Essays on Financial Crisis

by

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To My Family and Friends

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ABSTRACT

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My dissertation examines the effects of economic shocks on acquisition outcomes and the sources of housing market bubble. The first essay investigates how the combined effects of target firm- and industry-level distress affect acquisition outcomes through the fire-sale channel. I show that distressed targets are sold at discounts when the target industry is in distress. Consistent with the Shleifer and Vishny model, the fire-sale effects cause distressed targets to be sold to industry outsiders and acquirers to gain higher return by exploiting target's weakened bargaining power. I further demonstrate the fire-sale effects in acquisitions by showing that these findings are stronger for targets with acquirers that are in different industries or where targets have high industry asset-specificity. I then examine the contagion effects of fire-sale acquisitions on target rivals in the same industry. I find that rivals earn negative abnormal returns at the announcement due to negative information from fire-sale acquisitions. Overall, the results show that the fire-sale discount in distressed target acquisitions is an important determinant of financial distress costs of a firm and contributes to industry-specific contagion of economic shocks. In the second essay, I explore (with a coauthor) whether state-level variation in recourse mortgage laws affects housing prices and mortgage lending. In a state with non-recourse mortgage law, borrowers have limited liability on their mortgage loan. We find that non-recourse law results in larger bubbles in housing prices, and identify the causal effects by comparing housing prices in contiguous border county-pairs in the United States and examine discontinuities at state borders. We also explore whether mortgage lending behavior in non-recourse states reflects anticipation of additional risk. We find that loan-to-value ratio is lower and mortgage interest rate and loan denial rate are

higher in non-recourse states, which suggest that lenders are aware of additional risk in non-recourse loans. However, we find that because the emergence of the originate-to-distribute (OTD) model in the housing markets enables lenders to effectively shift the risks to other investors, mortgage lending behavior does not fully reflect the higher risk.

CHAPTER I

Fire-Sale Acquisitions and Intra-Industry Contagion

1.1 Introduction

Efficient reallocation of production inputs enables the economy to increase aggregate productivity and facilitates recovery from industry- and economy-wide recession. However, existing research on the cyclical properties of asset reallocation finds that transactions are procyclical, despite dispersion of capital productivity and potential benefits to reallocate being higher during downturns (*Eisfeldt and Rampini* (2006)). Frictions due to information asymmetry reduce asset liquidity, thereby distorting reallocation. The fire-sale is a central mechanism through which asset redeployment becomes more costly in response to negative economic shocks, and thus those shocks are amplified (*Shleifer and Vishny* (2011)).

Fire-sale acquisitions, although they account for two-thirds of asset reallocation[1], have received little academic attention relative to the widely documented existence of fire-sale discounts in real asset transactions. Acquisitions differ from asset markets in a number of important ways. For example, labor and patented R&D are considered to be transferred with the change in ownership in acquisitions. Acquisitions also have a unique advantage with respect to identifying the channel of a fire sale, buyer identity and return being readily observable in contrast to the limited availability of data in real asset transactions. The goal of this paper is therefore to examine fire-sale effects in distressed target acquisitions by identifying the detailed channel of the discount and the intra-industry contagion effects to which it gives rise.

A fire-sale is an urgent sale of assets in an illiquid market. The essential condition for a forced sale is a seller's financial constraint. Firms that face a severe liquidity

[1] See Figure 1.1.

constraint may be forced to sell some or all of their assets to avoid bankruptcy. Thus, distressed acquisitions play an important role as a restructuring mechanism. In an imperfect world, however, negative economic shocks can cause asset prices to fall below their fair market values. *Shleifer and Vishny* (1992) propose a theory in which industry insiders with higher valuation on a distressed firm's assets are financially constrained and sidelined due to financial frictions, while an industry outsider with high liquidity and a lower valuation can acquire assets at a lower bid. This model implies that demand-side frictions in an illiquid market create additional costs in urgent asset sales.

Empirically, calculating the fair market value of distressed targets in an illiquid market and examining fire-sale discounts in acquisitions are challenging for two reasons. First, a target's offer price reflects both fire-sale effects and the decline of the economic worth of its assets. Second, it is important to consider the creation and division of synergies. To circumvent the first identification problem, I estimate the combined effects of target firm- and industry-level distress on acquirer abnormal returns and offer price after controlling for the determinants of the economic worth of assets. More importantly, I examine the interaction effects of fire-sale and industry-level asset-specificity with which fire-sale effects are expected to be stronger, while a pure decline in economic worth of assets is less associated. Then, I address the second problem by decomposing the offer price into synergy and the target's bargaining power and analyzing these elements separately to identify the source of the discount.

Focusing on acquisitions between public firms that occurred between 1980 and 2010, I identify fire-sale acquisitions where both target industries and the targets themselves were distressed at the announcement. I find that acquirers in fire-sale acquisitions earn higher cumulative announcement returns relative to other acquirers over the -1 to +1 day window after controlling for other factors. I further confirm this result using buy-and-hold abnormal returns (BHARs) during the two years following the acquisitions. This directly supports fire-sale discounts in acquisitions because acquirers' return should be unaffected by target firm- and industry-level distress if acquirers pay the fair market value of a target.

I then analyze the source of this discount by examining the interaction effect of a target firm- and industry-level distress, separately, on offer price, synergy, and target's bargaining power. I find that a distressed target in a distressed industry, or fire-sale target, is acquired at a 14% discount compared to distressed targets in non-distressed industries. More specifically, the channel of fire-sale proposed by Shleifer and Vishny's model implies that fire-sales are inefficient and exhibit lower synergy. In testing this, I also consider whether target firm- and industry-level distress negatively affects a target's bargaining power, thereby inducing a fire-sale discount that results in greater gains to buyers. I find that while the target's bargaining power, measured as the difference in announcement returns between target and acquirer, is substantially weakened, synergy is insignificantly affected, by the interaction effect of firm- and industry-level distress. These results suggest that observable fire-sale discounts are caused largely by wealth transfer to acquirers.

Next, I investigate whether target firm- and industry-level distress affect a buyer's identity and whether they drive stronger fire-sale effects if acquirers are outside the industry. Consistent with the model predictions, the results show that industry-wide distress increases the likelihood of targets being sold to industry outsiders by 20 percentage points and the fire-sale effects on acquirer abnormal returns, offer price, and target's bargaining power are even stronger if targets are sold to acquirers outside an industry. Particularly, I also find a both economically and statistically significant decrease in total synergy gain conditional on industry outside acquirers, which implies a deadweight loss from inefficient fire-sales.

To further demonstrate that the findings are driven by the fire-sale channel, I examine the interaction effects of combined distress of target firm and industry and high asset-specificity in three dimensions —capital-specificity, labor union, and R&D intensity— in which the fire-sale effects are expected to be stronger. The Shleifer and Vishny model suggests that fire-sale effects are stronger if targets' assets are specialized to their industry and, thus, not easily redeployable to industry outsiders. I show that the fire-sale effects are particularly strong for targets with high industry-specific assets. Specific capital, strong labor unions, and high R&D intensity in target industries strengthen the fire-sale effects by driving up frictions in asset allocation across industries. These findings provide evidence that a significant fire-sale discount exists, in a manner that is consistent with the industry-equilibrium theory of Shleifer and Vishny. Multiple robustness checks also show that the results are not driven by stock market undervaluation or macroeconomic recession effects. Overall, using these multiple complementary approaches, this paper disentangles the fire-sale effects from declines in fundamental value and demonstrates the channel of the fire-sale effects in acquisitions.

Finally, I relate fire-sale acquisitions to target industry rivals' stock returns. The relevant literature highlights contagious effects that economic shocks can transmit through the fire-sale. Fire-sale acquisitions could have a negative information externality by providing lower reference prices to subsequent acquisitions coming to market, or have a negative "out-of-play effect[2]" by reducing potential for an acquisition partner among industry. I find that industry rivals of fire-sale targets experience economically and statistically significant negative abnormal stock returns. The stock price of industry rivals drops upon announcement of fire-sale acquisitions, on average, by 0.9% over the -1 to +1 day window. The effect of fire-sale acquisitions on rivals' returns is stronger in high R&D industries where are likely to have high information asymmetry. This evidence supports the view that fire-sale acquisitions contribute to an intra-industry contagion of economic shocks by conveying negative information.

This paper contributes to the literature in several important ways. By providing new evidence on fire-sales in the corporate control market, this paper expands on previous research on fire-sales.[3] *Pulvino* (1998) provides the first empirical evidence of fire-sale effects on real assets by studying prices of used airplanes, and *Campbell et al.* (2011) examine foreclosure discounts from forced home sales. Considerable research also documents the fire-sale of financial assets (e.g., *Shleifer and Vishny* (1997), *Coval and Stafford* (2007), and *Rajan and Ramcharan* (2013)). In contrast to asset sales in real asset or financial markets, buyers in acquisitions should consider such factors as labor continuation, technology transfer, successor liabilities, and control premium. I add to this literature by expanding the notion of resource reallocation beyond physical capital to general assets including labor and technology. These findings provide a better understanding of how frictions negatively influence efficient resource allocation during industry- and economy-wide distress.

This paper is closely related to previous studies that analyze how targets' financial constraints affect acquisition outcomes.[4] Evidence on fire-sale acquisitions is mixed, however, and confounded in the literature by the empirical challenge of calculating the fundamental value of a target. My examination of fire sales in acquisitions takes account of the combined effects of target and target industry-wide distress as well as cross-sectional differences in asset-specificity. Furthermore, my comprehensive anal-

[2] *Banerjee and Eckard* (1998), *Fridolfsson and Stennek* (2005), and *Campbell et al.* (2011)

[3] *Shleifer and Vishny* (1992), *Pulvino* (1998), *Aguiar and Gopinath* (2005), *Coval and Stafford* (2007), *Officer* (2007), *Bharath and Shumway* (2008), *Eckbo and Thorburn* (2008), *Campbell et al.* (2011), *Ang and Mauck* (2011), *Kim* (2012), and *Shleifer and Vishny* (2011). See *Shleifer and Vishny* (2011) for a survey of the research on fire-sale.

[4] *Officer* (2007) shows that financially constrained unlisted private targets are acquired at lower multiples than public targets are. *Eckbo and Thorburn* (2008), on the other hand, examining the acquisition outcomes of automatic bankruptcy auctions in Sweden, find insignificant discounts for going-concern sales. *Ang and Mauck* (2011) investigate the acquisition outcomes of distressed firms in crises and suggest the weak evidence of fire-sale discounts in acquisitions. A concurrently developed working paper by Kim (2012) highlights the negative effects of physical capital specificity on target premium and returns in acquisitions.

ysis of buyer identity, return, synergy, and bargaining power provides clear evidence of fire-sale effects in acquisition markets, and identifies the channel of inefficient asset reallocation during downturns.

This paper also suggests implications of widespread concerns about industry contagion effects resulting from fire-sales. The existence of negative spillover effects in asset fire-sales has been acknowledged in many papers.[5] Although fire sales have been shown to be a central channel that amplifies economic shocks, little empirical evidence exists on the relation between fire-sale acquisitions and industry rivals' returns. If such a relation exists, it could be argued that fire-sale acquisition contributes to the contagion of economic shocks. This paper shows that fire-sale acquisition has a negative contagious effect within an industry, even in corporate-level transactions.

The remainder of this paper is organized as follows. In Section 2, I develop hypotheses and discuss the related literature. In Section 3, I describe sample selection and variable construction, and present summary statistics. Effects of fire-sale on acquisition outcomes are examined in Section 4, which also reports the results of robustness checks. In Section 5, I investigate the impact of fire-sale acquisition on industry rivals. Section 6 concludes.

1.2 Hypothesis Development

The primary goal of this study is to address two questions: (1) whether firm- and industry-level distress cause firms to be sold at discounts due to a fire-sale effect, and (2) how fire-sale acquisitions affect a target's industry rivals. In this section, I discuss the prior literature related to these questions, and develop hypotheses that guide the empirical analysis.

1.2.1 Fire-Sale in Acquisitions

Distressed firms may face a severe liquidity constraint because they hold insufficient cash to meet debt obligations and have difficulties in raising capital. They can sell either some or all of their assets to generate cash needed to make debt payments, or attempt to renegotiate with creditors in order to restructure debt contracts. In a perfect world, the resolution of firm distress is costless. An absence of friction in

[5] *Kiyotaki and Moore* (1997) propose a macroeconomic model in which shocks can turn into systemic risk through the lowering of collateral value. *Campbell et al.* (2011) show that foreclosures due to default or death result in the lowering of other local house prices. *Benmelech and Bergman* (2011) also examine the spillover effects of the sale of a bankrupt aircraft company on its rivals' collateral value and increased external financing cost. See also *Allen and Gale* (2000b), *Oh* (2012), and *Hertzel and Officer* (2012).

renegotiating debt contracts would prevent the premature liquidation of assets. Even in times of industry distress, targets can sell assets at fair market value, which is based on their updated economic worth (P_1), as shown in Figure 1.2(a).

In the real world, however, high financial distress costs may be incurred. Debt renegotiation often fails due to such frictions as information asymmetry between a debtor and its creditors, or holdout problems among creditors (*Brown* (1989), *Gertner and Scharfstein* (1991), and *Asquith et al.* (1994)). Distressed firms may be forced to sell their assets or control rights, or to go through a formal legal proceeding such as Chapter 11 bankruptcy. However, asset restructuring involves a liquidation cost that depends on market liquidity which, in turn, is determined by the credit constraints of peer firms and asset redeployability. *Shleifer and Vishny* (1992) propose precise theoretical implications of how financial constraints in an industry give rise to a price that drops below an asset's revised economic value, a condition known as a fire-sale.

Because the subjects of asset sales are fairly specialized within industries, the first-best buyers are usually industry insiders that have invested in knowledge of, and managed, similar assets. However, industry insiders are likely to be financially constrained at the same time, if a negative shock is industry-wide. Therefore, the first-best buyer with the highest valuation of a distressed firm's assets is often sidelined due to financial frictions and industry-wide debt overhang (*Myers* (1977), and *Clayton and Ravid* (2002)). As a result, demand in the secondary asset market drops further, so prices frequently drop from P_1 to the fire-sale price P_{FS} in Figure 1.2, which does not reflect longer-term asset potential.

Hypothesis 1 (Fire-Sale Discount): *Distressed targets in a distressed industry, or fire-sale targets, are likely to be acquired at discounts.*

The Shleifer and Vishny model focuses on a demand-side channel that predicts inefficient sales to industry outsiders with high liquidity but lower synergy. I also consider whether fire-sale is attributed to greater distribution of total gains to buyers. Given that intense negotiations are required to set an acquisition's price, target firm- and industry-level distress may affect the sharing rule. The bargaining theory literature provides a rationale for this hypothesis (*Nash* (1950), *Rubinstein* (1982), *Binmore et al.* (1986), and *Gul* (1989)). A large body of literature suggests that two sources of impatience determine relative bargaining outcomes. The first is the relative cost of delay from discounting the future (*Rubinstein* (1982)) and the second, which views acquisition as a multiplayer bargaining game, is the desire to be the first to realize gains from a transaction (*Gul* (1989), and *Rhodes-Kropf and Robinson* (2008)[6]). Target firm- and industry-level distress are expected to negatively affect the first source of a target's bargaining power by increasing its discount rate or cost of capital relative to the acquirer's. In addition, the fact that more sellers with similar assets are competing in the secondary market during an industry downturn increases a target's impatience at the negotiation table.

Hypothesis 2-1 (Inefficient Sale): *Distressed targets in a distressed industry are acquired at discounts because of the lower synergy gain from a fire-sale acquisition.*

Hypothesis 2-2 (Wealth Transfer): *Distressed targets in a distressed industry are acquired at discounts because of a target's weaker bargaining power.*

The *inefficient sale hypothesis* and *wealth transfer hypothesis* are not mutually exclusive but distinguishable, that wealth transfer is not necessarily inefficient.

Applying the industry-equilibrium theory of Shleifer and Vishny to distressed target acquisition, I also expect that distressed targets in a distressed industry are more likely to be sold to industry outsiders relative to comparable distressed targets in a non-distressed industry, and I expect fire-sale targets acquired by industry outsiders to experience further discount.

Hypothesis 3 (Acquirer's Identity): *Distressed targets in a distressed industry are more likely to be acquired 1) by industry outsiders, and 2) at a further discount conditional on industry outside acquirers.*

The next hypothesis relates the fire-sale effect to cross-sectional differences in asset-specificity. The key underlying condition of asset illiquidity during an industry downturn is that assets are specialized, and can thus be fully utilized only by industry insiders with sufficient accumulated knowledge and investment to generate the highest value from them. Therefore, when assets are highly industry specific, the inefficient sale or wealth transfer incurred by demand-side constraints in a fire-sale becomes more severe because industry outsiders, who are unable to make the best use of them, have a lower reservation value on the assets. I consider a simple Cobb-Douglas

[6] They propose a model that relative bargaining power between target and acquirer depends on the relative scarcity of each firm's assets, the quality of the match, and the costs of finding another partner. Consistent with their model, when an industry experiences liquidity constraints, liquidity and financing ability become scarce assets that may give more bargaining power to an acquirer.

production function: a firm uses three factors —capital, labor, and technology— to produce output. The hypotheses that follow are that the fire-sale effects in acquisition should be stronger in industries with high capital-specificity, strong labor unions, and high R&D intensity. These characteristics increase the friction in asset allocation across industries, and thus make the distressed targets less redeployable.

Hypothesis 4 (Asset-specificity): *If assets are more specialized to industry insiders due to high capital-specificity, strong labor unions, or high R&D intensity, then the fire-sale discounts should be larger.*

1.2.2 Intra-Industry Contagion Effect

Having established the existence of fire-sale effects in acquisitions, I extend current research a step further by examining an industry-specific contagion effect from fire-sale acquisitions. The fire-sale effects can be contagious to a target's industry rivals.

Prior literature documents that acquisitions can affect a target's industry rivals by revealing new information about the value of industry assets.[7] Fire-sale prices can pull down the prices of subsequent acquisitions coming to market by providing a lower reference price, as *Campbell et al.* (2011) proposed in housing markets. This negative information externality can be socially inefficient because it may cause firms selling assets in distressed industries to play a non-cooperative game. The possibility that updated information from other targets might further discount the option value to waiting may lead them to be inefficiently urgent to sell their assets ahead of others.[8]

The fire-sale acquisitions are also likely to have negative "out-of-play effects" for a target's industry rivals (*Banerjee and Eckard* (1998), and *Fridolfsson and Stennek* (2005)). Given that the number of capable buyers is limited during an industry downturn, announcements of acquisitions reduce the potential partners and the market's expectation that a rival will be acquired (*Akdogu* (2011), and *Molnar* (2007)).

Hypothesis 5-1 (Negative Information): *Announcements of distressed target acquisitions in a distressed industry at fire-sale prices signal low reference prices and decreased demand that result in negative stock returns for a target's industry rivals.*

[7] *Eckbo* (1983), *Eckbo and Wier* (1985), *Song and Walkling* (2000), *Fee and Thomas* (2004), and *Shahrur* (2005)

[8] Contestants compete by escaping first in this game, in contrast to the famous game theory model, *war of attrition*, in which contestants compete by persisting with accumulating costs over time.

Previous studies suggest that acquisitions, distinct from the *negative information hypothesis*, have implications for industry rivals in terms of changing product market dynamics. *Eckbo* (1983) proposes that acquirers gain competitive advantage from productivity improvements in operating, marketing, distribution, or purchasing activities, and the resulting intense product market competition harms industry rivals. Recent studies by *Fee and Thomas* (2004) and *Shahrur* (2005) support this hypothesis based on evidence from horizontal mergers. This hypothesis predicts a negative stock return for industry rivals from diminished post-acquisition operating performance.[9]

Hypothesis 5-2 (Intense Competition): *Announcements of distressed target acquisitions in a distressed industry intensify industry competition that results in negative operating performance, and negative stock returns, for a target's industry rivals.*

Alternatively, acquisitions can benefit industry rivals by increasing the likelihood of anticompetitive collusion (*Stigler* (1964), *Eckbo* (1983), *Kim and Singal* (1993) and *Fee and Thomas* (2004)). *Stigler* (1964) proposes that acquiring firms can use their increased market power to collude with rivals in order to reduce output to monopoly levels and raise prices at the expense of consumers. If anticompetitive acquisition is loosely governed by antitrust laws during industry downturns, monopolistic collusion is likely to motivate acquisitions. Under this hypothesis, I expect rival firms to have positive stock returns at the announcement of a fire-sale acquisition, and improved operating performance to follow.

Hypothesis 5-3 (Market Power): *Announcements of distressed target acquisitions in a distressed industry result in positive stock returns and improved operating performance for industry rivals through anticompetitive collusion.*

Other externalities from fire-sale acquisitions may exist in the agency and labor market channels.[10] These, however, are beyond the scope of this paper and remain for future research.

[9]This hypothesis can be illustrated by a simple theoretical setting within which acquisition causes Cournot competition to become Stackelberg competition in which a leader, or combined firm, moves first and other rivals move later.

[10]Substantial discounts in fire-sale acquisitions perhaps convey a warning to shareholders and managers of industry rivals that results in intensified monitoring and reduces agency costs in general. Moreover, distressed acquisitions that entail intense restructuring and worker layoffs will affect labor-related decisions of targets' rivals.

1.3 Data and Methodology

1.3.1 Sample Construction

The sample of mergers is from the Securities Data Company's (SDC) U.S. Mergers and Acquisitions Database. This paper employs all completed mergers between U.S. non-bankrupt public targets and U.S. public bidders during the period 1980-2010. I require acquiring firms to control less than 50% of the shares of target firms before the announcement, and the transaction value of deals to be greater than one million dollars. Both acquirers and targets must be public firms listed on the Center for Research in Security Prices (CRSP) and Compustat databases during the event window. I further eliminate firms in a financial industry (SIC: 6000 - 6999) and utilities (SIC: 4900 - 4999), using their primary SIC code.

1.3.2 Identifying Fire-Sale Acquisitions

The Shleifer and Vishny model theoretically identifies firm distress combining with industry-wide distress as a set of necessary conditions for a fire-sale to occur. Following this model, acquisitions are defined as fire-sale acquisitions when both target industries and targets themselves are distressed at the announcement. The interaction variable of target firm- and industry-level distress is termed *Fire-Sale*. The variable constructions for firm- and industry-level distress are as follows.

1.3.2.1 Measures of Target Distress

To identify the distressed target mergers within the sample, I use two measures of firm distress widely employed in the literature. The first measure is based on the KMV-Merton model that provides a distance measure between expected asset value and the default threshold based on an option-pricing model (*Merton* (1974)). This model calculates default risk by considering equity as a call option on firm value and debt as a strike price. This measure is widely used in the literature (e.g., *Committee* (1999), *Vassalou and Xing* (2004), and *Chava and Purnanandam* (2010)), and its predictive power has been verified by many studies (e.g., *Bharath and Shumway* (2008), and *Duffie et al.* (2007)). Following *Bharath and Shumway* (2008), I construct expected default frequency (EDF) for each target from the distance to default. I call this continuous variable $Distress1_T$. The estimation process is detailed in Appendix A.

The second measure $Distress2_T$, following *Pulvino* (1998), defines a target as distressed if its leverage ratio is greater, and its current ratio (current assets/current liabilities) less, than the industry median. This measure implies that distressed targets face both short- and long-term financial constraints. I define a firm's industry as the set of firms with the same 3-digit SIC code.

1.3.2.2 Proxy for Industry Distress

The measure used in this paper for target industry distress should capture the degree of distress of a target's peer firms as a whole. I define an industry as distressed if its median firm's sales growth is negative in the year of acquisition. A firm's industry is defined as the set of firms with the same 3-digit SIC code. The target firms are excluded from the calculation of industry variables. This dummy variable is termed $Ind.Distress_T$.

Additionally, I construct, as a robusteness check, alternative measures of industry distress 1) if median sales growth is lower than -1% ($Ind.Distress2_T$), 2) if median sales growth is lower than +1% ($Ind.Distress3_T$), and 3) if median sales growth is negative for two consecutive years ($Ind.Distress4_T$). I report the main results of this paper based on the primary measure $Ind.Distress_T$. The results with alternative industry distress measures are reported in Internet Appendix. The results are qualitatively robust.[11]

1.3.3 Control Variables

In order to compare acquisition outcomes over different degrees of target firm- and industry-level distress, I control for other characteristics that may potentially drive the results. Control variables used in this study include target, acquirer, and deal and industry characteristics as well as year and industry fixed-effects. Firm- and industry-level proxies for future profitability and growth options are included to account for drops in the economic worth of assets. For the industry level, I add *median industry Q*, defined as the ratio of market value of asset (estimated as book value of total asset - book value of equity + market value of equity) to book value of asset. For the firm level, I include target *profitability* (profit margin: the ratio of operating income before depreciation (*OIBDP*) divided by total sales) and target market-to-book ratio.

[11] Following previous literature (e.g., *Gilson et al.* (1990); *Opler and Titman* (1994); *Acharya et al.* (2007); and *Ang and Mauck* (2011)), I also attempt to use as a measure of industry distress the negative industry median net income of all firms in an industry. Median net income appears to be a poor measure of industry distress, however, because of cross-industry variation in average net income levels. Negative net income for a substantial portion of high-tech industry firms in the public stock market does not necessarily mean that the high-tech industry is distressed.

Other firm characteristics considered in the specification include *size*, defined as the natural log of market value of equity 4 weeks before the announcement, *leverage*, defined as the ratio of debt (current debt plus long-term debt) to book value of assets, and *tangibility*, defined as the PP&E scaled by total book value of assets. *Median industry leverage* is defined as the 3-digit SIC-level median leverage ratio. Major deal characteristics suggested in the previous literature are also considered. Deal specific controls include *same industry*, *tender offer*, *toehold*, *competing*, *poison pill*, and *termination fee*. All variables are defined further in Table 1.1.

1.3.4 Summary Statistics

Table 1.2 presents summary statistics of key variables used in this study. Panel A of Table 1.2 identifies targets' pre-merger characteristics. The mean and median of $Distress1_T$, firm default risk EDF, is 0.111 and 0.001 with standard deviation of 0.227. This variable shows high positive skewness. Of 1572 acquisitions in the sample, 955 targets have lower than 1% EDF at the announcement of acquisition. Panel B presents the acquirers' characteristics. It shows that the acquirers, on average, have lower default risk than targets while having larger size, higher q, and higher profit margin.

Table 1.3 reports the major deal characteristics of the acquisition sample. The mean (median) premium based on targets' four weeks before the announcement is 50% (38%). The relative size between target and acquirer is, on average, 0.84. Tender offers account for 25% of total acquisitions, and acquirers hold, on average, 3% of a target's shares before acquisition. Acquirers are less likely to use cash for payment, in the distressed target acquisition sample. Lastly, 54% of acquisitions occur in the same industry.

1.4 Fire-Sale Effects on Acquisition Outcomes

I employ multiple empirical approaches to examine fire-sale effects from a target's firm- and industry-level distress and identify a channel for the effects. First, I estimate the combined effect of target firm- and industry-level distress on acquirers' abnormal returns. Under the null hypothesis, acquirers' return should be unaffected by target firm- and industry-level distress. I assess whether distressed targets in a distressed industry are sold at discounts by comparing acquirers' abnormal returns between fire-sale acquisitions and other acquisitions. Second, I estimate the fire-sale effects on offer price after controlling for industry-median Q, firm Q and the firm profitability measure. These firm- and industry-level growth option and profitability measures control for the decline in the economic worth of target assets by capturing future growth prospects of the assets. Then, I examine whether fire-sale affects synergy or target bargaining power by decomposing the offer price and analyzing each component separately. Fourth, I test whether target firm- and industry-level distress affect buyer's identity and whether they drive stronger fire-sale effects if acquirers are outside the industry. Finally, to demonstrate that the findings are driven by the fire-sale channel, I estimate cross-sectional regressions using industry asset-specificity in three dimensions: capital-specificity, labor union, and R&D intensity. This empirical design enables me to disentangle the fire-sale effects from the decline in economic worth and identify the channel of the fire-sale effects.

1.4.1 Acquirer Return in Fire-Sale Acquisitions

The first test relates the fire-sale effect to acquirers' return. To provide support for the proposed fire-sale channel in which firm- and industry-wide distress combine to force the sale of a target at a discount, I compare acquirers' abnormal return between fire-sale targets and distressed targets in a non-distressed industry. Following *Shleifer and Vishny* (1992), I define fire-sale acquisitions as when both target industry and target are distressed at the time of the deal announcement. The interaction term of target distress ($Distress_T$) and target industry distress ($Ind.Distress_T$) is termed *Fire-Sale*.

As shown in Figure 1.3, I begin by plotting the evolution of the cumulative abnormal returns of acquirers from 20 days before to 200 days after announcement of the acquisition. Abnormal returns are calculated as the acquirer's return minus a value-weighted market index. The figure shows that cumulative abnormal returns of acquirers in fire-sale acquisitions lie well above other acquisitions throughout the 200 days following the acquisition announcements. The graph implies that acquirers of distressed targets in distressed industries earn higher abnormal returns compared to other acquirers, which suggests that targets in distressed industries are sold at a discount.

I next compare the short-term announcement return of acquirers over the target's firm- and industry-level distress. The short-term return is estimated as the acquirer's three-day cumulative abnormal return (CAR) at announcement of the acquisition, using the standard method of *Bradley et al.* (1988).[12] Figure 1.4 plots the effect of industry-wide distress on acquirer's three-day cumulative abnormal returns (CARs)

[12] I use the Fama-French three-factor model with 240 daily returns covering (-300, -60) to estimate parameters for each acquirer.

over target firm distress measure, $Distress1_T$ (EDF). The dots represent the CARs for acquirers of targets in distressed industries, and the pluses are for non-distressed industries. The black solid line and navy dashed line show the fitted values of observations in distressed industries and non-distressed industries, respectively. Figure 1.4 shows that acquirers of targets in distressed industries earn positive CARs and outperform acquirers of targets in non-distressed industries as targets experience severe firm distress.[13] Panel A of Table 1.4 compares short-term announcement return of acquirers over the target's firm- and industry-level distress. It shows that acquirers' returns are significantly negative, on average, whereas acquirers in fire-sale acquisitions earn insignificant negative returns.

I also estimate acquirers' buy-and-hold abnormal returns (BHAR), which is a commonly used measure of long-term abnormal performance[14], of fire-sale acquisitions and those of other acquisitions. I use a two-year window for the long-term performance analysis to reduce potential noise from overlapping events that can influence performance.[15] I define BHAR as follows.

$$\mathrm{BHAR}_{i,t} = \prod_{j=1}^{T_i}(1 + r_{i,t+j}) - \prod_{j=1}^{T_i}(1 + r_{\text{Matched firm}_{t+j}})$$

where $r_{i,t}$ denotes the return to stock i over month t and T_i is the holding period for stock i.[16]

Matched firms are selected based on the following procedures. 1) Select all CRSP-listed companies at the year of the acquisition. 2) Select the subset of firms with total book asset values within ±30% of the total book asset values of the acquiring firm. 3) Rank the subset based on market-to-book ratio. 4) Choose the firm with the closest market-to-book ratio. 5) Matched firms are included for the full two-year holding period. Panel B of Table 1.4 shows that acquirers of distressed targets in a distressed industry earn positive BHARs. The abnormal returns of acquirers in fire-sale acquisitions are substantially higher than the returns of acquirers of distressed targets in non-distressed industries in the same two-year window. The difference between acquirer returns are statistically significant at the 5% level.

[13] It is also important note that the confidence interval becomes larger for targets in distressed industries.

[14] *Barber and Lyon* (1997), *Kothari and Warner* (1997), and *Lyon et al.* (1999).

[15] I estimate these results based on the 3- and 5-year window following the announcement date and find robust results.

[16] The potential bias of the BHAR measure, albeit well recognized, may not qualitatively affect the results because I concentrate on differences in performance in fire-sale and other acquisitions.

Because the previous analysis does not control for other variables that might be driving the differences in acquirer returns, I also examine the fire-sale effects on acquirers' short-term and long-term returns using a multivariate analysis. *Hypothesis 1* predicts a strong positive coefficient on the interaction term of target's firm- and industry-level distress for the following specification:

$$CAR^A_{ijdt} = \beta_1(\underbrace{Ind.D_{it} \times Distress_{it}}_{Fire\text{-}Sale}) + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma' X_{ijd} + \alpha_t + \alpha_i + \varepsilon_{ijdt}$$

$$BHAR^A_{ijdt} = \beta_1(\underbrace{Ind.D_{it} \times Distress_{it}}_{Fire\text{-}Sale}) + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma' X_{ijd} + \alpha_t + \alpha_i + \varepsilon_{ijdt}$$

where CAR^A_{ijdt} is the acquirer's three-day cumulative abnormal return (CAR) at announcement of acquisitions, estimated using a market model. $BHAR^A_{ijdt}$ is an acquirer buy-and-hold return during two years following acquisition announcement less a buy-and-hold return of the matched firm, $Distress_{it}$ and $Ind.D_{it}$ are the target firm and industry distress measures, respectively, of target i, and X_{ijd} represents control variables for target i, acquirer j, and deal characteristics d. Year fixed effect (α_t) and industry fixed effect (α_i) are also included. Control variables are as follows.

$$X_{ijd} = \begin{cases} \text{Target \& Acquirer Char.: Size, M/B, Leverage, Profitability, Tangibility} \\ \text{Deal Char.: Same industry, Tender offer, Toehold, Competing, Term. Fee} \\ \text{Industry Char.: Med. industry Q, Med. industry Leverage} \end{cases}$$

The variable of interest is *Fire-Sale*, the interaction between target firm- and industry-level distress. *Fire-Sale*$_1$ is the interaction between the continuous measure of target distress based on the distance-to-default model, $Distress1_T$ and $Ind.Distress_T$. *Fire-Sale*$_2$ is the interaction between the dummy measure, $Distress2_T$ and $Ind.Distress_T$. *Hypothesis 1* predicts all of these interaction effects to be positive.

Columns (1) and (2) in Table 1.5 present the results of examining the fire-sale effects on acquirers' cumulative abnormal returns at announcement (-1, +1). It shows that acquirers earn economically and statistically higher returns in fire-sale acquisitions. The economic magnitude of this effect is 2.5 percentage points based on the coefficient of *Fire-Sale*$_1$ and a one standard deviation increase in $Distress1_T$[17], and 5 percentage points based on the coefficient of *Fire-Sale*$_2$. The coefficients are statistically significant at the 1% level. I also find positive coefficients on the fire-sale

[17] The standard deviation of $Distress1_T$ is 0.23 in Table 1.2. The economic magnitude can be calculated by 0.11*0.23 = 2.5%

effect in Models (3) and (4). In Model (3), the coefficient implies that acquirer buy-and-hold abnormal returns are 23.2 percentage points higher in distressed industries with a one standard deviation increase in $Distress1_T$. This directly supports fire-sale discount in acquisitions because acquirers' return should be unaffected by target firm- and industry-level distress if they pay the fair market value of a target.[18]

1.4.2 Inefficient Sales or Wealth Transfer?

The previous results show that acquirers earn higher returns from fire-sale acquisitions. To provide evidence of a specific source for these higher returns, I estimate the combined effect of firm- and industry-level distress on offer price after controlling for firm- and industry-level investment opportunity measures. Then, I decompose offer price into synergy and target's bargaining power, and quantify the fire-sale effects on the components of division of gains separately.

$$P_i = V_i + \underbrace{S_{ij} * \omega_i^T}_{\text{Division of Gains}}$$

where

$P_i =$	total proceeds(offer price) for target i
$V_i =$	stand-alone value of target i
$S_{ij} =$	synergy from acquisition between target i by acquirer j
$\omega_i^T =$	target i's bargaining power

1.4.2.1 Fire-Sale Discount on Offer Price

To examine the effect of a fire-sale on the offer price a target receives, I employ three different measures of offer price for target shareholders from the SDC database. The first measure $Ln(Price1)$ is the log of total equity value (EQVAL). I use the log transformation for these variables to adjust skewed size distribution. The second measure $Ln(Price2)$ is the log of total transaction value ($TRANSACT$). Transaction value represents the equity value of the target company (i.e., offer price per share * shares outstanding plus cost to acquire convertibles) plus any assumed liabilities that are publicly disclosed.[19] The third measure, $Premium$, is offer price per share

[18] I report, as a robustness check, coefficient estimates from quantile regressions (25th, median, and 75th) on acquirer abnormal returns in Internet Appendix. While the coefficients vary across quantiles, the results show that the relationship between acquirer returns and fire-sale is robust at different points in the conditional distribution of acquirer returns.

[19] The correlation between $Ln(Price1)$ and $Ln(Price2)$ is 0.98.

divided by target stock price four weeks prior to announcement.[20]

Hypothesis 1 predicts a strong negative coefficient on the interaction term of target's firm- and industry-level distress for the following specification:

$$Price_{ijdt} = \beta_1 \underbrace{(Ind.D_{it} \times Distress_{it})}_{Fire\text{-}Sale} + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma^{'} X_{ijd} + \alpha_t + \alpha_i + \varepsilon_{ijdt}$$

where $Distress_i$ and $Ind.D_i$ are the target firm and industry distress measures, respectively, of target i, and X_{ijd} represents control variables for target i, acquirer j, and deal characteristics d. Year fixed effect(α_t) and target industry fixed effect (α_i) are also included. Standard errors are heteroskedasty-consistent and clustered at year-industry.

In Columns (1), (3) and (5) of Table 1.6, the coefficients on *Fire-Sale*$_1$ are negative and statistically significant to all measures of offer price. These results indicate that distressed targets in a distressed industry are acquired at a discount relative to distressed targets in a non-distressed industry. The economic magnitude can be interpreted as 14 percentage points discount relative to distressed targets in non-distressed industries for an increase of one standard-deviation of the default risk, $Distress1_T$.[21] As shown in Columns (2), (4), and (6) of Table 1.6, the results are robust to use of the dummy variable of firm distress, $Distress2_T$ and its interaction term *Fire-Sale*$_2$. In the presence of firm- and industry-level profitability, this significant interaction term in Table 1.6 provides support for the fire-sale effect in *Hypothesis 1*.

1.4.2.2 Synergy and Bargaining Power in Fire-Sale Acquisitions

Measuring the division of total gains on the basis of the abnormal stock return at the announcement date enables me to identify the source of fire-sale discount in the previous results. Synergy is measured in two ways based on *Bradley et al.* (1988). I use (1) combined CAR: market equity value weighted average of target's CAR and acquirer's CAR, and (2) Ln(Synergy): the log of the sum of acquirer's and target's abnormal dollar return ($CAR * MarketCap$). I employ a bargaining outcome measure that uses the difference in abnormal dollar returns between target and acquirer following *Ahern* (2011).[22] Basically, the bargaining outcome is the percentage of a

[20]Although *Premium* is widely used in literature to compare the offer price, this measure is affected by the reference stock price in the denominator, which is particularly confounded by target firm- and industry- distress. Therefore, I focus on the equity value in this paper.

[21]The standard deviation of $Distress1_T$ is 0.23 in Table 1.2. The economic significant can be calculated by Exp((-0.89+0.23)*0.23)-1 = -14%)

[22]Offer premium, which is used by most bargaining-related papers (e.g., *Officer* (2003), and *Subramanian* (2003)) does not necessarily capture a target's relative bargaining outcome because it does not properly consider the acquirer's share of gains.

firm's abnormal gain over total abnormal synergistic gain. One problem with using abnormal return to measure bargaining outcome is that it can be negative for the acquirer. A player with a negative expected bargaining outcome will not participate in the game.[23] I avoid this problem by using the difference in dollar gains between target and acquirer as a proxy for the target's bargaining outcome. Following *Ahern* (2011), I normalize this measure by dividing by the sum of the acquirer's and target's market values four weeks prior to the announcement. The measure of the acquirer's relative bargaining power is,

$$NDCAR_T = \frac{DCAR_{Target} - DCAR_{Acq}}{MV_{Target} + MV_{Acq}}$$

where DCAR: Dollar Cumulative Abnormal Return at the announcement (-1, +1).

I construct, as a robustness check, an alternative measure that calculates the ratio of the target's abnormal dollar return to the combined abnormal dollar return of acquirer and target, and winsorize this ratio by 0 and 1. This measure is more intuitive, but potentially downward biased if negative abnormal returns are frequent for acquirers.

$$Bargain_T = \begin{cases} \dfrac{DCAR_{Target}}{DCAR_{Target} + DCAR_{Acq}} \text{ if } DCAR_{Target} > 0, DCAR_{Acq} > 0 \\ 0 \text{ if } DCAR_{Target} < 0, DCAR_{Acq} > 0 \\ 1 \text{ if } DCAR_{Target} > 0, DCAR_{Acq} < 0 \end{cases}$$

where DCAR: Dollar Cumulative Abnormal Return at the announcement (-1, +1).

I then estimate the effect of firm- and industry-level distress on each component using the following specifications.

$$S_{ijdt} = \beta_1(\underbrace{Ind.D_{it} \times Distress_{it}}_{Fire\text{-}Sale}) + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma' X_{ijd} + \alpha_t + \alpha_i + \varepsilon_{ijdt}$$
$$\omega^T_{ijdt} = \beta_1(\underbrace{Ind.D_{it} \times Distress_{it}}_{Fire\text{-}Sale}) + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma' X_{ijd} + \alpha_t + \alpha_i + \varepsilon_{ijdt}$$

where S_{ijdt} denotes the measure for synergy and ω^T_{ijdt} denotes target's bargaining power. $Distress_i$ and $Ind.D_i$ are the target firm and industry distress measures, respectively, of target i, and X_{ijd} represents control variables for target i, acquirer

[23] Many studies explain the negative acquirer return based on such drivers of mergers as the hubris hypothesis, the market-driven misvaluation hypothesis, swarm behavior, and the market mania hypothesis (*Roll* (1986), *Malmendier and Tate* (2005) , *Malmendier and Tate* (2008), *Shleifer and Vishny* (2003)).

j, and deal characteristics d. Year fixed effect(α_t) and target industry fixed effect (α_i) are also included. Standard errors are heteroskedasty-consistent and clustered at year-industry.

Hypothesis 2-1 predicts lower synergy in fire-sale acquisitions and lower corresponding gain for targets. Columns (1)-(4) in Table 1.7, however, show that both measures of synergy have an insignificant relation with the interaction effects of target firm- and industry-level distress. One interpretation of this result is that fire-sale acquisitions with severe inefficiency are avoided by a conservative ex-ante debt structure or by alternative resolution of distress (*Morellec* (2001), and *Campello and Giambona* (2012)). Alternatively, this result is consistent with current research by *Almeida et al.* (2011) and *Erel et al.* (2013), that highlights the importance of financial synergy.

The results in Models (5)-(8) in Table 1.7, on the other hand, show that target firm- and industry-level distress has a negative and significant impact on a target's bargaining outcome. Models (5) and (6) present coefficient estimates on $NDCAR(\omega_T)$. The coefficient of the interaction effect is economically large and statistically significant, and the effect is robust to both measures of target distress. This result implies that distressed targets in a distressed industry receive a substantially lower portion of total gains relative to other targets in the sample. The economic magnitudes are \$40 million further transfer to acquirer for a one standard deviation increase in a target's default probability in a distressed industry or 5% * \$1.8 billion = \$90 million further transfer to acquirer based on *Fire-Sale*$_2$. Consistent with this result, the regression estimates in Models (7) and (8) indicate that targets have 10-20 percentage points lower bargaining share of total synergy gain in fire-sale acquisitions.

In sum, these results provide support for the bargaining channel of the fire-sale effects proposed in *Hypothesis 2-2*, which states that distressed targets in a distressed industry are acquired at discounts due to targets' weakened bargaining power.

1.4.3 Acquirer Identity in Fire-Sale Acquisitions

1.4.3.1 Effect of Industry-wide Distress on Acquirer Identity

Thus far, the results suggest that financial constraints of targets and their peer firms drives a price discount. To provide further evidence of fire-sale effects, I explore the effects of target firm- and industry-level distress on acquirers' identity, whether they are inside or outside the target's industry. The null hypothesis is that acquirer identity is unaffected by target firm- and industry-level distress. Alternatively, the main hypothesis of this paper is that targets are likely to sell to industry outsiders when their peer firms are financially constrained, as in *Hypothesis 3*. To test this hypothesis, I compare the probability of being acquired by industry outsiders over target firm- and industry-level distress using the following probit model to estimate probability.

$$Prob.(Outsider_{ijdt}) = \beta_1(\underbrace{Ind.D_{it} \times Distress_{it}}_{Fire\text{-}Sale}) + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma^{'} X_{ijd} + \alpha_t + \alpha_i + \varepsilon_{ijdt}$$

where $Outsider_{ijdt}$ is the dummy equals 1 if acquirer j, has a different 3-digit SIC code from target i., $Distress_i$ and $Ind.D_i$ are the firm and industry distress measures, respectively, of target i, and X_{ijd} represents control variables for target i, acquirer j, and deal characteristics d. Year fixed effect and industry fixed effect are also included.

Table 1.8 presents estimates of the probability that targets are sold to industry outsiders. Acquirer and deal characteristics are excluded in Models (1) and (3) to control for potential endogeneity.[24] I find large and significant coefficients for the industry distress measure in all Models (1)-(4). The coefficient on industry distress captures the difference in probability of being acquired by industry outsiders. The result, evaluated at the means of independent variables, indicates that targets in a distressed industry are more likely to sell to outside buyers by 20 percentage points compared with targets in a non-distressed industry. The stand-alone variable of target distress and the interaction term of target firm- and industry-level distress have insignificant coefficients. The results imply that when the target industry is distressed, peer firms in the same industry are not capable of buying the target.

1.4.3.2 Fire-Sale Acquisitions with Outsider

I next examine the triple-interaction effect of target firm distress, industry distress, and outside acquirer dummy. *Hypothesis 3* suggests that the effects on fire-sale targets should be stronger if the targets are sold to acquirers outside a target's industry.

Table 1.9 presents the estimates from regressions that explain the main acquisition outcomes using the interaction variable of fire-sale and acquirer's industry identity.[25] I find that the interaction effects of target firm- and industry-level distress on acquirer returns, offer price, and target's bargaining power are stronger when acquirers are from different industries. The triple-interaction effects are economically large and statistically significant. The results in Table 1.9 indicate that, if the acquirer is an industry outsider, a one standard deviation increase in the target's default probability during industry distress increases the acquirers' return by 4.6 percentage points, and decreases the offer price by 47.5% and the target's bargaining power by 5.8%.

[24] Acquirer and deal characteristics are determined simultaneously with acquirer identity.

[25] In this analysis, I report the results with *Fire-Sale*$_1$ due to the small sample size with *Fire-Sale*$_2$.

Crucially, I also find that the coefficient of triple interaction term on synergy becomes negative and statistically significant, which indicates that a deadweight cost incurred from inefficient fire-sales conditional on industry outside acquirers.

It is also important to note that the interaction term of target firm- and industry-level distress, *Fire Sale*$_1$ becomes insignificant in Models (1)-(3) when the triple interaction effect with industry outsider is included. This suggests that the results in the previous section is largely driven by fire-sale acquisitions with industry outsiders. This result supports *Hypothesis 3*, or the fire-sale channel suggested by the Shleifer and Vishny model.

1.4.4 Fire-Sale Effects with Specialized Assets

When assets are highly industry specific, inefficiency from demand-side constraints becomes more severe as industry outsiders are not able to utilize the assets to their best-use. The resulting prediction is that distressed targets in an industry with high asset specificity may be sold at a deeper discount in an illiquid market. I test this prediction with three main input factors —capital, labor, and technology— of production function.

1.4.4.1 Fire-Sale Effects and Capital-Specificity

I construct the proxy for industry (physical) capital-specificity using the Census-based industry-level measure provided by *Balasubramanian and Sivadasan* (2009). They calculate the ratio of firms' used capital expenditures to the aggregate industry capital expenditure, which captures capital re-salability or capital liquidity within an industry.[26] Their index is based on the U.S. Census Bureau dataset for manufacturing sectors for the years 1987 and 1992. Following the approach of *Almeida et al.* (2011), I create a time-invariant measure of industry-level capital-specificity by one minus the median value of this index for an industry within the 3-digit SIC code over the Census survey of 1987 and 1992.

Alternatively, I measure industry capital-specificity based on industry's property, plant, and equipment (PP&E) scaled by the book value of total assets. This measure, however, proxies for overall tangibility of the industry instead of industry capital-specificity because property, including real estate, is highly redeployable. I also attempt to use a further alternative measure that uses an industry's machinery and equipment (PPENME) scaled by the book value of total assets obtained from COM-

[26]This proxy is also used as a measure of capital salability within an industry by *Almeida and Campello* (2007) and *Almeida et al.* (2011).

PUSTAT. However, this analysis lacks statistical power because this value has been absent from COMPUSTAT since 1997. In untabulated results, I find statistically insignificant coefficients in related regression tests using these capital-specificity measures.

Table 1.10 presents estimates of target firm- and industry-level distress on the main dependent variables over industry capital-specificity. I examine the triple-interaction effect of target firm distress, industry distress, and industry capital-specificity measure on acquisition outcomes.[27] The dependent variables are acquirer's abnormal return (CAR_A), offer price ($Ln(Price1)$), target's bargaining power ($NDCAR(\omega^T)$) and synergy ($CAR_{combined}$).

I find that the fire-sale effects on acquirer's abnormal return, offer price, target's bargaining power, and synergy are economically large and statistically significant when industry-level capital-specificity is high. The magnitude of fire-sale effects, moreover, becomes greater than the regression results in the previous results.

With a one standard deviation increase in target industry-level capital specificity(0.03), the acquirer abnormal returns further increase by 1.3 percentage point, offer price decreases by 23.6%, and $NDCAR_T$ decreases by 1.9%. Particularly, in Model (4), the synergy, measured by combined abnormal returns at the announcement, decreases by around 2.0 percentage point.

These results indicate that the main results in the previous section are driven by asset illiquidity consistent with the proposed *Hypothesis 4* and thus provide strong evidence for the fire-sale channel.

1.4.4.2 Fire-Sale Effects and Target Labor Union

I further investigate the impact of target labor unions on the fire-sale effects. Labor unions play a significant role in protecting workers' rights through collective bargaining. Strong labor unions could increase restructuring costs by influencing layoff costs or severance payments and blocking restructurings and plant closings (*McLaughlin and Fraser* (1984)). Especially high costs may be incurred during industry downturns, when acquirers may need to restructure firms intensively. Therefore, industries with strong labor unions may thus experience less demand in acquisition markets during industry downturns. A strong labor union could also influence a distressed firm to sell all of its assets with a guarantee of labor continuation, thereby reducing the acquisition price and transferring wealth from the distressed target's

[27] The stand-alone variable for *Capital-Specificity* is omitted in the regression specification because *Capital-Specificity* is a time-invariant industry-level measure which is captured by the industry fixed effect.

shareholders to its workers. This hypothesis predicts that if a target industry has a strong labor union, then the fire-sale effects should be stronger because strong labor union increases restructuring costs and thus makes the distressed target less redeloyable.

Alternatively, a strong labor union can resist acquisitions, in particular, hostile takeovers, by refusing to tender workers' shares or voting against acquisitions (*Pagano and Volpin* (2005), and *Kim and Ouimet* (2013)). This will lower the probability of receiving a takeover bid, but increase the offer price. It is also possible for strong labor unions to make concessions to and create more synergy gain for acquirers by giving up their rents. This competing hypothesis predicts that the fire-sale effects are likely to be mitigated in industries with strong labor unions.

Therefore, it is empirical question to examine whether strong labor unions in target industries promote the fire-sale effects or not. I perform a subsample analysis using regressions with the same specifications as in main regressions, but dividing the total sample into strong labor union industries and weak labor union industries.

I employ a labor unionization measure that records the percentage of unionized workers in each 3-digit SIC industry from 1980-2010. The Union Membership and Coverage Database constructed by Barry Hirsch and David Macpherson compiles industry-level unionization data from the Current Population Survey (CPS) of the Bureau of Labor Statistics.[28] The database provides two unionization measures, (1) the percentage of labor union membership, and (2) the percentage of workers covered by a collective bargaining agreement.[29] CPS classifies industries based on firms' primary Census Industry Classification (CIC) codes. In the present study, I match each CIC industry to a 3-digit SIC industry by comparing the industry specification. Table 1.2 reports the descriptive statistics for the first labor union variable. I create a dummy variable for strong labor union industry that equals one if the labor union measure is above the median value of total sample.

The results in Table 1.11 show that the fire-sale effects combined with strong labor unions result in further increases in returns for acquirers, a deeper discount in offer prices, and weaker bargaining outcomes for targets. Comparing each column between Panels A and B, I find that the coefficients on fire-sale variable are economically larger and statistically more significant when the target industry has a strong labor union. These results suggest that strong labor unions promote the fire-sale effects by

[28] At www.unionstat.com, *Hirsch and Macpherson* (2002)

[29] I mainly employ the first measure. The correlation between two unionization measures is 0.99. The results are robust with the second measure.

generating further demand-side frictions.

1.4.4.3 Fire-Sale Effects and R&D Intensity

I next explore how asset-specificity in technology (intangible assets) affects fire-sale effects in distressed target acquisitions in a distressed industry. Technology-intensive industries play particularly important roles in acquisition markets. Previous literature documents that productive opportunity is a main motivation of acquisitions (e.g., *Higgins and Rodriguez* (2006), and *Levine* (2011)). However, there is little evidence on how variation in an industry's technology intensity affects acquisition outcomes across different industry-specific financial conditions.

Aboody and Lev (2000) suggests that R&D may increase firm- and industry-level information asymmetry for the following three reasons. First, contrary to capital or labor, R&D is more likely to be specific to a firm and its industry, so, across industries, firms have difficulty in sharing knowledge on their technologies and undergoing R&Ds. Second, relatively less organized markets for technology assets lead outsiders not to infer the precise value of the assets from market prices. Third, the current accounting rule does not require to report value and productivity changes of R&D after being expensed. Building on this argument, I develop a hypothesis that technology- or knowledge-based assets are likely to be less redeployable to industry outsiders, particularly during an illiquid market, therefore, strengthening fire-sale effects in acquisitions. Higher information asymmetry embedded in technology-intensive industry drives more frictions in asset allocation across industries because industry outsiders have more difficulty in valuing and operating the assets.

I examine this hypothesis by estimating the combined effect of target firm- and industry-level distress on acquisition outcomes with different R&D intensities. I measure R&D intensity based on research and development expenses divided by total sales. This variable is set to zero if total assets are reported for a firm in the same year but no record is reported for R&D expenses. I separate the total sample into high and low R&D industry subsamples. An observation is considered to be high (low) R&D industry if its industry-level R&D intensity is below (above) the median value of total sample. Subsample analysis with separate estimation enables coefficients of the control variables and fixed effects to vary across high and low R&D regimes.

In Table 1.12, results for the subsamples are reported in Panels A and B. Each panel presents the fire-sale effects on acquirer's abnormal returns (CAR_A), offer price ($Ln(Price1)$), target's bargaining power ($NDCAR(\omega^T)$) and synergy ($CAR_{combined}$). Comparing each column between the two Panels A and B of Table 1.12, I find that the fire-sale effects on acquirer's abnormal return, offer price, and target's bargaining power are economically large and statistically significant only in high R&D industries. In Panel A, these coefficients are sharper than those for the full sample. In contrast, in Panel B, they reveal no relation when R&D intensity is low. This is robust in both target firm distress measures. These results further support *Hypothesis 4* that price discounts in distressed target acquisitions in a distressed industry are driven by the fire-sale channel rather than the decline in economic worth of target assets.

1.4.5 Alternative Explanations

1.4.5.1 Stock Market Undervaluation in Fire-Sale Acquisitions

A potential concern with the previous results is that the fire-sale discount and related acquisition outcomes could be driven by stock market undervaluation. Many studies in the M&A literature show that stock market misvaluation drives acquisition activity and outcomes (*Shleifer and Vishny* (2003), *Rhodes-Kropf and Viswanathan* (2004), and *Rhodes-Kropf et al.* (2005)). If either firm- or industry-level distress causes systematic undervaluation of targets, it would be possible for informed acquirers to purchase undervalued targets at prices below their fundamental values.

As a robustness check, I re-estimate the fire-sale effects in the main regressions using the same explanatory variables and including measures for target firm- and industry-level undervaluation. Following *Rhodes-Kropf et al.* (2005), I measure target undervaluation by decomposing the market-to-book ratio of firms with the same 3-digit SIC code into three components: firm-specific error; industry-wide, short-run error; and long-run growth option. Details of this estimation are provided in Appendix A. Table 1.13 presents the descriptive statistics for the robustness checks. Panel A shows that the book-to-value ratio is lower for distressed than for non-distressed targets. Moreover, distressed targets are undervalued, on average, by 2% at the firm level.[30] Sector errors are -6% in all samples.

The regression results in Table 1.14 show that target misvaluation has significant effects on all dependent variables except target's bargaining power. Model (1) indicate that a negatively misvalued target receives a significantly lower offer price, and Model (2) show that the target undervaluation results in higher returns for acquirers. In Model (4), I also find that the negative misvaluation of a target can increase combined abnormal returns in acquisitions, which implies that target undervaluation is a source of additional synergy gain. The target industry misvaluation measures are insignificant in all specifications. The results support that fire-sale targets are priced

[30] A negative number of misvaluation implies that targets are undervalued.

below their fundamental values and it influences acquisition outcomes significantly. However, the fire-sale variable, the interaction of target firm- and industry-level distress, remains significant and consistent with the main results, even in the presence of the target misvaluation measure. The results thus show that the fire-sale channel is essential to explaining the outcomes of distressed target acquisition.

1.4.5.2 Fire-Sale Acquisitions in Recession

While the present study measures industry-specific distress and estimates the fire-sale effects on acquisition outcomes, *Ang and Mauck* (2011) investigated the effect of economy-wide recession on acquisitions and argued that recession drives a higher offer premium for distressed targets because acquirers assume the targets to be largely depressed during recession. In this section, I control for the recession dummy variable and examine the effect of target firm- and industry-level distress on key variables. Recessions are defined in terms of recessionary months identified by NBER, as in *Ang and Mauck* (2011).

Table 1.15 presents coefficient estimates from an OLS regression that uses the same explanatory variables as in the paper's main regressions, but includes the recession dummy variable. The results in Table 1.15 show that the recession dummy has a negative effect on acquirer's return. Target bargaining power is also positively related with the recession dummy. In all specifications, however, coefficients on the main explanatory variable, the interaction effect of target distress and target industry distress, are robust and consistent with the main regressions in the previous sections. This result provides evidence that industry-specific rather than economy-wide distress accounts for the fire-sale effects in distressed target acquisitions.

1.5 Intra-Industry Contagion of Fire-Sales

In this section, I examine the contagion effects of fire-sale acquisitions on target rivals in the same industry by exploring rivals' operating performance and abnormal stock returns following the announcement of a target's fire-sale acquisition. The *negative information hypothesis* predicts negative stock returns, but makes no particular prediction with respect to post-acquisition operating performance. However, the *intense competition hypothesis* predicts negative stock returns following negative operating performance whereas *market power hypothesis* implies positive stock returns following positive operating performance in the post-acquisition period. This mutually exclusive set of competing hypotheses enables me to identify a valid hypothesis by investigating post-acquisition stock returns and comparing operating performance, of rivals in the pre- and post-acquisition period.

1.5.1 Abnormal Stock Returns of Industry Rivals

I first estimate the impact of fire-sale on industry rivals' stock returns at the announcement of a fire-sale acquisition. To minimize other confounded effects in the broad industry classification, I focus on target industry rivals in the same 4-digit SIC code. I compare abnormal stock returns for industry rivals that share similar characteristics with the target. Matched industry rivals are selected based on size and market-to-book ratio. Among the subset of same industry rivals that have total book asset values within ±30% of the total book asset values of the target firm, I choose a rival with the closest market-to-book ratio to that of the target. Rival's cumulative abnormal return (CAR) at the announcement (-1, +1) of the acquisition of an industry target is estimated using the Fama-French three-factor model. I use 240 daily returns covering (-300, -60) to estimate parameters for each rival firm.[31]

Panel A in Table 1.16 presents abnormal stock returns for industry rivals at the announcement of acquisitions. The results show distressed target acquisitions in a distressed industry to have a significant impact on rivals' stock prices. Although their CARs in the total sample are positive, rivals, in response to fire-sale acquisitions, earn -0.9% abnormal returns, on average, at the 5% significance level (t-stat = -2.12). Figure 1.5 plots the equal-weighted average of short-term cumulative abnormal returns of matched target rivals from 10 days before to 50 days after the announcement of acquisitions. It also shows that matched target rivals of fire-sale acquisitions experience negative short-term returns relative to other rivals.

Previous results do not control for variables that could be driving the differences. I, therefore, turn to regression analysis and control for such factors including product market variables. I estimate the fire-sale effects on target industry rivals using the following specifications.

$$R^T_{ijdkt} = \beta_1(\underbrace{Ind.D_{it} \times Distress_{it}}_{\text{Fire-Sale}}) + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma' X_{ijdk} + \alpha_t + \alpha_i + \varepsilon_{ijdkt}$$

where R^T_{ijdkt} is the CAR for a matched industry rival of targets with same 4-digit SIC over the three-day period (-1, +1) surrounding the announcement of acquisition, X_{ijdk} represents control variables for target i, acquirer j, rival k, and deal characteristics d.

The coefficient estimates from the OLS regression in Table 1.17 show that the

[31]The results are robust after excluding the cases of multiple acquisitions occurring during the estimation period.

interaction effect of a target's firm- and industry-level distress negatively affects the stock returns of industry rivals. The coefficient is large and significant. The economic magnitude of the coefficient can be interpreted as 1-4 percentage points. These results support both the *negative information hypothesis* and *intense competition hypothesis*. Negative stock returns, however, do not allow me to determine whether the negative contagion effects are related to the negative information or acquiring firms' competitive advantage.

In the second matched sample test, I conduct subsample analysis with high and low industry-level R&D intensity. The previous section shows that high R&D intensity drives stronger fire-sale effects by creating greater information asymmetry between industry insiders and outsiders. If negative stock returns of target industry rivals are not driven by fire-sale effects, then there should be no difference between the stock market reactions of high and low R&D industries in this sub-sample. On the other hand, if high information asymmetry in high R&D industries reinforces negative information effects, then I should find greater impact for target industry rivals in high R&D industries. I show that the effects of a fire-sale acquisition on target industry rivals are stronger in high R&D industries. This evidence, therefore, supports the *negative information hypothesis*. Models (3)-(6) in Table 1.17 reports the subsample results. They reveal a significant relation when industry-level R&D intensity is high, but an insignificant relation when industry-level R&D intensity is low. The estimates in Models (3)-(4) show -1.4% rivals' abnormal return for a one standard deviation increase in $Distress1_T$, or -5.97% decrease by $Distress2_T$ when the target industry is distressed. These negative coefficients are economically larger and statistically more significant than those of the full matched rival sample.

1.5.2 Operating Performance of Industry Rivals

I next examine matched industry rivals' operating performance by comparing ROA and profitability margin (operating cash flow/total sales) pre and post acquisition, as presented in Panels B and C in Table 1.16. I find that matched industry rivals' ROA decrease by 0.007 in the total sample of acquisition, but increase in the sample of fire-sale acquisitions by 0.026. In Panel C of Table 1.16, profitability margin exhibits a slight negative change post acquisition. Figure 1.6 presents the operating performance (ROA and profit margin) of matched target rivals from t-3 years to t+3 years. The figure shows that matched rivals of fire-sale targets experience an insignificant decrease in operating performance during the post-acquisition period.

I next estimate the impact of acquisitions on industry rivals' operating performance using the following specifications.

$$\text{ROA-Diff}^T = \beta_1(\underbrace{Ind.D_{it} \times Distress_{it}}_{\textit{Fire-Sale}}) + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma^{'} X_{ijdk} + \alpha_t + \alpha_i + \varepsilon_{ijdkt}$$

$$\text{Profit-Diff}^T = \beta_1(\underbrace{Ind.D_{it} \times Distress_{it}}_{\textit{Fire-Sale}}) + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma^{'} X_{ijdk} + \alpha_t + \alpha_i + \varepsilon_{ijdkt}$$

where ROA-Diff$^T_{ijkdt}$ is the difference of return on asset for industry rivals between the average post-acquisition period (+3, +1) year and the average pre-acquisition period (-3, -1) year, and X_{ijkd} represents control variables for target i, acquirer j, rival k, and deal characteristics d. The error terms are clustered by target, industry and year. Profit-Diff$^T_{ijkdt}$ is the difference in profitability margin (operating cash flow/total sales) for industry rivals between the average post-acquisition period (+3, +1) year and the average pre-acquisition period (-3, -1) year. The coefficient estimates from the OLS regression in Table 1.18 indicate that the interaction of a target's firm- and industry-level distress has an insignificant effect on the post-acquisition operating performance of industry rivals.

Taken together, industry rivals' negative abnormal stock returns unaccompanied by diminished operating performance at announcements of acquisitions support *Hypothesis 5-1*, which states that negative information from fire-sale acquisitions causes a negative contagion effect for industry rivals of fire-sale targets.

1.6 Conclusion

Do fire-sales exist in acquisitions? If they do, how do fire-sale acquisitions affect target industry competitors? This paper addresses these two important questions by inferring the effect of the frictions involved in fire-sale acquisitions from an examination of the combined impact of firm- and industry-level distress on acquisition outcomes.

The main finding in this paper is that a target's firm- and industry-level distress is a robust and economically important determinant of acquisition outcomes. In particular, the evidence suggests that distressed targets with financially constrained industry peers are sold at substantial discounts, as proposed by *Shleifer and Vishny* (1992). Acquirers gain positive and higher announcement returns in fire-sale acquisitions and fire-sale targets are more likely to sell to outside acquirers. I demonstrate the fire-sale effects in acquisitions by showing that these findings are stronger when fire-sale targets are sold to industry outsiders or when targets' assets are highly industry-specific. The results are robust to stock market undervaluation and economic recession. I also find that fire-sale acquisitions negatively affect target industry rivals' stock returns by sending negative information without fundamental changes in product market competition.

Overall, this study shows that financial distress costs in an illiquid market are substantial, particularly, when the assets are less redeployable. It highlights implications for debt capacity and capital structure as well as the contagion channel through which economic shocks can transmit. The results suggest that information friction creates inefficiency in asset reallocation, which potentially slows recovery from recession. Direct government involvement through bailout being likely to create moral hazard problem, government policy should instead encourage intensive corporate filing and information sharing between banks as ways to improve selective screening and increase the efficiency of asset reallocation during downturns.

CHAPTER II

Recourse Mortgage Law and the Housing Bubble

2.1 Introduction

[1]A bubble is defined as a mispricing of assets, associated with dramatic price increases, that is not explained by fundamentals (*Brunnermeier* (2008)). Bubbles burst at some point and trigger collapses in asset prices that potentially spread to the banking system and the real economy. Understanding and identifying the mechanisms that create bubbles in the housing market are thus central challenges that both financial economists and policymakers are facing. This paper builds on the previous literature by showing that mortgage law plays an important role in the housing market. In particular, the paper sheds light on the effects of recourse mortgage law on housing price bubbles and mortgage lending by taking into account the growth of the mortgage securitization market.

U.S. mortgage law varies from state to state. Among many provisions included in mortgage law, recourse law governs lenders' right of deficiency judgment when borrowers default on mortgage loan payments.[2] Borrowers in recourse states have full liability for their mortgage loans because lenders, in the event that foreclosure value is insufficient to meet the debt obligation, are able to claim other assets. Lenders in non-recourse states are precluded from doing this and so bear some costs. This limited liability gives rise to the classic asset substitution problem in *Allen and Gale* (2000a), whereby borrowers increase risky investments to the point of creating a bubble by bidding up prices above fundamental values.

The primary goal of this paper is to analyze whether recourse law results in different magnitudes of housing price movement, with particular attention to identifying bubbles. This question is important because the debate over recourse law has

[1]This essay represents joint work with Tongyob Nam (tynam@umich.edu) of the University of Michigan.

[2]Figure 2.1 presents 11 states with non-recourse mortgage law.

become increasingly controversial between scholars and policymakers (*Pavlov and Wachter* (2004, 2006), *Ghent and Kudlyak* (2011), and *Solomon and Minnes* (2011)) and required extensive economic analysis to support housing system reform in many countries.[3] This paper focuses on a by-product of non-recourse law, namely, the social cost incurred as a consequence of households exploiting it by shirking their contractual mortgage obligations. Our key hypothesis is that non-recourse law amplifies the housing price cycle by encouraging risk-shifting behaviors. Mortgage borrowers in non-recourse states, because they can walk away when house values fall below remaining mortgage amount (i.e., are "underwater"), have speculative motives to increase their leverage and allocate more capital to risky assets in the housing market, in the expectation of high housing appreciation in the future. If the non-recourse law causes a larger increase beyond fundamentals during a period of economic expansion, then during a crisis housing prices in non-recourse states are likely to experience a larger drop than in recourse states.

If this households' investment incentive is well predicted, however, mortgage lenders may behave differently. The excessive risk-taking behavior in non-recourse states can be prevented if mortgage loans are properly priced. More specifically, lenders can control the risk of borrower's default by means of low loan-to-value ratios, high interest rates, and strict screening processes. Used appropriately, these tools can forestall borrowers shifting risk and bidding up prices above their fundamental values. This raises empirical questions regarding whether lenders are aware of additional risk in non-recourse states and what the net effects of recourse law on housing prices and bubble creation are.

We also consider how the excessive lending from the banks' participation in the originate-to-distribute (OTD) market interacts with non-recourse law during the housing boom period of the early 2000s. We conjecture that the emergence of the OTD model, together with credit expansion, enables lenders to effectively pass along the risks and reduces the screening incentive ex-ante (i.e., *Keys et al.* (2010) and *Purnanandam* (2011)), thereby promotes a disproportionately large increase in poor quality loan originations in non-recourse states and amplifies housing price cycle. This two-stage risk-shifting hypothesis (from non-recourse households to lenders and from lenders to the securitization market) predicts that more sub-prime mortgage loans are originated in non-recourse than in recourse states and non-recourse states with more sub-prime mortgage loans experience larger housing bubbles. We attempt to

[3] "Full Recourse Loans Won't Save Canada's Housing Market", 2013, http://www.cnbc.com/id/100736121

demonstrate the channel of the housing bubble using this cross-sectional variation in risk-shifting intensity.

To test these arguments, first, we empirically examine the effect of recourse law on housing prices using a difference-in-difference framework that focuses on counties that were disproportionately affected by the mortgage market collapse in 2007. To show a causal relation, we use a contiguous border county-pair sample. This identification strategy allows us to estimate the effect of recourse law on housing bubbles by controlling for fundamental asset value and unobserved spatial heterogeneity. Using ZIP code-level housing prices from Zillow Real Estate Research between 1998 and 2012, we find evidence that housing prices in non-recourse states increase more during housing market booms and drop more steeply during housing market recessions. The economic impact of recourse law is large. Prior to the crisis, recourse states experienced 9% annual growth and the crisis reduced the housing price growth rate by 3%. But states with non-recourse law experienced 13% growth, and the corresponding drop in housing prices was 6%. Such differences in growth rates provide evidence of the impact of recourse law. Controlling for the distance from state borders using ZIP codes, we also find that housing prices during the pre-crisis period increase abruptly upon crossing from recourse states into non-recourse states whereas during the crisis prices decrease abruptly.

We then identify the sources of larger housing bubbles in non-recourse states by examining household asset allocation and leverage decisions (intensive margin). During the housing market expansion, we find that the average ratio of home equity value to total household wealth is higher in non-recourse states by 7 percentage points. In addition, mortgage borrowers in non-recourse states have higher debt-to-income ratios by 1.74 percentage points. This higher leverage and greater asset allocation is evidence that speculative motives of households in non-recourse states drive higher housing price growth during economic expansion.

Having established the impact of recourse law on housing prices, we examine its effect on mortgage lending behavior. For this analysis, we obtain single-family loan-level origination data from two major Federal Home Loan Mortgage Corporations, Freddie Mac and Fannie Mae, at the 3-digit ZIP code-level and employ a state-border discontinuity design with the contiguous border county-pair sample. We also test the denial rate for loan applications from the Home Mortgage Disclosure Act (HMDA) to determine whether lenders' screening intensity varies. We find evidence that LTV ratio is lower whereas mortgage interest rates and denial rates are higher in non-recourse states than in recourse states. These results imply that lenders in non-recourse states are aware of the additional risks embedded in non-recourse loans.

Lastly, we test the two-stage risk-shifting hypothesis by estimating the effect of recourse law on the sub-prime mortgage ratio using HMDA data for 2003-2006. We find that lenders in non-recourse states originate, on average, 6% more sub-prime loans than lenders in recourse states (extensive margin). Furthermore, non-recourse states with high sub-prime loan ratios experience particularly large housing bubbles. Taken together, these results suggest that the housing bubble is likely to be larger in non-recourse states, because the OTD market and credit expansion dissuade lenders from controlling the consequent risk.

The paper offers novel contributions to a growing literature on housing bubbles. The extensive theoretical literature on bubbles notwithstanding, it remains empirically challenging to quantify a speculative bubble from estimates of fundamental economic value and distinguish a particular channel from many theoretical bubble models. Our empirical setting offers the unique advantage of the state-border discontinuity test by means of which we control for changes in fundamental values and examine whether the credit bubble is driven by investors' limited liability. We identify the bubble channel through a comprehensive analysis of lending behavior and sub-prime loan origination from the perspectives of both intensive and extensive margins of speculative investment. The paper's results, although mainly relevant to the housing market, are generalizable to the asset bubble literature that attributes bubbles to limited liability and the credit cycle.

This paper also has important implications for the housing price boom in the early 2000s. Previous literature attributes the housing boom to low, long-term real interest rates managed by monetary policy (*Himmelberg et al.* (2005) and *Taylor* (2007)). Other literature maintains that certain superstar cities experienced significant housing price appreciation due to an inelastic supply of land and growing number of high income households (*Glaeser et al.* (2008) and *Gyourko et al.* (2013)), and Shiller (2007) asserts that the real estate boom during this period was driven by a "social epidemic of optimism" that encouraged speculative investment. Our contribution to this literature, the suggestion that mortgage law has a significant impact on state variations in housing investment behavior and price patterns, enhances our understanding of cross-sectional variation in housing prices across states.

Several papers have examined the effect of recourse law on the mortgage default rate. A recent paper by *Ghent and Kudlyak* (2011) shows that mortgage defaults are more frequent in non-recourse states, but find no evidence that mortgage interest rates vary according to state laws. *Pavlov and Wachter* (2004, 2006) propose a model for the underpricing equilibrium of the put option embedded in non-recourse mortgage lending. Our paper mainly differs from these studies in emphasizing the impact of non-recourse law on the housing bubble and its interaction with mortgage lenders taking into account the growth of the mortgage securitization market.

By providing some of the first evidence of the combined effect of recourse law and the securitization market on housing markets, this paper also expands previous research on the recent mortgage crisis. Together with significant credit expansion from low interest rate policies, the role of the housing market preceding the crisis is highlighted (i.e., *Herring and Wachter* (2003), *Reinhart and Rogoff* (2008, 2009), *Mayer et al.* (2009), and *Makarov and Plantin* (2013)). Many studies have shown that sub-prime mortgage expansion promoted the unsustainable growth that led to the collapse of the market (*Agarwal and Ben-David* (2012), *Berndt and Gupta* (2009), *Himmelberg et al.* (2005), *Demyanyk and Van Hemert* (2011), *Jiang et al.* (2010), *Keys et al.* (2009, 2012), *Mian and Sufi* (2009) and *Purnanandam* (2011)). This paper further extends previous research by showing how recourse law, through its influence on borrower risk-taking behavior, accounts for variations in sub-prime mortgage expansion and the impact of the mortgage crisis.

The rest of this paper is organized as follows. The origins of recourse law are explored and hypotheses developed in Section 2. Sample data are described in Section 3. In Section 4, an empirical strategy is developed and the impact of recourse law on housing prices is examined. In Section 5, we investigate the impact of recourse law on household investment behavior. Mortgage lending behavior is investigated in Section 6 and the impact of recourse law on sub-prime mortgage expansion is analyzed in Section 7. Section 8 concludes.

2.2 Recourse Law and Hypotheses

2.2.1 Recourse Mortgage Law

2.2.1.1 Definition of Recourse Mortgage Law

U.S. mortgage law varies across states in many important ways. State-level mortgage law can be classified as recourse and non-recourse, depending on lenders' right of deficiency judgment when borrowers default on residential mortgage loans. Recourse law permits lenders to claim, in other assets and salary, the difference between a remaining mortgage amount and the foreclosure value of a house. Non-recourse law allows lenders to seize only the collateralized house in the event of a mortgage default.

Even though states are not strictly classified as recourse and non-recourse, it is widely accepted among both academics and practitioners that 11 states have non-recourse mortgage laws.[4] Figure 2.1 illustrates the classification of mortgage recourse law in the U.S.[5]

2.2.1.2 Origins of Recourse Mortgage Law

State-level recourse law has changed little since its enactment during the Great Depression of the 1930s. During that economic recession, foreclosure sales were sufficiently intense and widespread to distort the housing market and caused houses to be sold below their fundamental value. However, mortgage lenders sold borrowers' properties at a deep discount and then claimed deficiency judgments for the full amount of the debt, which amplified the depression. This prompted the anti-deficiency judgment legislation enacted in many states (*Solomon and Minnes* (2011)).

It is important to consider how states with non-recourse mortgage laws were chosen. Selection on the basis of particular economic motives could imply an unobserved factor responsible for both the legislation and recent housing market dynamics. To mitigate concerns about reverse causality and omitted variable bias, we look to *Ghent* (2013), who provides historical perspective on how individual states enacted divergent foreclosure laws, in particular, the recourse provision, in the wake of the Great Depression. The paper finds no clear economic or legal reasons why states developed different procedures in the event of mortgage default. According to *Mian et al.* (2013), the differences relate mainly to judges' idiosyncratic interpretations of case law. In any case, that the differences have persisted little changed since the 1930s mitigates concerns about bias in our empirical results.

2.2.2 Hypothesis Development

We attempt to understand in this paper whether the magnitude of housing market bubbles reflects differences between recourse and non-recourse laws. We hypothesize that a larger bubble is created during a housing market boom, and a larger burst experienced during a housing market recession, in non-recourse law states. The asset substitution model by *Allen and Gale* (2000a) provides the theoretical rationale for

[4] There have been debates over the identification of non-recourse states between scholars. *Zywicki and Adamson* (2009) argue that 15-20 states have non-recourse laws while *Ghent and Kudlyak* (2011) estimate that eleven states have non-recourse laws. We mainly employ the classification of *Ghent and Kudlyak* (2011). But we also check the robustness with the other classifications. http://www.foreclosurelaw.org/ provides a comprehensive description of state foreclosure laws in the United States.

[5] In Appendix B, we also compare the recourse law with the judicial foreclosure requirement, one of the major mortgage foreclosure laws that have been investigated in the literature. Figure 2.2 illustrates the classification of judicial requirement.

borrowers with limited liability investing aggressively in risky assets and creating a bubble by bidding up asset prices above their fundamental value.

Hypothesis 1: *A state with non-recourse law creates a larger housing bubble during an economic expansion, and experiences a steeper decline in housing prices during an economic recession.*

Specifically, the micro foundation of this housing price pattern is likely to come from household speculative behavior. The channels through which recourse law influences household investment behavior can be divided into the leverage decision and the asset allocation decision (intensive margin). Limited borrower's liability may encourage households to invest in their house with a higher debt-to-income ratio because highly leveraged investments will enable them to increase their returns without bearing additional downside risk. Additionally, households could differ in their asset allocations depending on the recourse law of their states. We expect that households in non-recourse states may allocate more capital to housing assets in anticipation of higher returns in the future.

Hypothesis 2: *Households in a state with non-recourse law 1) allocate more capital on housing and 2) invest in housing assets with higher debt-to-income ratio than in a state with recourse law.*

Having established a role and the micro foundation for recourse law in housing market bubbles, we turn to the question of whether mortgage lender behavior differs between recourse and non-recourse law states. The Allen and Gale model assumes the lending market to be competitive with unlimited credit supply, and lenders to not observe the riskiness of assets. In practice, however, mortgage lenders can be constrained by market incompleteness, capital market frictions, and regulatory capital requirements (*Stein* (2007)). Moreover, mortgage lenders can exercise some control over the riskiness of lending through loan-to-value ratio (down payment), mortgage spreads, and screening of borrowers. The corresponding hypothesis is that lenders in non-recourse states, to minimize costs from the lack of deficiency judgment, demand a lower loan-to-value ratio (higher down payment), higher mortgage interest rate and stricter loan screening than lenders in recourse states.

Hypothesis 3: *Mortgage lenders in non-recourse states demand a lower loan-to-*

value ratio, and higher mortgage interest rate and have stricter loan screening than mortgage lenders in recourse states.

This lending pattern is expected to be stronger for a property that is not a primary residence, that is, for a second home or investment property. Non-pecuniary costs that provide a disincentive to default even with limited liability include lowering of the defaulter's credit rating and the utility loss of losing one's home and having to move. We therefore expect households in non-recourse states to exhibit a stronger speculative incentive when purchasing homes for investment purposes.

It will be surprising if we observe larger housing bubbles in non-recourse states even in the presence of mortgage lenders' control of additional risk. Literature suggests that the originate-to-distribute (OTD) market, by enabling mortgage lenders to shift risk to other investors by securitizing mortgage loans and reselling them to third parties, thereby mitigates constraints in credit supply and the ex-ante incentive to screen borrowers (*Keys et al.* (2009, 2010), *Keys et al.* (2012) and *Purnanandam* (2011)).[6] It is likely that the origins of loans are concealed when loans are securitized in a complex structure of financial derivatives. *Piskorski et al.* (2013) argue that the true quality of loans in the residential mortgage-backed security (RMBS) market has frequently been misreported to investors. They show that for one out of ten loans in the RMBS market has misrepresentation in borrower occupancy status of borrowers or second lien information, which is not priced in the securities at their issuance. To the extent that it does not reflect the embedded risk in non-recourse mortgage loans, the OTD market promotes a disproportionately large increase in poor quality loan originations in non-recourse states. This is consistent with the argument that the OTD model induces excessively risky mortgage loan originations (*Pennacchi* (1988) and *Gorton and Pennacchi* (1995)). The corresponding hypothesis is as follows.

Hypothesis 4: *More sub-prime mortgage loans are originated in non-recourse than in recourse states.*

[6] Rapid expansion of this market was also accompanied by a relaxation of the regulation of mortgage lending.

2.3 Data

2.3.1 Housing Price Data

Housing market data used in this study are from Zillow Real Estate Research (www.zillow.com). The Zillow database, widely used in related literatures[7], provides ZIP code-level housing price data at the monthly level from 1999-2013.[8] The Zillow.com ZIP code-level data covers 45 states[9] and 36,577 ZIP codes representing 78% of U.S. ZIP codes. For each ZIP code, we use the median of sale prices scaled by a home's square footage as a measure of housing price. This reduces the total sample ZIP codes to 3700 major ZIP codes located in 38 states. Alternatively, we use the median of the total prices of homes sold. We calculate the rate of annual growth in housing price at time t based on the price in January in period t and t+1.

As another alternative measure for the housing bubble, we also employ the price-to-rent ratio, which is a commonly used measure for housing valuation. This ratio reflects the relative cost of owning a house relative to the "fundamental value" of asset, present value of future rental value. The housing price bubble may lead to an unsustainably high price-to-rent ratio. We acquire median rent value from American Community Survey data at the county level for the period of 2005-2011 and calculate the growth rate.

2.3.2 Households Investment Behavior

We use single-family loan-level origination data from two major Federal Home Loan Mortgage Corporations, Freddie Mac and Fannie Mae. This dataset has been developed with the support of the Federal Housing Finance Agency (FHFA) to improve transparency in the housing credit market and build a better credit performance model. This dataset includes mortgage loans that are acquired by Freddie Mac and Fannie Mae, which include 16 million loan originations from Freddie Mac and 18.7 million mortgage loans from Fannie Mae, respectively.[10] The data includes single-family

[7] i.e., *Huang and Tang* (2012), *Guerrieri et al.* (2013), and *Mian et al.* (2013)

[8] Our empirical results will be updated upon receipt of Census data from the American Housing Survey (AHS) (which provides detailed, tract-level information about housing and household characteristics including household-level panel data for each property), for which we have submitted a request.

[9] Missing states: Alaska, Idaho, Mississippi, New Mexico, North Dakota, South Dakota, and Wyoming.

[10] Both Fannie Mae and Freddie Mac purchase loans from approved mortgages sellers, then securitize into MBS and sell to investors in the secondary mortgage market with the guarantee of principal and interest payments. These agency MBSs, which are issued by government-sponsored enterprises, account for approximately 60% of the total MBS market for the sample period. This implies that the combined dataset from both primary Agency MBS players covers the majority of

mortgages acquired by Freddie Mac and Fannie Mae from 1999-2012 and 2000-2012 with the following characteristics: 30-year fixed-rate, fully amortizing, with full documentation, and conventional fixed-rate.[11] Data items are origination date, 3-digit ZIP code, credit score, original loan amount, original interest rate, original loan-to-value (LTV), debt-to-income ratio, loan purpose (purchase, cash-out refinance, no cash-out refinance, refinance non-specified), occupancy status (principal residence, second home, investment property), and mortgage insurance.

In particular, we focus on debt-to-income (DTI) ratio and occupancy status. DTI ratio is the sum of the borrowers' monthly debt payments divided by total monthly income of borrower at the origination date. We calculate the 3-digit ZIP code level average value of this variable. The occupancy status denotes whether the property for mortgage is owner occupied, second home or investment property. Second home and investment-purposed account for 5% of total data.

We then construct state-level asset allocations to housing assets. The Panel Study of Income Dynamics (PSID) provides a wide range of household portfolio data including total asset value, income, expenditure, and demographic information. The data set is based on a survey that the PSID has conducted to more than 8000 households every two years. From the PSID data for the period 1999 to 2009, we estimate household allocations on housing assets measured as the fraction of home equity to total wealth. Home equity is the value of a house minus the first and second mortgage on the house. Total wealth is the sum of home equity, farm/business assets, checking/saving accounts, stocks, vehicles, annuities, other assets and other real estate assets minus total debt. Examining the home equity share of each household in different states enables us to understand how households response to the variation of housing value during the period of the housing market bubble and burst.

2.3.3 Mortgage Lending Behavior

We obtain the loan-to-value (LTV) ratio and interest rate from the Freddie Mac and Fannie Mae loan purchase dataset. LTV is defined as the loan amount secured by a mortgaged property on the origination date divided by the purchase price. Mortgage interest rate is the annual percentage rate (APR) on mortgage loan. The mortgage application can be denied by the financial institution. The reasons for denial are

mortgage loan origination which will be securitized into the MBS market.

[11]This dataset does not include adjustable-rate mortgage loans, balloon mortgage loans, interest-only mortgage loans, government-insured mortgage loans, or Home Affordable Refinance Program (HARP) mortgage loans. This also excludes loans with LTVs are greater than 97 percent, Alt-A and other mortgage loans that are not available today.

variously related to (1) debt-to-income ratio; (2) employment history; (3) credit history; (4) collateral; (5) insufficient cash (downpayment, closing costs); (6) unverifiable information; (7) incomplete credit application; (8) denied mortgage insurance; and (9) other. Because we aim to calculate the denial rate consequent to a high risk of insolvency, we estimate the fraction of loan applications denied for reasons 1, 3, 4, or 5, listed above.

2.3.4 Proxy for Sub-prime loan ratio

As the HMDA data do not include an indicator for whether a given loan is sub-prime, various methodologies for identifying sub-prime borrowers are employed in the literature. We classify sub-prime loans based on lender identification. Using a list of sub-prime lender specialists compiled annually by HUD[12], we construct a sub-prime ratio measure. Specifically, it equals the number of sub-prime mortgage loans out of the total number of mortgage loans originated. Other papers classify a loan as sub-prime if the APR is three percentage points above a comparable Treasury APR (i.e., if the mortgage spread is beyond three percentage points). However, following HUD, this methodology potentially overestimates the sub-prime loan ratio. *Mian and Sufi* (2009) identify as sub-prime those borrowers with a credit score below 660, a threshold based on origination guidance provided by Freddie Mac and Fannie Mae.

2.3.5 Control Variables

To use the state-border discontinuity design, we need to construct a distance measure for every ZIP code. We use ArcGIS software and the geodatabase provided by Esri[13] to estimate the shortest distance in miles between the centroid of each ZIP code and the state border.

Other data used to supplement the mortgage information from the survey are from the American Community Survey (ACS), the Federal Housing Finance Agency (FHFA), and Federal Reserve Bank of New York. Complementary data from the ACS provides socioeconomic characteristics of households including population, income growth, and unemployment rate. This annual, county-level survey data is available from 2005 to 2011. We also use FHFA's Monthly Interest Rate Survey (MIRS).

We also use MSA-level housing supply elasticity values provided by Saiz (2010). This measure captures the restriction of housing expansion.

[12] U.S. Department of Housing and Urban Development, http://www.huduser.org/portal/datasets/manu.html

[13] Esri is an international supplier of Geographic Information System software and geodatabase management applications (http://www.esri.com/)

2.3.6 Descriptive Statistics

Table 2.1 presents summary statistics for key variables for our sample. The average housing price growth rate per square foot is 6%, and the median is 5%. This growth rate is higher than the average nominal GDP growth rate of 4%. It is noteworthy that housing price growth has a large standard deviation (41%) during our sample period as a result of the collapse of housing prices during the mortgage crisis. The population growth is 1% and the unemployment rate is 5%, on average, during our sample period.

Table 2.2 compares the main variables between recourse and non-recourse states. We hypothesize that housing prices in non-recourse states rise more during an economic expansion, and drop more steeply during an economic recession. In Panel A, which compares recourse and non-recourse states in the pre-crisis period from 2003-2006, non-recourse states are seen to have higher housing price growth, on average, by 4% annually, at the 1% significance level. This is consistent with our hypothesis. On the other hand, during the crisis period in our sample, housing prices show a larger drop in non-recourse states. As can be seen in Panel B of Table 2.2, during the crisis period (from 2007-2011), the housing price growth rate per square foot declined, on average, by 3% annually in recourse, and 6% in non-recourse states.

Table 2.2 also presents the comparison of lending behaviors across states. Both Panel A and Panel B of Table 2.2 shows that lenders in non-recourse states require lower loan-to-value ratio and higher mortgage interest, which is also consistent with *Hypothesis* 2.

2.4 Recourse Law and Housing Price Bubbles

Our first set of tests investigates whether recourse law has an effect on housing bubbles. Figure 2.3 presents the time-series behavior of the aggregate growth rate of housing price (Panel A) and price-to-rent ratio growth (Panel B) in recourse and non-recourse states. Although these growth rates move in a similar fashion, greater swing is observed in non-recourse states in both Panel A and B. NBER classifies the periods from March 2001 to November 2001 and from December 2007 to June 2009 as recessionary periods. As can be seen in Panel A of Figure 2.3, the housing price growth rate is higher during the pre-crisis period of 2002-2005, but falls below that of recourse states during the recent crisis period from 2007-2011.[14] It is also worth to noting from 1998-2000 the housing price growth rate is higher in non-recourse than in

[14]The housing price growth rate declined sharply in 2006 but remained positive, which indicates that housing prices peaked in 2006.

recourse states, but drops more steeply during the first recessionary period in 2001. Panel B of Figure 2.3 also shows that the price-to-rent ratio remained positive and higher in non-recourse state during the pre-crisis period but decreased more during the crisis. Figure 2.3 shows a repeating pattern of a larger housing price swing in non-recourse states. We next present the identification strategy for our tests and report the results.

2.4.1 Empirical Design and Identification Strategy

Multiple complementary approaches are employed to identify a causal relation between recourse law and housing price. The key prediction of the credit bubble model is that housing price bubbles result from non-recourse law interacting with an increasing credit supply. Two randomly selected locations, identical except for recourse law status, provide an ideal empirical setting for our experiments. There are, however, two challenges to examining the causal relation: (1) mortgage credit supply, an important determinant of housing price[15], is endogenously determined with other factors, and (2) in the absence of a randomized experiment, unobserved heterogeneity may lead to omitted variable bias.

We address these challenges by applying difference-in-difference specifications that exploit the nationwide credit supply shock of the mortgage market collapse in 2007 that affected states differentially. The key identifying assumption is that the shock induces a deviation from housing price trends that tracked together across both types of states in the absence of the treatment. Figure 2.3 plots the similar trends in the recourse (control group) and non-recourse (treatment group) states from which the treatment effect drove a deviation in 2007. The annual nationwide housing price growth rate was 12%-18% from 2002-2005, dropped to 1.5% in 2006, and turned negative in 2007 and remained so until 2011. We therefore define $Crisis$ as a dummy variable equal to zero before and including, and one after, the year 2006. If non-recourse law causes a larger bubble in the housing market, the crisis may precipitate a disproportionately larger drop in housing price in non-recourse states. Figure 2.3 shows the differential impact of the crisis on housing price growth rate in recourse and non-recourse states to be consistent with this argument. The identification of ZIP codes disproportionately affected by the crisis enables us to estimate difference-

[15] Credit supply is a main determinant of housing price and mortgage market dynamics that explains the business cycle (Bernanke and Gertler (1989), Holmstrom and Tirole (1997), Kiyotaki and Moore (1997), Diamond and Rajan (2005)).

in-difference regressions as follow:

$$\Delta ln(P_{it}) = \beta_0 + \beta_1 Non\text{-}recourse_i + \beta_2 Crisis_t + \beta_3 Crisis_t * Non\text{-}recourse_i + \beta^{'} X_{it} + \varepsilon_{it}$$

where the dependent variable, $ln(P_{it})$, is the growth rate of housing price per square foot in ZIP code i at time t from 2003-2011, $Crisis_t$ is a dummy variable equal to zero before and including 2006, and one after that year, $Non\text{-}recourse_i$ is a dummy variable equal to one if ZIP code i is located in a non-recourse state, and zero otherwise. In this specification, β_1 captures the average difference in housing price growth by non-recourse law, whereas β_2 captures the impact of crisis on housing price growth. Our hypothesis predicts a positive sign on β_1 and a negative sign on β_2. Then, the coefficient of main interest is β_3, which identifies the impact of the crisis in non-recourse states. Our hypothesis expects a negative sign on this coefficient, or $\beta_3 < 0$.

This difference-in-difference estimator suggests a causal relation between recourse law and housing market bubbles. However, this estimator can be confounded if housing prices are affected differently during the crisis for reasons unrelated to recourse law. We address this problem by including the set of other state- and county-level control variables, X_{it}, such as annual GDP growth, per capita income growth, population growth rate, unemployment rate, MSA-level housing supply elasticity, and state property tax that potentially affect demand and supply in the local housing market.

We also include a dummy variable for another major state-level mortgage foreclosure law, Judicial Foreclosure, which represents a state law on judicial requirements in the foreclosure process. Other literature (*Pence* (2006); and *Mian et al.* (2013)) emphasize that state-to-state variation in judicial foreclosure law is an important determinant of mortgage credit and foreclosure rates.

More importantly, however, this regression is still unable to control for unobserved spatial heterogeneity. Many other characteristics, such as a preference for home-ownership, dwelling patterns, and state-specific laws and policies, may affect the return on housing assets. Also, substantial heterogeneity may be observed in housing and demography within large states.[16] We control for unobserved spatial heterogeneity by performing difference-in-difference regressions at the ZIP code-level using the same explanatory variables, but focused on the counties close to a border between states with different recourse laws. We include county-pair fixed effects to

[16] For example, New York's Erie County and Westchester County have similar populations of 0.75 million, but median household income levels of \$47,533 and \$77,006, respectively, whereas Connecticut's Fairfield County is contiguous with, and has socioeconomic characteristics similar to those of, Westchester county.

capture county-pair specific characteristics. A number of studies have used the state border effects methodology to explore how differences in the socioeconomic environment affect various factors across counties and states (*Holmes* (1998); *Pence* (2006); *Dube et al.* (2010); and *Mian et al.* (2013)).

We also examine the impact of recourse law by exploiting the discontinuity at state borders. Our framework combines the strategy employed in *Pence* (2006) and *Mian et al.* (2013) with a difference-in-difference setting that is less susceptible to unobserved variation over time. For this analysis, we combine the ZIP code-level housing price growth rate with distance information, specifically, a measure of the shortest distance between a state border and the centroid of a ZIP code. Using this information and a recourse law indicator, we run the following regression:

$$\Delta ln(P_{it}) = \beta_0 + \beta_1 Crisis_t + \beta_2 Non\text{-}recourse_i + \beta_3 Crisis_t * Non\text{-}recourse_i$$
$$+\delta_1 Distance^R_{i,b} + \delta_2 Distance^{NR}_{i,b} + \delta_3 (Distance^R)^2_{i,b} + \delta_4 (Distance^{NR})^2_{i,b} + \beta\prime X_{it} + \phi_i + \varepsilon_{it}$$

where $\Delta ln(P_{it})$ is the average growth rate of housing price in ZIP code i, and $Non\text{-}recourse_i$ is an indicator that identifies whether ZIP code i is located in a non-recourse state. In the county-pair sample regression, we also includes distance measure from state-borders to focus on the jump at the state border, or discontinuity. $Distance^R_{i,b}$ represents the interaction of distance and an indicator I(recourse), which is zero for ZIP code i in non-recourse states. $Distance^{NR}_{i,b}$ represents the interaction of distance and an indicator I(non-recourse). The squared distances for each state, $(Distance^R)^2$ and $(Distance^{NR})^2$, are also controlled. We include the county-pair fixed effect ϕ_i to focus on the variation between two counties contiguous along a state border. Standard errors are heteroskedasty consistent and clustered at the county level.

The coefficient on *Non-recourse* captures a sharp discontinuous change in housing price when a border is crossed into a recourse state. Because we predict different directions of jump before and after 2007, our main coefficient of interest is β_3. The coefficient on the interaction of $Crisis$ and *Non-recourse* captures how discontinuous changes at state borders are affected by the crisis. Our hypothesis predicts a positive jump at the border in the pre-crisis period and negative jump during the crisis period, which suggests $\beta_3 < 0$.

There is a potential concern that some of the control variables are endogenously determined with housing price P_{it}. For example, households who expect increases in their property price may increase their consumption too. We address this possibility by performing the regression with lagged variables for time-varying controls.

We also examine the effect of recourse law on the housing bubble directly using the price-to-rent growth rate in the pre-crisis period.

$$\Delta ln(P_{it}/R_{it}) = \beta_0 + \beta_1 Crisis_t + \beta_2 Non\text{-}recourse_i + \beta_3 Crisis_t * Non\text{-}recourse_i + \beta\prime X_{it} + \varepsilon_{it}$$

where $\Delta ln(P_{it}/R_{it})$ is the average price-to-rent growth rate in ZIP code i, and $Non\text{-}recourse_i$ is an indicator that identifies whether ZIP code i is located in a non-recourse state.

2.4.2 Results

Models (1)-(2) in Table 2.3 estimate for the full sample with and without control variables. The estimates show that housing price growth in non-recourse states is higher than in recourse-states in the boom period but falls after the mortgage market collapse. In particular, the estimated coefficient on the interaction term shows that housing prices dropped more during the crisis in non-recourse states. These two changes produce a negative difference-in-differences, consistent with what we expect if non-recourse states created a larger bubble. The economic magnitude of the interaction effect is -6%, and the coefficient is significant at the 1% level. This indicates that housing prices declined more by 6% annually in non-recourse states during the crisis period. In Model (2), the coefficient accounts for an approximately 6% further decrease in housing price relative to the pre-crisis period. It is also important to note the stand-alone dummy variables, *Crisis* and *Non-recourse*. A negative and significant coefficient on the *Crisis* dummy variable indicates that housing prices decreased significantly following the crisis in 2007. On the other hand, a positive and significant coefficient on the *Non-recourse* dummy variable indicates that housing prices have grown higher by 2-3% annually in non-recourse states during the pre-crisis period.

In Models (3)-(5) of Table 2.3, we present results for the contiguous border county-pair sample with the county-pair fixed effect. This specification enables us to control for unobserved spatial heterogeneity. We find negative and significant coefficients on the interaction term $Crisis * Non\text{-}recourse$ in these models as well. The economic magnitude of the estimate is 3-5%, which is lower than in the earlier models. The coefficient on the *Crisis* dummy variable is similar, but the coefficient on the *Non-recourse* dummy variable is larger in the county-pair sample.

In Model (4), we present the results of the state-border discontinuity model which includes distance measure from state-borders. The main coefficient of interest is the interaction term $Crisis * Non\text{-}recourse$, which captures the effect of the crisis on discontinuous changes in housing price at state borders. Consistent with our prediction, we find a negative and significant coefficient on the interaction term. The economic magnitude of the coefficient is about 3%, and the coefficient is significant at the 5% level. The results indicate that housing prices drop more during the crisis in non-recourse than in recourse states, especially at state borders. By controlling for distance, we establish that changes in housing price growth rate at state borders are large and abrupt compared to within-border changes. Model (5) uses the lagged variable for state-level time-varying controls such as GDP growth, income growth, unemployment, and population growth. The coefficients imply that our main results are robust to the endogeneity problem between housing price growth and the control variables.

In Table 2.4, we report the evidence of higher price-to-rent growth rates in non-recourse states in the pre-crisis period 2005-2006. In Models (3)-(5), the results show that non-recourse states experience higher appreciation of housing prices by 7-8 percentage points relative to the present value of future rental value or "fundamental value" of the house.

The overall results provide support for our hypothesis that housing prices in non-recourse states experience a larger bubble in boom periods and a larger burst in recession periods.

2.5 Household Investment Behavior

In this section, we investigate the micro foundation of larger housing bubbles in non-recourse states by examining the impact of recourse law on households' asset allocation and leverage decisions. Our hypothesis predicts that households in non-recourse states allocate more wealth to housing assets and have higher debt-to-income ratio in housing purchases. Figure 2.4 provides evidence of the households' speculative investment behavior. Panel A in Figure 2.4 plots the households' average ratio of home equity to total wealth as a measure of asset allocation on the housing market. Panel B shows the pattern of the average debt-to-income ratio at origination, defined as the borrower's total monthly obligations divided by their monthly income. Figure 2.4 indicates that households in non-recourse states show significantly higher asset allocation and leverage ratio in their housing purchases. To identify a causal relation, we employ a similar identification strategy as in the previous section but focus on the pre-crisis period. The corresponding regression specifications are the following:

$$HouseShare_{it} = \beta_0 + \beta_1 Non\text{-}recourse_i + \delta_1 Distance^R_{i,b} + \delta_2 Distance^{NR}_{i,b}$$
$$+\delta_3(Distance^R)^2_{i,b} + \delta_4(Distance^{NR})^2_{i,b} + \beta\prime X_{it} + \phi_i + \varepsilon_{it},$$

$$DTI_{it} = \beta_0 + \beta_1 Non\text{-}recourse_i + \delta_1 Distance^R_{i,b} + \delta_2 Distance^{NR}_{i,b}$$
$$+\delta_3(Distance^R)^2_{i,b} + \delta_4(Distance^{NR})^2_{i,b} + \beta\prime X_{it} + \phi_i + \varepsilon_{it},$$

where $HouseShare_{it}$ is the average fraction of home equity value to total asset value of a household at the state level in year t, and DTI_{it} is the debt-to-income ratio, or average borrower's total monthly obligations divided by their monthly income, at loan origination in ZIP code i in year t. $Non\text{-}recourse_i$ is an indicator for whether ZIP code i is located in a non-recourse state. We also include the county-pair fixed effect ϕ_i and distance measures. Distance measures and other control variables are described in the previous section. Standard errors are robust to heteroskedasticity and clustered at the county level.

In this specification, the coefficient β_1 on the non-recourse indicator shows that the households' asset allocation and debt-to-income ratio change at the state borders that differ in their recourse law, while the coefficients δ_1 and δ_2 indicate how household portfolio choice varies with distance in the recourse state direction and in the non-recourse state direction. Our hypothesis predicts positive jumps in allocation of household wealth to housing assets and higher leverage decisions when the border is crossed from a recourse state to a non-recourse state, which corresponds to $\beta_1 > 0$.[17]

2.5.1 Results

Table 2.5 presents the coefficient estimates of regressions of household investment behavior for the contiguous border county-pair sample in the pre-crisis period from 2003-2006. Models (1)-(3) test for households' asset allocation using the average ratio of home equity to total wealth at the state level as the dependent variable. Models (4)-(6) test the leverage decision with the average debt-to-income ratio at the ZIP code-level. The main coefficient of interest is that on the *Non-recourse* dummy variable, which captures the effect of limited liability in mortgage borrowing

[17]The current version of the analysis on household asset allocation is limited since the asset allocation data is state-level and is not based on the origination date. The measure also depends on the housing value. Our empirical results will be updated upon receipt of Census data from the American Housing Survey (AHS).

on household investment behavior.

Our hypothesis predicts that households in non-recourse states allocate a higher fraction of capital to housing assets in anticipation of high housing appreciation in the future, or sustained mispricing of assets. The estimates in Models (1)-(3) support this hypothesis. The coefficient on the non-recourse dummy is positive and statistically significant for the full sample (Model 1). Then, it becomes larger when we examine with the county-pair sample (Model 2) and remains positive and statistically significant when we employ the state-border discontinuity design with distance measures (Model 3). The economic magnitude of the coefficient implies that households in non-recourse states allocate 7% more wealth to home equity. Given the identical investment opportunities in financial markets for both recourse and non-recourse households, the difference in portfolio choice supports the existence of speculative investment motives of households in non-recourse states.

Table 2.5 also shows that households in non-recourse states tend to invest in housing assets with higher debt-to-income ratios. We present the results for the full sample in Model (4). Then, we focus on the contiguous border county-pair sample with the county-pair fixed effect in Model (5) and add distance measures to test the state-border discontinuity in Model (6). The stand-alone *Non-recourse* dummy in all of Models (4)-(6) shows positive estimates that are statistically significant at the 1 % level. In Model (6), the coefficient estimate is 1.74%, which indicates that households in non-recourse states borrow 1.74 percentage points more debt given the same income. The discontinuous jump in their leverage decision at the state-border provides evidence of speculative motives in their investment.

Taken together, these results suggest that housing prices experience larger bubbles in non-recourse states than in recourse states because the risk-shifting feature of non-recourse mortgage law leads households to allocate more wealth to housing assets and invest in housing purchases with higher leverage.

2.6 Mortgage Lending Behavior

In this section, we examine the impact of recourse law on mortgage lending behavior. In the risk-shifting model developed by *Allen and Gale* (2000a), lenders are unable to monitor the types of assets invested in by borrowers and have limited means to control the risk of default. Lenders in the real mortgage market, however, are able to control the risk of default by means of lower loan-to-value ratios (higher down payment), higher mortgage interest rates, and stricter screening. We conjecture that mortgage lenders in non-recourse states could effectively respond to borrowers' riskier investment behaviors.

In particular, we highlight initial LTV ratio at the time of mortgage origination. While higher mortgage interest rates can potentially raise the mortgage default probability and subsequently lenders' expense from default, a low LTV ratio effectively decreases the probability of negative home equity.[18] Figure 2.5 plots the mortgage lending behaviors in recourse and non-recourse states. Panel A plots the average LTV ratio, defined as the loan amount secured by a mortgaged property on the origination date divided by the purchase price. It shows that the average LTV ratio in recourse states holds near the conventional median of 80% throughout the sample period whereas the average LTV ratio in non-recourse states remains considerably lower than in recourse states. This LTV pattern in non-recourse states is expected to be stronger for households whose occupancy status for the properties are not primary residence because they have less non-monetary utility loss from strategic default. Panel B of Figure 2.5, which plots the average loan-to-value ratio for a group of borrowers whose occupancy status is either second home or investment property, provides evidence in support of our hypothesis during the pre-crisis period.

To further test this insight, we examine our hypothesis using the state border discontinuity regression for the pre-crisis period 2003-2006.

$$
\begin{aligned}
LTV_{it} = \beta_0 + \beta_1 \textit{Non-recourse}_i + \delta_1 \textit{Distance}^R_{i,b} + \delta_2 \textit{Distance}^{NR}_{i,b} \\
+ \delta_3 (\textit{Distance}^R)^2_{i,b} + \delta_4 (\textit{Distance}^{NR})^2_{i,b} + \beta' X_{it} + \phi_i + \varepsilon_{it},
\end{aligned}
$$

where

$$
\text{LTV} = \frac{\text{Amount of mortgage when acquired}}{\text{Purchase price of unit}}
$$

and $\textit{Non-recourse}_i$ is an indicator that identifies whether ZIP code i is located in a non-recourse state. Distance measures and other control variables are described in the previous section. Standard errors are robust to heteroskedasticity and clustered at the county level. Hypothesis 3 predicts a negative jump in the LTV ratio at the border when one crosses into a non-recourse state, which suggests $\beta_1 < 0$. Then, we divide home purchases into residential-purpose transactions and investment-purpose transactions based on the occupancy status, and examine whether non-recourse drives stronger effects in investment-purpose properties.

We also test whether average interest rates and average denial rates for loan

[18] A non-recourse mortgage loan with a high down payment can be considered as a put option in deep out-of-the money.

applications differ over the recourse law. Our hypothesis predicts that both interest rates and denial rates are higher in non-recourse states because lenders require higher interest rates and stricter screening to control the additional risk. The regression specifications for these tests are the following:

$$\begin{aligned} \mathit{Interest}_{it} &= \beta_0 + \beta_1 \mathit{Non\text{-}recourse}_i + \delta_1 \mathit{Distance}^{R}_{i,b} + \delta_2 \mathit{Distance}^{NR}_{i,b} \\ &+ \delta_3 (\mathit{Distance}^{R})^2_{i,b} + \delta_4 (\mathit{Distance}^{NR})^2_{i,b} + \beta\prime X_{it} + \phi_i + \varepsilon_{it}, \end{aligned}$$

$$\begin{aligned} \mathit{Denial\ Rate}_{it} &= \beta_0 + \beta_1 \mathit{Non\text{-}recourse}_i + \delta_1 \mathit{Distance}^{R}_{i,b} + \delta_2 \mathit{Distance}^{NR}_{i,b} \\ &+ \delta_3 (\mathit{Distance}^{R})^2_{i,b} + \delta_4 (\mathit{Distance}^{NR})^2_{i,b} + \beta\prime X_{it} + \phi_i + \varepsilon_{it}, \end{aligned}$$

where $\mathit{Interest}_{it}$ is mortgage interest, the annual percentage rate (APR) on mortgage loans in ZIP code i at year t and Denial Rate_{it} is the average denial rate in ZIP code-level. Denial rate is defined in Section 3.3. Our main hypothesis predicts a positive jump of both the mortgage interest rate and the denial rate at the border when one crosses into the non-recourse states, corresponding to $\beta_1 > 0$.

2.6.1 Results

Table 2.6 test the hypothesis that $\beta_1 < 0$. If lenders are unable to control the additional risk in non-recourse states through the LTV ratio, then β_1 will not equal zero. Model (1) estimates the non-recourse dummy on a LTV ratio for the full sample in the pre-crisis period. The estimated coefficient presents the negative relationship between non-recourse law and LTV ratio. Estimates show that non-recourse law is associated with a LTV ratio decrease of 3.3 percentage points. This is significant relative to the standard deviation of LTV ratio across this period of 4 percentage points. In Models (2)-(3), estimates of β_1 remains robust with the county-pair sample with and without the distance measure suggesting evidence of lender's different behavior.

Models (4)-(6) of Table 2.6 focus on second home or investment-purpose properties with which households are more likely to take advantage of their limited liability in mortgage borrowing. In each model, the magnitudes of the coefficient estimates are larger and more significant relative to the comparable estimates in Models (1)-(3). This is consistent with our prediction.

Table 2.7 estimates the impact of recourse law on mortgage lending behaviors including the mortgage interest rate and denial rate. This analysis is based on the pre-crisis sample because the effect of the mortgage market collapse on mortgage interest rates is unclear as government policy and decreased demand in the housing market are confounded in the result.[19] We estimate the effect of recourse law on mortgage interest (%) for the full sample in Model (1), and for the county-pair sample in Models (2)-(3). The estimates present insignificant coefficients on the *Non-recourse* dummy in Models (1). But in our preferred Models (2) and (3) with state-border discontinuity regression, we find that the coefficient on *Non-recourse* is positive and statistically significant at the 1% level, which implies a positive jump in mortgage spread when the border is crossed from a recourse state into a non-recourse state.

Models (4)-(6) in Table 2.7 estimate the impact of recourse law on the denial rate for loan applications using the contiguous state border county-pair sample in the pre-crisis period. While the stand-alone *Non-recourse* dummy in Model (4) has a positive but statistically insignificant coefficient, it becomes positive when we focus on county-pair sample in Model (5) and remains significantly positive in our preferred state-border discontinuity model in Column (6). In Model (6), the coefficient estimate is 7%, which indicates that households in non-recourse states are more likely to be denied, on average, by 7 percentage points. The size is economically meaningful considering that the average denial rate is 17% in the aggregate economy.

The overall results suggest that mortgage lenders are aware of the additional risk embedded in non-recourse mortgage loans, and so charge higher interest rates and deny loan applications more frequently. The next question of this paper is then, why larger housing bubbles are observed in non-recourse states despite the lenders' exercise of control for the additional risk.

2.7 Recourse Effects on Sub-prime Mortgage

We conjecture that the surprising finding that housing prices experience larger bubbles in non-recourse states in the presence of lenders' control is attributable to the emergence of the OTD market, which enables lenders to effectively shift the risk of those costs to other investors. In other words, mortgage lending behavior does not fully reflect the higher risk in non-recourse states. Our two-stage risk-shifting hypothesis predicts that 1) more sub-prime mortgage loans are originated in non-recourse than in recourse states and 2) the effect of non-recourse law on housing bubbles should be larger in a state where the sub-prime ratio is high.

[19]One caveat to analyzing the interest rate and the denial rate is that they are also likely to be biased by different selections of loan applicants. To address this issue, we perform the regression after controlling for applicants' credit score and income level aggregated at the 3-digit ZIP code level and find robust results.

Figure 2.7 presents the time-series trend of the aggregate sub-prime ratio in both recourse and non-recourse states. Like the time-series pattern of housing price growth rate, these sub-prime ratios move in a similar pattern over time, but greater volatility is observed in non-recourse states. Consistent with our hypothesis, the sub-prime loan ratio in non-recourse states is higher during the pre-crisis period of 2002-2005 and peaks at a similar level in 2006, but falls below that in recourse states during the recent crisis period from 2007.

To test this relation, we first estimate the recourse effect on the sub-prime mortgage ratio, calculated as the number of sub-prime mortgage loans divided by the total number of mortgage loans originated using the specification in below.

$$\begin{gathered}\textit{Sub-prime}_{it} = \beta_0 + \beta_1 \textit{Non-recourse}_i + \delta_1 Distance^R_{i,b} + \delta_2 Distance^{NR}_{i,b} \\ + \delta_3 (Distance^R)^2_{i,b} + \delta_4 (Distance^{NR})^2_{i,b} + \beta\prime X_{it} + \phi_i + \varepsilon_{it},\end{gathered}$$

where $\textit{Sub-prime}_{it}$ is the aggregate ratio of sub-prime loan originations to total number of loan originations in ZIP code i at time t. Distance measures and other control variables are described in the previous section. Standard errors are robust to heteroskedasticity and clustered at the county level. Our main hypothesis predicts a positive jump in the sub-prime loan ratio at the border when one crosses into a non-recourse state, corresponding to $\beta_1 > 0$.

We provide evidence of a causal relation on this hypothesis by employing the difference-in-difference approach using the shock of the mortgage market collapse in 2007, which affected some states more than others. We run the following regression:

$$\begin{gathered}\textit{Sub-prime}_{it} = \beta_0 + \beta_1 \textit{Non-recourse}_i + \beta_2 Crisis_t + \beta_3 Crisis_t * \textit{Non-recourse}_i \\ + \delta_1 Distance^R_{i,b} + \delta_2 Distance^{NR}_{i,b} + \delta_3 (Distance^R)^2_{i,b} + \delta_4 (Distance^{NR})^2_{i,b} + \beta\prime X_{it} + \phi_i + \varepsilon_{it}\end{gathered}$$

where $Crisis_t$ is a dummy variable equal to zero before and including 2006, and one after that year. The coefficient of main interest is β_3, which captures the impact of the crisis in non-recourse states. Our hypothesis expects greater decline in the sub-prime loan ratio in non-recourse states, which would imply a negative sign on this coefficient, or $\beta_3 < 0$.

To further test whether subprime lending plays an important role as a channel for larger housing price swing in non-recourse states, we test the interaction effect of *Non-recourse* dummy variable and $\textit{Sub-prime}_{it}$ on the housing price growth rate. Our two-stage risk-shifting hypothesis predicts that the effect of non-recourse law on housing bubbles should be larger in states where the sub-prime ratio is high.

$$\Delta ln(P_{it}) = \beta_0 + \beta_1 Non\text{-}recourse_i + \beta_2 Sub\text{-}prime_{it} + \beta_3 Non\text{-}recourse_i * Sub\text{-}prime_{it}$$
$$+\delta_1 Distance^R_{i,b} + \delta_2 Distance^{NR}_{i,b} + \delta_3 (Distance^R)^2_{i,b} + \delta_4 (Distance^{NR})^2_{i,b} + \beta\prime X_{it} + \phi_i + \varepsilon_{it}$$

where the dependent variable is the growth rate of housing price per square foot in ZIP code i at year t. The interaction term between *Sub-prime*$_{it}$ and *Non-recourse*$_i$ is the main variable of interest. Our hypothesis predicts positive coefficient on this coefficient, or $\beta_3 > 0$.

2.7.1 Results

Table 2.8 presents the results of the regression estimation for the sub-prime loan ratio. In Models (1)-(3), we focus on the pre-crisis period of 2003-2006. We use the contiguous border county-pair sample with control variables in Model (2). We add distance measures in Model (3) to test the state-border discontinuity. In Model (1) with the full sample, we are unable to reject the null hypothesis that β_1 for the *Non-recourse* dummy variable equals zero. However, the results in our preferred Models (2)-(3) show that a larger fraction of sub-prime loans is originated in non-recourse states than in recourse states. The coefficients on the *Non-recourse* dummy variable in Model (2) is positive and statistically significant at the 1% level. The economic magnitude of this effect is 8%. We also find consistent results from the state border discontinuity test. The results show that lenders in non-recourse states originate 6 percentage points more sub-prime loans than lenders in recourse states. This effect is economically significant considering that the average sub-prime loan ratio for the sample period is approximately 17-18 %. These results are consistent with our hypothesis, which states that the OTD market encourages more risk shifting by lenders in non-recourse states than by lenders in recourse states.

To further test this insight, we test the relation using the difference-in-difference specification. Models (4)-(6) in Table 2.8 present the regression results. A negative and significant coefficient on the $Crisis$ dummy variable indicates that the sub-prime loan ratio declined significantly following the crisis in 2007. In Models (5)-(6), the coefficient accounts for a 7 percentage point decrease in the sub-prime loan ratio relative to the pre-crisis period. More importantly, the interaction effect of *Non-recourse* and $Crisis$ shows a negative coefficient at the 1% significance level. The evidence indicates that the mortgage market collapse in 2007 affected non-recourse states more than recourse states. The stand-alone variable *Non-recourse* remains positive but becomes statistically insignificant.

We next examine whether non-recourse law interacting with sub-prime lending drives a larger housing price in non-recourse states. This test emphasizes a channel through which a larger housing bubble can be created in non-recourse states. In Table 2.9, we report the interaction effect of *Non-recourse* dummy variable and $\textit{Sub-prime}_{it}$ on the housing price growth rate. We employ the full sample for the pre-crisis period of 2003-2006 in Models (1)-(2) and then focus on the contiguous border county-pair sample in Models (3)-(4).

As examined in the sub-prime literature, $\textit{Sub-prime}_{it}$ is positively associated with housing price growth rate in our specifications. More importantly, in all Models (1)-(4), we find positive and significant coefficients on the interaction term, which is consistent with our hypothesis. The economic magnitude of this effect can be interpreted as 0.9-2.5 percentage points higher housing price growth with a one standard deviation increase in the sub-prime loan ratio.[20] The individual coefficients for each control variable are generally in the right direction.

It is important to note that the coefficient on the stand-alone variable of *Non-recourse* remains significant with positive coefficient estimates. Combined with the findings on households' investment behavior in Section 5, these results suggests that non-recourse law drives a higher housing bubble through both the extensive margin from more sub-prime loan origination and the intensive margin from households' higher leverage decision.

Our overall results demonstrate an underlying mechanism in the recent housing bubbles and, in particular, why we observe larger bubbles in non-recourse states.

2.8 Conclusion

In this paper, we investigate the role of state-level variation in mortgage recourse law in the creation of a bubble in the housing market. We perform on contiguous state border pair-counties a state border discontinuity test combined with a difference-in-difference setting using the mortgage market collapse in 2007 as an exogenous shock. The results, which are economically large and robust, show that states with non-recourse law experience a larger bubble and burst in housing prices. Our evidence supports the bubble mechanism by the asset substitution problem, as proposed by *Allen and Gale* (2000a). We also examine the effect of recourse law on lending be-

[20]The standard deviation of the sub-prime loan ratio is 0.13 for the sample period. The economic magnitude is calculated by 0.13*0.19= 0.025 in Model (1) and 0.13*0.07 = 0.009 in Models (3) and (4).

havior. Although we find evidence that mortgage lenders are aware of the additional risk inherent in non-recourse loans, the higher sub-prime loan ratio in non-recourse states suggests that the OTD market enables lenders to effectively shift the risk to other investors.

The bubble and burst cycle in the housing market has been repeated and amplified in non-recourse states. Although recourse mortgage law has been adopted by most European countries and Canada, China, and Japan, it has become a subject of heated debate in relation to housing market reform. This paper identifies important implications for the evaluation of recourse mortgage law with respect to preventing future housing market crises and collapse. Non-recourse law, while protecting households from premature foreclosures and lenders' deficiency judgments, causes larger swings in housing prices as a result of being exploited by households to make riskier investments when housing markets are in a boom cycle.

APPENDICES

APPENDIX A

Fire-Sale Acquisitions and Intra-Industry Contagion

Figure 1.1: Components of Corporate Sector Asset Reallocation

This graph shows the components of corporate sector asset reallocation in billions of dollars between 1980 and 2010. The solid line denotes the total annual amount of asset reallocation: sum of acquisitions (Compustat: AQC) and sales of property, plant and equipment (Compustat: SPPE). The dotted line denotes total acquisitions of all firms in Compustat. The dashed line denotes sales of property, plant and equipment of all firms in Compustat. This graph shows that acquisitions account for around two-thirds of asset reallocation.

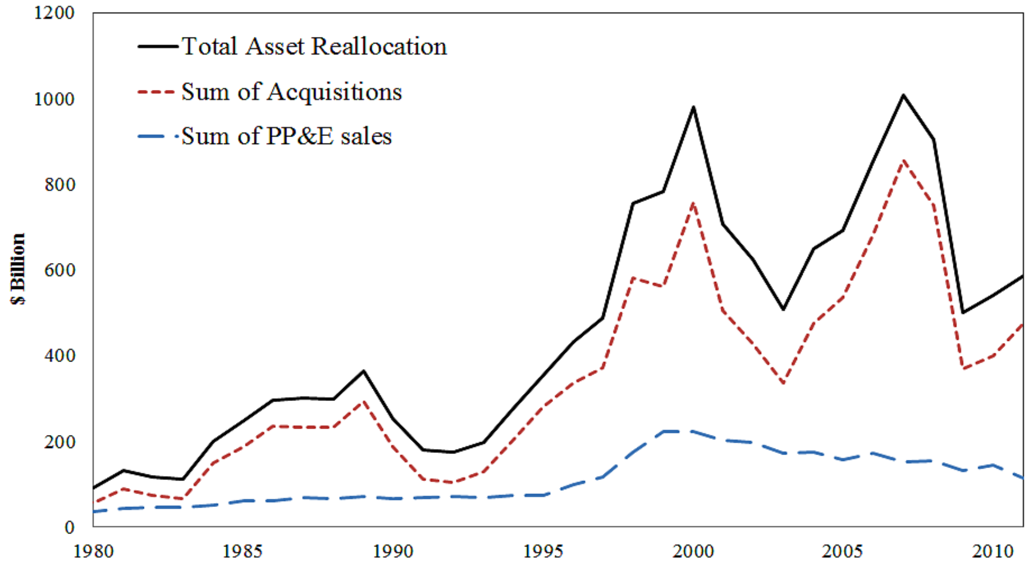


Figure 1.2: Financial Frictions and Fire-Sale

This graph shows the impact of a negative industry-wide shock on the secondary market for corporate assets. In a world without financial frictions, corporate assets are traded based on the future cash flows from the assets. A negative industry-wide shock drives price to fall from P_0 to P_1, which reflects the updated value of the assets, by shifting the supply (S) and demand (D) curves. With financial frictions, however, more firms within the industry are likely to be financially constrained due to an industry-wide debt overhang problem. Moreover, given that the assets are fairly specialized to the industry, industry outsiders with high liquidity have lower valuations of the assets due to frictions in capital allocation across industries. Thus, demand decreases further from D_1 to D_{FS} and supply increases further from S_1 to S_{FS}, which reduces the market price to P_{FS}, the fire-sale price.

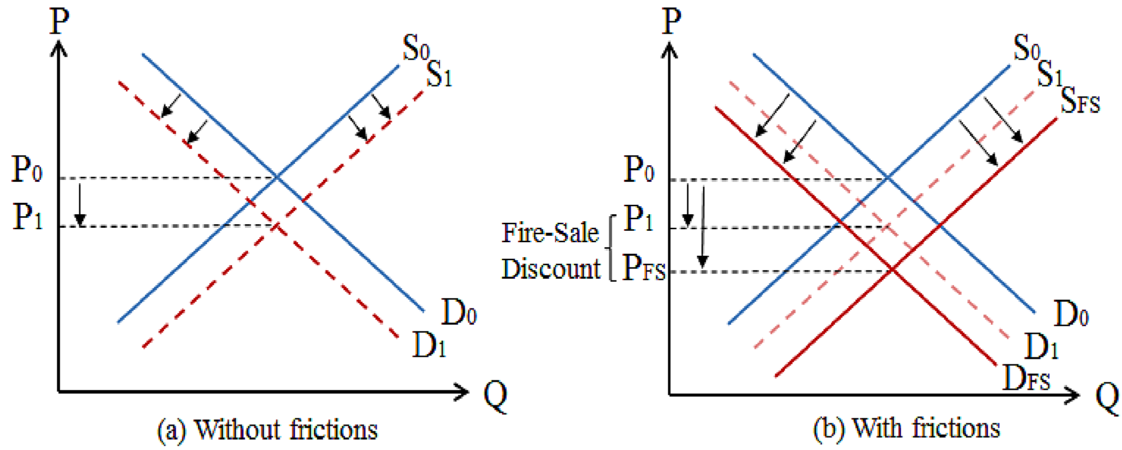


Figure 1.3: Long-term Abnormal Returns for Acquirers

This figure shows the cumulative abnormal returns (CARs) of acquirers from 20 days before to 200 days after the announcement of acquisitions. The solid line shows CARs for acquirers of a distressed target in a distressed industry, or fire-sale acquisition. The dotted line shows CARs for acquirers of a distressed target in a non-distressed industry. The dashed line shows CARs for acquirers of a non-distressed target in a non-distressed industry. Abnormal returns are calculated as the acquirer's return minus a value-weighted market index.

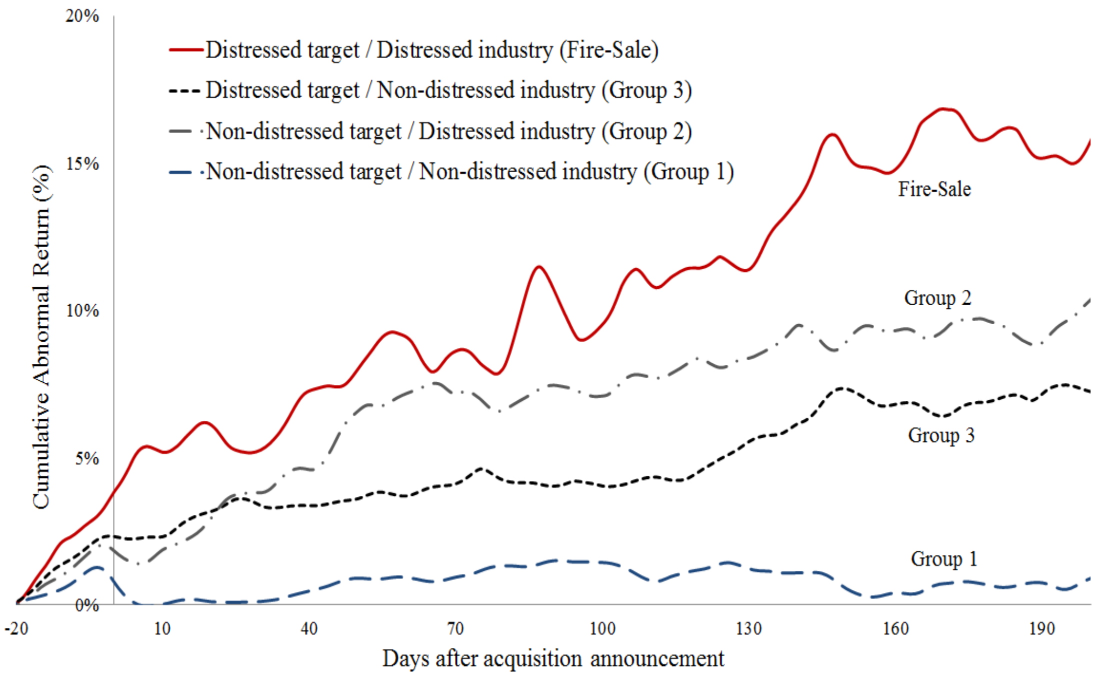


Figure 1.4: Short-term Abnormal Returns for Acquirers

This figure shows the cumulative abnormal returns (CARs) of acquirers over three days surrounding the announcement (-1,+1) using Fama-French three-factor model. The red dots show the CARs of acquirers when targets are in distressed industries, and the navy pluses are when targets are in non-distressed industries. The black solid line and navy dashed line show the fitted values of observations in distressed industries and non-distressed industries, respectively. Industry is defined as distressed if median sales growth is negative. The gray area shows the 95% confidence interval. Target firm distress measure (EDF) is a continuous measure, $Distress1_T$, based on distance-to-default model.

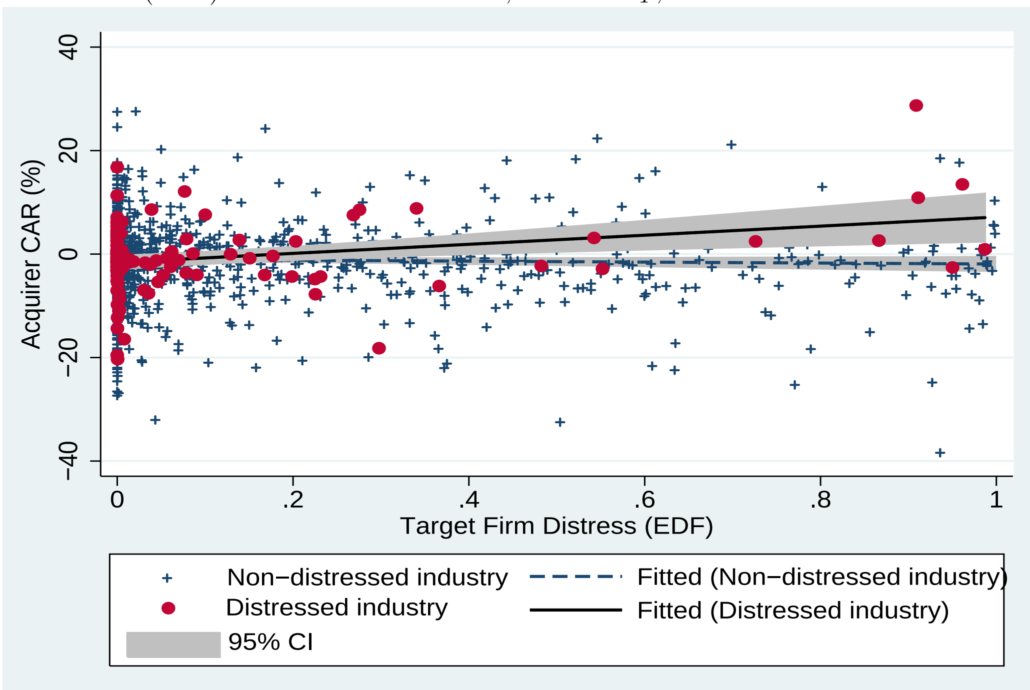


Figure 1.5: Abnormal Returns for Target Industry Rivals

This figure shows the short-term cumulative abnormal returns (CARs) of target industry rivals from 10 days before to 50 days after the announcement of acquisitions. The solid line shows CARs for acquirers of a distressed target in a distressed industry, or fire-sale acquisition. The dotted line shows CARs for acquirers of a distressed target in a non-distressed industry. The dashed line shows CARs for acquirers of a non-distressed target in a non-distressed industry. Abnormal returns are calculated as the acquirer's return minus a value-weighted market index.

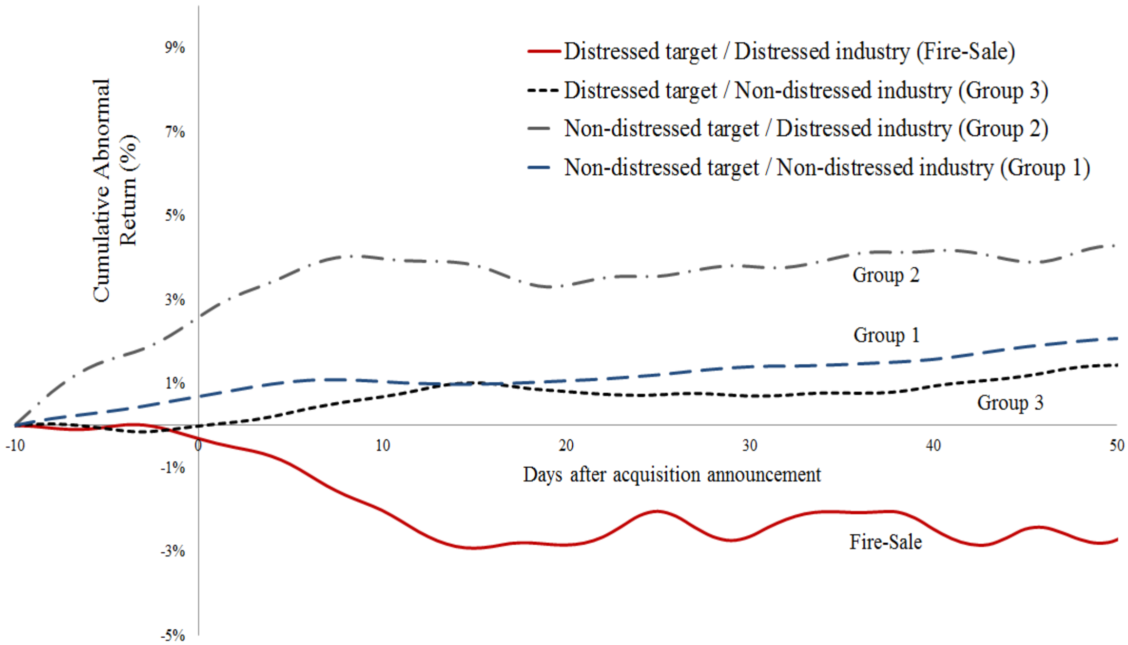


Figure 1.6: Operating Performance of Target Rivals

These figures show the operating performance of target industry rivals from t-3 year to t+3 year around the announcement of acquisition. Figure (a) shows median ROA (net income/total assets) and figure (b) shows median profit margin (operating cash flow/total sales).

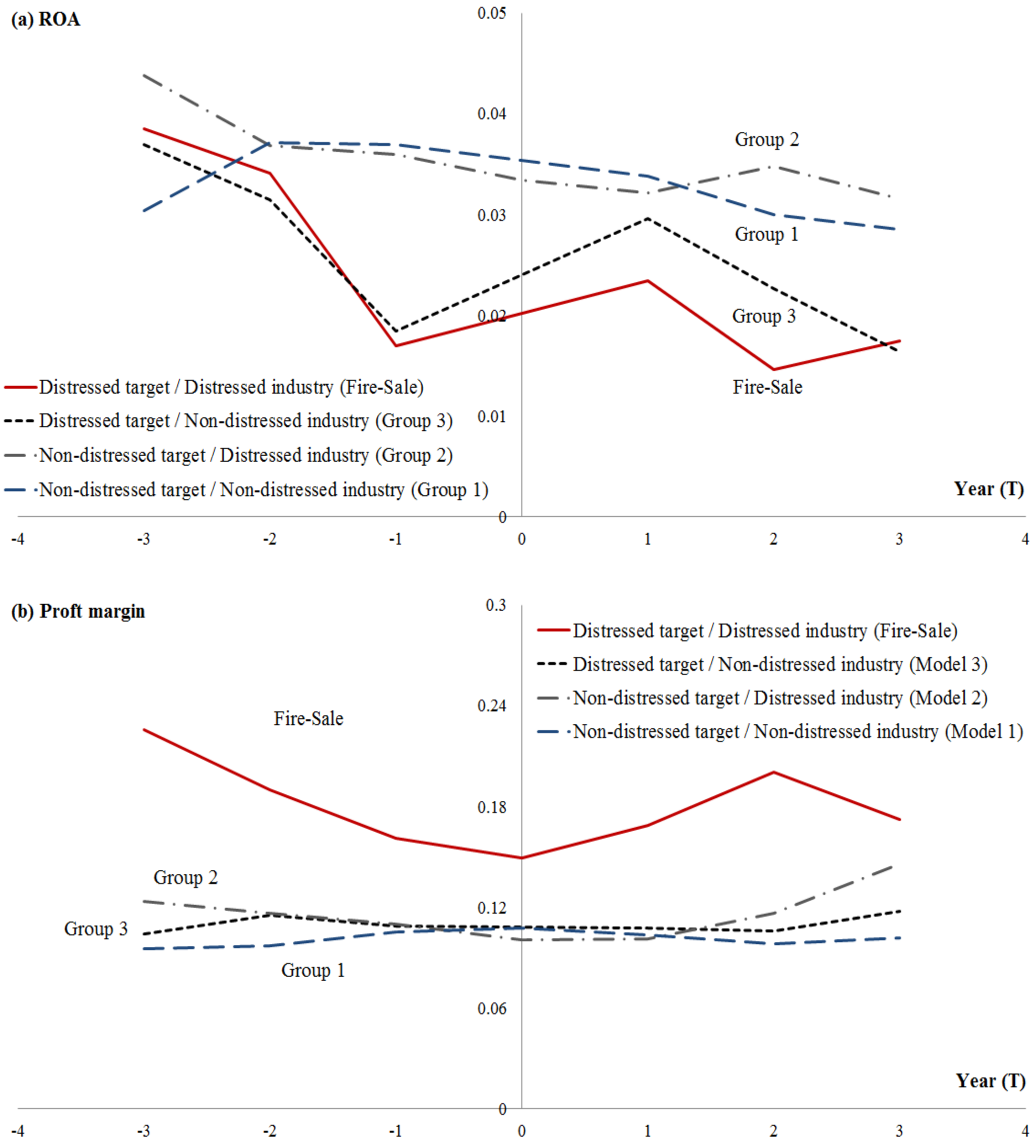


Table 1.1: Variable Definitions

Variable	Description	Source
$Distress1_T$	EDF index from Distance-to-Default model (*Merton* (1974))	COMPUSTAT, CRSP
$Distress2_T$	Dummy equal to one if leverage > industry median and current ratio < industry median	COMPUSTAT
$Ind.Distress_T$	Dummy equal to one if median sales growth is negative	COMPUSTAT
CAR(-1, +1)	Cumulative abnormal returns over three days surrounding the announcement (-1, +1) using Fama-French three-factor model	CRSP
$BHAR_A$	The acquirer's buy-and-hold returns during 2 years following acquisition less the buy-and-hold return of a matched firm	COMPUSTAT, CRSP
Ln(Price1)	The log of total equity value (EQVAL)	SDC
Ln(Price2)	The log of total transaction value (TRANSACT)	SDC
Premium	Offer price (PR) divided by target stock price 4 weeks before the announcement (SPRC_4WK)	SDC
$CAR_{Combined}$	The marget equity value weighted average of the target's CAR and acquirer's CAR	COMPUSTAT, CRSP
Log(Synergy)	The log of the sum of the acquirer's and target's abnormal dollar return (CAR*market cap.)	COMPUSTAT, CRSP
$DCAR$	CAR(-1, +1) times market equity value 4 weeks prior to the announcement	SDC
NDCAR (ω^T)	($DCAR_T$ - $DCAR_A$)/(target mkt cap. + acquirer mkt cap.)	*Ahern* (2011)
$Bargain_T$	$DCAR_T$ /($DCAR_T$ +$DCAR_A$)	CRSP
Outsider	Dummy equal to one if the acquirer's 3-digit SIC code is different from the target's	COMPUSTAT
Capital-Specificity	1 - (used capital expenditure within an industry/aggregate industry capital expenditure), *Balasubramanian and Sivadasan* (2009)	
Labor Union	Percentage of labor union membership in 3-digit SIC code, *Hirsch and Macpherson* (2002)	
R&D Intensity	Research and development expense divided by total sales	COMPUSTAT
Size	Log of market capitalization 4 weeks before announcement	CRSP
Market-to-book	Market value of total assets divided by book value assets	COMPUSTAT, CRSP
Leverage	Total debt (Debt in current liabilities + long-term debt) divided by total book assets	COMPUSTAT
Tangibility	(Total assets - Intangible assets)/Total assets	COMPUSTAT
Profitability	Operating income after depreciation divided by total sales (Profit margin)	COMPUSTAT
Same Industry	Dummy equal to one if target and acquirer in the same 3-digit SIC code	COMPUSTAT
Tender Offer	Dummy equal to one if acquirers issue tender offer	SDC
Toehold	The percentage of shares held by the acquirer at the acquisition announcement	SDC
Competing	Dummy equal to one if the acquirer had to make a counter-offer	SDC
Poison Pill	Dummy equal to one if the target has poison pill provision	
Termination Fee	Dummy equal to one if the merger agreement includes a target termination fee	SDC
Recession	NBER defined recession	NBER

Table 1.2: Summary Statistics: Target and Acquirer

This table presents the summary statistics for the U.S. acquisitions completed between 1980 and 2010 in which the publicly traded acquiring firm gains control of a public target as listed by SDC. Panels A and B provide pre-acquisition characteristics of target and acquirer, respectively. All variables are defined in Table 1.1.

	Mean	Median	Std. dev.	Min	Max	Obs.
Panel A. Target Characteristics						
$Distress1_T$	0.111	0.001	0.227	0.000	0.998	1572
Industry Distress	0.074	0.000	0.262	0.000	1.000	1572
Log (Assets)	11.78	11.66	1.644	7.183	17.60	1572
Log (Equity)	5.282	5.201	1.721	0.096	11.27	1572
Market/Book	2.087	1.479	2.018	0.297	28.40	1572
Cash	0.228	0.135	0.236	0.000	0.970	1572
Leverage	0.181	0.127	0.184	0.000	0.929	1572
Profitability	-0.198	0.095	1.671	-20.78	0.618	1556
Tangibility	0.892	0.972	0.159	0.171	1.000	1334
Industry Q	1.765	1.619	0.652	0.756	7.184	1572
Industry Leverage	0.147	0.120	0.119	0.000	0.663	1572
Capital-Specificity	0.937	0.940	0.033	0.786	1.000	866
Union Membership	9.560	5.700	10.909	0.000	78.40	1495
R&D Intensity	0.107	0.074	0.161	0.000	1.093	1513
Panel B. Acquirer Characteristics						
EDF	0.052	0.000	0.160	0.000	1.000	1427
Industry Distress	0.082	0.000	0.275	0.000	1.000	1569
Log (Assets)	14.17	14.11	2.092	7.632	19.82	1572
Log (Equity)	7.829	7.756	2.210	1.148	13.37	1572
Market/Book	2.505	1.807	2.675	0.354	58.04	1572
Cash	0.177	0.109	0.186	0.000	0.981	1572
Leverage	0.198	0.179	0.161	0.000	0.869	1572
Profitability	0.100	0.159	1.467	-55.09	0.812	1571
Tangibility	0.852	0.921	0.174	0.080	1.000	1313

Table 1.3: Summary statistics: Deal Characteristics

This table presents the summary statistics for key deal characteristics for the U.S. acquisitions completed between 1980 and 2010 in which the publicly traded acquiring firm gains control of a public target as listed by SDC. A firm's industry is defined as the set of firms with the same 3-digit SIC code. All variables are defined in Table 1.1.

	Mean	Median	Std. dev.	Min	Max	Obs.
Ln (Price1)	5.388	5.286	1.779	-1.808	11.39	1566
Ln (Price2)	5.404	5.325	1.752	-0.511	11.40	1572
Premium	0.504	0.377	0.934	-0.628	19.94	933
Relative Size	0.841	0.848	0.120	0.500	1.511	1572
Tender Offer	0.254	0.000	0.435	0.000	1.000	1572
Toehold	0.032	0.000	0.130	0.000	0.982	1572
Competing Bidder	0.050	0.000	0.217	0.000	1.000	1572
Cash Payment	0.373	0.000	0.484	0.000	1.000	1572
Stock Payment	0.280	0.000	0.449	0.000	1.000	1572
Termination Fee	0.601	1.000	0.490	0.000	1.000	1497
Same Industry	0.539	1.000	0.499	0.000	1.000	1572

Table 1.4: Effects of Fire-Sale on Acquirer Return: Univariate Analysis

This table compares acquirer returns over target firm- and industry-distress. Panel A compares the cumulative abnormal returns (CAR_A (%)) of acquirers over target firm- and industry-distress. Panel B compares the buy-and-hold returns ($BHAR_A$ (%)) during the two years following the acquisition, less the buy-and-hold return of a matched firm. CARs are presented for the (-1, +1) window surrounding the announcement of acquisitions. Target is classified as distressed, based on $Distress1_T$, if the firm's EDF index is greater than the median of the entire merger sample. Industry is defined as distressed, based on a dummy variable $Ind.Distress_T$. The industry of a firm is defined as the set of firms with the same 3-digit SIC code. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

	All	Distressed Target		Non-distressed Target	
	-	Dist. Ind.	Non-dist. Ind.	Dist. Ind.	Non-dist. Ind.
Panel A. CAR_A(%)					
Mean	-0.88***	-0.92	-1.04***	-0.94	-0.75***
Median	-0.57	-1.22	-0.89	-0.56	-0.33
Std. Dev.	7.30	6.56	8.02	7.28	6.82
Number of Obs.	2409	80	912	100	1317
Panel B. $BHAR_A$(%)					
Mean	-11.11***	4.10	-9.90***	-25.60*	-11.80***
Median	-6.57	0.70	-7.10	-15.90	-6.20
Std. Dev.	77.08	78.40	81.00	120.00	70.70
Number of Obs.	1651	52	611	58	930

Table 1.5: Effects of Fire-Sale on Acquirer Returns: Multivariate Analysis

This table presents the impact of fire-sale on short-run and long-run abnormal returns for acquirers. We specify a regression model:

$$Y_{ijdt} = \beta_1 \underbrace{(Ind.D_{it} \times Distress_{it})}_{Fire\text{-}Sale} + \beta_2 Ind.D_{it} + \beta_3 Distress_{it} + \gamma^{'} X_{ijd} + \alpha_t + \alpha_i + \varepsilon_{ijdt} \qquad \text{(A.1)}$$

where $Distress_{it}$ and $Ind.D_{it}$ are the target firm and industry distress measures, respectively, of target i, and X_{ijd} represents control variables for target i, acquirer j, and deal characteristics d. Year fixed effect (α_t) and industry fixed effect (α_i) are also included. In Models (1)-(2), the dependent variable is acquirer's three-day cumulative abnormal return (CAR_A) at announcement of acquisition, estimated using a market model. In Models (3)-(4), the dependent variable is acquirer's buy-and-hold returns ($BHAR_A$) during 2 years following acquisition less buy-and-hold return of a matched firm. The variable of interest is *Fire-Sale* — the interaction between target firm distress ($Distress1_T$, $Distress2_T$) and industry-level distress ($Ind.Distress_T$). $Ind.Distress_T$ is a dummy that equals 1 if the sales growth of the median firm in an industry is negative in the year of the transaction. Control variables for acquirer characteristics are *size*, *leverage*, *m/b*, *tangibility*, and *profitability*. Deal-specific controls include *same industry*, *tender offer*, *toehold*, *competing*, *poison pill*, and *termination fee*. Industry fixed effects are at the 3-digit SIC code level. Other variables are defined in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable:	CAR_A		$BHAR_A$	
	(1)	(2)	(3)	(4)
Fire-Sale$_1$	0.11***		1.01*	
	(0.03)		(0.53)	
Fire-Sale$_2$		0.05***		0.82***
		(0.01)		(0.19)
$Ind.Distress_T$	0.00	0.01	0.07	0.09
	(0.01)	(0.01)	(0.09)	(0.08)
$Distress1_T$	-0.01		-0.10	
	(0.01)		(0.17)	
$Distress2_T$		0.01		-0.07
		(0.01)		(0.06)
Med. Ind. Q	0.01**	0.01**	0.04	0.04
	(0.01)	(0.01)	(0.10)	(0.09)
Med. Ind. Leverage	0.01	0.01	1.45	1.52
	(0.05)	(0.05)	(1.16)	(1.17)
Target Size	-0.01***	-0.01***	-0.05***	-0.05**
	(0.00)	(0.00)	(0.02)	(0.02)
Target Leverage	-0.00	-0.02	-0.32*	-0.30*
	(0.01)	(0.02)	(0.17)	(0.17)
Target M/B	-0.00***	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.02)	(0.02)
Target Tangibility	0.03	0.03	0.02	0.01
	(0.02)	(0.02)	(0.19)	(0.18)
Target Profitability	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Control: Acq. & Deal	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Obs.	1098	1098	776	776
Adj-R^2	0.08	0.07	0.16	0.16

Table 1.6: Effects of Fire-Sale on Target Offer Price

This table tests for the impact of fire-sale on target offer price. The dependent variables are three different measures of offer price for target shareholders from the SDC database, defined as follows: *Ln*(*Price*1): the log of total equity value, *Ln*(*Price*2): the log of total transaction value, and *Premium*: per share offer price divided by target stock price four weeks before the announcement. The variable of interest is *Fire-Sale* — the interaction between target firm distress ($Distress1_T$, $Distress2_T$) and industry-level distress ($Ind.Distress_T$). Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable: Offer Price	Ln(Price1)		Ln(Price2)		Premium	
	(1)	(2)	(3)	(4)	(5)	(6)
$Fire\text{-}Sale_1$	-0.89*		-0.50***		-0.76***	
	(0.49)		(0.13)		(0.24)	
$Fire\text{-}Sale_2$		-0.24		-0.24*		-0.28**
		(0.22)		(0.12)		(0.13)
$Ind.Distress_T$	0.23**	0.14	0.07	0.05	0.09	-0.00
	(0.10)	(0.09)	(0.06)	(0.08)	(0.08)	(0.11)
$Distress1_T$	0.31***		0.29***		0.69**	
	(0.10)		(0.09)		(0.28)	
$Distress2_T$		-0.01		-0.05		0.02
		(0.05)		(0.04)		(0.06)
Med. Ind. Q	0.02	-0.02	-0.00	-0.05	-0.01	0.01
	(0.04)	(0.07)	(0.04)	(0.06)	(0.06)	(0.09)
Med. Ind. Leverage	0.91***	0.45	0.57*	0.17	-0.54	-0.19
	(0.32)	(0.38)	(0.31)	(0.41)	(1.28)	(1.56)
Target Size	0.89***	0.83***	0.90***	0.84***	-0.11***	-0.15***
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)
Target Leverage	0.80***	1.11***	0.27**	0.65***	-0.16	0.14
	(0.11)	(0.12)	(0.10)	(0.11)	(0.20)	(0.21)
Target M/B	0.01	0.02	-0.00	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Target Tangibility	-0.68***	-0.82***	-0.37***	-0.52***	-0.69**	-0.88*
	(0.15)	(0.19)	(0.11)	(0.17)	(0.32)	(0.45)
Target Profitability	0.00	0.00	0.00	0.00	0.00**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Control: Acq. & Deal	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1187	1300	1193	1306	1078	1167
Adj-R^2	0.92	0.87	0.94	0.89	0.29	0.21

Table 1.7: Effects of Fire-Sale on Synergy and Target Bargaining Power

This table presents the effect of fire-sale on synergy and target's bargaining power. In Models (1) and (2), the dependent variable is combined CAR, measured as the market equity value weighted average of the target's CAR and acquirer's CAR. In Models (3) and (4), $Ln(Synergy)$ is the log of sum of the target's and acquirer's abnormal dollar returns ($CAR * MarketCap$). In Models (5) and (6), the dependent variable is target's bargaining power, $NDCAR(\omega_T)$, estimated as the difference of abnormal dollar returns for the (-1, +1) window between target and acquirer divided by the sum of market equity value of target and acquirer four weeks prior to acquisition announcement. In Models (7) and (8), the dependent variable is $Bargain_T$, calculated as target's abnormal dollar return divided by the combined abnormal dollar returns of acquirer and target. The variable of interest is *Fire-Sale* — the interaction between target firm distress ($Distress1_T$, $Distress2_T$) and industry-level distress ($Ind.Distress_T$). Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable:	$CAR_{Combined}$		Ln(Synergy)		NDCAR (ω^T)		$Bargain_T$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fire-Sale$_1$	0.03		-0.14		-0.10**		-0.43***	
	(0.02)		(0.63)		(0.04)		(0.08)	
Fire-Sale$_2$		-0.01		0.18		-0.05***		-0.20**
		(0.02)		(0.45)		(0.02)		(0.08)
$Ind.Distress_T$	0.00	0.01	0.22	0.25	0.00	-0.00	0.00	-0.02
	(0.01)	(0.01)	(0.29)	(0.27)	(0.01)	(0.01)	(0.07)	(0.06)
$Distress1_T$	-0.01		0.98***		0.01		0.00	
	(0.01)		(0.30)		(0.01)		(0.07)	
$Distress2_T$		0.01		0.34*		-0.01		-0.05
		(0.01)		(0.17)		(0.01)		(0.04)
Med. Ind. Q	0.01	0.01	0.29	0.29	-0.01	-0.01	0.02	0.03
	(0.01)	(0.01)	(0.18)	(0.18)	(0.01)	(0.01)	(0.05)	(0.05)
Med. Ind. Lev.	0.08	0.08	-0.01	0.56	0.05	0.04	0.14	0.07
	(0.07)	(0.07)	(1.44)	(1.42)	(0.06)	(0.07)	(0.38)	(0.38)
Target Size	0.00**	0.01**	0.39***	0.36***	0.02***	0.02***	0.06***	0.06***
	(0.00)	(0.00)	(0.07)	(0.07)	(0.00)	(0.00)	(0.01)	(0.01)
Target Lev.	-0.01	-0.02	0.55	0.37	-0.01	-0.00	-0.12	-0.05
	(0.01)	(0.02)	(0.54)	(0.56)	(0.01)	(0.01)	(0.12)	(0.11)
Target M/B	-0.01***	-0.01***	-0.06	-0.08	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.06)	(0.06)	(0.00)	(0.00)	(0.01)	(0.01)
Tangibility	0.02	0.02	0.54	0.70*	-0.01	-0.01	-0.08	-0.11
	(0.02)	(0.02)	(0.36)	(0.36)	(0.01)	(0.02)	(0.09)	(0.09)
Profitability	0.00	0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1098	1098	668	668	1098	1098	1011	1011
Adj-R^2	0.10	0.10	0.63	0.62	0.18	0.18	0.06	0.06

Table 1.8: Effects of Fire-Sale on Acquirer Identity

This table presents estimates from probit regressions that explain acquirer identity using target firm- and industry-level distress and the interaction of these two variables. The dependent variable is *Outsider*, a dummy that equals 1 if the acquirer's 3-digit SIC code is different from the target's. Models (1) and (3) exclude control variables for acquirer and deal characteristics; Models (2) and (4) include control variables, as described in Table 1.5. The variable of interest is *Fire-Sale* — the interaction between target firm distress ($Distress1_T$, $Distress2_T$) and industry-level distress ($Ind.Distress_T$). Industry fixed effects are at the 3-digit SIC code level. A detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable: *Outsider*	(1)	(2)	(3)	(4)
Fire-Sale$_1$	-0.62	-0.23		
	(0.59)	(0.69)		
Fire-Sale$_2$			-0.35	-0.25
			(0.35)	(0.40)
$Ind.Distress_T$	0.55**	0.51**	0.51**	0.51**
	(0.22)	(0.23)	(0.20)	(0.22)
$Distress1_T$	-0.17	-0.18		
	(0.23)	(0.28)		
$Distress2_T$			-0.17	-0.11
			(0.13)	(0.15)
Med. Ind. Q	-0.30**	-0.33**	-0.29**	-0.32**
	(0.13)	(0.15)	(0.13)	(0.15)
Med. Ind. Leverage	-1.07	-2.09	-1.08	-2.12
	(1.15)	(1.38)	(1.16)	(1.39)
Target Size	0.02	-0.04	0.03	-0.03
	(0.03)	(0.04)	(0.03)	(0.04)
Target Leverage	-0.66**	-0.68**	-0.48	-0.58
	(0.29)	(0.32)	(0.32)	(0.36)
Target M/B	0.05***	0.06**	0.05***	0.06**
	(0.02)	(0.03)	(0.02)	(0.03)
Target Tangibility	-0.50	-0.54	-0.55*	-0.59*
	(0.33)	(0.35)	(0.33)	(0.36)
Target Profitability	0.01*	0.01	0.01*	0.01
	(0.00)	(0.01)	(0.00)	(0.01)
Control: Acq. & Deal	No	Yes	No	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Obs.	1111	916	1111	916
Pseudo-R^2	0.19	0.22	0.19	0.22

Table 1.9: Effects of Fire-Sale with Outside Acquirers

This table tests whether fire-sale effects are stronger when acquirers are industry outsiders. The dependent variables for acquisition outcomes are as follows. Acquirer return: CAR_A, target offer price: $Ln(Price1)$, target bargaining power: $NDCAR(\omega_T)$, and synergy: $CAR_{Combined}$. The variable of interest is the interaction between *Fire-Sale* and *Outsider*. *Fire-Sale* is the interaction between target firm distress ($Distress1_T$, $Distress2_T$) and industry-level distress ($Ind.Distress_T$). *Outsider* is a dummy variables that equals 1 if the acquirer's 3-digit SIC code is different from the target's. Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable:	CAR_A	Ln(Price1)	NDCAR (ω^T)	$CAR_{Combined}$
	(1)	(2)	(3)	(4)
$Fire\text{-}Sale_1$*$Outsider$	0.20**	-2.80**	-0.25***	-0.14*
	(0.08)	(1.31)	(0.09)	(0.08)
$Fire\text{-}Sale_1$	0.06	-0.36	-0.04	0.06***
	(0.04)	(0.34)	(0.04)	(0.02)
$Ind.Dist._T$*$Outsider$	-0.02	0.11	0.03**	0.01
	(0.02)	(0.15)	(0.01)	(0.02)
$Dist.1_T$*$Outsider$	-0.01	0.14	0.02	-0.00
	(0.03)	(0.23)	(0.02)	(0.02)
$Ind.Distress_T$	0.01	0.18*	-0.01	-0.00
	(0.01)	(0.10)	(0.01)	(0.01)
$Distress1_T$	-0.01	0.31**	0.00	-0.01
	(0.01)	(0.14)	(0.01)	(0.01)
Outsider	0.00	-0.11**	-0.01	-0.01
	(0.01)	(0.05)	(0.01)	(0.01)
Med. Ind. Q	0.01*	0.00	-0.01	0.01
	(0.01)	(0.05)	(0.01)	(0.01)
Med. Ind. Leverage	0.01	0.37	0.05	0.07
	(0.05)	(0.39)	(0.06)	(0.06)
Target Size	-0.01***	0.88***	0.02***	0.00**
	(0.00)	(0.03)	(0.00)	(0.00)
Target Leverage	-0.01	0.80***	-0.01	-0.01
	(0.02)	(0.10)	(0.01)	(0.01)
Target M/B	-0.00***	0.01	0.00	-0.01***
	(0.00)	(0.01)	(0.00)	(0.00)
Target Tangibility	0.02	-0.67***	-0.01	0.02
	(0.02)	(0.13)	(0.02)	(0.02)
Target Profitability	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Control: Acq. & Deal	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Obs.	1098	1093	1098	1098
Adj-R^2	0.08	0.92	0.18	0.11

Table 1.10: Effects of Fire-Sale and Industry Capital-Specificity

This table tests whether fire-sale effects are stronger when targets have high industry-level capital-specificity. The dependent variables for acquisition outcomes are as follows. Acquirer return: CAR_A, target offer price: $Ln(Price1)$, target bargaining power: $NDCAR(\omega_T)$, and synergy: $CAR_{Combined}$. Industry capital-specificity is one minus the ratio of used capital expenditure within an industry to the aggregate industry capital expenditure as calculated by *Balasubramanian and Sivadasan* (2009). I define an industry as a high capital-specificity industry if industry-level capital-specificity is above the median value of the aggregate industry. The variable of interest is the interaction between *Fire-Sale* and *Capital-Specificity*. Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable:	CAR_A	Ln(Price1)	NDCAR (ω^T)	$CAR_{Combined}$
	(1)	(2)	(3)	(4)
Fire-Sale$_1$**Capital-Specificity*	3.84*	-81.49***	-5.74***	-6.03***
	(2.27)	(20.41)	(2.00)	(1.39)
Fire-Sale$_1$	0.30***	-3.87***	-0.34***	-0.14***
	(0.10)	(0.75)	(0.08)	(0.04)
$Ind.Dist._T$**Capital-Specificity*	-0.15	1.99	0.30	0.19
	(0.30)	(2.24)	(0.25)	(0.31)
$Dist.1_T$**Capital-Specificity*	1.64**	-9.93*	-1.40*	1.20*
	(0.70)	(5.85)	(0.72)	(0.65)
$Ind.Distress_T$	0.01	0.28*	-0.01	0.01
	(0.02)	(0.15)	(0.02)	(0.02)
$Distress1_T$	-0.04**	0.27	0.05**	-0.02
	(0.02)	(0.19)	(0.02)	(0.02)
Med. Ind. Q	0.01	-0.00	0.01	0.02
	(0.01)	(0.12)	(0.02)	(0.01)
Med. Ind. Leverage	-0.02	0.30	0.13	0.11
	(0.09)	(0.70)	(0.12)	(0.13)
Target Size	-0.01**	0.88***	0.02***	0.01**
	(0.00)	(0.05)	(0.00)	(0.00)
Target Leverage	0.01	0.54***	-0.04*	-0.02
	(0.02)	(0.18)	(0.02)	(0.03)
Target M/B	-0.00	-0.00	-0.00	-0.01**
	(0.00)	(0.02)	(0.00)	(0.00)
Target Tangibility	0.00	-0.74***	0.01	0.00
	(0.03)	(0.20)	(0.02)	(0.03)
Target Profitability	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Control: Acq. & Deal	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Obs.	570	567	570	570
Adj-R^2	0.08	0.91	0.24	0.12

Table 1.11: Effects of Fire-Sale and Labor Union

This table examines whether fire-sale effects are stronger when target industries have strong labor unions. Industry labor unionization is measured by the percentage of unionized workers in each industry. I define an industry to be a strong labor union industry if the union membership at 3-digit SIC industry-level is above the overall median. Panel A includes only acquisitions in strong labor union industries and Panel B includes only acquisitions in weak labor union industries. The dependent variables for acquisition outcomes are as follows. Acquirer return: CAR_A, target offer price: $Ln(Price1)$, target bargaining power: $NDCAR(\omega_T)$, and synergy: $CAR_{Combined}$. Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Panel A. Strong Labor Union Industries

Dep. variable:	CAR_A	Ln(Price1)	NDCAR (ω^T)	$CAR_{Combined}$
	(1)	(2)	(3)	(4)
Fire-Sale$_1$	0.20***	-4.26**	-0.19***	0.01
	(0.05)	(1.67)	(0.04)	(0.05)
$Ind.Distress_T$	-0.00	0.36*	-0.03	-0.03
	(0.01)	(0.19)	(0.02)	(0.03)
$Distress1_T$	-0.05*	0.66***	0.06**	-0.03
	(0.03)	(0.19)	(0.03)	(0.03)
Target & Industry	Yes	Yes	Yes	Yes
Acq. & Deal	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Obs.	491	490	491	491
Adj-R^2	0.03	0.91	0.21	0.17

Panel B. Weak Labor Union Industries

Dep. variable:	CAR_A	Ln(Price1)	NDCAR (ω^T)	$CAR_{Combined}$
	(1)	(2)	(3)	(4)
Fire-Sale$_1$	0.08*	-0.29	-0.07	0.08**
	(0.04)	(0.32)	(0.05)	(0.03)
$Ind.Distress_T$	0.00	0.08	0.01	0.01
	(0.01)	(0.12)	(0.01)	(0.01)
$Distress1_T$	0.00	0.38***	-0.01	-0.00
	(0.02)	(0.14)	(0.02)	(0.01)
Target & Industry	Yes	Yes	Yes	Yes
Acq. & Deal	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Obs.	572	568	572	572
Adj-R^2	0.14	0.92	0.19	0.07

Table 1.12: Effects of Fire-Sale and R&D Intensity

This table examines whether fire-sale effects are stronger when target industries have high R&D intensity. R&D intensity is measured by research and development expenses scaled by sales. I define an industry to be a high (low) R&D industry if the R&D intensity at 3-digit SIC industry-level is above (below) the overall median. Panel A includes only acquisitions in intense R&D industries and Panel B includes only acquisitions in low R&D industries. The dependent variables for acquisition outcomes are as follows. Acquirer return: CAR_A, target offer price: $Ln(Price1)$, target bargaining power: $NDCAR(\omega_T)$, and synergy: $CAR_{Combined}$. Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Panel A. High R&D Industries

Dep. variable:	CAR_A	Ln(Price1)	NDCAR (ω^T)	$CAR_{Combined}$
	(1)	(2)	(3)	(4)
Fire-Sale$_1$	0.16***	-1.08**	-0.13***	0.08
	(0.05)	(0.43)	(0.05)	(0.05)
$Ind.Distress_T$	-0.01	0.07	0.02	0.02
	(0.04)	(0.29)	(0.03)	(0.04)
$Distress1_T$	0.01	0.26*	-0.01	-0.01
	(0.02)	(0.15)	(0.02)	(0.02)
Target & Industry	Yes	Yes	Yes	Yes
Acq. & Deal	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Obs.	538	533	538	538
Adj-R^2	0.09	0.91	0.21	-0.05

Panel B. Low R&D Industries

Dep. variable:	CAR_A	Ln(Price1)	NDCAR (ω^T)	$CAR_{Combined}$
	(1)	(2)	(3)	(4)
Fire-Sale$_1$	-0.04	1.53	0.13	0.11
	(0.17)	(1.05)	(0.21)	(0.20)
$Ind.Distress_T$	-0.10	0.08	0.12	-0.05
	(0.07)	(0.45)	(0.09)	(0.09)
$Distress1_T$	-0.02	0.97***	0.01	-0.01
	(0.04)	(0.27)	(0.05)	(0.05)
Target & Industry	Yes	Yes	Yes	Yes
Acq. & Deal	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Obs.	522	522	522	522
Adj-R^2	0.25	0.96	0.09	0.26

Table 1.13: Descriptive Statistics for Alternative Explanations

The table contains the descriptive statistics for key variables in robustness tests. Panel A provides the summary for target misvaluation by decomposing market-to-book ratio (M/B) into target firm-specific error, industry-wide short-run error, and long-run growth option based on Appendix A. Panel B provides the summary for macroeconomic variables including *Recession*, annual GDP growth rate(%) and spread between Aaa corporate bond and Bbb bond (%).A target is classified as distressed, based on a dummy variable $Distress2_T$, if the firm's leverage ratio is greater than the median leverage ratio of all firms in the same industry, and the firm's current ratio (current assets/current liabilities) is less than the median current ratio of the industry. Industry is defined as distressed, based on a dummy variable $Ind.Distress_T$. $Ind.Distress_T$ is a dummy that equals 1 if the sales growth of the median firm in an industry is negative in the year of the transaction. The industry of a firm is defined as the set of firms with the same 3-digit SIC code. All variables are further defined in Appendix 1.1.

	All		Distressed Target		Non-distressed Target	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Panel A. Target Misvaluation						
Ln(M/B): $m_{it} - b_{it}$	0.52	0.60	0.42	0.51	0.55	0.63
Target error: $m_{it} - v(\theta_{it}; \alpha_{jt})$	0.05	0.55	-0.02	0.49	0.07	0.58
Sector error: $v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	-0.06	0.21	-0.08	0.23	-0.05	0.20
Growth Option: $v(\theta_{it}; \alpha_j) - b_{it}$	0.55	0.40	0.54	0.43	0.55	0.38
Panel B. Recession						
Recession	0.11	0.32	0.13	0.33	0.11	0.31
Annual GDP growth (%)	5.50	2.09	5.42	1.98	5.53	2.13
Spread (Aaa-Bbb) (%)	0.96	0.41	0.95	0.44	0.97	0.40
Number of Observations	1627		421		1206	

Table 1.14: Effects of Fire-Sale and Stock Market Misvaluation

This table presents coefficient estimates from OLS regressions on outcome variables after controlling for the misvaluation of target. *Target Ind. Misvaluation* is target industry-wide short-run error and *Target Misvaluation* is target-specific error. The dependent variables for acquisition outcomes are as follows. Acquirer return: CAR_A, target offer price: $Ln(Price1)$, target bargaining power: $NDCAR(\omega_T)$, and synergy: $CAR_{Combined}$. The variable of interest is the interaction between *Fire-Sale* and *Outsider*. *Fire-Sale* is the interaction between target firm distress, $Distress1_T$, and industry-level distress $Ind.Distress_T$. Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable:	CAR_A	Ln(Price1)	NDCAR (ω^T)	$CAR_{Combined}$
	(1)	(2)	(3)	(4)
Fire-Sale$_1$	0.10***	-1.03*	-0.10**	0.02
	(0.03)	(0.60)	(0.04)	(0.02)
$Ind.Distress_T$	0.01	0.20*	-0.00	0.01
	(0.01)	(0.12)	(0.01)	(0.01)
$Distress1_T$	-0.02	0.42***	0.01	-0.02
	(0.01)	(0.11)	(0.01)	(0.01)
Target Misvaluation	-0.02**	0.18***	0.01	-0.02**
	(0.01)	(0.06)	(0.01)	(0.01)
Target Ind. Misvaluation	-0.01	-0.03	0.01	-0.00
	(0.02)	(0.12)	(0.02)	(0.02)
Med. Ind. Q	0.01**	-0.02	-0.01	0.01
	(0.01)	(0.06)	(0.01)	(0.01)
Med. Ind. Leverage	0.01	0.41	0.05	0.08
	(0.05)	(0.42)	(0.06)	(0.07)
Target Size	-0.01***	0.86***	0.02***	0.01***
	(0.00)	(0.03)	(0.00)	(0.00)
Target Leverage	-0.00	0.75***	-0.01	-0.01
	(0.01)	(0.12)	(0.01)	(0.01)
Target M/B	-0.00	-0.02*	-0.00	-0.00
	(0.00)	(0.01)	(0.00)	(0.00)
Target Tangibility	0.03	-0.69***	-0.01	0.02
	(0.02)	(0.15)	(0.01)	(0.02)
Target Profitability	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Control: Acq. & Deal	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Obs.	1098	1093	1098	1098
Adj-R^2	0.08	0.92	0.18	0.11

Table 1.15: Effects of Fire-Sale and Recession

This table presents coefficient estimates from OLS regressions on outcome variables after controlling for the recession. Recessions is defined as recessionary months identified by NBER. The dependent variables for acquisition outcomes are as follows. Acquirer return: CAR_A, target offer price: $Ln(Price1)$, target bargaining power: $NDCAR(\omega_T)$, and synergy: $CAR_{Combined}$. The variable of interest is the interaction between *Fire-Sale* and *Outsider*. *Fire-Sale* is the interaction between target firm distress, $Distress1_T$, and industry-level distress $Ind.Distress_T$. Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable:	CAR_A	Ln(Price1)	NDCAR (ω^T)	$CAR_{Combined}$
	(1)	(2)	(3)	(4)
Fire-Sale$_1$	0.11***	-1.11*	-0.10**	0.03
	(0.03)	(0.63)	(0.04)	(0.02)
$Ind.Distress_T$	0.00	0.22*	0.00	0.00
	(0.01)	(0.12)	(0.01)	(0.01)
$Distress1_T$	-0.01	0.37***	0.01	-0.01
	(0.01)	(0.10)	(0.01)	(0.01)
Recession	-0.02*	-0.03	0.02***	-0.01
	(0.01)	(0.06)	(0.01)	(0.01)
Med. Ind. Q	0.01**	-0.00	-0.01	0.01
	(0.01)	(0.06)	(0.01)	(0.01)
Med. Ind. Leverage	0.01	0.38	0.05	0.08
	(0.05)	(0.43)	(0.06)	(0.07)
Target Size	-0.01***	0.88***	0.02***	0.00**
	(0.00)	(0.03)	(0.00)	(0.00)
Target Leverage	-0.01	0.79***	-0.01	-0.01
	(0.01)	(0.11)	(0.01)	(0.01)
Target M/B	-0.00***	0.01	0.00	-0.01***
	(0.00)	(0.01)	(0.00)	(0.00)
Target Tangibility	0.03	-0.69***	-0.01	0.02
	(0.02)	(0.16)	(0.01)	(0.02)
Target Profitability	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Control: Acq. & Deal	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Obs.	1098	1093	1098	1098
Adj-R^2	0.08	0.91	0.18	0.10

Table 1.16: Descriptive Statistics for Target Industry Rivals

The table contains descriptive statistics for matched target industry rivals. The target rivals are matched based on same industry, size and M/B. Target is classified as distressed, based on a dummy variable $Distress2_T$, if the firm's leverage ratio is greater than the median leverage ratio of all firms in the same industry, and the firm's current ratio (current assets/current liabilities) is less than the median current ratio of the industry. Industry is defined as distressed, based on a dummy variable $Ind.Distress_T$. $Ind.Distress_T$ is a dummy that equals 1 if the sales growth of the median firm in an industry is negative in the year of the transaction. The industry of a firm is defined as the set of firms with the same 3-digit SIC code. Panel A provides the summary for target industry rivals' abnormal returns at announcement. Rival CARs(%) are rivals' cumulative abnormal returns for the (-1, +1) window surrounding the announcement of acquisitions. Panel B provides the median ROA (net income/total assets), before (t-3, t-1) and after (t+1, t+3) acquisition. Panel C provides the median profitability margin (operating cash flow/total sales) for target industry rivals at announcement.

	All	Distressed Target		Non-distressed Target	
	-	Dist. Ind.	Non-dist. Ind.	Dist. Ind.	Non-dist. Ind.
Panel A. Rival CAR (%)					
Mean	0.280	-0.895	0.559	0.278	0.233
Std. Dev.	5.632	5.944	6.080	4.983	5.505
Number of Obs.	1154	19	287	72	750
Panel B. Rival ROA (Median)					
Before (-3,-1)	0.032	-0.002	0.039	0.018	0.030
After (+1,+3)	0.025	0.024	0.031	0.016	0.024
Change	-0.007	0.026	-0.008	-0.002	-0.006
Number of Obs.	1249	19	319	74	837
Panel C. Rival Profitability Margin (Median)					
Before (-3,-1)	0.101	0.190	0.104	0.108	0.094
After (+1,+3)	0.105	0.175	0.113	0.113	0.099
Change	0.004	-0.016	0.008	0.005	0.005
Number of Obs.	1160	19	281	65	795

Table 1.17: Effects of Fire-Sale on Target Industry Rival CARs(%)

This table presents the impact of fire-sale on abnormal returns for target industry rivals. The dependent variables are matched rivals' abnormal stock returns (%) at the announcement of acquisition. Models (1) and (2) are for all matched rivals, Models (3)-(4) for the matched sample in high R&D industries, and Models (5)-(6) for the matched sample in low R&D industries. I define an industry to be a high (low) R&D industry if the R&D intensity at 3-digit SIC industry-level is above (below) the overall median. R&D intensity is measured by research and development expenses scaled by total sales. The target rivals are matched based on same industry, size, and M/B. CARs (%) are cumulative abnormal returns for the (-1, +1) window surrounding the announcement of acquisitions. The variable of interest is *Fire-Sale* — the interaction between target firm distress ($Distress1_T$, $Distress2_T$) and industry-level distress ($Ind.Distress_T$). Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Additional control variables for rival characteristics are *industry concentration(HHI)*, *size*, *leverage*, *m/b*, *tangibility*, and $profitability$. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable:	All Matched Rivals		High R&D Industry		Low R&D Industry	
Rival CAR(%)	(1)	(2)	(3)	(4)	(5)	(6)
Fire-Sale$_1$	-4.59*		-6.15**		-3.88	
	(2.45)		(2.75)		(3.56)	
Fire-Sale$_2$		-3.96**		-5.97***		-4.19
		(1.97)		(2.18)		(2.67)
$Ind.Distress_T$	0.44	0.35	0.22	-0.17	2.60	3.14
	(1.19)	(1.30)	(1.66)	(1.61)	(1.81)	(2.57)
$Distress1_T$	-0.06		-1.15		1.12	
	(1.83)		(2.52)		(2.58)	
$Distress2_T$		0.30		-1.26		1.88
		(0.68)		(1.02)		(1.14)
Med. Ind. Q	0.93	0.89	1.65	1.45	-0.41	0.39
	(0.87)	(0.83)	(1.09)	(1.04)	(1.78)	(1.60)
Med. Ind. Leverage	5.06	5.74	9.19	6.76	-5.70	0.53
	(7.19)	(7.16)	(12.24)	(12.17)	(10.34)	(10.73)
HHI	-4.19	-3.43	-8.82	-8.26	-5.56	-3.07
	(4.28)	(4.25)	(5.69)	(5.93)	(8.80)	(8.05)
Rival Size	0.26	0.18	0.94	0.74	-0.54	-0.52
	(0.59)	(0.50)	(0.79)	(0.70)	(1.06)	(0.79)
Rival Leverage	0.49*	0.45*	0.48	0.28	0.74	1.07*
	(0.27)	(0.26)	(0.34)	(0.35)	(0.65)	(0.61)
Rival M/B	2.76	2.45	1.88	1.06	2.69	2.81
	(1.80)	(1.70)	(2.86)	(2.94)	(2.39)	(2.07)
Rival Tangibility	-1.91	-2.25	0.32	0.53	-8.28**	-8.77**
	(2.00)	(2.14)	(2.43)	(2.77)	(3.70)	(3.61)
Rival Profitability	0.00***	0.00***	0.00***	0.00***	-0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)
Control: Target & Deal	Yes	Yes	Yes	Yes	Yes	Yes
Control: Acq.	No	No	No	No	No	No
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	714	753	367	382	347	371
R^2	0.24	0.24	0.21	0.20	0.40	0.40

Table 1.18: Effects of Fire-Sale on Target Industry Rivals' Operating Performance

This table presents the impact of fire-sale on matched target rivals' operating performance. In Models (1) and (2), the dependent variable is the difference of average ROA (net income/total book assets), before (t-3, t-1) and after (t+1, t+3) acquisition. In Models (3) and (4), the dependent variable is the difference of average profitability margin (operating cash flow/total sales), before (t-3, t-1) and after (t+1, t+3) acquisition. The variable of interest is *Fire-Sale* — the interaction between target firm distress ($Distress1_T$, $Distress2_T$) and industry-level distress ($Ind.Distress_T$). Industry fixed effects are at the 3-digit SIC code level. Control variables are described in Table 1.5 and a detailed description of each variable is included in Table 1.1. Additional control variables for rival characteristics are *industry concentration(HHI)*, *size*, *leverage*, m/b, *tangibility*, and $profitability$. Robust standard errors clustered at year-industry are reported in parentheses. Coefficients marked ***, ** and * are significant at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Profit_Diff		ROA_Diff	
	(1)	(2)	(3)	(4)
$\textit{Fire-Sale}_1$	1.05		-0.44	
	(15.98)		(0.60)	
$\textit{Fire-Sale}_2$		-3.42		-0.29
		(10.00)		(0.39)
$Ind.Distress_T$	-4.11	0.34	0.15	0.38
	(6.60)	(6.28)	(0.31)	(0.38)
$Distress1_T$	11.35		0.10	
	(16.70)		(0.27)	
$Distress2_T$		6.20		0.26
		(6.70)		(0.23)
Med. Ind. Q	10.45	5.71	0.03	0.12
	(8.98)	(7.66)	(0.24)	(0.29)
Med. Ind. Leverage	54.08	38.10	2.88	3.22
	(58.16)	(50.08)	(3.01)	(3.26)
HHI	-23.12	-31.65	-0.05	0.03
	(31.08)	(30.19)	(0.56)	(0.75)
Rival Size	-1.59	-1.90	-0.03	-0.03
	(2.96)	(3.13)	(0.06)	(0.11)
Rival Leverage	-17.51	-15.06	0.10	0.08
	(11.89)	(11.16)	(0.08)	(0.12)
Rival M/B	-24.71	-20.88	0.01	0.41
	(19.02)	(17.05)	(0.28)	(0.46)
Rival Tangibility	13.00	13.38	-0.14	0.02
	(16.55)	(15.69)	(0.26)	(0.40)
Rival Profitability	0.00***	0.00***	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Control: Target	Yes	Yes	Yes	Yes
Control: Acq. & Deal	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Obs.	286	305	294	314
Adj-R^2	0.65	0.68	0.30	0.37

Distance-to-Default Model

The KMV-Merton model estimates a default probability based on the bond pricing model by *Merton* (1974). It calculates the probability that the value of the firm will be less than the face value of debt at given point in time. The model requires market equity value (E) and face value of debt (F) from COMPUSTAT and risk-free rate of return(r). Following *Vassalou and Xing* (2004), the face value of debt (F) is calculated by (Current liability + 0.5 * Long-term debt).[1] I follow *Bharath and Shumway* (2008) to construct this measure as given below.

Step 1: Estimate the equity volatility (σ_E) from historical stock returns over the past one year (set T=1).

Step 2: Simultaneously solve the below two equations numerically for values of V and σ_V.

$$E = VN(d_1) - e^{-rT}FN(d_2)$$
$$\sigma_E = (\frac{V}{E})N(d_1)\sigma_V$$

Step 3: Calculate the distance to default using

$$DD = \frac{ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$$

The corresponding probability of default (EDF) is $N(-DD)$.

[1] *Vassalou and Xing* (2004) highlights that long-term liabilities should be taken into account for corporate default risk because long-term debt influences the solvency of firm through interest payments and the roll-over decision of short-term debt.

Computation of Target Undervaluation

Follow *Rhodes-Kropf et al.* (2005), I construct the measure for target undervaluation by decomposing the market-to-book ratio into three components: the firm-specific error; industry-wide short-run error and long-run growth option based on the below equation.

$$m_{it} - b_{it} = \underbrace{m_{it} - v(\theta_{it};\alpha_{jt})}_{\text{firm}} + \underbrace{v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_{j})}_{\text{sector}} + \underbrace{v(\theta_{it};\alpha_{j}) - b_{it}}_{\text{long-run}}$$

Where $m_{it} - b_{it}$ is the natural log of the market to book ratio. $v(\theta_{it};\alpha_{jt})$ is the estimated fundamental value of the firm at year t by applying firm-specific model parameter α_{jt} and $v(\theta_{it};\alpha_j)$ is the long-run average fundamental value of the firm estimated based on industry average parameter α_j. The first step is to estimate the market value of firm i at time t, m_{it} based on the below regression (Model 3 in *Rhodes-Kropf et al.* (2005)).

$$m_{it} = \alpha_{0jt} + \alpha_{1jt}b_{it} + \alpha_{2jt}ni_{it}^{+} + \alpha_{3jt}I_{(<0)}(ni^{+})_{it} + \alpha_{4jt}Lev_{it} + \varepsilon_i$$

Where b_{it} is the logs of book asset value, ni_{it}^{+} is natural log of the absolute value of net income and $I_{(<0)}$ is an indicator function for negative net income. This estimation provides the set of firm-specific loading α_{jt} for each accounting variable. Then, I calculate α_j by aggregating α_{jt} over the sample period. Lastly, using the fitted parameters, I calculate $v(\theta_{it};\alpha_{jt})$ and $v(\theta_{it};\alpha_j)$.

$$\begin{aligned} v(\theta_{it};\alpha_{jt}) &= \alpha_{0jt} + \alpha_{1jt}b_{it} + \alpha_{2jt}ni_{it}^{+} + \alpha_{3jt}I_{(<0)}(ni^{+})_{it} + \alpha_{4jt}Lev_{it} \\ v(\theta_{it};\alpha_{j}) &= \alpha_{0j} + \alpha_{1j}b_{it} + \alpha_{2j}ni_{it}^{+} + \alpha_{3j}I_{(<0)}(ni^{+})_{it} + \alpha_{4j}Lev_{it} \end{aligned}$$

APPENDIX B

Recourse Mortgage Law and the Housing Bubble

Figure 2.1: State-level Variation in Mortgage Recourse law

This figure illustrates the classification of mortgage recourse law. States shaded in dark are non-recourse states. These states with non-recourse law are Alaska, Arizona, California, Iowa, Minnesota, Montana, North Carolina, North Dakota, Oregon, Washington, and Wisconsin.

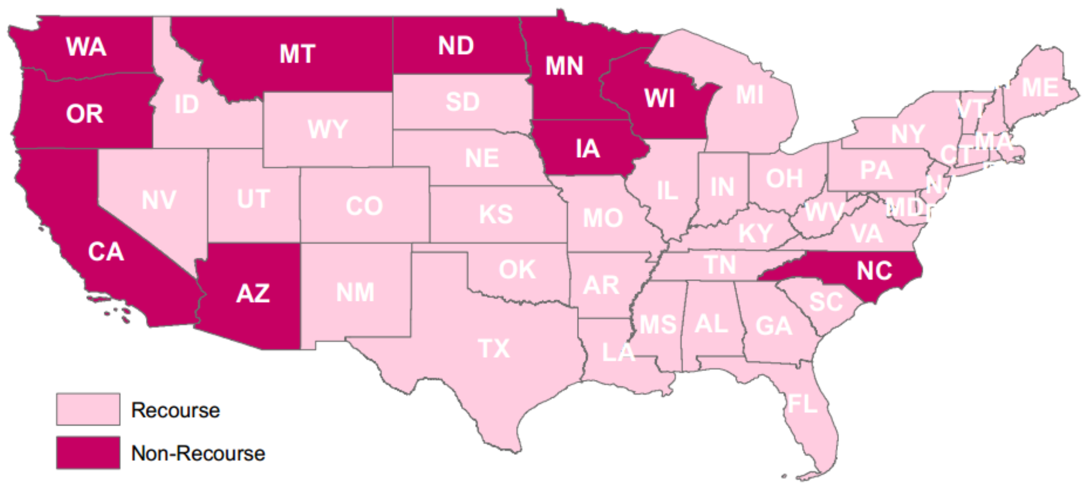


Figure 2.2: State-level Variation in Judicial Foreclosure Requirement

This figure illustrates the classification of judicial requirement. States shaded in dark mandate a judicial process when lenders foreclose on property. Among eleven non-recourse states, three states (Iowa, North Dakota and Wisconsin) have the judicial foreclosure requirement.

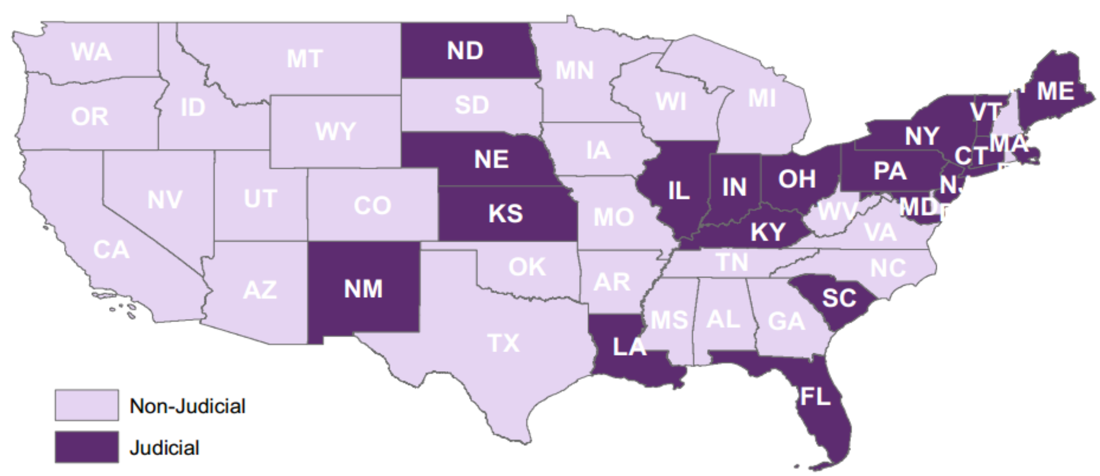
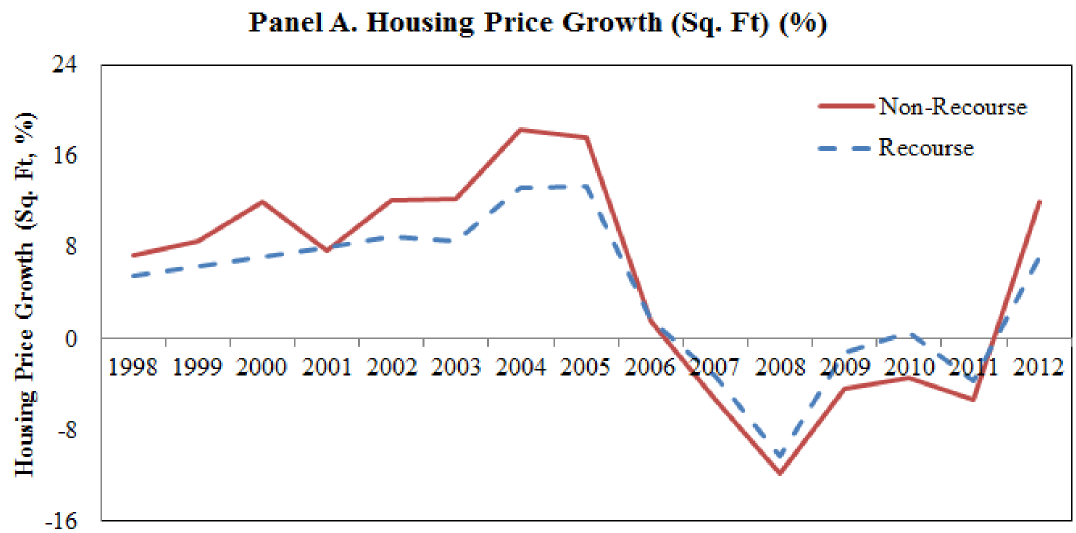


Figure 2.3: Recourse Law and Housing Price Growth Rate

This figure plots the aggregate housing price growth rates in recourse and non-recourse states. Panel A shows the housing price growth rate per square foot over recourse law from zipcode-level data from 1998-2012. Panel B shows the median price-to-rent growth rate from 2006-2011. Housing Price Growth (Sq. Ft) is the percentage annual growth rate of the median of sale prices scaled by the square footage of a home. Price-to-Rent growth rate is the county-level median rent value divided by county-level median housing price from the American Community Survey Census data.



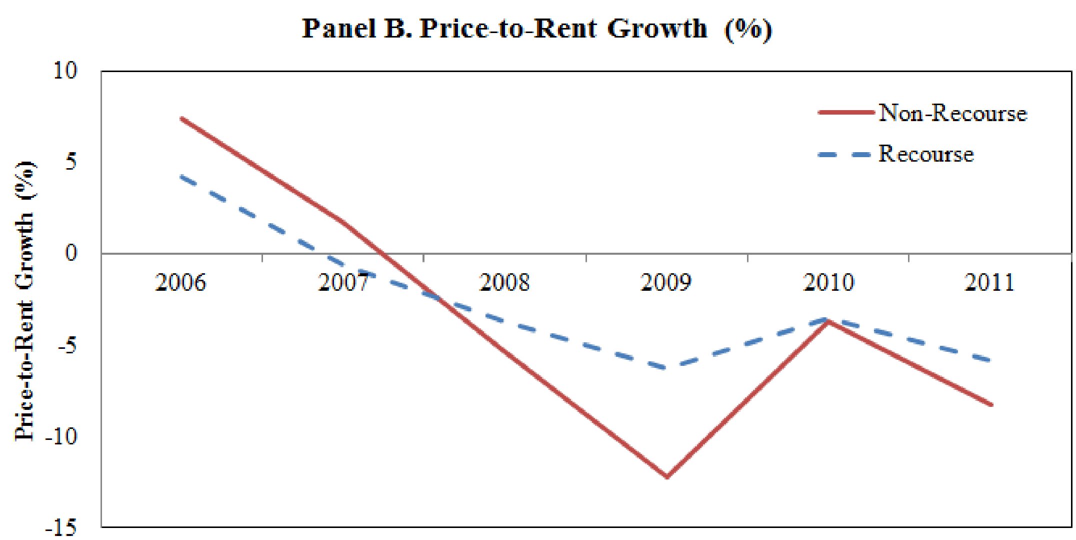


Figure 2.4: Recourse Law and Household Investment Behavior

This figure plots the households' investment behaviors in housing market in recourse and non-recourse states. Panel A plots households' average ratio of home equity to total wealth. Panel B plots the average debt-to-income ratio at origination, defined as the borrower's total monthly obligations divided by their monthly income.

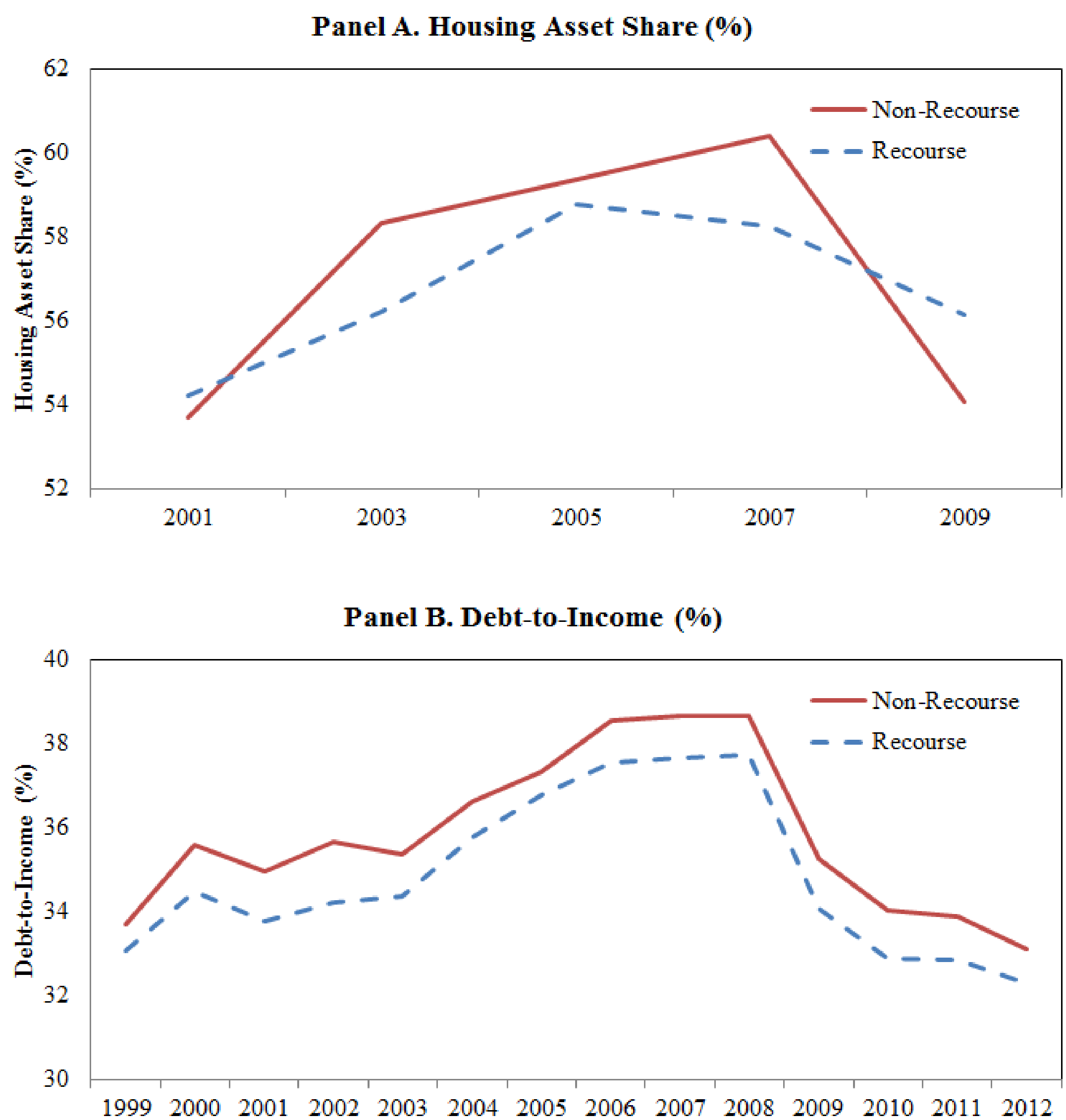
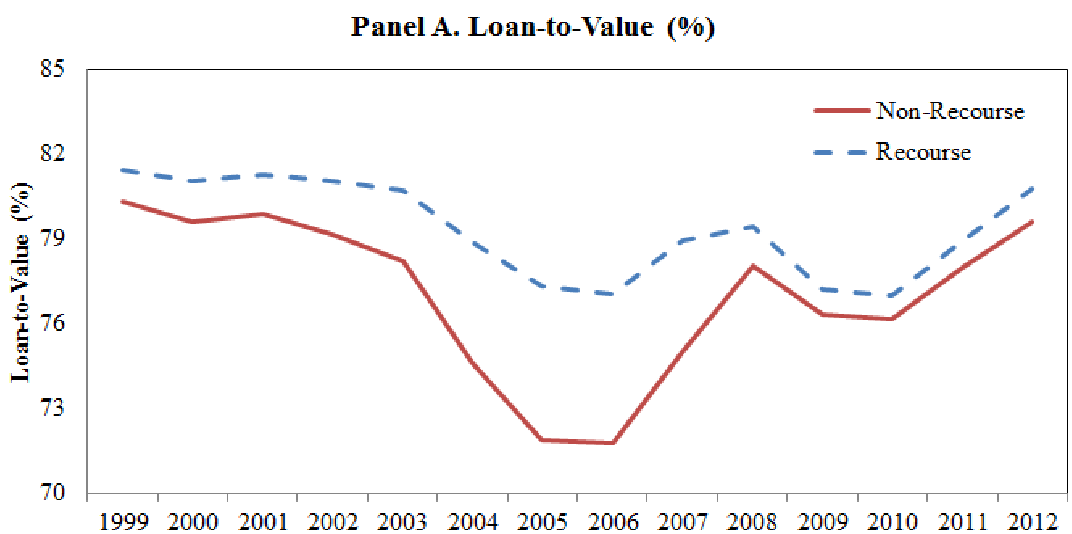


Figure 2.5: Recourse Law and Mortgage Lending Behavior: LTV Ratio
This figure plots the mortgage lending behaviors in recourse and non-recourse states. Panel A plots the average loan-to-value ratio, defined as the loan amount secured by a mortgaged property on the origination date. Panel B plots the average loan-to-value ratio for a group of borrowers whose occupancy status is either second home or investment property.



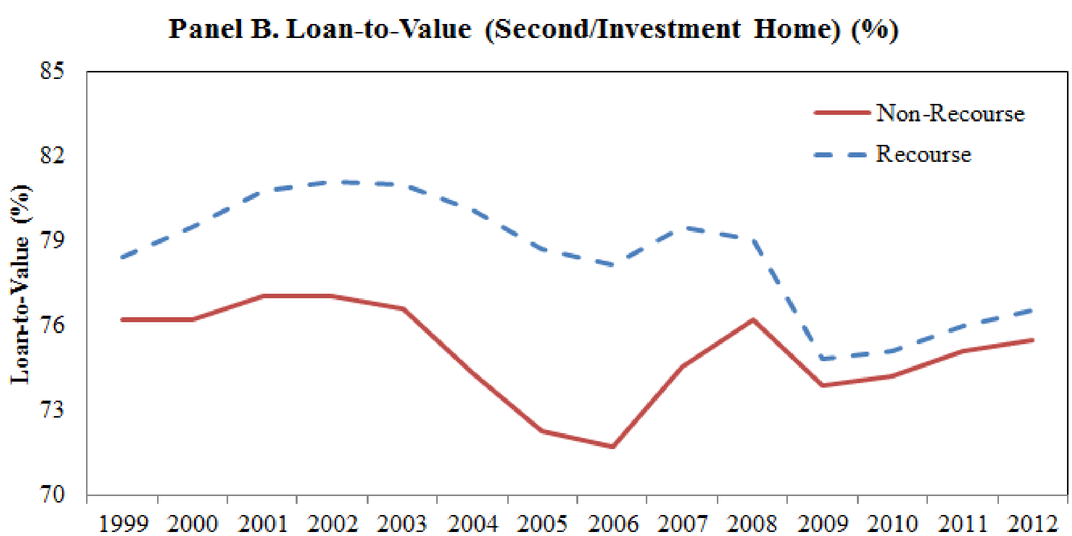
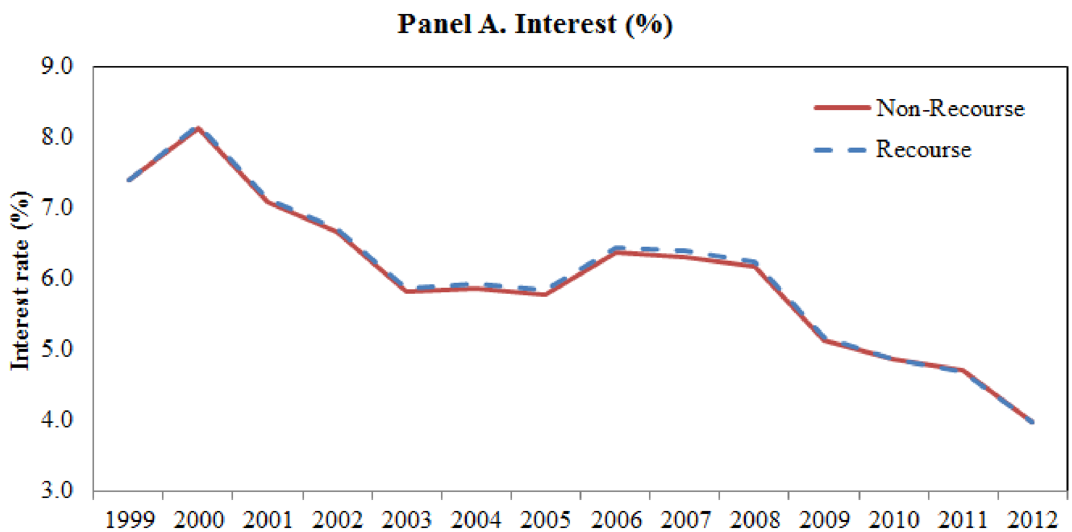


Figure 2.6: Recourse Law and Mortgage Lending Behavior: Interest Rates and Denial
This figure plots the mortgage lending behaviors in recourse and non-recourse states. Panel A plots the average interest rate on the origination date. Panel B plots the average rate of mortgage application denial due to a high risk of insolvency.



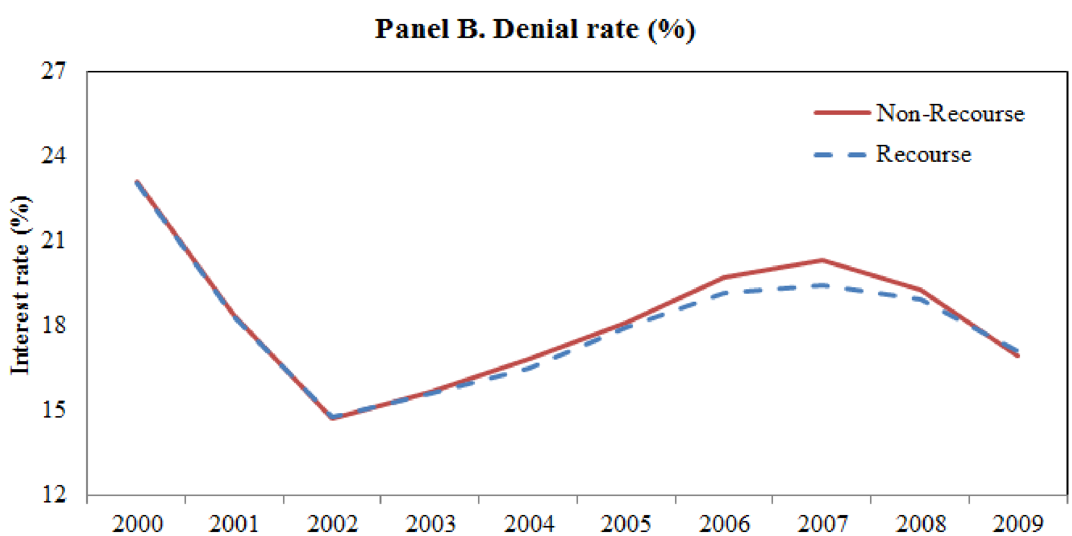


Figure 2.7: Recourse Law and Sub-Prime Ratio

This figure illustrates the time-series trend of the average sub-prime ratio in recourse and non-recourse states. We classify sub-prime loans based on lender identification. Using a list of sub-prime lender specialists compiled annually by HUD (http://www.huduser.org/portal/datasets/manu.html), we construct a sub-prime ratio measure; specifically, the number of sub-prime mortgage loans out of the total number of mortgage loans originated.

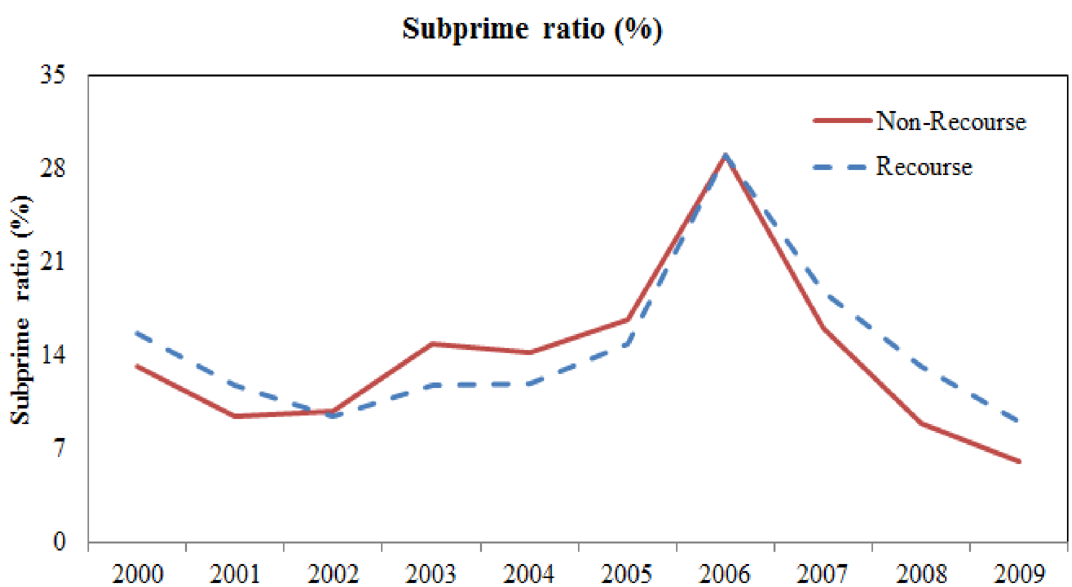


Table 2.1: Summary Statistics

This table presents summary statistics for the main variables used in the analysis for the period 1998-2012. Housing Price Growth (Sq. Ft) is the percentage annual growth rate of the median of sale prices scaled by the square footage of a home. Housing Price Growth represents the percentage annual growth of the median of sale prices without scaling. Both measures for housing price are aggregated at the ZIP code-level. Price-to-Rent Growth rate is the percentage annual growth rate of the county-level median rent value divided by the county-level median housing price from the American Community Survey data from 2006-2011. House Share is the average ratio of home equity to total wealth of households aggregated at the state level. Debt-to-Income is the borrower's total monthly obligations divided by their monthly income at origination at the ZIP code-level. LTV is the loan-to-value ratio, defined as the loan amount secured by a mortgaged property on the origination date divided by the purchase price. LTV (investment home) is the average loan-to-value ratio for a property that is for a second home or investment at purchase. Interest is the annual percentage rate (APR) on mortgage loans. Denial rate is the rate of mortgage application denial due to a high risk of insolvency. Sub-prime loan ratio is the aggregate ratio of the number of sub-prime mortgage loans to the total number of mortgage loans originated at the ZIP code-level. Housing supply elasticity is the MSA-level variable provided by *Saiz* (2010). The other variables are all state-level statistics. GDP Growth rate is the annual percentage growth rate of nominal GDP. Income Growth Per Capita is the growth rate of (total income/population). Unemployment rate is the annual unemployment rate.

	Mean	Std. Dev.	10th	50th	90th	N
Housing Price Growth (Sq. Ft)	0.06	0.41	-0.11	0.05	0.25	29,779
Housing Price Growth	0.07	0.43	-0.11	0.06	0.26	30,800
Price-to-Rent Growth, 2006-2011	-0.03	0.07	-0.11	-0.03	0.07	17,930
House Share, 2001-2009	0.56	0.08	0.45	0.56	0.63	255
Debt-to-Income	0.36	0.03	0.32	0.36	0.39	282,304
LTV	0.79	0.04	0.74	0.80	0.84	282,327
LTV (investment home)	0.79	0.05	0.74	0.79	0.84	280,440
Interest (%)	5.88	0.54	5.02	5.94	6.48	282,327
Interest (investment home, %)	6.11	0.55	5.2	6.18	6.72	280,440
Denial rate	0.17	0.09	0.00	0.19	0.25	253,609
Sub-prime loan ratio	0.14	0.16	0.00	0.10	0.36	251,430
GDP Growth	0.04	0.01	0.03	0.04	0.06	441
Income Growth Per Capita	0.03	0.01	0.03	0.03	0.04	441
Unemployment	0.05	0.01	0.04	0.06	0.07	441
Population Growth	0.01	0.01	0.00	0.01	0.02	441
Housing Supply Elasticity	1.94	1.12	0.81	1.67	3.25	83
Property Tax (%)	1.44	0.49	0.74	1.42	2.11	51

Table 2.2: Univariate Analysis

This table presents the comparisons of the main variables between Recourse state and non-Recourse state. Panel A presents the statistics for the sample period 2003-2006 (Expansion). Panel B presents the statistics for the sample period 2007-2011 (Recession). States are classified as recourse states if lenders are permitted to claim deficiency judgments in the event of mortgage default. We report the differences in average value in recourse states and in non-recourse states. ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

	Recourse			Non-recourse			Diff.
Panel A. Expansion (2003-2006)	Mean	SD	p50	Mean	SD	p50	-
Housing Price Growth (Sq. Ft)	0.09	0.13	0.08	0.13	0.13	0.12	0.04***
Housing Price Growth	0.10	0.14	0.08	0.14	0.14	0.13	0.04***
Price-to-Rent Growth (2006)	0.02	0.06	0.02	0.05	0.07	0.05	0.03***
House Share	0.58	0.07	0.58	0.59	0.07	0.60	0.01***
Debt-to-Income	0.36	0.02	0.36	0.37	0.02	0.38	0.01***
LTV	0.79	0.04	0.79	0.74	0.07	0.76	-0.04***
LTV (investment home)	0.80	0.04	0.80	0.74	0.07	0.76	-0.06***
Interest (%)	6.10	0.28	5.96	6.03	0.27	5.90	-0.07***
Interest (investment home, %)	6.36	0.30	6.31	6.23	0.27	6.12	-0.13***
Denial rate	0.18	0.05	0.18	0.18	0.05	0.18	0.00***
Sub-prime loan ratio	0.17	0.13	0.14	0.18	0.13	0.15	0.01***
GDP Growth	0.05	0.02	0.05	0.06	0.02	0.05	0.01***
Income Growth Per Capita	0.05	0.02	0.04	0.04	0.02	0.04	-0.01***
Unemployment	0.05	0.01	0.05	0.05	0.01	0.05	0.00***
Population Growth	0.01	0.01	0.01	0.01	0.01	0.01	0.00***
Panel B. Recession (2007-2011)							
Housing Price Growth (Sq. Ft)	-0.03	0.87	-0.05	-0.06	0.21	-0.06	-0.03*
Housing Price Growth	-0.01	0.92	-0.04	-0.04	0.17	-0.05	-0.03*
Price-to-Rent Growth	-0.05	0.06	-0.05	-0.07	0.09	-0.08	-0.02***
House Share	0.56	0.07	0.57	0.54	0.03	0.55	-0.02***
Debt-to-Income	0.34	0.03	0.34	0.35	0.03	0.35	0.01***
LTV	0.78	0.03	0.78	0.77	0.03	0.77	-0.01***
LTV (investment home)	0.76	0.03	0.76	0.75	0.03	0.75	-0.01***
Interest (%)	5.23	0.61	4.98	5.22	0.58	5.01	-0.01*
Interest (investment home, %)	5.52	0.65	5.27	5.46	0.62	5.23	-0.06***
Denial rate	0.18	0.05	0.18	0.18	0.05	0.18	0.00
Sub-prime loan ratio	0.11	0.11	0.08	0.07	0.07	0.06	-0.04***
GDP Growth	0.01	0.03	0.01	0.01	0.03	0.02	0.00
Income Growth Per Capita	0.00	0.05	0.03	0.00	0.04	0.02	0.00***
Unemployment	0.08	0.02	0.08	0.09	0.02	0.09	0.01***
Population Growth	0.01	0.01	0.01	0.01	0.00	0.01	0.00***

Table 2.3: Recourse Law and Housing Price Growth

This table reports estimates and standard errors for regressions of housing price growth on non-recourse law indicators for the period 2003-2011 for the full sample and contiguous border county-pair sample. The dependent variable is Housing Price Growth (Sq. Ft), the percentage annual growth rate of the median of sale prices scaled by the square footage of a home. This measure is aggregated at the ZIP code level. *Crisis* is a dummy variable that equals zero before and including 2006, and one after that year. A state is classified as a *Non-recourse* state (*Non-recourse*=1) if the state does not allow lenders to claim deficiency judgments in the event of mortgage default. Distance is the shortest distance between the closest border and the centroid of a ZIP code. $Distance^R$ represents the interaction of distance and an indicator (I(recourse)). $Distance^{NR}$ represents the interaction of distance and an indicator (I(non-recourse)). The other control variables are defined in Table 1.2. All standard errors are robust to heteroskedasticity and clustered at the county level. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Non-recourse	0.03***	0.02**	0.29***	0.30***	0.45***
	(0.01)	(0.01)	(0.03)	(0.04)	(0.04)
Crisis	-0.13***	-0.03***	-0.06***	-0.06***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
*Crisis***Non-recourse*	-0.06***	-0.06***	-0.03**	-0.03**	-0.05***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
GDP Growth		1.85***	1.87***	1.86***	2.09***
		(0.31)	(0.15)	(0.15)	(0.13)
Income Growth		-0.01	0.07	0.07	-0.94***
		(0.14)	(0.13)	(0.13)	(0.12)
Unemployment		-0.62**	-0.03	-0.02	1.30***
		(0.24)	(0.24)	(0.24)	(0.18)
Pop. Growth		-0.53	4.08***	4.15***	6.72***
		(0.55)	(0.65)	(0.65)	(0.59)
Supply Elasticity		-0.02***	0.03	0.02	0.08
		(0.00)	(0.05)	(0.05)	(0.05)
Judicial Foreclosure		0.03***	0.01	0.01	0.01
		(0.01)	(0.02)	(0.02)	(0.02)
Property Tax		-0.04***	-0.03	-0.02	-0.04
		(0.01)	(0.03)	(0.03)	(0.03)
$Distance^R$				-0.00*	-0.00
				(0.00)	(0.00)
$Distance^{NR}$				-0.00	-0.00
				(0.00)	(0.00)
$(Distance^R)^2$				0.00	0.00
				(0.00)	(0.00)
$(Distance^{NR})^2$				0.00	0.00
				(0.00)	(0.00)
Constant	0.09***	0.09***	-0.11	-0.11	-0.27***
	(0.01)	(0.02)	(0.10)	(0.10)	(0.10)
County-Pair Sample	No	No	Yes	Yes	Yes
County-Pair FE	No	No	Yes	Yes	Yes
Lagged Controls	No	No	No	No	Yes
N	29777	17558	4154	4149	4432
R^2	0.03	0.29	0.38	0.39	0.39

Table 2.4: Recourse Law and Price-to-Rent Growth

This table reports estimates and standard errors for regressions of the price-to-rent growth rate on non-recourse law indicators in the pre-crisis period 2005-2006 for the full sample and contiguous border county-pair sample. The dependent variable is Price-to-Rent growth rate is the percentage annual growth rate of the county-level median rent value divided by the county-level median housing price from the American Community Survey data. A state is classified as a *Non-recourse* state (*Non-recourse*=1) if the state does not allow lenders to claim deficiency judgments in the event of mortgage default. Distance is the shortest distance between the closest border and the centroid of a ZIP code. $Distance^R$ represents the interaction of distance and an indicator (I(recourse)). $Distance^{NR}$ represents the interaction of distance and an indicator (I(non-recourse)). The other control variables are defined in Table 1.2. All standard errors are robust to heteroskedasticity and clustered at the county level. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Non-recourse	0.03***	0.01***	0.07***	0.07***	0.08**
	(0.00)	(0.00)	(0.01)	(0.02)	(0.03)
GDP Growth		0.04	0.29***	0.29***	1.92***
		(0.10)	(0.10)	(0.10)	(0.10)
Income Growth		1.92***	3.16***	3.15***	-1.42***
		(0.12)	(0.10)	(0.10)	(0.12)
Unemployment		0.81***	2.71***	2.71***	3.69***
		(0.17)	(0.54)	(0.54)	(0.53)
Pop. Growth		1.55***	5.24***	5.31***	1.61*
		(0.21)	(0.66)	(0.67)	(0.85)
Supply Elasticity		0.00	0.08***	0.07***	0.02**
		(0.00)	(0.01)	(0.01)	(0.01)
Judicial Foreclosure		0.02***	0.04***	0.04***	0.04***
		(0.00)	(0.01)	(0.01)	(0.01)
Property Tax		0.00	-0.05***	-0.05***	-0.05***
		(0.00)	(0.01)	(0.01)	(0.01)
$Distance^R$				-0.00	0.00
				(0.00)	(0.00)
$Distance^{NR}$				-0.00	-0.00
				(0.00)	(0.00)
$(Distance^R)^2$				0.00	-0.00
				(0.00)	(0.00)
$(Distance^{NR})^2$				0.00	0.00
				(0.00)	(0.00)
Constant	0.02***	-0.15***	-0.41***	-0.40***	-0.20***
	(0.00)	(0.01)	(0.03)	(0.03)	(0.04)
County-Pair Sample	No	No	Yes	Yes	Yes
County-Pair FE	No	No	Yes	Yes	Yes
Lagged Controls	No	No	No	No	Yes
N	5950	2866	2854	2846	2846
R^2	0.02	0.16	0.60	0.60	0.56

Table 2.5: Recourse Law and Household Investment Behaviors

This table reports estimates and standard errors for regressions of household investment behaviors for the pre-crisis period 2003-2006. In Columns (1)-(3), the dependent variable is the average ratio of home equity to total wealth at the state level. In Columns (4)-(6), the dependent variable is the average debt-to-income ratio at the ZIP code level. A state is classified as a *Non-recourse* state (*Non-recourse*=1) if the state does not allow lender to claim deficiency judgments in the event of mortgage default. Distance is the shortest distance between the closest border and the centroid of a ZIP code. $Distance^R$ represents the interaction of distance and an indicator (I(recourse)). $Distance^{NR}$ represents the interaction of distance and an indicator (I(non-recourse)). The other control variables are defined in Table 1.2. All standard errors are robust to heteroskedasticity and clustered at the county level. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

Dep. Variable:	Asset Allocation			Debt-to-Income		
	(1)	(2)	(3)	(4)	(5)	(6)
Non-recourse	0.02**	0.07**	0.07**	0.01***	0.02***	0.02***
	(0.01)	(0.03)	(0.03)	(0.00)	(0.01)	(0.00)
GDP Growth	0.35**	1.35**	1.35**	-0.20***	-0.21***	-0.21***
	(0.17)	(0.64)	(0.64)	(0.03)	(0.04)	(0.04)
Income Growth	0.66	-1.83*	-1.83*	0.37***	0.24***	0.24***
	(0.47)	(0.99)	(0.99)	(0.03)	(0.05)	(0.05)
Unemployment	-0.06	-4.51***	-4.53***	-0.69***	-1.91***	-1.91***
	(0.54)	(1.60)	(1.61)	(0.06)	(0.16)	(0.16)
Pop. Growth	-1.32**	-6.17**	-6.20**	-0.05	-0.92***	-0.94***
	(0.56)	(2.71)	(2.71)	(0.12)	(0.31)	(0.32)
Supply Elasticity	-0.02***	-0.07***	-0.08***	-0.01***	-0.02***	-0.02***
	(0.00)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)
Judicial Foreclosure	0.03***	-0.00	-0.00	-0.00*	0.01***	0.01***
	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Property Tax	-0.05***	0.05*	0.06**	0.00*	-0.00	-0.00
	(0.01)	(0.03)	(0.03)	(0.00)	(0.01)	(0.01)
$Distance^R$			-0.00			0.00
			(0.00)			(0.00)
$Distance^{NR}$			-0.00**			0.00
			(0.00)			(0.00)
$(Distance^R)^2$			-0.00			-0.00
			(0.00)			(0.00)
$(Distance^{NR})^2$			0.00**			-0.00***
			(0.00)			(0.00)
Constant	0.64***	0.90***	0.91***	0.41***	0.51***	0.50***
	(0.04)	(0.12)	(0.12)	(0.01)	(0.01)	(0.01)
County-Pair Sample	No	Yes	Yes	No	Yes	Yes
County-Pair FE	No	Yes	Yes	No	Yes	Yes
N	17769	4395	4383	29615	7325	7305
R^2	0.28	0.53	0.53	0.44	0.75	0.76

Table 2.6: Recourse Law and Mortgage Lending Behavior: Loan-to-Value

This table reports estimates and standard errors for regressions of mortgage lending behavior in the pre-crisis period. In Columns (1)-(3), the dependent variable is the loan-to-value ratio, defined as the loan amount secured by a mortgaged property on the origination date divided by the purchase price. In Columns (4)-(6), the dependent variable is LTV (investment purpose) which equals the average loan-to-value ratio for a group of borrowers whose occupancy status is either second home or investment property at purchase. A state is classified as a *Non-recourse* state (*Non-recourse*=1) if the state does not allow lender to claim deficiency judgments in the event of mortgage default. Distance is the shortest distance between the closest border and the centroid of a ZIP code. $Distance^R$ represents the interaction of distance and an indicator (I(recourse)). $Distance^{NR}$ represents the interaction of distance and an indicator (I(non-recourse)). The other control variables are defined in Table 1.2. All standard errors are robust to heteroskedasticity and clustered at the county level. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

Dep. Variable:	LTV			LTV_Invest		
	(1)	(2)	(3)	(4)	(5)	(6)
Non-recourse	-0.03***	-0.03*	-0.04**	-0.05***	-0.05**	-0.06***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
GDP Growth	-0.22**	-0.24**	-0.23**	-0.18*	0.03	0.03
	(0.09)	(0.11)	(0.11)	(0.10)	(0.07)	(0.07)
Income Growth	-0.50***	-0.07	-0.07	-0.55***	-0.05	-0.05
	(0.09)	(0.12)	(0.12)	(0.11)	(0.09)	(0.09)
Unemployment	0.47**	1.80***	1.80***	-0.02	1.54***	1.54***
	(0.23)	(0.35)	(0.35)	(0.25)	(0.25)	(0.25)
Pop. Growth	0.94***	1.56**	1.57**	0.66*	1.02**	1.04**
	(0.34)	(0.61)	(0.60)	(0.37)	(0.40)	(0.41)
Supply Elasticity	0.02***	0.03***	0.03***	0.02***	0.02**	0.01
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Judicial Foreclosure	0.02***	0.03***	0.03***	0.02**	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Property Tax	0.01*	-0.03***	-0.03***	0.01**	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Distance^R$			-0.00**			0.00
			(0.00)			(0.00)
$Distance^{NR}$			0.00			0.00
			(0.00)			(0.00)
$(Distance^R)^2$			0.00			-0.00
			(0.00)			(0.00)
$(Distance^{NR})^2$			-0.00			0.00
			(0.00)			(0.00)
Constant	0.73***	0.66***	0.67***	0.76***	0.72***	0.72***
	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
County-Pair Sample	No	Yes	Yes	No	Yes	Yes
County-Pair FE	No	Yes	Yes	No	Yes	Yes
N	29615	7325	7305	29611	7325	7305
R^2	0.46	0.68	0.68	0.51	0.70	0.71

Table 2.7: Recourse Law and Mortgage Lending Behavior: Interest Rates and Denial
This table reports estimates and standard errors for regressions of mortgage lending behavior in the pre-crisis period. In Columns (1)-(3), the dependent variable is mortgage interest, the annual percentage rate (APR) on mortgage loans. This measure is aggregated at the ZIP code level from loan purchase data by two major Federal Home Loan Mortgage Corporations: Freddie Mac and Fannie Mae. In Columns (4)-(6), the dependent variable is the denial rate of mortgage loan applications aggregated at the ZIP code level. A state is classified as the *Non-recourse* state (*Non-recourse*=1) if the state does not allow lender to claim deficiency judgments in the event of mortgage default. Distance is the shortest distance between the closest border and the centroid of a ZIP code. $Distance^R$ represents the interaction of distance and an indicator (I(recourse)). $Distance^{NR}$ represents the interaction of distance and an indicator (I(non-recourse)). The other control variables are all state-level statistics and defined in Table 1.2. All standard errors are robust to heteroskedasticity and clustered at the county level. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

Dep. Variable:	Interest (%)			Denial rate		
	(1)	(2)	(3)	(1)	(2)	(3)
Non-recourse	0.04	0.30***	0.29***	0.01	0.08***	0.07***
	(0.03)	(0.08)	(0.08)	(0.01)	(0.02)	(0.02)
GDP Growth	-7.74***	-9.43***	-9.40***	-0.34***	-0.36***	-0.35***
	(0.87)	(1.75)	(1.75)	(0.10)	(0.09)	(0.08)
Income Growth	8.76***	9.21***	9.20***	0.70***	0.15	0.14
	(0.89)	(1.68)	(1.69)	(0.10)	(0.10)	(0.10)
Unemployment	-9.70***	-22.92***	-22.98***	-0.09	-3.28***	-3.29***
	(1.49)	(3.77)	(3.78)	(0.25)	(0.30)	(0.30)
Pop. Growth	6.88***	12.53*	12.51*	0.35	-1.53***	-1.45**
	(1.20)	(7.10)	(7.09)	(0.24)	(0.58)	(0.57)
Supply Elasticity	-0.01	-0.01	-0.02	-0.00	0.01	-0.03**
	(0.02)	(0.04)	(0.05)	(0.00)	(0.01)	(0.01)
Judicial Foreclosure	0.03	0.16**	0.17***	-0.01	0.01	0.01*
	(0.05)	(0.06)	(0.06)	(0.01)	(0.01)	(0.01)
Property Tax	0.06*	0.09	0.10	0.01	0.02	0.02***
	(0.03)	(0.08)	(0.08)	(0.01)	(0.01)	(0.01)
$Distance^R$			-0.00**			-0.00**
			(0.00)			(0.00)
$Distance^{NR}$			-0.00			0.00
			(0.00)			(0.00)
$(Distance^R)^2$			0.00			0.00
			(0.00)			(0.00)
$(Distance^{NR})^2$			0.00*			-0.00
			(0.00)			(0.00)
Constant	6.44***	7.00***	7.03***	0.15***	0.31***	0.37***
	(0.08)	(0.33)	(0.32)	(0.02)	(0.03)	(0.03)
County-Pair Sample	No	Yes	Yes	No	Yes	Yes
County-Pair FE	No	Yes	Yes	No	Yes	Yes
N	29615	7325	7305	29479	7289	7274
R^2	0.44	0.68	0.68	0.04	0.28	0.32

Table 2.8: Recourse Law and Sub-prime Loan Ratio

This table reports estimates and standard errors of regressions of the sub-prime mortgage loan ratio for the period 2003-2009. Models (1)-(3) employ the sample for the pre-crisis period 2003-2006 and Models (4)-(6) employ the total sample for 2003-2009 using the difference-in-difference approach. *Crisis* is a dummy variable equals to zero before and including 2006, and one after that. The dependent variable is the aggregate ratio of the number of sub-prime mortgage loans to the total number of mortgage loans originated at the ZIP code-level. A state is classified as a *Non-recourse* state (*Non-recourse*=1) if the state does not allow lenders to claim deficiency judgments in the event of mortgage default. Distance is the shortest distance between the closest border and the centroid of a ZIP code. $Distance^R$ represents the interaction of distance and an indicator (I(recourse)). $Distance^{NR}$ represents the interaction of distance and an indicator (I(non-recourse)). The other variables are defined in Table 1.2. All standard errors are robust to heteroskedasticity and clustered at the county level. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

	Sub-prime Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-recourse	0.00	0.08***	0.06*	0.00	0.02	0.01
	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)
Crisis				-0.07***	-0.07***	-0.07***
				(0.01)	(0.00)	(0.00)
*Crisis*Non-recourse*				-0.06***	-0.02***	-0.02***
				(0.02)	(0.01)	(0.01)
GDP Growth	-1.39***	-2.76***	-2.72***	-0.96***	-0.72***	-0.71***
	(0.34)	(0.50)	(0.50)	(0.18)	(0.10)	(0.10)
Income Growth	2.94***	1.89***	1.88***	1.50***	0.59***	0.57***
	(0.33)	(0.47)	(0.47)	(0.19)	(0.09)	(0.09)
Unemployment	0.13	-7.82***	-7.81***	0.66*	-1.91***	-1.92***
	(0.67)	(1.25)	(1.27)	(0.37)	(0.19)	(0.19)
Pop. Growth	2.61***	0.49	0.65	2.74***	0.57	0.63
	(0.72)	(1.84)	(1.85)	(0.65)	(0.45)	(0.45)
Supply Elasticity	-0.02**	0.07***	0.01	-0.01	0.10***	0.04***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Judicial Foreclosure	-0.04*	0.07***	0.07***	-0.02	0.04***	0.05***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Property Tax	0.02	-0.02	-0.01	0.01	-0.03***	-0.02**
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
$Distance^R$			-0.00			-0.00***
			(0.00)			(0.00)
$Distance^{NR}$			0.00			0.00
			(0.00)			(0.00)
$(Distance^R)^2$			0.00			0.00
			(0.00)			(0.00)
$(Distance^{NR})^2$			-0.00**			-0.00
			(0.00)			(0.00)
Constant	0.14***	0.52***	0.62***	0.13***	0.14***	0.24***
	(0.05)	(0.10)	(0.10)	(0.03)	(0.03)	(0.03)
County-Pair Sample	No	Yes	Yes	No	Yes	Yes
County-Pair FE	No	Yes	Yes	No	Yes	Yes
N	23517	5810	5798	40927	10106	10085
R^2	0.11	0.36	0.37	0.17	0.33	0.34

Table 2.9: Interaction of Recourse Law and Sub-prime Loan Ratio

This table reports estimates and standard errors for regressions of housing price growth on the interaction term of non-recourse law indicators and sub-prime loan ratio for the full sample and the contiguous border county-pair sample for the pre-crisis period 2003-2006. The dependent variable is Housing Price Growth (Sq. Ft), the percentage annual growth rate of the median of sale prices scaled by the square footage of a home. This measure is aggregated at the ZIP code-level. The sub-prime loan ratio is the aggregate ratio of the number of sub-prime mortgage loans to the total number of mortgage loans originated at the ZIP code-level. A state is classified as a *Non-recourse* state (*Non-recourse*=1) if the state does not allow lender to claim deficiency judgments in the event of mortgage default. Distance is the shortest distance between the closest border and the centroid of a ZIP code. $Distance^R$ represents the interaction of distance and an indicator (I(recourse)). $Distance^{NR}$ represents the interaction of distance and an indicator (I(non-recourse)).The other variables are all state-level statistics. The other variables are defined in Table 1.2. All standard errors are robust to heteroskedasticity and clustered at the county level. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
Non-recourse	-0.01	0.01	0.05**	0.05**
	(0.01)	(0.01)	(0.02)	(0.03)
Subprime ratio	0.14***	0.11***	0.08***	0.08***
	(0.04)	(0.02)	(0.02)	(0.02)
Subprime ratio * *Non-recourse*	0.19***	0.14***	0.07**	0.07*
	(0.05)	(0.04)	(0.04)	(0.04)
GDP Growth		1.65***	1.67***	1.66***
		(0.24)	(0.16)	(0.16)
Income Growth		-0.55***	-0.71***	-0.71***
		(0.19)	(0.14)	(0.14)
Unemployment		-2.16***	-1.31***	-1.25***
		(0.43)	(0.41)	(0.42)
Pop. Growth		-0.78**	1.09*	1.14*
		(0.39)	(0.62)	(0.65)
Judicial Foreclosure		0.06***	0.01	0.01
		(0.01)	(0.01)	(0.01)
Property Tax		-0.07***	-0.03*	-0.03
		(0.01)	(0.02)	(0.02)
$Distance^R$				-0.00
				(0.00)
$Distance^{NR}$				-0.00
				(0.00)
$(Distance^R)^2$				0.00*
				(0.00)
$(Distance^{NR})^2$				0.00
				(0.00)
Constant	0.09***	0.20***	0.12***	0.12***
	(0.01)	(0.03)	(0.04)	(0.04)
County-Pair Sample	No	No	Yes	Yes
County-Pair FE	No	No	Yes	Yes
N	17177	17177	4126	4122
R^2	0.08	0.24	0.29	0.29

Comparison with Judicial Requirement

U.S. states have different laws regarding mortgage foreclosure. One of related provisions in mortgage foreclosure laws is judicial foreclosure requirement. In judicial foreclosure states lenders are required to go through the courts for a foreclosed sale whereas in non-judicial foreclosure states lenders have the own right to sell the property when borrowers are behind schedule on mortgage payments. According to *Mian et al.* (2013), twenty states are classified as judicial foreclosure states. The distribution of judicial foreclosure requirement is illustrated in Panel B of Figure 2.2. It shows that non-recourse states are mostly located in West coast and upper Midwest while the judicial foreclosure laws are mostly enacted in East coast. Among eleven non-recourse states, three states (Iowa, North Dakota and Wisconsin) have the judicial foreclosure requirement. *Ghent* (2013) and *Mian et al.* (2013) argue that the joint distribution of The mortgage laws were not caused by a certain economic reason or state-level policy differences.

Impacts of the judicial foreclosure requirement on the supply of mortgage loans and house prices have been examined by *Pence* (2006) and *Mian et al.* (2013). *Pence* (2006) finds that the judicial foreclosure requirement reduces mortgage credit supply by imposing greater costs on lenders seeking foreclosures on houses. *Mian et al.* (2013), on the other hand, highlight that non-judicial foreclosure requirements have a significant negative impact on house prices by increasing the supply of houses through the foreclosure process. Recourse law, which is not emphasized in these studies, clearly differs from the judicial foreclosure requirement. Although the judicial requirement has an effect on the foreclosure decision of homeowners, the liability of borrowers is distinct from this judicial process. The judicial requirement does not protect borrowers from unlimited liability.

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