.0972	-0.233	-0.358**	-0.475***	-0.602***	-0.713***	-0.748***	-0.842***	-0.846***	-0.859***	-0.892***
	(0.25)	(-0.84)	(-1.65)	(-2.27)	(-3.03)	(-3.15)	(-3.72)	(-3.45)	(-3.88)	(-3.77)	(-4.06)	(-3.95)
LEV	1.410	-3.211	-15.31	-24.08**	-30.56**	-38.49***	-46.81***	-46.92***	-48.68***	-42.32***	-43.39***	-42.34***
	(0.25)	(-0.43)	(-1.48)	(-2.08)	(-2.42)	(-2.80)	(-3.18)	(-3.01)	(-3.29)	(-3.41)	(-3.86)	(-3.74)
Constant	-1.239	4.723	17.73	27.63**	35.17***	44.31***	53.53***	54.14***	57.41***	51.81***	53.06***	52.59***
	(-0.20)	(0.57)	(1.59)	(2.21)	(2.61)	(2.96)	(3.38)	(3.17)	(3.51)	(3.62)	(4.08)	(3.95)
Observations	457	456	455	454	453	452	451	450	449	449	449	449
Adjusted R2	0.536	0.489	0.381	0.330	0.328	0.303	0.302	0.280	0.272	0.270	0.240	0.238

t-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table 11: Definition of control variables.

For control variables, I use the same definitions as in Allen et al. (2012).

Variable	Definition
CFNAI	Chicago Fed National Activity Index, is a monthly index that determines increases and decreases in economic activity and is designed to assess overall economic activity and related inflationary pressure.
Control Variables	
DEF	The default spread, i.e., the difference between the BAA-rated and AAA-rated corporate bonds.
TERM	The term spread, i.e., the difference between the ten-year T-bond and one-month T-bill yields.
RREL	Is the relative short-term interest rate, defined as the difference between one-month T-bill rate and its twelve-month backward-moving average.
FIN_RET	The value-weighted average excess returns of all financial firms(i.e., the average excess return on the financial market index).
FIN_VOL	The realized monthly volatility of excess returns of all financial firms, defined as the square root of the sum of squared daily returns in a month.
FIN_SKEW	The realized monthly skewness of excess returns of all financial firms.
FIN_BETA	The average market beta of all financial firms estimated from monthly returns over the past five years.
MKT_RET	The monthly excess return on the CRSP value-weighted index.
MKT_VOL	The realized monthly volatility of excess returns of the aggregate stock market portfolio, defined as the square root of the sum of squared daily returns in a month.
CORR	The average correlation between excess returns on individual financial firms and excess returns on the financial market index, and the correlation measurement window is twentyfour months, updated on a monthly basis.
SIZE	The natural logarithm of the average market capitalization of firms in the financial sector.
LEV	The aggregate leverage in the financial sector defined as the ratio of total liabilities to total assets of the entire financial sector.
Aggregate Lending (Call Reports)	
Total_loans (rcon1400)	The aggregate gross book value of total loans (before deduction of valuation reserves). Beginning in the first quarter of 1984 this item includes rcon 2165, lease financing receivables. The inclusion of this series results in an inconsistency in the total loan series. We correct by adding lease financing receivables to total loans prior to 1984.
C&I_loans (rcon1600)	Includes commercial and industrial loans to business enterprises.
RealEstate_loans (rcon1410)	Includes all loans, whatever the purpose, secured primarily by real estate as evidenced by mortgages, deeds of trust, land contracts, or other instruments, whether first or junior liens (e.g., equity loans, second mortgages) on real estate.
Consumer_loans (rcon1975)	Includes all loans, not secured primarily by real estate, to individuals for medical expenses, personal taxes, vacations, consolidation of personal (nonbusiness) debts.

Future Research

First chapter can be extended as follows.

1. Extant literature find that higher non-interest income (i.e., non-core activities like investment banking and trading) is associated with a higher contribution to systemic risk relative to traditional banking (i.e., deposit taking and lending) (see, e.g., Brunnermeier, Dong, and Palia, 2012; Shleifer and Vishny, 2010; Dittmar and Thakor, 2007). Therefore, we can classify the acquisitions into activity diversifying and focusing based on similarity of their business models. This classification methodology will help investigate whether the business model is a driver of our results.

2. Bond prices provide a more direct measure of default risk relative to stock prices. Change in stock prices can be driven by many other factors. Therefore, to strengthen our argument, we can investigate the change in the price of acquirers' bonds around the acquisition announcement.

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