IN TIMES OF FINANCIAL DISTRESS: PERSPECTIVES FROM VALUATION, INFORMATION ASYMMETRY AND RETURNS

by

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To my husband Praveen and my little one Guru Sashank

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Abstract

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INFORMATION ASYMMETRY AND RETURNS

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The dissertation addresses unanswered questions in asset valuation through the lens of financial distress in three different asset markets namely equity market, residential property market and REITs market. The first two essays explore the valuation impact of financial distress in equity and residential property markets while the third essay examines the role of information asymmetry in REITs market around credit rating announcements.

In the first essay, I investigate why highly distressed firms earn low returns. By employing a direct misvaluation measure, I find that distressed firms with substantial overvaluation earn negative returns. I also further study the characteristics of the overvalued distressed firms by examining the joint roles of short-sale constraints and heterogeneous beliefs in the financial markets.

The second essay advances the knowledge of the distressed sale discounts associated with residential properties during the Liquidity Crisis of 2008 and subsequent housing market crisis in California introducing a new and important temporal and geographic perspective. Using a unique set of instrumental variables for time on market, I find that the discounts on distressed properties varies over time and sub-markets but are consistent across different model specifications.

In the third essay, I examine the informational content of REITs' changes in their long term or unsecured credit ratings and empirically test the presence of insider trading, prior to the announcements. I find that credit rating downgrades disseminate some new information to market participants prior to the liquidity crisis while they lose their informational content post crisis. While news of credit rating upgrades appe ars to be more transparent before the crisis, they provide relevant new information after crisis. I find evidence of insider trading prior to credit rating upgrades post crisis and it is present among REITs with high information asymmetry and poor corporate governance. Also, an analysis of the magnitude of REIT abnormal returns on possible explanatory variables points towards market condition as being a significant moderating variable.

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Chapter 1

Introduction

The dissertation consists of three separate essays centered on the valuation impact of financial distress and the role of information asymmetry. The dissertation addresses unanswered questions in asset valuation through the lens of financial distress in three different asset markets namely equity market, residential property market and real estate investment trusts (REITs) market.

The first essay is “Misvaluation and Financial Distress”. Till date there has not been an attempt to empirically explain the distress anomaly using a direct misvaluation measure. The primary goal of this essay is to examine the extent to which misvaluation contributes to negative stock returns among highly distressed firms. It further provides the characteristics of overvalued distressed firms by examining the joint roles of short-sale constraints and heterogeneous beliefs in the financial markets. I raise three important empirical questions in this study. First, are the equities of these highly distressed firms overvalued? Second, if it can be explained, do divergence of opinion and limits to arbitrage explain distress anomaly? Third, why is it important to examine how stock overvaluation impacts the distress anomaly? This essay addresses the gap by investigating the interaction between financial distress and overvaluation.

The second essay is entitled “The Valuation Impact on Distressed Residential Transactions: Anatomy of a Housing Price Bubble”. It examines the discounts associated with foreclosure and short sale status in the Fresno, California from 2006 to 2010, a time period containing significant housing market distress and price volatility. Most previous empirical studies on foreclosure price discounts are based on data from housing-market during periods of relative stability and even fewer studies have examined the pricing implications of short sale transactions. This essay addresses this gap by investigating the discounts for distressed residential transactions and contributes to the existing foreclosure research and literature by introducing a new and important temporal and geographic perspective.

The third essay is entitled “Information Asymmetry, Credit Ratings and REIT Returns”. It investigates the role of private information in the relationship between information asymmetry and financial distress of REITs. Prior literature have not examined the role of private information prior to credit rating changes in REITs and this essay attempts to fill the gap by empirically investigating the insiders’ trading activities. This essay also adds to the limited existing empirical evidence about corporate governance’s impact upon information asymmetry by examining the quality of REIT corporate governance in the context of credit rating changes.

The remainder of this chapter describes each of these essays in more detail.

1.1 Misvaluation and Financial Distress

Why do highly distressed firms earn low returns? Few papers have proposed rational explanations. George and Hwang (2010) show that the low returns of distressed stocks could be explained by their choice of financial leverage. Garlappi and Yan (2010) demonstrate a hump shaped relationship between distress risk and stock returns and show that the possibility of debt renegotiation drives a negative relation between leverage and equity betas in highly distressed stocks. While the above studies offer rational explanations, many papers suggest alternate behavioral explanations. Campbell, Hilscher, and Szilagyi (2008) conclude that the negative relationship between distress and return is inconsistent with rational explanation and they suggest that valuation errors by irrational investors as the most likely explanation for distress anomaly. Agarwal and Taffler (2008) argue that a low or negative risk premium would result from investors not reacting to the risk of failure which may result in distressed stocks not being adequately discounted and thus remain overvalued.

Although studies that examine asset pricing anomalies have alluded to equity overvaluation as a potential explanation but they have largely overlooked using direct measures of misvaluation to address this. The primary goal of this essay is to examine the extent to which misvaluation contributes to negative stock returns among highly distressed firms. Using the RKRV (2005) methodology from the mergers and acquisitions literature, I decompose market to book ratio into three components, firm-specific misvaluation (FMISV), industry-specific misvaluation(IMISV) and future growth potential(GP). I find that distressed firms have both greater misvaluation measures and lesser long-run growth opportunities relative to the overall market. Also, I find that firm-specific misvaluation and future growth potential are related to financial distress premium while industry-specific misvaluation is not. While I run Fama-MacBeth regressions of stock returns on prior period O-Score alone, I find a negative premium. But, when FMISV, IMISV and GP are included in the model, I find that the slope on O-score changes from negative to positive. FMISV has a negative premium while IMISV is insignificant and GP has a positive premium.

I argue that the bizarre results that prior literature find (negative risk premium) is mostly attributable to a "small" set of overvalued firms. If high distress firms earn abnormally bad subsequent returns, then why aren't smart investors exploiting the mispricing? So, I ask the next question "Are there common stock characteristics among these overvalued distressed firms?" This essay then further explores this question by examining the joint roles of short-sale constraints and heterogeneous beliefs in the financial markets. Miller (1977) theorized that stocks are overvalued in the presence of short selling restrictions and that the overvaluation increases in the degree of divergence of opinion. Therefore the stocks that are subject to both short-sale constraints and high dispersion in opinion are overvalued and generate low subsequent returns. Due to short-sale constraints, pessimistic traders cannot enter into the market and, therefore, only optimistic investors continue to buy driving prices up. Such overvaluation will increase in the degree of divergence of opinion. Once the divergence in opinion is narrowed, more investors realize that the stock is overvalued and start off-loading their holdings. If this prediction holds, stocks that were initially overvalued should earn low or negative subsequent returns. Therefore, Miller's overvaluation hypothesis' insights on the effects of short-sale constraints and the divergence in opinion on the value of stocks can be extended to examine the low returns for distressed firms.

I find that stocks with high distress have high values of short sale constraints and greater divergence of opinion and the values of the indicator variables are monotonically increasing with the distress risk. After triple sorting on distress, short sale constraints and divergence of opinion, I also find that the distress premium is substantially stronger among firms that have greater information uncertainty and are more difficult to arbitrage, while the premium is insignificant among firms that have low information uncertainty and are easy to arbitrage. By examining the joint roles of limits to arbitrage and divergence of opinion on the distress anomaly, I find that the abnormally low returns of distressed stocks are predominant in the overvalued stock quintiles. Negative returns occur only in highest quintiles of divergence of opinion and the returns get monotonically lower with increasing short sale constraints in line with the overvaluation hypothesis explanation.

1.2 The Valuation Impact on Distressed Residential Transactions: Anatomy of a Housing Price Bubble

There have been several academic studies designed to estimate the influence of foreclosure status on the price of single-family residences. Generally, empirical results have revealed about a 20% discount associated with foreclosure status and this greatly depends on the estimated model and location. These foreclosure studies are based on data from relatively stable periods in housing-market prices (Baton Rouge, Louisiana; Arlington, Texas; and Las Vegas, Nevada in 1980s and 1990s). The few studies that have examined the foreclosure discount during the housing market crash were focused on the Las Vegas housing market (Clauretie and Daneshvary, 2009; Clauretie and Daneshvary, 2010; and Daneshvary and Clauretie, 2012).

This study advances the knowledge of the distressed sale discounts associated with residential properties during the Liquidity Crisis of 2008 and subsequent housing market crisis in California, a state ranking among the top ten states in residential foreclosures. The city of Fresno ranks number 14 in the top 100 metros with the highest foreclosure rates. The study's sample consists of data for single-family detached home transactions between 2006 and 2010 in Fresno, California. After substantial housing price appreciation from 1999 to 2006, house prices began falling and mortgage interest rates began rising. Households were no longer able to refinance, causing many new homeowners to fall into delinquency and foreclosure. As an alternative to foreclose, the mortgagee may consider a short sale. A short sale is when a lender discounts a mortgage to avoid a possible foreclosure auction or bankruptcy. Short sales are used as alternatives to foreclosures because it mitigates foreclosure fees and costs to both creditor and borrower. A short sale can be a preferred solution for 'under water' homeowners, who owe more on their homes than the property value, who need to sell. In the past, it was rare for a bank or lender to accept a short sale. Today, however, due to overwhelming market changes, banks and lenders have become much more amiable to these transactions. While several studies estimate foreclosure discounts, studies estimating price discounts associated with "short sale" status are limited (Clauretie and Daneshvary, 2010; Daneshvary and Clauretie, 2012).

I examine price discounts associated with foreclosure and short-sale status during the development of a distressed market. I find that the foreclosure discounts are about 20% and short-sale discounts are about 13% in the Fresno, California market irrespective of the model specification. This study controls for the yearly and quarterly time trends, the types of distressed property status (short sales and foreclosure sales), in addition to a usual set of control variables. Since marketing time is most likely jointly determined with the sales price, I use an instrumental variables model using six atypical indicator variables and property demand variables to control for time on market endogeneity. I also control for possible latent characteristics of the distressed properties using a self-selection model.

The foreclosure and short-sale coefficients are consistent across all models suggesting that the discount on distressed transactions is in fact large. This is expected considering the market conditions during the sampling period. I further investigate the distress discounts by examining the distressed variables over time. I find that both the foreclosure and short sale discounts are time varying with both peaking in the height of the distressed market conditions in 2008 and 2009.

The dataset corresponds to a time period characterized by mortgage interest rate volatility, high residential mortgage default rates, and declining transaction prices. The found foreclosure and short sale discounts are averages for the entire time period and I suspect the distressed sale-transaction price relationship varies over time. Therefore, I examine the time varying discounts associated with both the foreclosure and short-sale status variables. For foreclosure transactions, discounts are 17% in 2008 and increase to 22% in 2009, declining back to 17% in 2010. For short sale transactions, discounts increase from 11% in 2008 to15% in 2009, fall back to14% in 2010. Also, foreclosure status is associated with a decrease in time-on-the-market while short sale status increases time on the market.

1.3 Information Asymmetry, Credit Ratings and REIT Returns

Over the past couple of decades, the market for REITs has grown dramatically. REITs have restricted ability to invest in activities other than real estate. Also, they incline to focus on a single real estate property type and/or focused geographic locations. REITs must distribute 90 percent of taxable income to investors each year (95 percent before 1999). Due to these special characteristics, REITs should be more transparent and less susceptible to asymmetric information in general (Damodaran, John, and Liu (1997) and Hardin and Hill (2008)).

However the notion of informational transparency in REIT literature is still a source of debate. Hartzell, Kallberg and Liu (2005) and Hartzell, Kallberg and Liu (2008) propose that equity REITs are fairly simple to value since they hold portfolios of tangible assets and have a transparent structure. Also, REITs principally depend on external sources of funding for financing their capital projects and asset acquisitions. Also, the REIT corporate structure is distinctive in the aspect of their relative inability to retain earnings due to the regulatory provision requiring a minimum 90% distribution of taxable income (Ooi, Ong, and Li 2010). This special regulatory characteristic has motivated many prior researchers to examine REIT transparency, and financing decisions.

Credit rating changes are significant in impacting external financing decisions and in mitigating asymmetric information. REITs target debt levels to obtain credit ratings just above the investment grade cutoff point where clear differences in financing cost and length to maturity can be observed (Highfield, Roskelley and Zhao (2007)). Given the competing views of REIT transparency and the role of credit ratings in being a factor that impacts external financing, this study uses the credit rating changes in REITs as a natural laboratory to study the presence of information asymmetry in REITs. I test the price reaction of REIT shares following credit rating actions. If a credit rating change contains a substantial amount of non-public information about the REIT, it should have an effect on the price.

Prior research examining insider information and REIT returns found that REIT insiders have considerable information advantages relative to outside shareholders. Therefore, REITs with credit rating changes are expected to have higher levels of insider trading measured by top executives' net selling (i.e. sales less purchases). Damodaran and Liu (1993) show that REIT insiders have significant information advantages compared to outside shareholders. This essay empirically tests the presence of insider trading with respective to the REITs' changes in their long term or unsecured credit ratings.

Anglin, Edelstein, Gao, and Tsang (2011) examine the quality of REIT corporate governance and find that information asymmetries are present in REITs although they are less in REITs with high quality corporate governance. Good corporate governance can affect market efficiency by decreasing the level of asymmetric information between informed insiders, such as managers, and public shareholders. I study the link between REIT governance and information asymmetry by examining the role of insiders. This essay adds to the limited existing empirical evidence about corporate governance's impact upon information asymmetry (Kanagaretnan, Lobo and Whalen 2007) by focusing on the presence of insider trading.

The contributions of this essay to current literature are threefold. First, this is one of the first few papers to test the price reaction of REIT shares following credit rating actions. Second, no other papers till date have examined the role of private information as a source of information asymmetry in REITs market. I test the presence of private information in the context of credit rating changes by empirically investigating the insiders' trading activities. Third, I also examine the quality of corporate governance and its role in mitigating information asymmetry specifically through the lens of insiders' trades.

Chapter 2

Misvaluation and Financial Distress

2.1 Introduction

Basic financial principles suggest that financially distressed firms have higher risks and lower market values and, therefore, that expected returns should be higher for high distress firms than for low distress risk firms. Distress risk has been examined in several papers, producing results that contradict rational asset pricing theory. Specifically, relative to low distress risk firms, high distress firms earn lower subsequent stock returns.

Why do highly distressed firms earn subsequent low returns? Few papers have proposed rational explanations while others suggest valuation errors by irrational investors to be a probable explanation. This paper sheds light on the latter potential explanation by examining to what extent misvaluation contributes to negative stock returns among highly distressed firms. Using a misvaluation measure that decomposes the market to book ratio, this paper finds that undervalued distressed stocks earn positive distress premium while overvalued distress stocks earn negative distress premium, confirming the presence of a distress anomaly only among overvalued stocks.

If high distress firms earn abnormally bad subsequent returns, then why aren't smart investors exploiting the mispricing? Due to limits to arbitrage, pessimistic traders cannot enter the market. Therefore, only optimistic investors participate, continuing to drive prices upward. When the divergence of opinion is large, investors fail to perceive distressed stocks to be overvalued and are surprised by the poor performance realized by distressed firms. This is the first paper that examines to what extent negative returns of financially distressed firms are associated with limits to arbitrage and divergence of opinion and find that the negative distress premium is substantially stronger among firms that have greater divergence of opinion and are more difficult to arbitrage.

Lower subsequent returns by financially distressed firms is documented as early as Dichev (1998) and confirmed by many other studies like Griffin and Lemmon (2002), Campbell, Hilscher, and Szilagyi's (2008), Garlappi, Shu, and Yan (2008), Gilchrist, Yankov, and Zakrajsek (2009) and George and Hwang (2010). In contrast, Vassalou and Xing (2004) estimate default likelihood indicators for individual firms using equity data and find evidence of a positive financial distress premium. Chava and Purnanandam (2010), use ex ante estimates of expected returns based on the implied cost of capital and find positive cross-sectional relationship between expected stock returns and default risk. Friewald,Wagner, and Zechner (2011) provide evidence of a positive relationship between risk premia extracted from CDS spreads and equity returns.

While few of these papers have proposed rational explanations (see George and Hwang (2010), Garlappi and Yan (2010)) many others suggest alternate behavioral explanations. Campbell, Hilscher, and Szilagyi (2008) conclude that the negative relationship between distress and return is inconsistent with rational explanations and suggest valuation errors by irrational investors as a likely explanation for distress anomaly. Agarwal and Taffler (2008) argue that a low or negative risk premium is due to the failure of investors to react to the risk of default, which causes distressed stocks to remain overvalued.

Managers of firms with overvalued stocks may have more opportunity or inclination to be myopic, investing in projects that fail to align with the mission of the firm. Firm value is then destroyed by this pursuit of the negative net present value projects (Berk and DeMarzo, 2011). Therefore, there may be a direct link between overvalued equity and financial distress of the firm, but empirical evidence examining overvaluation in financially distressed firms is nonexistent.

The primary goal of this paper is to examine the extent to which misvaluation contributes to negative stock returns among highly distressed firms. Misvaluation measures have been extensively used in exploring the role of overvalued equity in acquisitions (Shleifer and Vishny, 2003; Rhodes–Kropf, Robinson and Vishwanathan, 2005 (henceforth RKRV); and Dong et al., 2006), seasoned equity offerings (SEOs) (Hertzel and Li, 2010), analyst coverage (Doukas, Kim, and Pantzalis, 2005), and bankruptcy prediction (Lyandres and Zhdanov, 2013). Although studies that examine asset pricing anomalies have alluded to equity overvaluation as a potential explanation, they have largely overlooked the use of direct measures of misvaluation to test the propositions.

Using the RKRV (2005) methodology from the mergers and acquisitions literature, I decompose market to book ratio(M/B) into three components, firm-specific misvaluation (FMISV), industry-specific misvaluation(IMISV) and future growth potential(GP). Firm-specific misvaluation measures firm-specific deviation from current industry valuation, and is believed to capture the idiosyncratic misvaluation component of the M/B ratio. Industry misvaluation measures deviation between current period industry valuation and long-run industry valuation. This component indicates whether the industry is overvalued. Future growth potential or the long-run value-to-book measures the long-run industry valuation relative to book value and is a proxy for growth opportunities.

Using the RKRV (2005)'s decomposed components, I find that distressed firms have both greater misvaluation and lower long-run growth opportunities relative to the overall market. Also, I find that firm-specific misvaluation and future growth potential are related to financial distress premiums while industry-specific misvaluation is not. When I run Fama-MacBeth regressions of stock returns on prior period O-Score alone, I find a negative distress risk premium. But, when FMISV, IMISV and GP are included in the model, I find that the slope on O-score changes from negative to positive. FMISV has a negative premium while IMISV is insignificant and GP has a positive premium.

Only those distressed stocks that are highly overvalued (high FMISV) or have lower growth potential (GP) have negative returns. However, it should be noted that the negative (H-L) distressed returns present in overvalued stocks are almost three times the negative (H-L) distressed returns present in stocks with low future growth potential. Firm-specific misvaluation explains the negative returns of highly distressed stocks. Therefore, I argue that the bizarre results that prior literature find (negative risk premium) are mostly attributable to a "small" set of overvalued firms.

Are there common stock characteristics among these overvalued distressed firms? Avramov et al. (2007), while exploring for commonalities across asset-pricing anomalies, find that highly distressed firms are hard to short sell, which could establish nontrivial hurdles for exploiting these anomalies in real time. Most investors are overly optimistic about the valuations of financially distressed companies, and end up using overly positive assumptions about growth, discount rates and profitability (Damodaran, 2006). When the divergence of opinion is large, investors fail to perceive distressed stocks to be overvalued and are surprised by the poor performance realized by distressed firms. Once the divergence in opinion narrows, more investors realize that the stock is overvalued and start off-loading holdings. If this prediction holds, distressed stocks that were initially overvalued should earn low or negative subsequent returns.

Miller (1977) theorized that stocks are overvalued in the presence of limits to arbitrage and that the overvaluation increases in the degree of divergence of opinion. Zhang (2006) finds that the momentum strategy works well only among stocks with high divergence of opinion. Using different proxies for limits to arbitrage, previous studies find that many anomalies are more pronounced among firms that are more difficult to arbitrage (e.g., Ali, Hwang and Trombley (2003), Nagel (2005), Lam and Wei (2009), and Li and Zhang (2010)). Although prior studies have looked at effects of either divergence of opinion or limits to arbitrage (the two conditions of Miller's overpricing hypothesis) on asset pricing anomalies, they have not considered the consequences of considering them simultaneously and, specifically, in the context of overvaluation. More specifically, this paper aims to address the following questions: (1) using direct misvaluation measures, can we conclude that financially distressed firms are overvalued? (2) while examining common characteristics of overvalued distressed stocks, to what extent are the negative returns of financially distressed stocks related to limits to arbitrage and divergence in opinion?

I employ a large set of standard proxies for divergence of opinion and limits to arbitrage in the literature and create aggregate measures for limits to arbitrage (LTA-Score) and divergence of opinion (DO-Score). It is not the objective of this paper to create an optimal aggregate measure to capture divergence of opinion or limits to arbitrage but to analyze the effects of them on distressed stock returns. I find that stocks with high distress have high values of limits to arbitrage and greater divergence of opinion and the values of the indicator variables are monotonically increasing with the distress risk. Further, after triple sorting on distress, limits to arbitrage and divergence of opinion, I find that the negative distress premium is substantially stronger among firms that have greater divergence of opinion and are more difficult to arbitrage, while the premium is insignificant among firms that have low divergence of opinion and are easy to arbitrage. Negative returns occur only in higher quintiles of limits to arbitrage and the returns get monotonically lower with increasing divergence of opinion and these quintiles also have the highest firm-specific misvaluation values in line with Miller's overvaluation hypothesis explanation. By examining the joint roles of limits to arbitrage and divergence of opinion on the distress anomaly, I confirm that the abnormally low returns of distressed stocks are predominant in the overvalued (high divergence of opinion and difficult to arbitrage) stock quintiles.

I expect this research to be of interest to both financial academics and practitioners. From an academic perspective, this study contributes to the extant literature in many ways. First, this study is one of the first to use a direct measure of misvaluation and provides empirical evidence of overvaluation among financially distressed stocks. Prior studies have used book to market ratio as a proxy for distress risk and have come up with contradictory explanations. This study, by decomposing the market to book into misvaluation and fundamental growth components, also provides explanations and clarifications to research questions addressed in this stream of literature.

Second, this study contributes to the literature that examines the role of limits to arbitrage or divergence of opinion in asset-pricing anomalies. Notable recent papers include Ali, Hwang, and Trombley (2003) on book-to-market, Nagel (2005) on book-to-market, analyst forecast dispersion, turnover, and volatility, Zhang (2006) on price continuation anomalies, Mashruwala, Rajgopal, and Shevlin (2006) on total accruals, Li and Zhang (2010) on investment growth, net operating assets and net stock issues, and Lam and Wei (2009) on asset growth, among others.

Third, this paper contributes to the literature attempting to reconcile the financial distress anomaly. Anomalously low returns from distressed stocks originate from initial overvaluation brought on by excessively optimistic investors in the presence of limits to arbitrage (short-sale constraints). High costs and/or the impossibility of short-selling distressed stocks prohibit arbitrageurs from taking an appropriate position to exploit the profit opportunities and correct overpricing. From the perspective of investors, this research enhances our understanding of the effect of short-sale constraints on a trading strategy that is based on distress. The limits in short-selling distressed stocks defeat the idea of constructing a self-financing (hedge) portfolio to profit from the distress anomaly.

The rest of the paper is organized as follows. Section 2 describes the data and the measures of distress and misvaluation. Section 3 presents and discusses the main empirical findings. Section 4 discusses the common characteristics of overvaluation in financial distressed stocks by providing supportive empirical findings using proxies for limits to arbitrage and divergence of opinion. Section 5 offers concluding remarks.

2.2 Data and Descriptive Statistics

The full sample consists of the intersection of all US firms listed on NYSE, AMEX, and NASDAQ with available monthly returns in CRSP. Data on accounting information are from the COMPUSTAT Annual and Quarterly Industrial Files. Institutional holdings records are from Thomson Reuters. Information on analyst forecasts is from I/B/E/S. The sample period is from January 1980 to December 2011. The starting date is restricted by the availability of institutional ownership data. I exclude financial firms and firms with negative book equity. I delete observations for which the absolute value of earnings forecast revision exceeds 100% of the prior year-end stock price, because these observations are likely to be erroneous. Following Jegadeesh and Titman (2001), I exclude stocks with a share price below $5 at the portfolio formation date to make sure that the results are not driven by small, illiquid stocks or by the bid–ask bounce. To avoid any potential confounding effect of recent IPOs, I also exclude firms with less than 12 months of past return data on CRSP.

There are many measures that capture financial distress of firm. Dichev (1998) finds the negative relation between stock returns and default probability using Ohlson

(1980) (henceforth O-Score) and Altman (1969) Z-score to proxy for distress risk. He documents that O-score predicts CRSP delistings better than Z-score. Because of this, Griffin and Lemmon (2002) focus on O-score to capture distress risk. This measure is also used in numerous recent studies including Opler and Titman (1994) and George and Huang (2010). A more recent measure is by Campbell, Hilscher and Szilagyi (2008) who use hazard model to predict bankruptcy. CHS distress measure is estimated from the number of corporate bankruptcies from 1963 to 2003 and it excludes any stock with share price greater than $15. Moreover, while O-score uses only accounting variables, CHS relies on both accounting and market data, especially on the number of firm failures. They show that their measure can predict corporate failures better than O-score, but the results using this model in asset pricing are consistent with those using O-score.

I follow Griffin and Lemmon (2002) and George and Huang (2010) to calculate O-score as described in the footnote 6 of Griffin and Lemmon (2002):

(1) O-score = –1.32 – 0.407 log(total assets) +6.03 (total liabilities/total assets) –1.43 (working capital/total assets) + 0.076(current liabilities/current assets) – 1.72(1 if total liabilities>total assets, or 0 otherwise) – 2.37 (net income/total assets) – 1.83(funds from operations/total liabilities) +0.285 (1 if net loss for the last two year, 0 otherwise) – 0.521(CHIN)

where CHIN is the ratio of change in net income to absolute total net income in last 2 years.

I also robustly check the findings by using CHS measure. I follow Campbell, Hilscher, and Szilagyi (2008) to calculate CHS.

$$CHS= –9.16 –20.26(NIMTAAVG) + 1.42(TLMTA)–7.13(EXRETAVG) +1.41(SIGMA) –0.045(RSIZE) – 2.13(CAHMTA) +0.075(MB) – 0.058(PRICE)$$

where NIMTAAVG is a geometrically declining average of past values of the ratio of net income to the market value of total assets, TLMTA is total liabilities to the market value of total assets, EXRETAVG is a geometrically declining weights on past monthly log excess stock return relative to S&P500 index, SIGMA is the standard deviation of daily stock returns over previous three months, RSIZE is the log ratio of market capitalization to the market value of the S&P 500 index, CASHMTA is cash and short term investments to the market value of total assets, MB is market to book ratio, and PRICE is the log price per share truncated from above at $15.

Panel A of Table A.1 shows the summary statistics for variables used in O-Score estimation. I run model (1) for each cross section and then estimate O-scores. Panel B of Table A.1 shows the summary statistics for variables used in O-Score estimation for all five O-Score quintiles. I find that the working capital (WCAP), total assets (AT), total current assets (ACT), net income (NI), and funds from operations (FOPT) monotonically decreases as the financial distress increases. However there are no significant changes in total liabilities (LT) or total current liabilities (LCT).

In this study I revisit and confirm prior empirical evidence on returns among financially distressed stocks. Table A.2 shows The returns statistics of portfolios formed on the basis of O-Score including average excess returns , CAPM abnormal returns, Fama-French 3 factor abnormal returns and Carhart 4 factor abnormal returns. Using Ohlson’s (1980) as a proxy for distress risk, I find portfolios of distressed stocks have the lowest average returns. I sort stocks based on O-score and find that a long-short portfolio that is long in the quintile of the least distressed stocks and short in the most distressed stocks earns about 1% per month. These returns are not subsumed by the Fama and

French (1993) factors or the momentum factor. The high distress portfolio underperforms the lowest distress portfolio.

2.3 O-Score, Misvaluation and Returns

I employ RKRF (2005)'s methodology for decomposing M/B into misvaluation (M/V) and growth (V/B) components as follows:

(2) M/B   M/V x V/B

which in log form can be written as

(3) $m - b \equiv (m - v) + (v - b)$

where lower case letters indicate logarithms of the respective variables. The term (m–v) will capture the misvaluation component of the market-to-book ratio.

The most important piece in identifying the components of the market-to-book ratio is determining the true firm value, v. For estimation purposes, for each firm i in industry j at time t, v can be written as a linear function of firm-specific accounting information, θ_{it}, and both a vector of time-t accounting multiples, α_{jt}, and a vector of long-run accounting multiples, α_j. Thus, the market-to-book ratio for firm i at time t can be further decomposed as:

(4) $$m_{it} - b_{it} = \underbrace{\underbrace{m_{it} - v(\theta_{it};\alpha_{jt})}_{firm} + \underbrace{v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_j)}_{industry}}_{total} + \underbrace{v(\theta_{it};\alpha_j) - b_{it}}_{growth-potential}$$

The first term, $m_{it} - v(\theta_{it};\alpha_{jt})$, referred to as firm-specific misvaluation, measures the difference between the market value and the fundamental value established from firm's accounting data and the industry multiples at time t. The second term, $v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_{j})$, referred to as industry misvaluation, measures the difference in estimated fundamental value at time t, α_{jt} and long-run industry multiples, α_{j}. This difference reflects the extent to which the whole industry may be misvalued at time t. The first two terms collectively referred to as total misvaluation, capture the overall misvaluation component of the market-to-book ratio. The third term, $v(\theta_{it};\alpha_{j}) - b_{it}$, is long-run value-to-book or growth-potential. It measures the difference between firm value implied by the vector of long-run industry multiples and book value. This measure can be interpreted as the investment or growth opportunity component of the market-to-book ratio.

RKRV(2005) use three different models to estimate $v(\theta_{it};\alpha_{jt})$ and $v(\theta_{it};\alpha_{j})$. The models[1] differ only with respect to the accounting items that are included in the accounting information vector θ_{it}. I use RKRV's third model (the one with most predictability), which includes book value (b), net income (NI) and market leverage ratio (LEV) in the accounting information vector θ_{it}. Lee, Myers, and Swaminathan (1999), Ang and Cheng (2006), and Dong, et al (2006), use a residual income model from the accounting literature to estimate the intrinsic value. But the fairly restrictive assumptions of residual income model and also the use of analyst forecasts (to compute residual income) could bias the tests towards large firms. In RKRV's method, the assumptions of residual income model are relaxed and a firm's intrinsic value is assumed to be a linear function of its book value of equity, net income and leverage. The parameters of the

[1] The first model in RKRV (2005) includes only book value; the second model includes book value and net income.

linear function are allowed to vary over time and across industries and can also capture differences in discount rates amongst firms. Expressing market value as a simple linear model of these variables

(5) $$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt} \ln(NI)^{+}_{it} + \alpha_{3jt} I_{(<0)} \ln(NI)^{+}_{it} + \alpha_{4jt} LEV_{it} + \varepsilon_{it}$$

Since net income can be negative sometimes, it is expressed as an absolute value $(NI)^{+}$ along with a dummy variable, $I_{(<0)}$, to indicate when net income is negative.

Each year I group CRSP/Compustat firms according to the 12 Fama and French industry classifications (I exclude financial companies and therefore there are only 11 industries in the sample) and run annual, cross-sectional regressions for each industry and generate estimated industry accounting multiples for each year t, $\hat{\alpha}_{jt}$. The estimated value of $v(\theta_{it};\alpha_{jt})$ is the fitted value from regression Eq. (6):

(6) $$\begin{aligned} & v(b_{it}, NI_{it}, LEV_{it}; \hat{\alpha}_{0jt}, \hat{\alpha}_{1jt}, \hat{\alpha}_{2jt}, \hat{\alpha}_{3jt}, \hat{\alpha}_{4jt}) \\ & = \hat{\alpha}_{0jt} + \hat{\alpha}_{1jt} b_{it} + \hat{\alpha}_{2jt} \ln(NI)^{+}_{it} + \hat{\alpha}_{3jt} I_{(<0)} \ln(NI)^{+}_{it} + \hat{\alpha}_{4jt} LEV_{it} \end{aligned}$$

Then I calculate the long-term industry multiples, α_j, by averaging the yearly $\hat{\alpha}_{jt}$'s from the annual regressions: $\overline{\alpha}_j = 1/T \sum_t \alpha_{jt}$ for all α_k, where k=0, 1, 2, 3, 4. Our estimate of $v(\theta_{it};\alpha_j)$ is then the fitted value of Eq. (7) using the $\overline{\alpha}_j$'s:

(7) $$\begin{aligned} & v(b_{it}, NI_{it}, LEV_{it}; \overline{\alpha}_{0j}, \overline{\alpha}_{1j}, \overline{\alpha}_{2j}, \overline{\alpha}_{3j}, \overline{\alpha}_{4j}) \\ & = \overline{\alpha}_{0j} + \overline{\alpha}_{1j} b_{it} + \overline{\alpha}_{2j} \ln(NI)^{+}_{it} + \overline{\alpha}_{3j} I_{(<0)} \ln(NI)^{+}_{it} + \overline{\alpha}_{4j} LEV_{it} \end{aligned}$$

Table A.3 presents the time-series averages of the regression coefficients for Eq. (7) for the 12 Fama and French industries[2]. The results are similar to those reported in Table A.4 of RKRV (2005).

The table reports that the average adjusted-R2 for these regressions ranges from 82% to 92%, which shows that within an industry, the three accounting variables explain a large majority of the cross-sectional variation in firm market values in a given year.

Using the above estimates, I calculate the three decomposed market to book ratio components, namely, firm-specific misvaluation (FMISV), industry-specific misvaluation(IMISV) and growth potential(GP)

The first component, FMISV is the misvaluation at the firm level which is the difference between the market value of firm and the fundamental value of the firm. Positive (negative) misvaluation at the firm level (FMISV) indicates that the firm is overvalued (undervalued). Time-series industry misvaluation (IMISV) measures valuation deviations between current industry multiples from long-run industry multiples - this could indicate if the industry is overvalued. Positive (negative) misvaluation at the industry level (IMISV) indicates that the industry is overvalued (undervalued). Growth potential (Long-run value-to-book) measures value implied by long-run industry accounting multiples relative to book value -it is a proxy for growth opportunities.

Table A.4 summarizes the descriptive statistics of the main variables used in this essay. The mean distress measure is positive indicating that most of the firms are financially healthy in the sample. The mean FMISV is positive indicating most of the firms are overvalued than undervalued in the sample. The magnitude of firm level misvaluation is higher than the industry level misvaluation. The fundamental growth potential

[2] Financial firms are excluded from the sample

component is positive on average. Panel B of Table A.4 shows the correlations between the main variables and I find that the financial distress measured by O-Score is positively related to the misvaluation component and negatively related to the growth component.

Over the sample period of 1980 to 2011, at the end of each month, stocks are sorted into 25 groups. First, stocks are sorted into 5 portfolios based on their most recently calculated O-Score. Next, stocks are sorted into 5 groups independently based on each of their most recently calculated decomposed component (FMISV, IMISV, MISV and GP). Once the portfolios are formed, each stock is held for 1 month. I then report in Table A.5, the computed equally-weighted Carhart 4 factor abnormal returns for the (High-Low) distress portfolio for the highest and lowest quintiles of FMISV, IMISV, MISV and GP over the next month. H-L, the long-short portfolio that is long in the least quintile and short in the highest quintile of each of the components is also presented in Table A.5.

I find that (High-Low) distress returns is negative for overvalued firms (high FMISV) and positive for undervalued firms (low FMISV) and the difference between high and low FMISV is also negative and statistically significant. Also, I find that (High-Low) distress returns is negative for firms with low growth potential (low GP) and positive for firms with greater growth potential (high GP) and the difference between high and low FMISV is also negative and statistically significant. I find that IMISV does not have any significant(both economically and statistically) relationship with returns implying that there is no impact of industry level misvaluation on returns which is counter-intuitive to the practice of investing based on industry's prospects. I will have to further dissect into this by performing sub-sample analysis.

To further examine the evidence I have presented thus far, I now turn to a regression analysis. While the sub-portfolio analysis presents a nonparametric examination of the cross-sectional difference in the relationship between financial distress and stock returns, a regression analysis provides a structural and multivariate view of this cross-sectional difference and further illuminates the role of misvaluation. I carry out my analysis using the methodology of Fama and MacBeth (1973): first, in each month, we regress monthly returns on a set of firm characteristics, and then we average the time series of regression coefficients and calculate corresponding t-statistics, which are adjusted for auto-correlation and heteroskedasticity (Newey and West 1987).

The set of independent variables also contains characteristics, such as beta (obtained from CRSP), book-to-market ratio, momentum measured by past 6-month returns, that are known to affect returns, and equity market capitalization. For regressions that include the decomposed components of market to book ratio, I exclude book-to-market ratio due to high correlations with the misvaluation component. The main test of my hypothesis relies on examining the coefficients of misvaluation components (FMISV, IMISV and MISV), fundamental growth potential component (GP) and the distress risk measure (O-Score). I find that in the model, excluding the decomposed components, the distress premium is negative but the coefficient changes from negative to positive after including the decomposed components of market to book ratio. The overall misvaluation component has a negative premium and the growth potential component has a positive premium. Among the misvaluation components, the firm specific misvaluation is negatively related to returns while the industry specific misvaluation is unrelated to returns. The results of Fama-Macbeth regressions are shown in Table A.6.

2.4 Common Characteristics among Overvalued Distressed Stocks

Why are some highly distressed firms overvalued and the others not? Are there common stock characteristics among overvalued distressed stocks? Miller (1977) in his overvaluation hypothesis theorized that stocks with high limits to arbitrage and high divergence in opinion are overvalued. With greater divergence of opinion, psychological biases are increased and information is more asymmetric among investors, leaving more room for mispricing. The overvaluation however, is more likely to sustain only in the presence of higher limits to arbitrage. In spite of its plausibility, no prior study has examined the joint implications of both these conditions of Miller's overvaluation hypothesis (limits to arbitrage and divergence in opinion) on returns of financially distressed stocks. In this section I examine stock characteristics classified as proxies for these two conditions in explaining the distress anomaly.

2.4.1 Divergence of Opinion Measures

The proxies for divergence of opinion are the same as in Zhang (2006), which explores the sensitivity of momentum to information uncertainty. By examining the distress premium among firms with more and less information uncertainty, one can explore the role of information uncertainty in the distress premium.

The first proxy is firm size(SIZE). I measure size as the market capitalization at the portfolio formation date. Small firms are less diversified and have less information available for the market than large firms. Therefore, smaller firms are subject to more severe information asymmetry. Specifically, I compute Size as the natural log of a firm's market capitalization at the end of its most recent fiscal quarter.

The second proxy is firm age (AGE). I measure age as the number of years since the firm was first covered by CRSP. A longer history implies that more information is available to the market. Therefore, age inversely proxies for information uncertainty and younger firms are subject to more severe information asymmetry.

The third proxy is individual stock volatility (RETVOL). I measure stock volatility as the standard deviation of weekly excess returns over the year ending at the portfolio formation date. Predicting future returns of a stock with more volatile returns in the past year would be more difficult. Therefore, the more volatile the stock returns are, the more uncertain its future returns.

The fourth proxy is cash flow volatility (CFVOL). I measure cash flow volatility as the standard deviation of cash flow from operations in the past five years with a minimum of three years of data. Cash flow from operations is measured as earnings before extraordinary items minus total accruals, scaled by average total assets. Here, total accruals equal changes in current assets minus changes in depreciation expense, cash, and changes in current liabilities plus changes in short-term debt. The more volatile the past cash flow, the more uncertain the underlying business.

The fifth proxy is analyst coverage (NUMEST).I measure analyst coverage as the number of analysts following the firm in the previous month. Larger analyst coverage corresponds to more information available about the firm (e.g., Hong, Lim, and Stein (2000)). Therefore, more analyst coverage implies less information uncertainty. The last proxy is dispersion in analyst forecast (STDEV). Dispersion in analyst forecast is measured as the standard deviation of analyst one-year earnings forecasts at the portfolio formation date scaled by the prior year-end stock price to mitigate heteroskedasticity. It is a proxy for the uncertainty about future earnings or the degree of consensus among analysts or market participants (e.g., Diether, Malloy, and Scherbina (2002) and Johnson (2004)). Thus, wider analyst disagreement on the next-year earnings implies more information uncertainty.

2.4.2 Limits to Arbitrage Measures

I identify seven commonly used proxies for limits on arbitrage in the literature (e.g., Amihud (2002), Ali et al. (2003), Nagel (2005), Mashruwala et al. (2006), Avramov et al.(2010), Lam and Wei (2009) and Duan et al. (2010)). By examining the distress premium among firms with more and less severe limits on arbitrage, one can explore the role of arbitrage cost in the distress premium.

The first proxy is the number of institutional investors holding a firm's shares at the portfolio formation date (NUM). It is a commonly used proxy for shareholder sophistication (e.g., Chen et al. (2002) and Ali et al. (2003)). The more sophisticated the investors are, the less mispricing would take place.

The second proxy is the percentage of outstanding shares held by institutional investors at the portfolio formation date (PCT). Low institutional holdings make it difficult to borrow stocks for short selling (e.g., D'Avolio (2002)). Hence, the second proxy is inversely related to short-sale constraints. Higher short-sale constraints imply higher transaction costs and hence more severe limits to arbitrage.

The third proxy for arbitrage cost is idiosyncratic stock return volatility (IDIOVOL). Shleifer and Vishny (1997) argue that professional arbitrage is conducted by a relatively small number of highly specialized investors using other people's capital. Such arbitrage is ineffective when prices diverge further from fundamental values before they converge. Furthermore, arbitrageurs are risk averse and typically poorly diversified, and hence they are concerned about the idiosyncratic risk of their portfolios. Thus, Shleifer and Vishny (1997) predict that idiosyncratic volatility will deter arbitrage activities.

The fourth proxy is dollar trading volume (DOLVOL). Dollar trading volume is the timeseries average of the monthly share trading volume multiplied by the monthly closing price over the 12 months prior to the portfolio formation date. This proxy measures how quickly an investor can trade a large block of shares (e.g., Bhushan (1994)). Higher dollar volume implies less price pressure and hence fewer arbitrage costs. The fifth proxy is the bid-ask spread (BIDASKAV). The bid-ask spread measures the trading cost, so the higher the bid-ask spread is, the higher the arbitrage cost.

The last proxy is Amihud's (2002) illiquidity (AMIHUD). Amihud (2002) defines illiquidity as the annual average ratio of stock illiquidity at the end of each month over the 12 months prior to the portfolio formation date. A higher illiquidity value implies a larger impact on the stock price per order flow, so a larger transaction cost for investors. Thus, the larger the illiquidity measure, the higher the arbitrage cost.

2.4.3 Aggregated Variables: LTA Score and DO-Score

To assess the aggregated effect of combining the proxies, I compute two simple summary quantitative measures (LTA-Score and DO-Score). To construct LTA-Score, I first calculate the median values for each of the 6 individual limits to arbitrage indicators and then create a dummy variable that could be treated as a binary signal. For variables that are expected to be positively related to limits to arbitrage, I assigned a value of 1 to the binary signal if it is higher than its median value in a given quarter and 0 otherwise. For variables that are expected to be negatively related to limits to arbitrage, I assigned a value of 1 to the binary signal if it is lower than its median value in a given quarter and 0 otherwise. After getting six dummy variables, I then compute the LTA-Score for each stock by aggregating its 6 LTA binary signals. Similarly, to construct DO-Score, I first calculate the median values for each of the 6 individual divergence of opinion indicators and then create a dummy variable that could be treated as a binary signal. For variables that are expected to be positively related to divergence of opinion, I assigned a value of 1 to the binary signal if it is higher than its median value in a given quarter and 0 otherwise. For variables that are expected to be negatively related to divergence of opinion, I assigned a value of 1 to the binary signal if it is lower than its median value in a given quarter and 0 otherwise. After getting six dummy variables, I then compute the DO-Score for each stock by aggregating its 6 DO binary signals.

I rely on the evidence in the prior literature to determine the expected sign of the correlation between the variables and divergence of opinion, rather than on the evidence during our sample period. This aggregation process gives a summary measure that captures how these signals work together. Following Jegadeesh et. al. (2004) I choose this simple way of using an aggregated measure rather than conduct a search for a more efficient proxy for divergence of opinion or limits to arbitrage because it is not the objective of this essay to create an optimal measure to capture these but to analyze the effects of divergence of opinion and limits to arbitrage on distressed stock returns.

2.4.4 Divergence of Opinion, Limits to Arbitrage and O-Score

Tables A.7 and A.8 show the descriptive statistics of all divergence of opinion proxy variables and limits to arbitrage proxy variables respectively.

Table A.9 reports the average values for the limits to arbitrage (LTA) proxies and divergence of opinion (DO) proxies for the five default quintiles. In each panel quintile 1 represents a portfolio consisting of firms with the lowest default and quintile 5 represents a portfolio consisting of firms with the highest default.

I note that LTA and DO variables are monotonically decreasing with high O-Score. This indicates that the firms that are more likely to default, also have lower levels of LTA and DO. Panel A of Table A.10 reports the time series correlations between default probability and DO(difference of opinion) variables. Panel B of Table A.10 provides the time series correlations between default probability and LTA(limits to arbitrage) variables. Panel C of Table A.10 provides the time series correlations between DO variables and LTA variables.

Table A.11 shows return statistics for portfolios based on limits to arbitrage and divergence of opinion proxy variables and also the aggregate variables: LTA-Score and DO-Score.

In Panel A, at the end of each month, stocks are sorted into 5 groups by six of the limits to arbitrage proxies and the LTA-Score and assigned to five quintile portfolios. Once the portfolios are formed, each stock is held for 1 month. I then compute the equally-weighted raw returns over the next month. In this panel quintile 1 represents a portfolio consisting of firms with the lowest limits to arbitrage and quintile 5 represents a portfolio consisting of firms with the highest limits to arbitrage. The returns presented in Panel B are the equally-weighted raw returns of the five quintile portfolios formed by sorting the stocks by six of the difference of opinion proxies and the DO-Score. In this panel quintile 1 represents a portfolio consisting of firms with the lowest differences of opinion and quintile 5 represents a portfolio consisting of firms with the highest differences of opinion.

Over the sample period of 1980 to 2011, at the end of each month, stocks are sorted into 25 groups. First, stocks are sorted into 5 portfolios based on their most recently calculated O-Score. Next, stocks are sorted into 5 groups independently based on each of their most recently calculated Do-Score and LTA-Score. Once the portfolios are formed, each stock is held for 1 month. I then compute the equally-weighted returns over the next month. The returns presented in Table A.13 are Carhart 4 factor abnormal returns for the (High-Low) distress portfolio for the highest and lowest quintiles of DO-Score and LTA-Score. H-L, the long-short portfolio that is long in the least quintile and short in the highest quintile is also presented.

I find that (High-Low) distress returns is negative for firms with high divergence of opinion(high DO) and positive for firms with divergence of opinion (low DO) and the difference between high and low DO is also negative and statistically significant.Also, I find that (High-Low) distress returns is negative for firms with high limits to arbitrage(high LTA) and positive for firms with limits to arbitrage (low LTA) and the difference between high and low LTA is also negative and statistically significant. Furthermore, I find that the stocks with both high DO and high LTA underperforms the stocks with both low DO and low LTA. The (High-Low) distress returns on stocks with both high DO and high LTA is negative while that of stocks with both low DO and low LTA is positive and the difference is negative and statistically significant.

For each month, stocks are first independently sorted divergence of opinion (DO-Score) and limits to arbitrage (LTA-Score) into three quintiles, and then for each divergence of opinion and limits to arbitrage portfolio they are dependently sorted by financial distress (O-Score) into five portfolios. Stocks in each of 45 portfolios are held in the portfolios for 1 month. The returns presented in Table A.13 are Carhart 4 factor abnormal returns. I find that the distress premium is substantially negative among firms that have greater information uncertainty and are more difficult to arbitrage, while the premium is positive among firms that have low information uncertainty and are easy to arbitrage.

2.4.5 Robustness Checks

I conduct two robustness checks. First, I examine the joint effects of limits to arbitrage and divergence of opinion after removing highly distressed stocks from the sample. Over the sample period of 1980 to 2011, I remove those stocks that are at the highest two quintiles of distress and the remaining stocks are sorted into 25 groups at the end of each month. First, stocks are sorted into 5 portfolios based on their most recently calculated LTA-Score. Next, stocks in each of these portfolios are sorted into 5 groups based on their most recent DO-Score. Once the portfolios are formed, each stock is held for 1 month. We then compute the equally-weighted returns over the next month. The returns presented in the Panel A of Table A. 16 are average raw returns over risk-free rate. Also CAPM abnormal returns, Fama-French 3 factor abnormal returns and Carhart

4 factor abnormal returns are computed and are reported in Panels A, B and C, respectively. I find that the overvalued stocks are still earning substantially negative returns even after removing the highest two quintiles of distressed stocks from the sample.

Next, I examine the presence of distress anomaly after removing highly overvalued stocks from the sample. Over the sample period of 1980 to 2011, at the end of each month, I remove those stocks that are at the highest two quintiles of LTA and DO and the remaining stocks are sorted into 5 groups by their most recently calculated O-Score and assigned to five quintile portfolios. Once the portfolios are formed, each stock is held for 1 month. We then compute the equally-weighted returns over the next month. The returns presented in Table A.17 are average raw returns, CAPM abnormal returns, Fama-French 3 factor abnormal returns and Carhart 4 factor abnormal returns over all formation periods. I find that the distressed stocks do not earn negative returns after removing the highest two quintiles of overvalued stocks from the sample providing indication that the distress anomaly could be because of the fact that these stocks are overvalued.

2.5 Conclusion

Till date there has not been an attempt to empirically explain the distress anomaly using the overvaluation hypothesis. I raise three important empirical questions in this study. First, do divergence of opinion and limits to arbitrage explain distress anomaly? Second, if it can be explained, are the equities of these highly distressed firms overvalued? Third, why is it important to examine how stock overvaluation impacts the distress anomaly? This essay addresses the gap by investigating the interaction between financial distress and overvaluation.

While Griffin and Lemmon (2002) interpret the puzzle as evidence of market mispricing, recent papers have proposed rational explanations. Chen, Novy-Marx, and Zhang (2010) explain the low average returns for distressed firms using their newly developed three-factor model that includes mimicking portfolios based on investment and productivity. Garlappi and Yan (2011) demonstrate a hump shaped relationship between distress risk and stock returns and show that the possibility of debt renegotiation drives a negative relation between leverage and equity betas in highly distressed stocks. Campbell, Hilscher and Szilgayi (2008) suggest that the distress anomaly is influenced by behavioral factors such as low share price and low turnover, limited institutional ownership and analyst coverage making it too expensive to arbitrage.

Using the RKRV (2005)'s decomposed components, I find that distressed firms have both greater misvaluation measures and lesser long-run growth opportunities relative to the overall market. Firm-specific misvaluation explains the negative returns of highly distressed stocks. Undervalued distressed stocks earn positive returns while overvalued distress stocks earn negative returns confirming the presence of distress anomaly only among overvalued stocks. I argue that the bizarre results that prior literature find (negative risk premium) is mostly attributable to a "small" set of overvalued firms. If high distress firms earn abnormally bad subsequent returns, then why aren't smart investors exploiting the mispricing? So, I ask the question "Are there common stock characteristics among these overvalued distressed firms?"

This essay provides an alternative explanation for the distress risk puzzle by examining the joint roles of short-sale constraints and heterogeneous beliefs in the financial markets. Therefore the stocks that are subject to both short-sale constraints and high dispersion in opinion are overvalued and generate low subsequent returns. Due to short-sale constraints, pessimistic traders cannot enter into the market and, therefore, only optimistic investors continue to buy driving prices up. Such overvaluation will increase in the degree of divergence of opinion. Once the divergence in opinion is narrowed, more investors realize that the stock is overvalued and start off-loading their holdings. If this prediction holds, stocks that were initially overvalued should earn low or negative subsequent returns. Therefore, Miller's overvaluation hypothesis' insights on the effects of short-sale constraints and the divergence in opinion on the value of stocks can be extended to examine the low returns for distressed firms.

I find that stocks with high distress have high values of short sale constraints and greater divergence of opinion and the values of the indicator variables are monotonically increasing with the distress risk. The negative returns of distressed firms occur only in highest 2 quintiles of short sale constraints and within the highest limits to arbitrage quintiles the highest two quintiles of O-Score has the lowest returns. Double sorts on distress and divergence of opinion show that the negative returns predominantly occur only in highest 2 quintiles of divergence of opinion and the highest quintile of distress risk is negative only in the presence of high divergence of opinion.

Furthermore, after triple sorting on distress, short sale constraints and divergence of opinion, I also find that the distress premium is substantially stronger among firms that have greater information uncertainty and are more difficult to arbitrage, while the premium is insignificant among firms that have low information uncertainty and are easy to arbitrage. By examining the joint roles of limits to arbitrage and divergence of opinion on the distress anomaly, I find that the abnormally low returns of distressed stocks are predominant in the overvalued stock quintiles. Negative returns occur only in highest quintiles of divergence of opinion and the returns get monotonically lower with increasing short sale constraints in line with the overvaluation hypothesis explanation.

This study contributes to the extant literature in many ways. First, it belongs to a large and growing literature that examines the role of limits to arbitrage and information uncertainty in asset-pricing anomalies. Second, this essay is the first to explain distress risk puzzle by investigating the role of short-sale constraints and divergence of opinion in isolation and simultaneously. Third, this essay contributes to the literature attempting to reconcile the financial distress anomaly.

Chapter 3

The Valuation Impact on Distressed Residential Transactions Anatomy of a Housing Price Bubble[3]

3.1 Introduction

There have been several academic studies designed to estimate the influence of foreclosure status on the price of single-family residences. Generally, empirical results have revealed about a 20% discount associated with foreclosure status and this greatly depends on the estimated model and location. These foreclosure studies are based on data from relatively stable periods in housing-market prices (Baton Rouge, Louisiana; Arlington, Texas; and Las Vegas, Nevada in 1980s and 1990s). The few studies that have examined the foreclosure discount during the housing market crash were focused on the Las Vegas housing market (Clauretie and Daneshvary 2009; Clauretie and Daneshvary 2010; and Daneshvary and Clauretie 2012).

This study advances the knowledge of the distressed sale discounts associated with residential properties during the Liquidity Crisis of 2008 and subsequent housing market crisis in California, a state ranking among the top ten states in residential foreclosures. The study's sample consists of data for single-family detached home transactions between 2006 and 2010 in Fresno, California.

After substantial housing price appreciation from 1999 to 2006, house prices began falling and mortgage interest rates began rising. Households were no longer able to refinance, causing many new homeowners to fall into delinquency and foreclosure. As an alternative to foreclose, the mortgagee may consider a short sale. A short sale is

[3]A part of this essay is published in the Journal of Real Estate Finance and Economics and can be found online at http://link.springer.com/article/10.1007/s11146-013-9425-0

when a lender discounts a mortgage to avoid a possible foreclosure auction or bankruptcy. Short sales are used as alternatives to foreclosures because it mitigates foreclosure fees and costs to both creditor and borrower. A short sale can be a preferred solution for ‘under water’ homeowners, who owe more on their homes than the property value, who need to sell. In the past, it was rare for a bank or lender to accept a short sale. Today, however, due to overwhelming market changes, banks and lenders have become much more amiable to these transactions. While several studies estimate foreclosure discounts, studies estimating price discounts associated with “short sale” status are limited (Clauretie and Daneshvary 2010; Daneshvary and Clauretie 2012).

I examine price discounts associated with foreclosure and short-sale status during the development of a distressed market. I find that the foreclosure discounts are about 20% and short-sale discounts are about 13% in the Fresno, California market irrespective of the model specification. This study controls for the yearly and quarterly time trends, the types of distressed property status (short sales and foreclosure sales), in addition to a usual set of control variables. Since marketing time is most likely jointly determined with sales price, I use an instrumental variables model using six atypical indicator variables and property demand variables to control for time on market endogeneity. I also control for possible latent characteristics of the distressed properties using a self-selection model. The foreclosure and short-sale coefficients are consistent across all models suggesting that the discount on distressed transactions is in fact large. This is expected considering the market conditions during our sampling period. I further investigate the distress discounts by examining the distressed variables over time. I find that both the foreclosure and short sale discounts are time varying with both peaking in the height of the distressed market conditions in 2008 and 2009.

Our dataset corresponds to a time period characterized by mortgage interest rate volatility, high residential mortgage default rates, and declining transaction prices. The found foreclosure and short sale discounts are averages for the entire time period and I suspect the distressed sale-transaction price relationship varies over time. Therefore, I examine the time varying discounts associated with both the foreclosure and short-sale status variables. For foreclosure transactions, discounts are 17% in 2008 and increase to 22% in 2009, declining back to 17% in 2010. For short sale transactions, discounts increase from 11% in 2008 to15% in 2009, fall back to14% in 2010. Also, foreclosure status is associated with a decrease in time-on-the-market while short sale status increases time on the market.

Also, this study sheds more light into the discounts by slicing the market into four predominant submarkets and finds that the discounts for distressed transactions are also different for different submarkets. Therefore this study acknowledges that submarkets matter in this context and finds that the discounts of the lower priced homes are substantially lower and the discounts of premium homes are very high while those of the medium priced homes are around the middle. This study hence contributes to the hedonic sub markets literature asserting the importance of examining sub markets in valuation of properties. Cash sales dynamics also change within the submarkets and across market conditions. Also, the foreclosure status decreases time on the market while the short-sale status increases time on the market. I also find that an extra day on market for a foreclosed property has a higher impact on price discount compared to an extra day on market for a shortsale property.

Next, I clarify the difference between a foreclosure and a short sale transaction. In the following sections, I review the relevant literature; then, I present the data and empirical results. The last section is the conclusion.

3.2 Disposition of distressed properties: foreclosure and short sales

A property goes into distressed status when a mortgagor defaults on a mortgage payment or indicates that future payments will not be made. As collateral for the loan, the mortgagee has the right to take the mortgaged property. However, for decision making purposes the mortgagee will determine the value of the distressed property by a formal appraisal or broker's price opinion to decide whether to allow the property to go through the foreclosure process or to pursue a short sale strategy. If the mortgagee chooses foreclosure, the property may be sold before the lender takes possession at a foreclosure auction, otherwise the mortgagee takes possession of the property and classifies it as REO, or real estate owned. The mortgagee will obtain the services of a REO asset manager and dispose of the property by either selling the property directly, in a bulk sale, or market the property through the services of a local real estate broker and a multiple listing service. This present study is concerned with transactions occurring through the local multiple listing service.

As an alternative to foreclose, the mortgagee may consider a 'short sale' strategy. A short sale is a transaction in which the sale proceeds are less (or short) than the outstanding mortgage balance. Basically, the mortgagee and other stakeholders agree to discount the outstanding mortgage balance due to some economic or financial hardship faced by the mortgagor. Short sale transaction can be complicated because in addition to a primary lender, additional approvals maybe required by holders of junior liens, HOA liens, tax liens, and mechanic's liens. A short sale agreement has a contingency requiring the mortgagee and other appropriate parties to approve the short sale transaction.

Mortgagees may prefer a short sale to moderate potentially greater costs, including legal fees, and potential price losses associated with a foreclosure sale. A mortgagor may prefer short sales to foreclosures because a short sale may result in forgiveness of a portion of the outstanding debt and may create less damage to the mortgagor's credit rating, as compared to a foreclosure. It should be noted that a short sale does not automatically include debt forgiveness unless this is explicitly negotiated and stated on the settlement agreement. If no debt forgiveness is stated, the mortgagee may have the option to pursue uncollected mortgage balances through a deficiency judgment. Although both the mortgagor and mortgagee must consent to a short sale, neither party is a winner in this transaction. The primary advantage to the mortgagee is that a short sale is typically faster and less costly than a foreclosure resulting in less loss to the mortgagee, as compared to foreclosure or continued non-payment.

Mortgagees have loss mitigation specialists and departments to evaluate prospective short sale situations. The lender will typically determine the amount of negative equity by estimating the property's market value through an appraisal or, less formally, by a broker price opinion. Short sale transactions have increased in the past several years due to the large percentage of 'under-water' mortgagors and subsequent mortgage failures triggered by the Liquidity Crisis of 2008 and subsequent decline in residential property values. In fact, the recent wide spread use of the short sale concept has made 'short sale' a household term.

Short sales have gained a reputation of being lengthy and difficult transactions. First, the mortgagee, mortgagor, or buyer could back out at any time before being contractually locked in to the agreement. In some markets, such as the Fresno market, mortgagees have been overwhelmed by both foreclosure and short sale transactions and have been slow to respond to short-sale offers. In California, there could also be tax consequences if the loans are not purchase money mortgages. However, if the loans are purchase money mortgages and “non-recourse,” portions of the debt can be forgiven upon short sale settlement without tax implications during out sample period.

3.3 Literature review and research questions

The foreclosure literature dates back to a 1985 sample of 62 condominium transactions (number of foreclosure transaction not disclosed) in Baton Rouge, Louisiana (see Shilling, Benjamin, and Sirmans 1990). The authors found a 24% discount attributed to foreclosure sale status. Forgey, Rutherford, and VanBuskirk (1994) also found a 23% foreclosure discount in a sample of 2,483 residential transaction (of which 12% were foreclosure sales) collected in 1991 to 1993 in Arlington, Texas. Using the same Arlington, Texas market, Springer (1996) collected 2,317 residential transactions (of which 270 were foreclosure sales) from 1989 to 1993 and found a smaller foreclosure status discount of between 4% and 6%.

Carroll, Clauretie, and Neill (1997) point out that real estate markets are not perfectly efficient but also not likely inefficient to the extent that would allow average foreclosure discounts in excess of 20%. A discount of this magnitude exceeds typical transaction costs and would allow arbitrage opportunities to buy foreclosure properties and sell them quickly at significant profits. Carroll, Clauretie, and Neill’s hypothesis is that the larger foreclosure sale discounts found could be explained by weak or flawed controls for location quality. To test their intuition, they collect 1,974 residential transactions (of which 20% were HUD and bank owned foreclosure sales) from 1990 to 1993 in Las Vegas, Nevada. They initially find a foreclosure status discount of 12% to 14%, but after controlling for location-based difference with 31 zip code based indicator variables, the foreclosure discount does in fact decrease to 8.5% to 9.7%.

Clauretie and Daneshvary (2009) studied a sample of 8,498 single-family residential transaction (of which 15% are foreclosure sales) collected from 2004 to 2007, also based on the Las Vegas, Nevada housing market. In this study, the authors control for physical characteristics, location quality, and endogeneity between marketing time and price. They find that foreclosure status reduced transaction prices by about 10%, in an ordinary lease squares (OLS) model specification. Using a two stage least squares (2SLS) specification and controlling for property quality, a variable not commonly found in transaction price databases but unique to their dataset, the foreclosure status discount reduces to 7.9% and after further controls for occupancy status and cash sales, this discount reduced to 7.5%. They concluded that the true foreclosure status discount is about one-third of the prior 23% (found in Forgey, Rutherford, and VanBuskirk 1994) and higher, reported discounts but caution that the relative size of this overestimation rule-of-thumb may be different in other localities and time periods and further research is warranted. This challenge is the motivation for this present study.

I found few published studies directly addressing the pricing effects of short sale status on residential transaction prices. Perhaps the only hedonic based short sale study was Clauretie and Daneshvary (2010). Clauretie and Daneshvary developed a model that allows for simultaneous estimation of price and time-on-the-market effects of short sales and foreclosures. They found that the short sale option had the lowest price discounts but had higher costs associated with time-on-the-market. They used a three stage least squares (3SLS) specification. After controlling for property quality, the foreclosure status discount was 11% while the short sale discount was close to 6%.

Perhaps the most reliable hedonic based foreclosure/short sale study in terms of model specification and controls is Daneshvary, Clauretie, and Kader (2011). They examine the Las Vegas market during 2008, a period when distressed transactions dominated this market. Using a three stage least squares (3SLS) specification and controlling for property quality and time-on-the-market endogeneity and other self-selection issues, they found a foreclosure sale discount of 13% and a short-sale discount of about 12%.

Although the short-sale based literature is limited, our a priori expectations for the short sale influence come from a comparatively developed and related branch of literature on the pricing impacts of foreclosure transactions. After reviewing the foreclosure body of literature outlined in this section, I develop our expectations and research hypothesis for the pricing influences of both foreclosure and short-sale transactions.

In summary, the extant literature indicates a foreclosure sale discount ranging from 4% to 24%. I agree with the more recent literature that is critical of the early foreclosure discount studies that did not sufficiently control for improvement quality and location. However, I pose that both foreclosures and short-sale discounts will be sensitive to market conditions and time varying. I expect to find relatively larger discounts in periods of extreme distress. In market conditions described in the next section, I expect foreclosure transactions to sell at substantial price discounts. Based on our understanding of the foreclosure literature, I next consider the pricing implications specifically for short-sale transactions.

Because the option of a short sale is at the mortgagee's discretion, I anticipate that a rational lender will not pursue a short sale strategy unless the short sale option is a superior alternative to pursuing a foreclosure. In other words, rational and competent mortgagees will not participate in short sale transactions unless expected losses from the short sale is less than expected losses, including time and legal fees, from a foreclosure strategy. Therefore, our expectations of the valuation impact on short sale transactions will be constrained by the discounted level of foreclosure sales, less a spread for the additional expenses and fees associated with foreclosures. I also expect short sale discounts to be time varying and greatest during periods of extreme market stress.

3.4 Setting and sample data

The study setting is within Central California's San Joaquin Valley, often referred to informally as the "Central Valley." The Central Valley has experienced perhaps some of the most extreme housing price volatility in the United States over the sample time period. Central Valley cities and communities such as Sacramento, Modesto, Los Banos, Madera, Bakersfield, and Fresno were often near or top the lists of national housing price declines and foreclosure-short sale transaction volumes. 2006 represents relatively 'normal' market conditions with 2007 a period of transition before the housing price bubble bust in 2008 and subsequent fallout in 2009 and 2010. With respect to severe housing market conditions, this region of the United States (US) is ideal for observing the pricing impact of distressed sales on single-family residential transaction prices.

The Central Valley city selected for study is Fresno, California. The Fresno Metropolitan Area has a population of just fewer than one million and is the second largest Central Valley region after the Sacramento Metropolitan Area. The City of Fresno has a population of about 500,000 making it the largest inland Californian city, the fifth largest Californian city overall, and the 35th largest US city. Fresno is situated almost equal distance between Los Angeles and San Francisco and is the closest (approximately 60 miles to the south) major city in proximity to Yosemite National Park.

Fresno was founded in 1872 and incorporated in 1885. The land area measures 104.8 square miles and is covered by 19 zip codes and one area code. With the exception of a few small communities, most notably Clovis, agricultural, unused land, and the foothills of the Sierra Nevada mountain range essentially surround Fresno. With respect to housing price modeling, I view this somewhat isolated and protected location as desirable for research purposes over some larger and more integrated urban areas.

The sample data consists of 22,362 brokered single-family residential sale transactions collected from a local multiple listing service. I remove outliers from the dataset in a few steps. First, I exclude transactions that cannot be classified as either single family, multifamily, or condominiums, and transactions that take place at extreme prices, below the 1st or above the 99th percentile of the distribution of raw prices. Whenever the dataset reports property characteristics that are improbable like zero rooms, I consider those as missing. Finally, I Winsorize square footage at the 1st and 99th percentiles and numbers of bedrooms at the 99th percentile.

The time period ranges from January 1, 2006 to December 31, 2010. This time period is characterized by declining residential property values. A five-year period is an appropriate balance between the number of sampled transaction and controlling for rapidly changing market conditions. Table B.1 defines the dependent variable and each control variable and Table B.2 presents the descriptive statistics.

Most independent variable definitions and expectations are intuitive but a few warrant discussions. The variables of interest, foreclosure and short sale, are identified in the dataset in a unique field. Almost 37% of the sample data consists of foreclosure transactions while 8% of the transactions are short sales. Sirmans, Macpherson and Zietz (2005) reviewed approximately 125 studies that employed a hedonic model in estimating selling price. They identified five studies that included foreclosure as an independent variable, likely the same five studies that I reviewed. All five studies found negative and statistically significant relationships between transaction prices and foreclosure status.

Note that I include variables ‘bedrooms,’ ‘fireplaces,’ ‘bathrooms,’ ‘garage_spaces’ as continuous variables rather than creating sets of indicator variables to save degrees of freedom. I feel that this is the best approach to incorporate information from these building characteristics fields while retaining model power and parsimony. The variable ‘bedrooms’ measures the number of bedrooms. The expectation of a discount reflects a common consumer design preference for larger bedrooms after control for building size (lnsqft). This market preference is evident in broker listings advertising ‘large main bedroom’ and similar comments. Improvement age is included and expected to have an inverse relationship with the dependent variable, as older properties are typically in inferior condition.

With approximately 85% single-family one-story structures, one-story is the market standard, particularly with an aging population. After control for property size, I anticipate two story designs will reflect a significant price discount. Knight (2002) finds that vacant properties are more difficult to market and may signal seller weakness. They find that vacant residential properties sell at discounts. With a significant large portion of vacant sales, about 70%, I also anticipate a significant ‘vacant’ price discount. With summer months in the upper 90 degrees and days breaking 100 degrees, I anticipate a price premium for pools.

In the 2007 to 2010 period, mortgage qualification standards had been tightened and mortgage financing relatively difficult to obtain compared to the early part of the decade. I anticipate that cash buyers can negotiate significant price discounts during our sample period. Asabere, Huffman, and Mehdian (1992) and Lusht and Hansz (1994) document cash discounts of 13% and 16%, respectively, in residential transaction prices. These two studies comprise the whole of the real estate literature directly examining cash financing, an important topic in real estate finance.

I include zip code indicator variables as our first control for locational differences. The local brokers and multiple listing service use zip codes to segment the market. Figure 3.1 shows the foreclosure heat map for Fresno based on the zip codes. In addition, longitude and latitude are also included as important locational controls (see Fik et.al, 2003).

To control for changes in market conditions, a decreasing market in the sample period, I use two sets of control variables, years and quarters. The year variables reflect the overall annual change in market conditions while a set of quarterly indicator variables reflects seasonal fluctuations in transaction prices (Goodman, 1992).

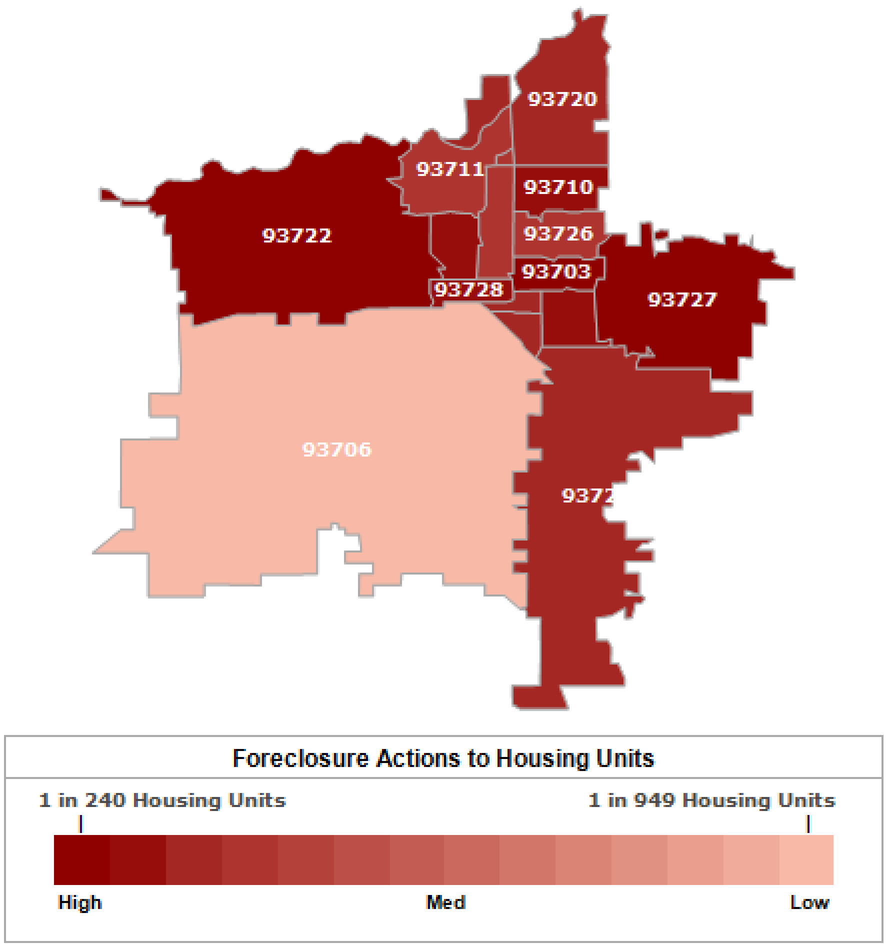

Figure 3-1 Fresno Foreclosure Heat Map

3.5 Foreclosure and Shortsale Discounts

Rosen (1974) argued that the value of any asset is the sum value of the asset's components and he has been credited as a pioneer in early hedonic pricing theory. Subsequently, regression based hedonic modeling has become a dominate research paradigm in real estate research for over four decades (see Cho (1996) for a survey of theoretical and emprical issues in hedonic housing price estimation and Sirmans et. al, (2006) for an overview of this literature). In this tradition, I use a hedonic pricing method to estimate the marginal transaction price influences of foreclosure and short sale transactions on residential property values.

To determine the effect of distressed market conditions on residential prices, I estimate the follow models:

$$\ln(\text{sale price}) = \beta_0 + \sum\beta X + \beta_{TOM} + \beta_{foreclosure} + \beta_{short\text{-}sale} + u_1 \qquad (1)$$

where X_i is a (n x k) matrix of traditional structural, site, quality, and location variables. The statistical models are estimated using ordinary least squares (OLS). The dependent variable is the natural log of sale price. Sirmans, Macpherson, and Zietz (2005) discussed the advantages of using the semi-log specification in hedonic modeling. This specification allows for variation in the dollar value of each characteristic and coefficients are interpreted as the percentage change in the price per unit change for each characteristic. The semi-log specification also helps to minimize the problem of heteroskedasticity.

The first two columns in Table B.3 details the results using ordinary least squares (OLS) with Davidson and MacKinnon (1993) heteroscedasticity-consistent errors, the first column including time-on-the-market as an explanatory variable and column 2 does not include time-on-the-market variable. With a coefficient of determination (R^2) of 88%, the explanatory power of the model is acceptable and consistent with published hedonic research pertaining to residential transaction prices.

These results demonstrate a price discount associated with both types of distressed transactions, foreclosure and short sales, as compared to the baseline of non-distressed transactions. After controlling for price differences associated with structure size, property qualities, and location, properties with a foreclosure status sell at about 21% discount and those with a short sale status sell at about 13% discount, both statistically significant at the 1% level. This finding is in line with the existing foreclosure literature suggesting that property foreclosures generate a discount of about 4% to 24%, depending on time period, location, and model specification (e.g., Shilling, Benjamin, and Sirmans 1990; Forgey, Rutherford, and VanBuskirk 1994; Hardin and Wolverton 1996; Springer 1996; Carroll, Clauretie, and Neill 1997; Pennington-Cross 2006; Clauretie and Daneshvary 2009).

Foreclosure status reduces the seller's reservation price, increases motivation to sell, and reduces time-on-the-market (Springer 1996). Therefore, transaction prices are influenced by distressed status both directly and indirectly through time-on-the-market. Therefore, omitting time-on-the-market variable induces endogeneity and may produce biased estimates of transaction price distress. The second column in Table B.3, the time-on-market variable is excluded and foreclosure status transactions sell at a discount of 21%. Short-sale transactions transfer at a discount of 14%. Both coefficients are statistically significant at the 1% level.

The OLS estimate of the time-on-the-market variable in specification (1) is economically and statistically insignificant, perhaps due to the endogeniety of this variable. The meta-analysis by Sirmans, Macpherson and Zietz (2005) identified 18 hedonic models that included time-on-the-market as an independent variable. In only one study the time-on-the-market coefficient was positive. In the remaining 17 studies, time-on-the-market was either negative (8) or statistically insignificant (9), mostly depending on whether time-on-the-market was entered as an endogenous variable or not. Consistent with the majority of the prior literature, I find that the time-on-the-market coefficient is either negative or insignificant.

As the most recent literature suggests, time-on-the-market is an endogenous variable in the price equation. Thus, simultaneous estimations of price and time-on-the-market equations are deemed appropriate.[4] The time-on-the-market equation can be expressed as

$$TOM = \beta_0 + \sum \beta X + \beta_{Price} + \beta_{foreclosure} + \beta_{short\text{-}sale} + u_2 \quad (2)$$

Estimated coefficients of the time-on-the-market equation indicate that the higher the transaction prices the shorter the marketing periods[5]. This could be because most of the transactions in this sample are distressed and selling at discounts. I also find that the foreclosure status has a negative influence on time-on-the-market and short-sale status has a positive impact on time-on-the-market.

OLS estimation for equations (1) and (2) assume that all of the explanatory variables, including time-on-the-market (in equation 1) and price (in equation 2), are exogenous. Clearly, these variables are endogenous, correlated with their respective disturbance, and OLS estimators are inconsistent. Therefore, I estimate these equations using two-stage least square (2SLS) instrumental variable estimators. The instrumental variables for the time-on-the-market variable are chosen with utmost care. There are six variables of *atypicality* – unusually large homes, unusually small homes, extremely old homes, extremely new homes, and unusually higher number of beds and baths – that I include. The idea is that homes with atypical characteristics take more time to sell and have subsequent pricing implications. I include variables capturing housing demand that include median income, unemployment rate, and population change. These demand variables influence the time the property is on the market. I find that the variable indicating extremely old dwellings is insignificant and all other instruments are significant. I also conduct a Sargan's over-identification test and find that the statistic is significant at

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[4] For examples of time-on-the-market and price endogeniety studies, see Sirmans, Turnbull, and Benjamin (1991), Yang and Yavas (1995), Yavas and Yang (1995), Knight (2002), Harding, Knight, and Sirmans (2003), and Clauretie and Thistle (2007).
5 The results of this table are available on request.

the 1% level showing that these instruments are jointly significant. The null in Sargan's test cannot be rejected for median income, unusually large homes, unusually small homes, and unusually higher number of beds and baths as instruments. So these variables are valid instruments since the Sargan's test statistic is not significant now. Estimated coefficients for the first stage regression are reported in Column 1 of Table B.4. These estimates indicate that foreclosure status has a negative effect on time-on-the-market and short- sale status has a positive effect on time-on-the-market.

The results of the two-stage least square (2SLS) instrumental variable estimation is shown in Column 3 of Table B.3. I find that the properties with a foreclosure status sell at a 20% discount and those with a short-sale status sell at a 16% discount, both statistically significant at the 1% level. After controlling for endogeneity, I find that the time-on-the-market variable is not significant. With a coefficient of determination of 88%, the explanatory power of the model is acceptable and consistent with published hedonic research pertaining to residential transaction prices.

Although the 2SLS estimators are consistent, they yield inefficient estimates since they do not use information from cross-equation correlations of disturbances, u_1 and u_2. To account for endogeneity of the price and time-on-the-market variables and to utilize information from the cross-equation correlations of disturbances, Green (2003, pp.404–07) suggests a three-stage least squares (3SLS) estimation method. Using this method consistent and efficient estimate of the parameters of the system of the two equations can be obtained. The results are shown in Column 4 of Table B.3. I find that foreclosure status transactions are discounted 21% and short sale transactions are discounted 13%, both statistically significant at the 1% level.

There is a possibility that house price and distressed transaction indicators in equation (1) are jointly determined. Therefore, the distressed variables may be endogenous in the price equation and may not sufficiently control for possible latent characteristics of the distressed properties. For example, if distressed properties have ‘‘unknown’’ stigma attached to them, then OLS would underestimate the negative effect of distressed-type variables. Applying an endogenous treatment effect model endogenizes the type of sale decision. A dichotomous variable is created that is equal to one if the house was sold under distressed conditions (foreclosure or short sale) and is equal to zero otherwise. Estimation of a two-equation system, the continuous price and the probit treatment effect equations, correct for any self-selection bias and endogeneity of the decision to sell a distressed property (Heckman 1979; and Vella and Verbeek 1999).

The estimation of the probit equation includes all the explanatory variables in the price equation (except distress indicators). From the results of the probit model, the inverse Mills ratio for each observation is estimated and included, along with the indicator variable for distressed status, as an independent variable in the price equation. Although the estimated coefficient of the inverse Mills ratio was statistically significant, it was negative and small in size. The results are shown in column 5 of Table B.3.

I find that the properties with a foreclosure status sell at 21% discount and those with a short-sale status sell at 13% discount, both statistically significant at the 1% level. There is no change in the magnitude and the signs of the coefficients for the distress indicator variables. The estimates of the Heckman self selection model are available in Table B.5. Column 2 of Table B.5 shows the estimates of the first stage regressions for time-on-the-market including the inverse Mills ratio.

The foreclosure and short-sale coefficients are consistent across all models suggesting that the discount on distressed transactions is in fact large. This is expected considering the market conditions during our sampling period.

3.6 Time Varying Distress Discounts

I further investigate the distress discounts by examining the distressed variables over time. Table B.6 shows the number of sales transactions and the foreclosure/short sale transactions for the sample period by year. I find that the foreclosure and short-sale transactions are too few in 2006 and 2007 to have statistically meaningful analysis. I remove years 2006 and 2007 from the sample period to further analyze the distressed transactions price discounts by year.

The dataset to examine time varying discounts span from 2008 to 2012. Table B.7 defines the dependent variable and each control variable and Table B.8 presents the descriptive statistics of this dataset between 2008 and 2012. I created interaction variables by multiplying the year indicator variables by the distressed sale indicator variables to created new indicator variables called foreclosure_2008, foreclosure_2009, foreclosure_2010, foreclosure_2011, foreclosure_2012, short-sale_2008, short-sale_2009, short-sale_2010, short-sale_2011 and short-sale_2012.

Table B.9 presents the descriptive statistics of all variables comparing them between traditional, foreclosed and shortsale properties between 2008 and 2012.

I then included these yearly-distressed variables (10 variables) in equation 2 in place of the two original distressed indicator variables, foreclosure and short sale and develop five models (OLS1, OLS2, 2SLS, 3SLS1 and 3SLS2). In Table B.10 I report the modeling results.

In Table B.11 I tabulate these coefficients for foreclosure and short sales discounts by year. I find that both the foreclosure and short sale discounts are time varying, increasing from 2008 to 2009 and decreasing in 2010. The foreclosure discount in 2008 is 17% and 22% in 2009. In 2010 it falls back to 17%. The short-sale discount is

11% in 2008 followed by 15% in 2009. In 2010 it declines to 14%. Note that the short-sale discounts are consistently lower than the foreclosure discounts.

Finally, I find approximately a 20% discount for cash sales, regardless of model specification. This found discount is about one-third higher than the cash discounts found in Asabere, Huffman, and Mehdian (1992) and Lusht and Hansz (1994). I attribute this greater cash discount to the unique market conditions during the sample period of extreme distress combined with high credit standards. Investors yielding cash were definitely 'king' during this sample period and this is reflected in our model. Table B.12 has yearly cash variables and these cash variables have higher discount coefficients attributable to the distressed market conditions. The coefficients on all the property and neighborhood characteristics, as well as other control variables, are statistically significant, have the expected signs, robust across methods, and consistent with the findings of previous research.

3.7 Submarket Analysis

Figures 3.2 and 3.3 present the heat maps of foreclosure and shortsale from 2008 to 2012. I find that foreclosures and shortsales are concentrated in specific neighborhoods and in this section I conduct tests to disentangle the distress discounts across different submarkets. Housing consumers do not necessarily limit their search to spatially concentrated areas and may search similarly priced neighborhoods located throughout a metropolitan area when making housing consumption decisions and therefore homes with different price ranges could be treated as different submarkets (Goodman and Thibodeau, 2007).

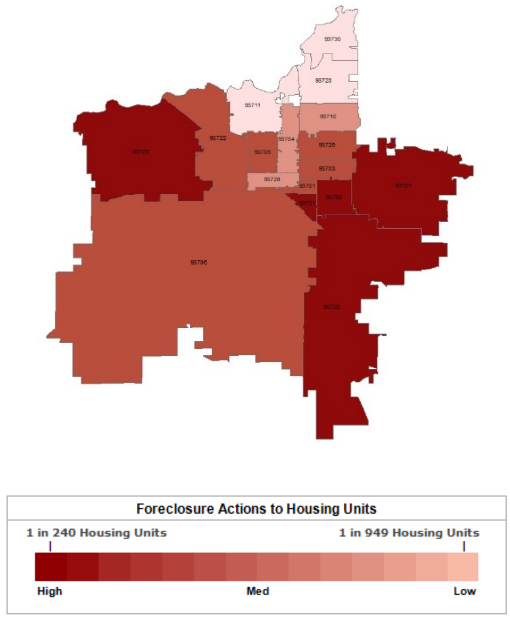


Figure 3-2 Foreclosure Heat Map (2008-2012)

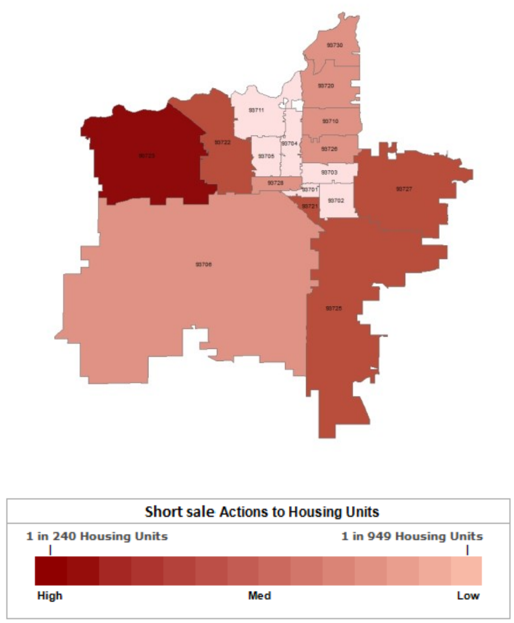
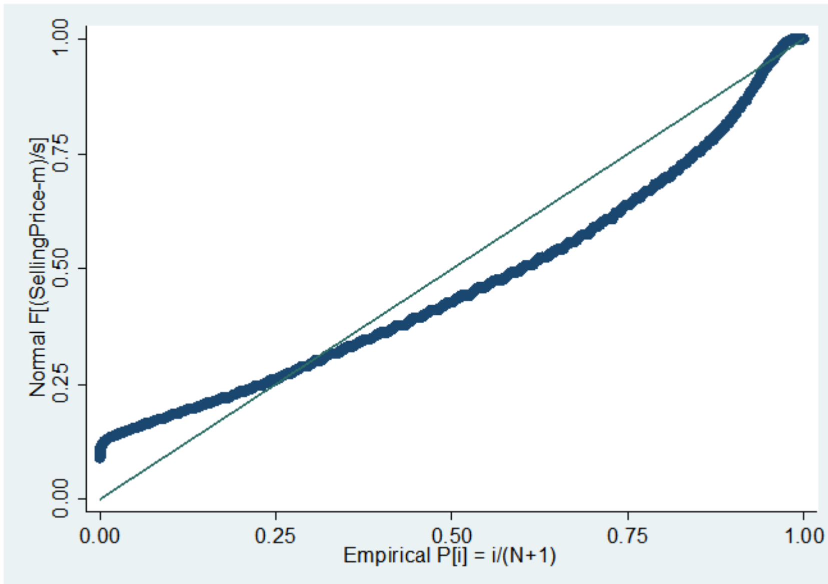
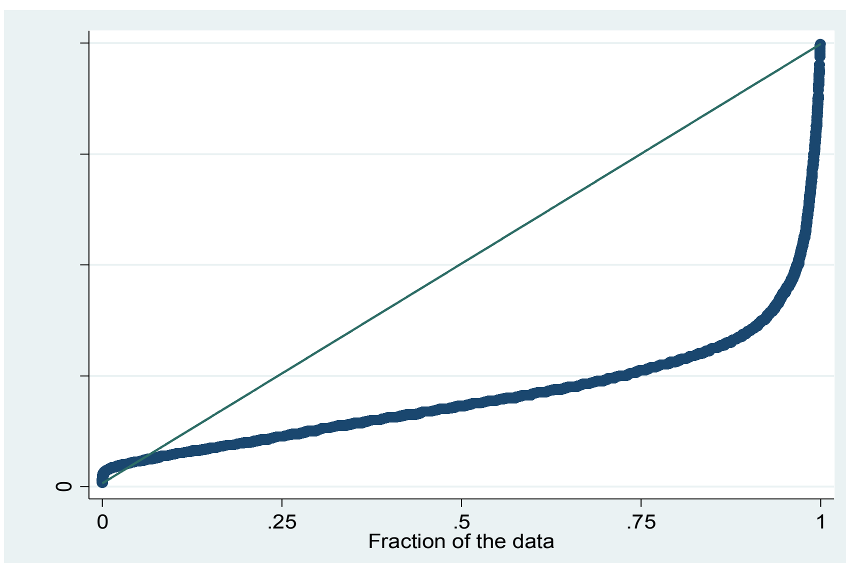


Figure 3-3 Shortsale Heat Map (2008-2012)



(a)



(b)

Figure 3-4 (a) Normal Probability Plot (b) Quantiles Plot

This study sheds more light into the distressed sale discounts by slicing the market into three predominant submarkets and finds that the discounts for distressed transactions are different for different submarkets. In this study I segregate the markets into submarkets based on their transaction prices. The transaction prices ranged from as low as \$15,000 to as large as \$3.6 M. Although the range is this diverse, 90% of the sales ranged from \$100,000 to \$400,000. The cross-sectional variation of the distress discounts can be examined by conducting quantile regressions. However the normal probability plot and the quantile plot show that the majority of the transactions lie between 100,000 to 400,000. The 25th, 50th and 75th percentile of the sample all lie within the 100,000 to 400,000 range. I segregate the submarkets into four submarkets, the lowest being the one less than the 100000 transaction price and the highest being greater than the 400000 transaction price. The medium submarket is further broken into two submarkets one being the lower end of the medium market (100000-200000) while the other being the upper end of the medium submarket (200000-400000). Table B.13 shows the descriptive statistics of all the variables across the four submarkets between 2008 to 2012.

Table B.14 presents the results of the average foreclosure and shortsale discounts from 2008 to 2012 across four different submarkets. I find that the distressed discounts are the lowest for the lower submarket and the highest for the premium submarket. The medium submarkets have their discounts around the middle. The discounts increase with the transaction price. The cash discounts vary across the submarkets. The lower submarket has lower foreclosure/shortsale discounts however they have higher cash discounts. The higher submarket has higher foreclosure/shortsale discounts however they have cash premiums. This indicate that the lower end submarket is mainly a “flipper” market where the distressed properties were mainly bought by cash for investment purposes with the intention of selling them back for a profit. On the other hand, the premium market has buyers that buy a specific property. They are rich and wealthy investors who will be willing to pay a premium for properties that they want to buy.

Table B.15 presents the results of time varying foreclosure and shortsale discounts from 2008 to 2012 across four different submarkets. The discounts of all the submarkets are time-varying. The discounts vary across time and submarkets.

In Table B.16, I examine the time varying cash discounts across submarkets and find that the cash discounts are time varying and are submarket-varying.

In Table B.17, I examine the interaction between TOM and the foreclosure and shortsale discounts. I find that an extra day on the market reduces the price of the property if the price is either a shortsale or a foreclosure. However the magnitude of the discount is higher for a foreclosed property than for a shortsale property.

3.8 Discussion

Table B.18 presents the found discounts for foreclosures and short sales. The foreclosure discounts range from 17% to 22% with an average of about 19% for the sample between 2008 and 2010. The short sale is a relatively new phenomena resulting from the housing price bubble bursting in 2008. With the flood of foreclosure transactions hitting the market in 2008, mortgagees are more commonly considering the implementing the short sale option. The short sale discounts ranged from 11% to 15% during the crisis period. The average short sale discount was about 14%. The spread between foreclosure and short sale transaction discounts ranges from 3% to 7% with an average spread of about 5%. From Table B.6, I can conclude that both the foreclosure and short sale discounts are time varying with both peaking in the height of the distressed market conditions in 2008 and 2009.

Generally, I feel that the found coefficients are reasonable and the models are consistent, parsimonious, and relatively robust. With the typical coefficient of determination of about 88% the explanatory power of our models is consistent with other hedonic studies of residential housing prices. However, a R^2 of 88% means that our model does not explain 12% of sale price variation and I should consider omitted variables. With controls for location, market conditions, and physical attributes, a likely omitted variable is property condition. Our best control proxy for property condition is age, an imperfect measure of property condition, as I understand that some newer properties can be in bad condition and some older properties can be in excellent condition. Our dataset does not include a measure of property condition beyond age. Even if the multiple listing service did report property condition, I expect that this information may not be very useful as property condition is a subjective measure and real estate brokers are expected to present their properties to the market as positively as they can.

Clauretie and Daneshvary (2009) find that the true foreclosure status discount is about one-third of the prior 23% plus reported discounts. However, this one-third rule-of-thumb accounts for both inadequate locational and quality controls. Since I appropriately include locational controls in our study, this one-third rule-of-thumb may overestimate just the impact of condition on our found coefficients. Look more closely at the Clauretie and Dhaneshvary (2009) study, they find that the foreclosure discount is about 10% in Las Vegas market after controlling for endogeneity but not accounting for property condition. After controlling for the property condition, a variable unique to their dataset, they find that the discount drops to about 8%, a decrease of 20%. If distressed sales in our dataset are systematically in inferior condition and this phenomena is not captured in our control variable ‘age’, I estimate that the coefficient estimates maybe overestimated by as much at 20%.

3.9 Conclusion

The contributions of this present study are as follows. First, this essay contributes to the existing foreclosure research and literature. Despite the volume of foreclosure transactions and the profound influences of foreclosure sales on residential housing markets and the national economy, there are just a handful of published papers focused exclusively on the pricing effects of foreclosure status on single-family residential transactions. Furthermore, most of the existing studies focus on just three markets (Baton Rouge, Louisiana; Arlington, Texas; and Las Vegas, Nevada) during relatively stable time periods (1980s and 1990s). The few studies that examined the housing market crash were all focused on the Las Vegas market. This study updates the foreclosure body of knowledge and, by studying the pricing influences of foreclosure transactions where foreclosures represent about half of the distressed sales and distressed sales account for almost two-thirds of all brokered transactions, introduces a new and important temporal and geographic perspective.

Second, this essay is one of the first few studies to introduce the metric ‘short sale’ to the hedonic pricing literature. Born from the extreme housing market volatility, the short sale is a relatively recent phenomenon and not traditionally measured in transaction databases. However, short sale transactions are an important component of many housing markets suffering from high levels of housing price volatility and mortgage default. In the present study, I find a significant discount for short sale transactions, but a discount not as large as attributed to foreclosure transactions. It is anticipated that short sales will be a future variable of interest or a control variable in research conducted in distressed markets. I look forward to observing future empirical estimates of short sale effects, both the magnitude of the short sale variable and the relationship to foreclosure transactions, in other settings and time periods.

Third, I introduce a set of instrumental variables, perhaps unique to distressed market conditions that aid in the explanation of marketing time-transaction price endogeneity. This study controls for the overall market trend, distressed property status (short sales and foreclosure sales), and endogenous time-on-the-market for each transaction. Irrespective of the estimated model, the foreclosure and short-sale discounts remain consistent at 20% and 13%, respectively.

Fourth, this study examines foreclosures and short sales over distressed market conditions. I find that the discounts are time varying, dependent on market conditions. However, I remove years 2006 and 2007 from the sample period to further analyze the yearly price discounts since I find that the foreclosure and short-sale transactions are too few in 2006 and 2007 to have statistically meaningful analysis. The foreclosure discounts range from 17% in 2008 to 22% in 2009. The short sale discounts ranged from 11% in 2008 to 15% in 2009. Furthermore, the spread between foreclosure and short sale transaction discounts ranged from 3% to 7% with an average spread of about 5%. By examining this market over a five-year time period I can see the behavior of a distressed market as it transitions from a normal market in 2006 to a distressed market in 2008. I find that distressed transaction discounts, along with the spread between foreclosure and short sale discounts, increases as market conditions deteriorate. In interpreting these results, I caution that property condition maybe an omitted variable and that the found discounts could be overestimated by up to 20%.

The study finds that the discounts of the lower priced homes are substantially lower and the discounts of premium homes are very high while those of the medium priced homes are around the middle. The findings of this analysis acknowledges that submarkets matter in the context of distressed sales and hence contributes to the hedonic submarkets literature asserting the importance of examining submarkets in the valuation of properties. The study also finds that the discounts across submarkets ate also time varying.

Finally, I make a modest contribution to a relatively thin stream of literature addressing cash financing. Similar to the existing cash financing studies, I find a significant and robust cash discount of approximately 20% in our sample's distressed market conditions combined with high credit standards. Cash sales dynamics also change within the submarkets and across market conditions.

Chapter 4

Information Asymmetry, Credit Rating Changes and REIT Returns

4.1 Introduction

Over the past couple of decades, the market for REITs has grown dramatically. REITs primarily depend on outside sources of financing since their corporate structure is unique. They cannot retain earnings because of the regulatory provision requiring a minimum 90% distribution of taxable income (Ooi, Ong, and Li 2010). Credit rating changes are significant in impacting external financing decisions and in mitigating asymmetric information. Use of credit ratings has increased in practice in recent years primarily because of the mounting complexity of financial instruments and an increasing usage of ratings in financial regulation (Frost, 2007). Most of the studies on REIT credit ratings focus on the impact of credit ratings on external financing decisions and thereby the capital structure of REITs (Brown and Riddiough, 2003; Highfield, Roskelley and Zhao, 2007; Hardin and Wu, 2010).

Credit rating agencies such as Standard and Poor's (S&P), Moody's Investors Service (Moody's), or Fitch, Inc., provide information about the creditworthiness of REITs and their financial obligations. They are information specialists that receive information from many sources such as internal audit reports, meetings with company executives etc. that are not available to the public domain (Elliot et. al., 1984). This information if and when it becomes public may have an effect in the company's value (Avramov et.al., 2007).

Studies show that credit ratings about a firm's debt provide additional information to the market for non-REIT firms (Lin and Thakor, 1984; Reiter and Zeibart, 1991). Research on the informational content of credit rating announcements in broader US equity market shows that downgrades affect stock prices negatively. Holthausen and

Leftwitch (1986), Goh and Ederington (1993), Hand, Holthausen, and Leftwitch (1992), Jorion and Zhang (2007), Kim and Nabar (2007) find negative stock returns associated with credit rating downgrades announcements.

However, Jorion, Liu, and Shi (2005) find that the results changed after the implementation of Regulation Fair Disclosure. They find significant positive stock returns for both upgrade announcements and negative stock returns for downgrade announcements. But the significance of the positive stock returns for upgrades is weaker than that of the negative stock returns for downgrades.

Studies examining the informational content of credit rating changes on REITs' performance are minimal (Tidwell et.al., 2014). Tidwell et al.(2014) examine the short-run and long-run price reaction of equity REIT shares after credit rating announcements and find the presence of significant negative stock returns for downgrade announcements but no positive stock returns for upgrade announcements. They also document a significant increase in trading volume in reaction to downgrade credit rating changes, with lesser response to upgrades. Their findings support the view that REITs could be more publicly forthcoming about the positive news in comparison to negative news. My study shed new light on this topic by considering how overall market conditions can influence the market's reaction to credit rating changes.

Consistent with prior literature, I find that credit rating downgrades disseminate some new information to market participants prior to the liquidity crisis. However, I find that downgrades are not associated with a significant market reaction during the crisis. Therefore, downgrades appear to lose their informational content during periods of crisis. Hence, the overall market conditions appear to influence how the market reacts to downgrades. This is consistent with the market not anticipating bad news during periods of overall positive performance.

Overall market conditions can influence the market's reaction to positive credit rating changes as well. I find an insignificant market reaction to credit rating upgrades prior to the crisis. However, there is a significant positive market reaction for upgrades during the crisis. Therefore, credit rating upgrades do not appear to reveal new information prior to the crisis but provide relevant new information after crisis. This is consistent with the market not anticipating good news during periods of overall negative performance. These findings suggest the market does not appear to anticipate bad news during periods of stability and good news during the financial crisis.

Prior studies interpret the significant negative market reaction to downgrades and insignificant reaction to upgrades as evidence that the informational content associated with upgrades is more transparent than that of downgrades. However, the results above suggest that the different market reaction to upgrades and downgrades is associated with the overall market conditions. These indicate that the market reaction is not just a function of credit rating changes but also associated with expectations based on overall market conditions.

The results of informational content on REITs credit ratings in prior research are attributed to REITs informational transparency. In cases of credit rating downgrades where the results of REIT transparency are less pronounced, the scholars compare them to non-REIT stocks subsequent Regulation Fair Disclosure and find the results to be parallel. Due to the special regulatory characteristics REITs are expected to be more transparent and less susceptible to asymmetric information in general (Damodaran, John, and Liu (1997) and Hardin and Hill (2008)). However the concept of informational transparency in REIT literature is still a source of debate. Hartzell, Kallberg and Liu (2005) and Hartzell, Kallberg and Liu (2008) propose that equity REITs ar could be easier to value since they hold tangible assets and hence could have a transparent structure.

Given the competing views of REIT transparency and the role of information asymmetry being attributed to the informational content of REIT credit ratings, this study examines the role of information asymmetry in explaining the market reactions to credit rating changes. By testing for systematic determinants impacting the magnitude of CARs produced as a result of credit rating changes, I find that there is higher information asymmetry before downgrades compared to upgrades. Bid ask spreads are significant before downgrades but not significant before upgrades.

Theoretically, information asymmetry could enable rent seeking behavior by information possessing corporate managers and other insiders in comparison to other outside shareholders. Given the presence of information asymmetry, do insiders take advantage of it before credit rating changes? Piotroski and Roulstone (2004) document that insiders hold greater information about firm’s future cash flows. This study investigates the relationship between credit rating changes and insider trading, and the information value of insider trading on the magnitude of CARs for REITs. In this study, I document that insiders are more likely to purchase shares before an upgrade rather than before a downgrade. For instance, the net ratio of the number of shares purchased by insiders to the number of shares traded by insiders of an upgraded firm is greater than that of a downgraded firm. A positive relationship between insider trading and REIT returns means that firms with extensive insider purchase ratio earn positive abnormal REIT returns. Further exploring the effects of information asymmetry and insider trading on the informational content of credit rating changes on REIT return, I find that after controlling for information asymmetry, insider trading is insignificant.

Prior literature on corporate governance in corporate finance like Gompers, Ishii, and Metrick, 2003; and Cremers and Nair, 2005 find that higher corporate governance improves market efficiency, and reduces information asymmetry. Due to the unique organizational structure and the special regulatory environment REITs are generally presumed to be more informational transparent and having lesser information asymmetry. They have to be on the market often to raise external financing. The external governance mechanisms do not have an impact on REITs. However internal corporate governance becomes critical to ensure that a REIT's manager's goals are aligned with those of outside shareholders. Better corporate governance can play a role in decreasing the level of asymmetric information between informed insiders, such as managers, and public shareholders. This study adds to the limited existing empirical evidence about role of corporate governance on REIT 's impact on information transparency (e.g., Chung, Elder, and Kim, 2010).Ie focus on the relationship between the internal governance of REITs, as measured by characteristics of the board of directors. The empirical results indicate that information asymmetry is related to the quality of corporate governance. I generally find strong evidence that high-quality governance on the board of directors increases information transparency and decreases information asymmetry.

Feng, Ghosh, and Sirmans (2005) find companies with higher corporate governance perform better. Friday and Sirmans (1998) show that increased board independence generally increases a firm's market-to-book ratio which is an indication of the firm's financial health. However, they find that the investors seem to discount REIT shares when outside representation becomes too large which is consistent to what I find in this study. In this essay I further explore the effects of information asymmetry and insider trading on the informational content of credit rating changes on REIT returns after controlling for corporate governance. I find that better corporate governance increases REIT transparency reflected in lesser abnormal returns.

The remainder of this essay is organized as follows. Section 4.2 describes data and descriptive statistics. In section 4.3, I discuss the main results. Section 4.4 concludes the chapter.

4.2 Data

4.2.1. Credit Announcement Data

I use the SNL database containing historical credit ratings of US real estate firms rated by Moody's, Standard and Poor's, Fitch and Dominion Bond Rating Service (DBRS) during January 2000 to August 2013 time period. To estimate the cumulative abnormal return (CAR), the daily returns from January 2000 to December 2013 were used as appropriate given the estimation period or holding period.

My dataset consists of firm-level credit ratings, from which we use the ratings for long-term and senior unsecured debt. During the sample period long-term and senior unsecured debt ratings account for 1221 credit rating actions, with yearly totals increasing progressively in the first part of the decade, peaking in 2006 with 143. Rating actions can include: 'initiate', 'affirm', 'upgrade', 'downgrade' or 'remove'. The largest number (750) was 'affirm'. Downgrades outnumber upgrades (208 to 114), a comparison showing credit rating research on non-REITs (Hand et al. 1992). Table C.1 presents these yearly numbers by rating agency. Standard and Poor's and Moody's are the most active agencies with a combined share of approximately 75% of all rating actions and 81% share of all rating changes.

The sample of 322 U.S. REIT rating changes (upgrades/downgrades) is then reduced to filter out redundant actions, actions whose effect is contaminated by other announcements, and cases where I do not have all necessary daily returns. Like Dichev and Piotroski (2001) and Tidwell et.al (2014), I only retain the event that occurs first if the rating actions for the same firm's long-term and senior unsecured debt are announced within a four-day window. I also use an additional filter where the information content of credit rating announcements may be tainted by other firm-specific news (i.e. earnings announcements, dividend distributions, mergers and acquisitions activity, debt retirements). I consider an announcement contaminated where any firm-specific substantial price-relevant news event is detected by Lexis-Nexis within a three-day window surrounding the day of a rating action.

Additionally, my analysis requires the availability of daily price returns, to calculate abnormal returns during our estimation window. The sample of US REIT credit rating upgrades and downgrades during January 2000 to December 2013 is accordingly reduced from 322 to 259. The filtering process resulted in approximately 20% data loss. However while merging the CAARs with the firm specific data from COMPUSTAT and IBES for the cross sectional regressions results in a decrease of observations bringing it to 200. The cross-sectional sample consists of 127 credit rating upgrades (60 pre-estimation time period) and 73 credit rating downgrades, totaling 200 U.S. equity REIT rating changes.

4.2.2 Information Asymmetry

To measure information asymmetry, I use three measures. (1) Bid Ask Spread, (2) Number of analysts following and (3) the standard deviation in analysts' recommendations. To calculate the first measure, I follow Anglin, Edelstein, Gao, and Tsang (2011) and use the percentage bid-ask spread calculated as Bid Ask Spread= 2*(Ask Price-Bid Price)/ (Ask Price +Bid Price). I calculate the daily bid ask spread for the last quarter and average them to get the final measure. I also run the tests based on previous short term averages of bid ask spread and do not find differences in the findings. The second and third measures are obtained from I/B/E/S. The second measure Analyst is the number of analysts following the REIT at the end of last quarter. The third measure Stdev is the standard deviation of analysts' recommendations at the end of last quarter.

In subsequent tests I use dummy variables to control for high/low information asymmetry. There are two such dummy variables that are used. The first one is HighAnalyst which is equal to one when the number of analysts following is greater than the median analysts in the sample. The second one is HighInfoAsymm variable that equals one if the bid ask spread is greater than the median bid ask spread in the sample.

4.2.3 Measurement of Insider Trading Activities

I measure the magnitude of insider trading using net purchase ratio (denoted by NPR) in my analysis. It is defined as

$$NPR = [\ PURCHASE_{i,t} - SALE_{i,t}\ ] / [\ PURCHASE_{i,t} + SALE_{i,t}\ ]$$

where $PURCHASE_{i,t}$ ($SALE_{i,t}$) is the number of shares purchased (sold) by insiders of firm i for three months. The maximum (minimum) of the NPR is +1 (-1). The NPR of a firm with net insider purchases is greater than zero. The NPR of a firm with net insider sales less than zero. Since the NPR is a flow variable, I compute the NPR from insider transactions for three months (the quarterly NPR). When there is no insider trading, the NPR is set to zero[6].

I aggregate insider transactions for three months to compute the NPR and set the NPR to zero if no insider transaction is observed. Insider trading is prohibited by law when insiders possess material and non-public information[7] I suspect that insiders may avoid transactions right before credit rating changes. Accordingly, I examine in detail

[6] For robustness I also check the results using alternate measures for NPR=PURCHASEi,t / [PURCHASEi,t + SALEi,t]

[7] Refer to section 10 and 16 of the Securities and Exchange Act of 1934 .

insider trading activities for the three months prior to credit rating change announcements.

4.2.4 Corporate governance variables

I measure corporate governance by using a wide range of variables for the structure and activities of the board of directors. I use Boardsize, BoardIndependence, BoardBusyness, BoardTenure and CEODuality variables to capture corporate governance. The corporate governance data is obtained from RiskMetrics. Boardsize is the total number of directors on the board. BoardIndependence is defined as the percentage of fully independent directors on the board to the total board size. BoardBusyness is the average number of boards the directors sit on while on tenure with the REIT's board. BoardTenure is the average tenure of a board director. CEODuality is a dummy variable that takes the value 1 if CEO is not the chairman.

I then create four different dummy variables, Boardsizedummy, BoardTenuredummy, BoardIndependencedummy, BoardBusynessdummy where they equal one if the respective variables are greater than the median values of Boardsize, BoardTenure, BoardIndependence and BoardBusyness respectively. I tehn calculate a governance index that equals to the sum of the five dummy variables Boardsizedummy, BoardTenuredummy, BoardIndependencedummy, BoardBusynessdummy and CEODuality. Finally, I create a governance dummy variable than equals to one if the governance index is greater than the median governance index.

After merging the RiskMetrics dataset, I lose a lot of observations. Out of the 200 credit rating changes, I retain only 61 observations that has corporate governance data. The tests incorporating corporate governance variables therefore use only 61 observations.

4.2.5 Control Variables

The selection of control variables is based on prior literature. I obtain accounting data including market capitalization, total assets, total debt, net income from COMPUSTAT. Dividends per share were collected from the CRSP data set. LTA is calculated as the natural logarithm of total assets in the last fiscal quarter. The leverage is captured by DE (debt equity ratio) calculated as the ratio of long term debt to total equity in the last fiscal quarter. VOL is calculated as the average trading volume in the last fiscal quarter. NI is calculated as the net income scaled by total assets in the last fiscal quarter. SIZE is the market capitalization in the last fiscal quarter

Table C.3 describes all the variables and Table C.4 presents descriptive statistics of all variables.

4.3 Methods and Findings

In this Section I explain the methods employed and present the results of the tests measuring abnormal returns during 'windows' that (1) are during the credit rating announcement date, (2) before the credit rating announcement, and (3)after the credit rating announcement. I also explain the method used in the analysis of cumulative abnormal returns (CARS), as I look for potential firm-specific explanatory variables.

I begin by examining the informational content of the credit rating actions as reflected in REIT stock price movements especially the presence and magnitude of any abnormal return (AR) during an announcement window(s). Following the market model event study methodology by Brown and Warner (1980, 1985), I estimate a firms abnormal return on each day of the announcement event window. I then aggregate the daily abnormal returns to produce the cumulative abnormal return (CAR) for that window. I do this for six separate windows treating the day of the announcement as listed by SNL as Day 0, these windows are: (1) Day -20 to Day -10; (2) Day -10 to Day -4; (3) Day -4 to Day 0; (4) Day 0 to Day +4, (5) Day +4 to Day +10 and (6) Day +10 to Day +40.

The abnormal returns for event j are thus calculated as:

$$CAR_j = \sum_{t=d_1}^{d_n} [R_{jt} - (\alpha_j + \beta_j R_{jmt})]$$

where d represents each day of the event window, Rjt is the actual daily return for the firm and Rjmt is the market return over the event's estimation period. The market return is estimated using the CRSP value-weighted index as the market proxy. I estimate the model parameters αj and βj using an estimation window beginning on Day -46 with a maximum estimation length of 255 trading days. As a robustness measure, I also examine a post-event estimation window beginning on Day 60 with an estimation length of 255 days. After calculating event CARs, I then calculate and report the cumulative average abnormal return (CAAR) where, the CAAR is the arithmetic average of all sample event CARs.

In addition to the equally-weighted CAAR, I also calculate the precision-weighted CAAR. The precision-weighted CAAR weights each event's CAR in inverse proportion to the variability in their prediction errors. The Patell (1976) test is used when the precision-weighted CAAR is reported and represents a standardized abnormal return test that estimates a separate standard error for each credit event. The nonparametric generalized sign test was also conducted using the normal approximation to the binomial distribution as described by Cowan (1992).

The generalized sign test compares the fraction of positive abnormal returns during the event period with the fraction obtained during the estimation period. The null hypothesis is that these fractions are the same. The results for the CAAR, precision-weighted CAAR and generalized sign test using the CRSP value-weighted index for upgrades and downgrades are shown in Tables 5 and 6 respectively. In this study, I generally do not observe a significant stock market reaction to upgrades across the contemporaneous event windows when we use the CRSP value-weighted index as the market proxy. For upgrades, CAAR is not statistically significant at 0.2% and 0.5% respectively for the post and pre estimation event time periods. The precision-weighted CAAR is also not statistically significant having parameter estimates of 0.11% and 0.11%. Furthermore, the nonparametric generalized sign test did not detect an abnormal number of positive market adjusted returns, based on the respective estimation periods.

However, I observe a significant stock market reaction to downgrades across the contemporaneous event windows when we use the CRSP value-weighted index as the market proxy. For upgrades, CAAR is statistically significant at -1.7% for the pre estimation event time period. The PWCAAR is also statistically significant having a parameter estimate of -1.03%. Furthermore, the nonparametric generalized sign test did not detect an abnormal number of negative market adjusted returns, based on the respective estimation period.

I further extend this analysis to test if there is a significant difference before and after crisis and find that the information content has shifted from downgrades to upgrades post crisis. Consistent with prior literature, I find that credit rating downgrades disseminate some new information to market participants prior to the liquidity crisis. However, I find that downgrades are not associated with a significant market reaction during the crisis. Therefore, downgrades appear to lose their informational content during periods of crisis. Hence, the overall market conditions appear to influence how the market reacts to downgrades. This is consistent with the market not anticipating bad news during periods of overall positive performance.

Overall market conditions can influence the market's reaction to positive credit rating changes as well. I find an insignificant market reaction to credit rating upgrades prior to the crisis. However, there is a significant positive market reaction for upgrades during the crisis. Therefore, credit rating upgrades do not appear to reveal new information prior to the crisis but provide relevant new information after crisis. This is consistent with the market not anticipating good news during periods of overall negative performance. These findings suggest the market does not appear to anticipate bad news during periods of stability and good news during the financial crisis.

Prior studies interpret the significant negative market reaction to downgrades and insignificant reaction to upgrades as evidence that the informational content associated with upgrades is more transparent than that of downgrades. However, the results above suggest that the different market reaction to upgrades and downgrades is associated with the overall market conditions. These indicate that the market reaction is not just a function of credit rating changes but also associated with expectations based on overall market conditions.

I then employ an OLS regression model to examine the relationship between abnormal returns and a set of potential firm-specific variables. The first column combines samples of upgrades and downgrades, where the CAR is the two-day (0, 1) absolute value of the cumulative abnormal return. The selection of firm specific variables employed in the CAR analysis is based on prior literature and empirical findings. Along with the other control variables I include information asymmetry variables i.e. BidAskSpread, Analyst and Stdev. I find that the higher the information asymmetry higher the abnormal return. In the first column Model (1) I run the regressions on control variables, information asymmetry variable and the dummy variable that takes the value one if it is a downgrade.

I do not find the Downgrade variable significant providing evidence that the informational content of credit rating changes is not dependent on the type of change. In the second panel I include variables capturing market condition. I create dummy variables UMC and DMC where UMC captures the average market return for an upgrade during crisis and DMC captures the average market return for a downgrade pre-crisis. I find that the market condition variables are significant. The third and fourth column presents the second model for downgrades and upgrades respectively. The market condition variables are significant in these models as well. I also find that the information asymmetry is prominent before a downgrade compared to an upgrade.

Table C.8 tests for the presence of insider trading activities before credit rating announcements. The first column replicates the same model as the previous table without the sellpct and buypct variables because they have very high correlation with the insider trading variable NPR. I find the overall insider trading is insignificant in the second column. However in the third column I interact NPR with downgrade and upgrade to provide insider trading activity before a downgrade and an upgrade respectively. I find that there is no insider trading before a downgrade. However there is evidence of insider trading before upgrades and they are negatively related to abnormal returns. The market condition variables are highly significant in all these models. In the fourth and fifth columns, I include the analyst and information asymmetry dummy variables respectively and I find that after controlling for these information asymmetry proxies the insider trading is no longer significant. I also find that the returns are increased with an increase in information asymmetry.

Table C.9 tests for the role of corporate governance in determining the abnormal returns during credit rating announcements. The first column includes the overall governance dummy variable that indicates one if the governance index is greater than the median value. I find that the governance is negatively related to abnormal returns indicating that REITs with higher governance showing evidence of lower abnormal returns indirectly possessing better transparency. In the second column I include the individual governance dummy variables, five of them, and find the above results validated. Not all the five dummies are significant. I find BoardSizeDummy and BoardBusynessDummy significant among the five.

4.4 Conclusion

Credit rating agencies use both public and private information to come up with credit ratings. If a credit rating change contains a considerable amount of non-public information about the change in the firm value, it should have an effect on the price of the firm under asymmetric information. Studies examining the informational content of credit rating changes on REITs' performance are minimal (Tidwell et.al, 2014). Consistent with prior literature, I find that credit rating downgrades disseminate some new information to market participants prior to the liquidity crisis. However, I find that downgrades are not associated with a significant market reaction during the crisis. Therefore, downgrades appear to lose their informational content during periods of crisis. Hence, the overall market conditions appear to influence how the market reacts to downgrades. This is consistent with the market not anticipating bad news during periods of overall positive performance.

Overall market conditions can influence the market's reaction to positive credit rating changes as well. I find an insignificant market reaction to credit rating upgrades prior to the crisis. However, there is a significant positive market reaction for upgrades during the crisis. Therefore, credit rating upgrades do not appear to reveal new information prior to the crisis but provide relevant new information after crisis. This is consistent with the market not anticipating good news during periods of overall negative performance. These findings suggest the market does not appear to anticipate bad news during periods of stability and good news during the financial crisis.

Prior studies interpret the significant negative market reaction to downgrades and insignificant reaction to upgrades as evidence that the informational content associated with upgrades is more transparent than that of downgrades. However, the results above suggest that the different market reaction to upgrades and downgrades is associated with the overall market conditions. These indicate that the market reaction is not just a function of credit rating changes but also associated with expectations based on overall market conditions.

The results of informational content on REITs credit ratings in prior research are attributed to REITs informational transparency. By testing for systematic determinants impacting the magnitude of CARs produced as a result of credit rating changes, I find that there is higher information asymmetry before downgrades compared to upgrades. Bid ask spreads are significant before downgrades but not significant before upgrades.

Given the presence of information asymmetry, do insiders take advantage of it before credit rating changes? In this study, I document that insiders are more likely to purchase shares before an upgrade rather than before a downgrade. For instance, the net ratio of the number of shares purchased by insiders to the number of shares traded by insiders of an upgraded firm is greater than that of an upgraded firm. A positive relationship between insider trading and REIT returns means that firms with extensive insider purchases (sales) earn positive (negative) abnormal REIT returns. Further exploring the effects of information asymmetry and insider trading on the informational content of credit rating changes on REIT return, I find that after controlling for information asymmetry, insider trading is insignificant.

Prior research on REIT corporate governance find that information asymmetries are present in REITs although they are less in REITs with high quality corporate governance. In this essay I further explore the effects of information asymmetry and insider trading on the informational content of credit rating changes on REIT returns after controlling for corporate governance. I find that better corporate governance increases REIT transparency reflected in lesser abnormal returns.

Chapter 5

Conclusion

The dissertation consists of three separate essays centered on the valuation impact of financial distress and the role of information asymmetry. The dissertation addresses unanswered questions in asset valuation through the lens of financial distress in three different asset markets namely equity market, securitized real estate market (real estate investment trusts (REITs)) and the residential property market.

The first essay is “Misvaluation and Financial Distress”. Till date there has not been an attempt to empirically explain the distress anomaly using a direct misvaluation measure. The primary goal of this essay is to examine the extent to which misvaluation contributes to negative stock returns among highly distressed firms. I find that the overvalued distressed firms drive the distress anomaly. The essay further provides the characteristics of overvalued distressed firms by examining the joint roles of short-sale constraints and heterogeneous beliefs in the financial markets. I raise three important empirical questions in this study. First, are the equities of these highly distressed firms overvalued? Second, if it can be explained, do divergence of opinion and limits to arbitrage explain distress anomaly? Third, why is it important to examine how stock overvaluation impacts the distress anomaly? This essay finds that the highly distressed firms are overvalued and they have common stock characteristics that help investors identify them and they are systematically linked to divergence of opinion and limits to arbitrage proxies. It is important to understand the role of overvaluation in distress because my findings suggest that the negative distress premium is primarily driven by the highly overvalued firms. In the absence of these overvaluation the distress anomaly vanishes.

The second essay is entitled “The Valuation Impact on Distressed Residential Transactions: Anatomy of a Housing Price Bubble”. It examines the discounts associated with foreclosure and short sale status in the Fresno, California from 2006 to 2010, a time period containing significant housing market distress and price volatility. Most previous empirical studies on foreclosure price discounts are based on data from housing-market during periods of relative stability and even fewer studies have examined the pricing implications of short sale transactions. This essay addresses this gap by investigating the discounts for distressed residential transactions and contributes to the existing foreclosure research and literature by introducing a new and important temporal and geographic perspective. The study finds that the discounts of the lower priced homes are substantially lower and the discounts of premium homes are very high while those of the medium priced homes are around the middle. The findings of this analysis acknowledges that submarkets matter in the context of distressed sales and hence contributes to the hedonic submarkets literature asserting the importance of examining submarkets in the valuation of properties. The study also finds that the discounts across submarkets ate also time varying. Finally, I make a modest contribution to a relatively thin stream of literature addressing cash financing. Similar to the existing cash financing studies, I find a significant and robust cash discount of approximately 20% in our sample’s distressed market conditions combined with high credit standards. Cash sales dynamics also change within the submarkets and across market conditions.

The third essay is entitled “Information Asymmetry, Credit Ratings and REIT Returns”. Consistent with prior literature, I find that credit rating downgrades disseminate some new information to market participants prior to the liquidity crisis. However, I find that downgrades are not associated with a significant market reaction during the crisis. I find an insignificant market reaction to credit rating upgrades prior to the crisis. However, there is a significant positive market reaction for upgrades during the crisis. Prior studies interpret the significant negative market reaction to downgrades and insignificant reaction to upgrades as evidence that the informational content associated with upgrades is more transparent than that of downgrades. However, the results above suggest that the different market reaction to upgrades and downgrades is associated with the overall market conditions. These indicate that the market reaction is not just a function of credit rating changes but also associated with expectations based on overall market conditions. By testing for systematic determinants impacting the magnitude of CARs produced as a result of credit rating changes, I find that there is higher information asymmetry before downgrades compared to upgrades. Bid ask spreads are significant before downgrades but not significant before upgrades.

Also, I document that insiders are more likely to purchase shares before an upgrade rather than before a downgrade. A positive relationship between insider trading and REIT returns means that firms with extensive insider purchases (sales) earn positive (negative) abnormal REIT returns. Further exploring the effects of information asymmetry and insider trading on the informational content of credit rating changes on REIT return, I find that after controlling for information asymmetry, insider trading is insignificant. I further explore the effects of information asymmetry and insider trading on the informational content of credit rating changes on REIT returns after controlling for corporate governance. I find that better corporate governance increases REIT transparency reflected in lesser abnormal returns.

Appendix A

Tables for Chapter 2: Misvaluation and Financial Distress

Table A-1 Summary Statistics for O-Score Estimation

I follow Griffin and Lemmon (2002) and George and Huang (2010) to calculate O-score as described in the footnote 6 of Griffin and Lemmon (2002). Sample descriptive statistics for the variables used in O-score estimation is presented in Panel A of Table A.1 clca is current liabilities/current assets, ffotl is funds from operations/total liabilities, lta is log(total assets), nita is net income/total assets, tlta is total liabilities/total assets and wcta is working capital/total assets. Panel B summarizes the mean of the same variables across the five O-Score quintiles. The sample period is from 1980 to 2011.

Panel A

Variables	MIN	MAX	MEAN	STD DEV	MEDIAN
clca	-14221	18828	3.78	120.37	0.55
ffotl	-163	3143	0.02	5.35	0
lta	-6.91	12.92	4.58	2.57	4.56
nita	-20733.8	3541	-0.15	29.04	0.01
tlta	-3072	15416	1.6	47.85	0.53
wcta	-15415	2516	-0.73	46.11	0.21

Panel B

O-Score quintiles	clca	ffotl	lta	nita	tlta	wcta
0	-0.29	0.18	5.2	0.08	0.24	0.46
1	0.52	0.02	5.36	0.01	0.41	0.3
2	0.68	0.01	5.24	0	0.53	0.22
3	0.86	0	4.58	-0.01	0.64	0.16
4	17.07	-0.12	2.53	-0.85	6.17	-4.78

Table A-2 Portfolios Sorted on the Basis of O-Score

Over the sample period of 1980 to 2011, at the end of each month, stocks are sorted into 5 groups by their most recently calculated O-Score and assigned to five quintile portfolios. Once the portfolios are formed, each stock is held for 1 month. I then compute the equally-weighted returns over the next month. The returns presented in Panel A are average excess returns, CAPM abnormal returns, Fama-French 3 factor abnormal returns and Carhart 4 factor abnormal returns over the formation period. H-L is the long-short portfolio that is long in the quintile of the least distressed stocks and short in the most distressed stocks.

	Panel A					
	1	2	3	4	5	(H-L)
Raw return	0.0066	0.0049	0.0052	0.0042	0.0019	-0.005***
CAPM Alpha	0.0055	0.0047	0.0050	0.0040	0.0015	-0.004***
FF3 Alpha	0.0071	0.0047	0.0045	0.0029	0.0000	-0.007***
Carhart Alpha	0.0062	0.0039	0.0038	0.0024	-0.0001	-0.006***

Table A-3 Time-series average conditional regression multiples

This table reports the time-series average multiples from the following regression.

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt} \ln(NI)^{+}_{it} + \alpha_{3jt} I_{(<0)} \ln(NI)^{+}_{it} + \alpha_{4jt} LEV_{it} + \varepsilon_{it}$$

The dependent variable is the natural log of market value (M). The independent variables are the natural log of book value of equity (B), the natural log of the absolute value of net income (NI+), a dummy variable indicating when the net income is negative (I(<0)) and leverage (LEV). The regression is estimated cross-sectionally at the industry-year level for each of the Fama and French 12 industries (1-12) from fiscal year 1980 to 2011. We exclude financial firms from the sample and therefore do not include the parameters for industry 11.The subscripts i, j and t refer to firm, industry and year, respectively. $E_t(\hat{\alpha}_k)$ is the time-series average regression multiple for the kth accounting variable. We also report the Fama-Macbeth standard errors below the average estimated multiples. The reported R2 is the average adjusted-R2 for each industry.

Parameter	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**12**
$E_t(\hat{\alpha}_0)$	2.26	2.43	2.06	2.10	2.52	2.32	2.59	2.32	2.18	2.51	2.22
	0.07	*0.11*	*0.07*	*0.08*	*0.06*	*0.06*	*0.15*	*0.14*	*0.06*	*0.05*	*0.06*
$E_t(\hat{\alpha}_1)$	0.62	0.58	0.66	0.68	0.59	0.61	0.62	0.79	0.66	0.60	0.62
	0.01	*0.02*	*0.01*	*0.02*	*0.03*	*0.02*	*0.02*	*0.03*	*0.01*	*0.02*	*0.01*
$E_t(\hat{\alpha}_2)$	0.31	0.30	0.28	0.25	0.36	0.34	0.29	0.18	0.29	0.34	0.31
	0.01	*0.02*	*0.01*	*0.01*	*0.02*	*0.01*	*0.02*	*0.03*	*0.01*	*0.02*	*0.01*
$E_t(\hat{\alpha}_3)$	0.00	-0.02	-0.04	-0.04	-0.01	-0.07	0.04	-0.15	-0.06	-0.10	-0.06
	0.02	*0.02*	*0.01*	*0.03*	*0.03*	*0.01*	*0.10*	*0.11*	*0.01*	*0.02*	*0.01*
$E_t(\hat{\alpha}_4)$	-2.66	-2.53	-2.30	-2.25	-3.00	-2.64	-2.38	-2.68	-2.28	-2.68	-2.05
	0.08	*0.11*	*0.09*	*0.13*	*0.10*	*0.10*	*0.18*	*0.24*	*0.06*	*0.09*	*0.07*
R^2	0.85	0.83	0.87	0.87	0.86	0.85	0.87	0.92	0.87	0.88	0.85

Table A-4 Summary Statistics

Table A.4 summarizes the descriptive statistics of the main variables used in this paper. The sample period is from 1980 to 2011. O-score is Ohlson (1980)'s O-score, FMISV is firm specific misvaluation, IMISV is industry specific misvaluation, MISV is overall misvaluation (sum of firm specific and industry specific misvaluation)and GP is growth potential, all derived from the decomposition of market to book ratio using RKRV(2005)'s methodology. Panel A provides the descriptive statistics and Panel B provides the correlations between the variables.

Panel A

Variables	MEAN	STD DEV	MIN	MAX
O-Score	-1.3569	1.4019	-9.2265	7.9974
FMISV	0.1901	0.6643	-0.9032	6.1416
IMISV	0.0084	0.2415	-0.4881	1.1812
MISV	0.1879	0.6813	-0.8426	3.4341
GP	0.5044	0.1672	-0.2994	0.9551

Panel B

	O-score	FMISV	IMISV	MISV	GP
O-Score	1.00	0.10	0.03	0.11	-0.06
FMISV		1.00	-0.08	0.89	0.03
IMISV			1.00	0.32	-0.01
MISV				1.00	0.02
GP					1.00

Table A-5 Portfolios Sorted on the Basis of O-Score and RKRV (2005) Decomposed Components

Over the sample period of 1980 to 2011, at the end of each month, stocks are sorted into 25 groups. First, stocks are sorted into 5 portfolios based on their most recently calculated O-Score. Next, stocks are sorted into 5 groups independently based on each of their most recently calculated decomposed component (FMISV, IMISV, MISV and GP). Once the portfolios are formed, each stock is held for 1 month. I then compute the equally-weighted returns over the next month. The returns presented are Carhart 4 factor abnormal returns for the (High-Low) distress portfolio for the highest and lowest quintiles of FMISV, IMISV, MISV and GP. H-L is the long-short portfolio that is long in the least quintile and short in the highest quintile.

	(High – Low) Distress Returns		
	Low	High	High – Low
FMISV	0.001**	-0.017***	-0.018***
IMISV	0.001	-0.001	0.000
MISV	0.003***	-0.018***	-0.021***
GP	-0.005***	0.009***	0.004***

Table A-6 Distress and Misvaluation: Regression Analysis

This table presents the results from the Fama-MacBeth regression analysis of the cross-sectional variation of the relationship between O-Scores and stock returns. For each model, I first run a cross-sectional regression every month. Next, I calculate and report the time-series averages and Newey-West adjusted t-statistics of regression coefficients. For cross-sectional regressions, the dependent variables are monthly returns measured in month t+1 , and the independent variables are as follows: Beta, calculated at the end of the previous year and obtained from CRSP; Ln(BM) ,the natural log of a firm's book-to-market ratio; Ret(−6,−1), the 6-month average monthly returns from month t−5 to month t; size is the equity capitalization, O-Score is the distress measure, FMISV is firm-specific misvaluation, IMISV is industry specific misvaluation, MISV is the overall misvaluation and GP is the future growth potential.

	Model 1	Model 2	Model 3
Beta	0.001	0.001	0.001
	0.57	0.76	1.06
SIZE	-8.83E-11	-1.46E-11	-3.63E-10
	-2.98	-4.78	-3.54
Ln(BM)	0.010		
	21.28		
O-Score	-0.006	0.001	0.001
	-4.27	2.98	2.67
Ret(-6,-1)	0.020	0.021	0.019
	1.78	1.85	1.96
FMISV		-0.027	
		-32.73	
IMISV		-0.003	
		-0.76	
GP		0.066	0.069
		31.64	12.70
MISV			-0.027
			-31.51

Table A-7 Summary Statistics for Divergence of Opinion Proxies

Table A.8 summarizes the descriptive statistics of the proxies for divergence of opinion used in this essay. The sample period is from 1980 to 2011. AGE is number of years since the firm was first covered by CRSP, SIZE as the natural log of a firm's market capitalization at the end of its most recent fiscal quarter, NUMEST is the total number of analysts following the firm in the previous month, STDEV is the standard deviation of analyst one-year earnings forecasts at the portfolio formation date scaled by the prior year-end stock price, RETVOL is the standard deviation of weekly excess returns over the year ending at the portfolio formation date, CFVOL is cash flow volatility measured as the standard deviation of cash flow from operations in the past five years with a minimum of three years of data.

	MIN	MAX	MEAN	STD	MEDIAN
SIZE	63	602432919	2132532	11453271	208570
AGE	0.000	86.000	23.190	17.790	18.000
NUMEST	2.000	45.000	5.260	4.410	4.000
RETVOL	0.000	5.336	0.139	0.097	0.119
CFVOL	0.000	17.770	0.070	0.100	0.047
STDEV	0.000	28.150	0.080	0.490	0.030

Table A-8 Summary Statistics of Limits to Arbitrage Proxies

Table A.9 summarizes the descriptive statistics of the proxies for limits to arbitrage used in this essay. The sample period is from 1980 to 2011. BIDASKAV is the natural log of bidask spread which is time-series average of 2*(Price -(Ask + Bid)/2)/Price at the end of each month over the 12 months prior to the portfolio formation date, where Price is the closing stock price and Ask (Bid) is the ask (bid) price., AMIHUD is the illiquidity factor,calculated as the annual average of the daily ratio of absolute stock return to its daily dollar trading volume, DOLVOL is timeseries average of the monthly share trading volume multiplied by the monthly closing price over the 12 months prior to the portfolio formation date, IDIOVOL standard deviation of the residual values from three-factor Fama-French (1993) regression over past 36 months. NUM is number of institutional investors holding a firm's shares at the portfolio formation date. PCT is the percentage of outstanding shares held by institutional investors at the portfolio formation date.

	MIN	MAX	MEAN	STD	MEDIAN
NUM	1.000	1699.000	85.500	131.730	39.000
PCT	0.000	11.280	0.410	0.290	0.376
DOLVOL	22	1426486182	3048535	17178739	176726
BIDASKAV	0.000	349.060	1.090	4.100	0.178
AMIHUD	0.000	0.010	0.000	0.000	0.000
IDIOVOL	0.000	5.330	0.140	0.080	0.118

Table A-9 Divergence of Opinion and Limits to Arbitrage Characteristics for Portfolios Sorted on the Basis of O-Score

Over the sample period of 1980 to 2011, at the end of each month, stocks are sorted into 5 groups by their most recently calculated O-Score and assigned to five quintile portfolios. In Table 10, Panel A reports the average values for divergence of opinion proxies and the aggregate DO-score for the five default quintiles. Panel B reports the average values for limits to arbitrage proxies and the aggregate LTA-score for the five default quintiles In each panel quintile 1 represents a portfolio consisting of firms with the lowest default and quintile 5 represents a portfolio consisting of firms with the highest default.

Panel A					
	1	2	3	4	5
1/SIZE	0.0097	0.0125	0.0141	0.0186	0.0384
1/AGE	0.0863	0.0772	0.0747	0.0784	0.0950
1/NUMEST	0.0308	0.0325	0.0359	0.0358	0.0277
RETVOL	0.1382	0.1344	0.1284	0.1327	0.1620
CFVOL	0.0600	0.0686	0.0642	0.0661	0.0831
STDEV	0.0004	0.0003	0.0004	0.0005	0.0007
Panel B					
	1	2	3	4	5
1/NUM	0.035870	0.044910	0.047860	0.060760	0.105780
1/PCT	234	273	395	147	458
1/DOLVOL	0.000026	0.000035	0.000038	0.000055	0.000116
BIDASKAV	0.873990	0.912450	0.837660	1.086640	1.761700
AMIHUD	0.000004	0.000006	0.000007	0.000010	0.000023
IDIOVOL	0.123800	0.129880	0.126310	0.129850	0.157060

Table A-10 Divergence of Opinion, Limits to Arbitrage and O-Score

Panel A reports the time series correlations between default probability and DO(difference of opinion) variables. Panel B provides the time series correlations between default probability and LTA(limits to arbitrage) variables. Panel C provides the time series correlations between DO variables and LTA variables.

Panel A

	O-Score	SIZE	AGE	NUMEST	STDEV	RETVOL	CFVOL
O-Score	1.00	-0.14	-0.04	-0.17	0.02	0.09	0.02
SIZE		1.00	0.22	0.23	0.00	-0.09	-0.06
AGE			1.00	0.02	0.02	-0.28	-0.18
NUMEST				1.00	-0.04	0.01	-0.02
STDEV					1.00	0.00	0.01
RETVOL						1.00	0.25
CFVOL							1.00

Panel B

	OSCORE	NUM	PCT	DOLVOL	BIDASKAV	AMIHUD	IDIOVOL
OSCORE	1.00	-0.25	-0.25	-0.15	0.06	0.13	0.08
NUM		1.00	0.47	0.62	-0.11	-0.12	-0.21
PCT			1.00	0.15	-0.14	-0.20	-0.19
DOLVOL				1.00	-0.04	-0.03	-0.05
BIDASKAV					1.00	0.15	-0.04
AMIHUD						1.00	0.10
IDIOVOL							1.00

Panel C

	SIZE	AGE	NUMEST	STDEV	RETVOL	CFVOL
NUM	0.72	0.41	0.28	0.01	-0.19	-0.12
PCT	0.12	0.15	0.08	0.02	-0.16	-0.11
DOLVOL	0.75	0.12	0.34	0.01	-0.04	-0.03
BIDASKAV	-0.04	-0.01	-0.01	0.00	-0.05	0.00
AMIHUD	-0.03	-0.03	-0.09	-0.01	0.10	0.03
IDIOVOL	-0.09	-0.30	0.00	0.00	0.76	0.26

Table A-11 Portfolios Sorted on the Basis of Limits to Arbitrage and Difference of Opinion

In Panel A, at the end of each month, stocks are sorted into 5 groups by six of the limits to arbitrage proxies and the LTA-Score and assigned to five quintile portfolios. LTA-Score is the sum of six limits to arbitrage signals. Once the portfolios are formed, each stock is held for 1 month. I then compute the equally-weighted raw returns over the next month. In this panel quintile 1 represents a portfolio consisting of firms with the lowest limits to arbitrage and quintile 5 represents a portfolio consisting of firms with the highest limits to arbitrage. The returns presented in Panel B are the equally-weighted raw returns of the five quintile portfolios formed by sorting the stocks by six of the difference of opinion proxies and the DO-Score. DO-Score is the sum of six difference of opinion signals In this panel quintile 1 represents a portfolio consisting of firms with the lowest differences of opinion and quintile 5 represents a portfolio consisting of firms with the highest differences of opinion.

		Panel A			
	1	2	3	4	5
NUM	0.0064	0.0145	0.0062	-0.0013	-0.0079
PCT	0.0062	0.0125	0.0057	0.0013	-0.0068
DOLVOL	0.0121	0.0072	0.0040	0.0001	-0.0047
BIDASKAV	0.0114	0.0117	0.0130	0.0120	0.0202
AMIHUD	0.0123	0.0063	0.0027	-0.0005	-0.0052
IDIOVOL	0.0069	0.0082	0.0038	0.0004	-0.0036
LTA-Score	0.0099	0.0101	0.0025	-0.0019	-0.0052
		Panel B			
	1	2	3	4	5
SIZE	0.0157	0.0110	0.0054	-0.0033	-0.0156
AGE	0.0085	0.0070	0.0061	0.0028	-0.0077
NUMEST	0.0113	0.0143	0.0126	0.0135	0.0112
RETVOL	0.0075	0.0053	0.0027	0.0009	0.0050
CFVOL	0.0077	0.0060	0.0034	0.0023	-0.0030
STDEV	0.0141	0.0148	0.0122	0.0085	0.0208
DO-Score	0.0108	0.0080	0.0050	-0.0035	-0.0083

Table A-12 Portfolios Sorted on the Basis of O-Score, Divergence of Opinion and Limits to Arbitrage

Over the sample period of 1980 to 2011, at the end of each month, stocks are sorted into 25 groups. First, stocks are sorted into 5 portfolios based on their most recently calculated O-Score. Next, stocks are sorted into 5 groups independently based on each of their most recently calculated Do-Score and LTA-Score. Once the portfolios are formed, each stock is held for 1 month. I then compute the equally-weighted returns over the next month. The returns presented are Carhart 4 factor abnormal returns for the (High-Low) distress portfolio for the highest and lowest quintiles of DO-Score and LTA-Score. H-L is the long-short portfolio that is long in the least quintile and short in the highest quintile

(High – Low) Distress Returns			
	Low	High	High - Low
DO-Score	0.002**	-0.004***	-0.006***
LTA-Score	0.004***	-0.010***	-0.014***
DO-Score & LTA-Score	0.006***	-0.010***	-0.016***

Table A-13 Portfolios Sorted on the Basis of O-Score, LTA-Score and DO-Score

The sample period ranges from January 1980 to December 2011. For each month, stocks are first independently sorted based on divergence of opinion (DO-Score) and limits to arbitrage (LTA-Score) into three quintiles, and then for each divergence of opinion and limits to arbitrage portfolio they are dependently sorted by financial distress (O-Score) into five portfolios. Stocks in each of 45 portfolios are held in the portfolios for 1 month. The returns presented are Carhart 4 factor abnormal returns.

LTA	DO	Low Distress 1	2	3	4	High Distress 5	H-L
1	1	0.002	0.004	0.004	0.005	0.008	0.006**
1	2	0.002	0.002	0.003	0.005	0.007	0.005***
1	3	0.003	0.005	0.005	0.006	0.006	0.003***
2	1	0.002	0.003	0.002	0.003	0.006	0.004*
2	2	-0.002	-0.002	0.001	-0.002	-0.003	-0.001***
2	3	-0.010	-0.010	-0.008	-0.008	-0.014	-0.004**
3	1	0.003	0.002	0.001	0.002	-0.002	-0.004***
3	2	-0.002	-0.003	0.000	-0.006	-0.009	-0.008***
3	3	-0.007	-0.010	-0.005	-0.009	-0.017	-0.010**

Table A-14 Portfolios Sorted on the Basis of LTA-Score and DO-Score – Sample with no distressed stocks

Over the sample period of 1980 to 2011, I remove those stocks that are at the highest two quintiles of distress and the remaining stocks are sorted into 25 groups at the end of each month, First, stocks are sorted into 5 portfolios based on their most recently calculated LTA-Score. Next, stocks in each of these portfolios are sorted into 5 groups based on their most recent DO-Score. Once the portfolios are formed, each stock is held for 1 month. We then compute the equally-weighted returns over the next month. The returns presented in the Panel A are average raw returns over risk-free rate. Also CAPM abnormal returns, Fama-French 3 factor abnormal returns and Carhart 4 factor abnormal returns are computed and are reported in Panels B, C and D, respectively.

			Panel A -	Raw return	
	Low LTA				High LTA
	1	2	3	4	5
(Low DO) 1	0.0110	0.0110	0.0108	0.0129	0.0094
2	0.0111	0.0112	0.0068	0.0063	0.0031
3	0.0120	0.0127	0.0097	0.0063	0.0045
4	0.0109	0.0112	0.0036	-0.0012	-0.0002
(High DO) 5	0.0122	-0.0001	-0.0059	-0.0111	-0.0037

			Panel B -	CAPM Alpha	
	Low LTA				High LTA
	1	2	3	4	5
(Low DO) 1	0.0066	0.0070	0.0066	0.0092	0.0064
2	0.0063	0.0061	0.0015	0.0024	-0.0003
3	0.0050	0.0043	0.0009	0.0003	-0.0014
4	0.0041	0.0042	-0.0050	-0.0080	-0.0065
(High DO) 5	0.0020	-0.0070	-0.0145	-0.0193	-0.0114

			Panel C -	3 Factor Alpha	
	Low LTA				High LTA
	1	2	3	4	5
(Low DO) 1	0.0050	0.0053	0.0049	0.0077	0.0037
2	0.0050	0.0058	0.0010	0.0012	-0.0022
3	0.0043	0.0046	0.0017	-0.0008	-0.0025
4	0.0038	0.0050	-0.0025	-0.0072	-0.0068
(High DO) 5	0.0007	-0.0074	-0.0134	-0.0184	-0.0109

			Panel D -	4 Factor Alpha	
	Low LTA				High LTA
	1	2	3	4	5
(Low DO) 1	0.0054	0.0052	0.0053	0.0077	0.0030
2	0.0049	0.0061	0.0022	0.0015	-0.0022
3	0.0047	0.0049	0.0035	0.0007	-0.0012
4	0.0050	0.0059	-0.0009	-0.0060	-0.0043
(High DO) 5	0.0012	-0.0082	-0.0105	-0.0149	-0.0084

Table A-15 Portfolios Sorted on the Basis of O-Score – Sample with no high LTA/DO stocks

Over the sample period of 1980 to 2011, at the end of each month, I remove those stocks that are at the highest two quintiles of DO and LTA and the remaining stocks are sorted into 5 groups by their most recently calculated O-Score and assigned to five quintile portfolios. Once the portfolios are formed, each stock is held for 1 month. We then compute the equally-weighted returns over the next month. The returns presented are average raw returns, CAPM abnormal returns, Fama-French 3 factor abnormal returns and Carhart 4 factor abnormal returns over all formation periods.

	O-Score Quintiles				
	1	2	3	4	5
Raw return	0.011	0.008	0.010	0.010	0.004
CAPM Alpha	0.004	0.003	0.005	0.005	0.001
FF3 Alpha	0.005	0.002	0.003	0.004	0.003
Carhart4 Alpha	0.005	0.002	0.004	0.004	0.002

Appendix B

Tables for Chapter 3: The Valuation Impact on Distressed Residential Transactions

Anatomy of a Housing Price Bubble

Table B-1 Variable Descriptions

Variable	Description
ln(sale price)	Natural logarithm of sales price
Foreclosure	Dummy variable equal to 1 if property status is "foreclosure"
Short-sale	Dummy variable equal to 1 if property status is "short-sales"
Distress	Dummy variable equal to 1 if property status is either "foreclosure" or "short-sales"
ln(sqft)	Natural logarithm of square footage
Age	Property age
TOM	Days on market
FHA	Dummy variable equal to 1 if property is financed using FHA loan
VA	Dummy variable equal to 1 if property is financed using VA loan
Govt	Dummy variable equal to 1 if property is financed using FHA or VA loan
Cash	Dummy variable equal to 1 if property is financed using cash
Conv	Dummy variable equal to 1 if property is financed using conventional loan
Vacant	Dummy variable equal to 1 if property is vacant
Pool	Dummy variable equal to 1 if pool is present
Stories	Dummy variable equal to 1 if stories=2
Wood	Dummy variable equal to 1 if property has wood flooring
Bedrooms	Number of bedrooms
Fireplaces	Number of fireplaces
Bathrooms	Number of bathrooms
Garage_spaces	Number of garage spaces
Large	Dummy variable equal to 1 if size of property is more than 1percentile of the sample
Small	Dummy variable equal to 1 if size of property is less than 1percentile of the sample
Bedsmore	Dummy variable equal to 1 if bedrooms is more than 4
Bathsmore	Dummy variable equal to 1 if bathrooms is more than 3
Old	Dummy variable equal to 1 if age of property is more than 1percentile of the sample
New	Dummy variable equal to 1 if age of property is less than 1percentile of the sample
Longitude	Longitude of the property
Latitude	Latitude of the property
Zip_93701	Dummy variable equal to 1 if property is located in the zip code 93701
Zip_93702	Dummy variable equal to 1 if property is located in the zip code 93702
Zip_93703	Dummy variable equal to 1 if property is located in the zip code 93703
Zip_93704	Dummy variable equal to 1 if property is located in the zip code 93704
Zip_93705	Dummy variable equal to 1 if property is located in the zip code 93705
Zip_93706	Dummy variable equal to 1 if property is located in the zip code 93706
Zip_93710	Dummy variable equal to 1 if property is located in the zip code 93710
Zip_93711	Dummy variable equal to 1 if property is located in the zip code 93711
Zip_93720	Dummy variable equal to 1 if property is located in the zip code 93720
Zip_93722	Dummy variable equal to 1 if property is located in the zip code 93722
Zip_93725	Dummy variable equal to 1 if property is located in the zip code 93725
Zip_93726	Dummy variable equal to 1 if property is located in the zip code 93726

Table B.1 – *Continued*

Zip_93727	Dummy variable equal to 1 if property is located in the zip code 93727
Zip_93728	Dummy variable equal to 1 if property is located in the zip code 93728
Zip_93730	Dummy variable equal to 1 if property is located in the zip code 93730
Year_2006	Dummy variable equal to 1 if property is sold in year 2006
Year_2007	Dummy variable equal to 1 if property is sold in year 2007
Year_2008	Dummy variable equal to 1 if property is sold in year 2008
Year_2009	Dummy variable equal to 1 if property is sold in year 2009
Year_2010	Dummy variable equal to 1 if property is sold in year 2010
Q1	Dummy variable equal to 1 if property is sold in quarter 1
Q2	Dummy variable equal to 1 if property is sold in quarter 2
Q3	Dummy variable equal to 1 if property is sold in quarter 3
Q4	Dummy variable equal to 1 if property is sold in quarter 4

Table B-2 Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
ln(sale price)	22362	12.08	0.66	9.55	15.07
Foreclosure	22362	0.37	0.48	0	1
Short sale	22362	0.08	0.28	0	1
Distress	22362	0.46	0.5	0	1
Ln(sqft)	22362	7.37	0.35	5.99	8.97
Age	22362	31.36	25.37	1	107
Tom	22362	66.64	76.65	0	901
FHA	22362	0.22	0.42	0	1
VA	22362	0.02	0.12	0	1
Govt	22362	0.24	0.42	0	1
Conv	22362	0.55	0.50	0	1
Cash	22362	0.21	0.41	0	1
Vacant	22362	0.7	0.46	0	1
Pool	22362	0.19	0.39	0	1
Stories	22362	0.14	0.35	0	1
Wood	22362	0.19	0.39	0	1
Bedrooms	22362	3.24	0.79	1	12
Fireplaces	22362	0.65	0.62	0	18
Bathrooms	22362	1.97	0.64	1	7
Garage_spaces	22362	1.46	1.13	0	39
Large	22362	0.01	0.1	0	1
Small	22362	0.01	0.1	0	1
Bedsmore	22362	0.3	0.46	0	1
Bathsmore	22362	0.03	0.16	0	1
Old	22362	0.28	0.45	0	1
New	22362	0.29	0.45	0	1
Longitude	22362	-119	9.68	-120.05	0
Latitude	22362	36.55	2.97	0	37.17
Zip_93701	22362	0.01	0.11	0	1
Zip_93702	22362	0.06	0.23	0	1
Zip_93703	22362	0.05	0.22	0	1
Zip_93704	22362	0.06	0.23	0	1
Zip_93705	22362	0.06	0.25	0	1

Table B.2 – *Continued*

Zip_93706	22362	0.04	0.19	0	1
Zip_93710	22362	0.04	0.2	0	1
Zip_93711	22362	0.06	0.24	0	1
Zip_93720	22362	0.11	0.31	0	1
Zip_93722	22362	0.19	0.39	0	1
Zip_93725	22362	0.03	0.17	0	1
Zip_93726	22362	0.07	0.25	0	1
Zip_93727	22362	0.14	0.35	0	1
Zip_93728	22362	0.04	0.18	0	1
Zip_93730	22362	0.02	0.15	0	1
Year_2006	22362	0.18	0.38	0	1
Year_2007	22362	0.13	0.33	0	1
Year_2008	22362	0.19	0.39	0	1
Year_2009	22362	0.27	0.44	0	1
Year_2010	22362	0.23	0.42	0	1
Q1	22362	0.22	0.41	0	1
Q2	22362	0.27	0.45	0	1
Q3	22362	0.26	0.44	0	1
Q4	22362	0.25	0.43	0	1

Table B-3 Ordinary Least Squares, Two-Stage Least Squares and Three-Stage Least Squares

Estimation of the Log of Selling Price

VARIABLES	OLS 1	OLS 2	2SLS	3SLS 1	3SLS 2
foreclosure	-0.210***	-0.208***	-0.204***	-0.210***	-0.210***
	(0.00422)	(0.00420)	(0.00621)	(0.00420)	(0.00420)
short-sale	-0.135***	-0.141***	-0.155***	-0.134***	-0.134***
	(0.00640)	(0.00621)	(0.0179)	(0.00620)	(0.00620)
ln(sqft)	0.846***	0.844***	0.841***	0.846***	0.846***
	(0.00871)	(0.00871)	(0.00960)	(0.00870)	(0.00869)
age	-0.00206***	-0.00207***	-0.00208***	-0.00207***	-0.00206***
	(9.06e-05)	(9.06e-05)	(9.21e-05)	(9.05e-05)	(9.05e-05)
TOM	-7.77e-05***		0.000198		
	(2.2e-05		(0.000228)		
Govt	0.037***	0.036***	0.037***	0.037***	0.035***
	(0.00494)	(0.00495)	(0.00498)	(0.00494)	(0.00494)
Cash	-0.221***	-0.221***	-0.220***	-0.221***	-0.221***
	(0.00449)	(0.00449)	(0.00452)	(0.00449)	(0.00449)
vacant	-0.0340***	-0.0346***	-0.0361***	-0.0339***	-0.0342***
	(0.00400)	(0.00400)	(0.00439)	(0.00400)	(0.00400)
pool	0.0296***	0.0295***	0.0294***	0.0296***	0.0296***
	(0.00432)	(0.00432)	(0.00434)	(0.00432)	(0.00432)
stories	-0.0860***	-0.0861***	-0.0866***	-0.0860***	-0.0861***
	(0.00518)	(0.00518)	(0.00522)	(0.00517)	(0.00517)
wood	-0.0220***	-0.0221***	-0.0224***	-0.0220***	-0.0219***
	(0.00398)	(0.00399)	(0.00401)	(0.00398)	(0.00398)
bedrooms	-0.0188***	-0.0185***	-0.0179***	-0.0189***	-0.0190***
	(0.00286)	(0.00286)	(0.00295)	(0.00285)	(0.00285)
fireplaces	0.0321***	0.0319***	0.0316***	0.0321***	0.0321***
	(0.00283)	(0.00284)	(0.00288)	(0.00283)	(0.00283)
bathrooms	0.0812***	0.0809***	0.0802***	0.0809***	0.0809***
	(0.00448)	(0.00448)	(0.00457)	(0.00447)	(0.00447)
garage_spaces	-0.00332**	-0.00334**	-0.00338**	-0.00332**	-0.00332**
	(0.00136)	(0.00136)	(0.00136)	(0.00136)	(0.00136)
longitude	0.303***	0.306***	0.313***	0.302***	0.303***
	(0.0229)	(0.0229)	(0.0246)	(0.0229)	(0.0229)
latitude	0.985***	0.995***	1.019***	0.984***	0.985***
	(0.0746)	(0.0746)	(0.0801)	(0.0745)	(0.0745)
zip_93701	-0.383***	-0.384***	-0.386***	-0.383***	-0.383***
	(0.0184)	(0.0184)	(0.0186)	(0.0184)	(0.0184)
zip_93702	-0.267***	-0.268***	-0.269***	-0.268***	-0.268***
	(0.0137)	(0.0137)	(0.0138)	(0.0137)	(0.0137)
zip_93703	-0.198***	-0.198***	-0.199***	-0.198***	-0.198***
	(0.0136)	(0.0136)	(0.0137)	(0.0136)	(0.0136)
zip_93704	0.0237*	0.0232*	0.0218	0.0237*	0.0239*
	(0.0136)	(0.0136)	(0.0137)	(0.0135)	(0.0135)
zip_93705	-0.136***	-0.137***	-0.138***	-0.136***	-0.136***
	(0.0132)	(0.0132)	(0.0133)	(0.0132)	(0.0132)
zip_93706	-0.298***	-0.298***	-0.299***	-0.298***	-0.298***

Table B.3 – *Continued*

	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0149)
zip_93710	-0.0708***	-0.0709***	-0.0714***	-0.0706***	-0.0707***
	(0.0146)	(0.0146)	(0.0146)	(0.0146)	(0.0146)
zip_93711	0.0886***	0.0881***	0.0868***	0.0886***	0.0888***
	(0.0136)	(0.0136)	(0.0137)	(0.0136)	(0.0136)
zip_93720	0.0517***	0.0509***	0.0488***	0.0518***	0.0518***
	(0.0145)	(0.0145)	(0.0148)	(0.0145)	(0.0145)
zip_93722	-0.0408***	-0.0408***	-0.0408***	-0.0408***	-0.0409***
	(0.0119)	(0.0120)	(0.0120)	(0.0119)	(0.0119)
zip_93725	-0.111***	-0.110***	-0.110***	-0.111***	-0.111***
	(0.0150)	(0.0151)	(0.0151)	(0.0150)	(0.0150)
zip_93726	-0.158***	-0.158***	-0.158***	-0.158***	-0.158***
	(0.0133)	(0.0133)	(0.0134)	(0.0133)	(0.0133)
zip_93727	-0.0510***	-0.0510***	-0.0509***	-0.0510***	-0.0510***
	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)
zip_93728	-0.0977***	-0.0981***	-0.0990***	-0.0978***	-0.0978***
	(0.0147)	(0.0147)	(0.0148)	(0.0147)	(0.0147)
zip_93730	0.246***	0.245***	0.241***	0.246***	0.246***
	(0.0178)	(0.0178)	(0.0184)	(0.0178)	(0.0178)
year2006	0.637***	0.637***	0.638***	0.638***	0.638***
	(0.00594)	(0.00594)	(0.00605)	(0.00594)	(0.00594)
year2007	0.511***	0.509***	0.505***	0.510***	0.510***
	(0.00616)	(0.00615)	(0.00781)	(0.00614)	(0.00614)
year2008	0.212***	0.210***	0.204***	0.211***	0.211***
	(0.00498)	(0.00495)	(0.00779)	(0.00494)	(0.00494)
year2009	-0.00837*	-0.00940**	-0.0120**	-0.00782*	-0.00820*
	(0.00437)	(0.00436)	(0.00531)	(0.00436)	(0.00436)
q1	0.0882***	0.0879***	0.0873***	0.0885***	0.0884***
	(0.00453)	(0.00453)	(0.00459)	(0.00452)	(0.00452)
q2	0.0738***	0.0738***	0.0736***	0.0742***	0.0741***
	(0.00426)	(0.00426)	(0.00427)	(0.00425)	(0.00425)
q3	0.0397***	0.0398***	0.0400***	0.0398***	0.0398***
	(0.00428)	(0.00429)	(0.00431)	(0.00428)	(0.00428)
Constant	5.568***	5.575***	5.595***	5.563***	5.563***
	(0.0617)	(0.0617)	(0.0660)	(0.0616)	(0.0616)
Observations	22,362	22,362	22,362	22,362	22,362
R-squared	0.880	0.880	0.879	0.879	0.879

Table B-4 First stage regression: TOM

VARIABLES	Endogeneity only	Endogeneity and Self selection
foreclosure	-20.69***	-11.99***
	(1.338)	(1.312)
short-sale	74.65***	61.49***
	(1.959)	(1.922)
ln(sqft)	18.57***	64.35***
	(2.866)	(3.001)
age	-0.00882	0.167***
	(0.0541)	(0.0525)
Govt	0.674	23.54***
	(1.563)	(2.142)
Cash	-1.675	-36.83***
	(1.416)	(1.631)
vacant	7.529***	-104.4***
	(1.261)	(3.074)
pool	0.145	-14.54***
	(1.377)	(1.382)
stories	1.627	-28.40***
	(1.642)	(1.758)
wood	1.389	18.35***
	(1.256)	(1.287)
bedrooms	-5.196***	-13.25***
	(1.285)	(1.259)
fireplaces	1.885**	10.37***
	(0.895)	(0.891)
bathrooms	1.035	-4.785***
	(1.552)	(1.507)
garage_spaces	0.120	1.023**
	(0.428)	(0.414)
longitude	-38.18***	79.10***
	(7.229)	(7.587)
latitude	-123.9***	250.9***
	(23.54)	(24.64)
zip_93701	8.597	6.966
	(5.836)	(5.641)
zip_93702	5.920	-4.395
	(4.327)	(4.190)
zip_93703	5.701	0.364
	(4.333)	(4.190)
zip_93704	7.235*	41.49***
	(4.275)	(4.222)
zip_93705	6.565	11.78***
	(4.176)	(4.038)
zip_93706	3.259	22.85***
	(4.691)	(4.561)
zip_93710	2.492	-4.109
	(4.624)	(4.473)
zip_93711	5.083	53.78***

Table B.4 – *Continued*

	(4.324)	(4.356)
zip_93720	9.288**	8.521*
	(4.605)	(4.451)
zip_93722	-0.437	-28.76***
	(3.792)	(3.735)
zip_93725	-3.602	-20.77***
	(4.758)	(4.619)
zip_93726	1.657	-9.957**
	(4.208)	(4.078)
zip_93727	-0.271	-2.266
	(3.806)	(3.679)
zip_93728	4.771	15.14***
	(4.666)	(4.517)
zip_93730	16.30***	43.71***
	(5.631)	(5.487)
year2006	768.6***	1,354***
	(158.6)	(154.0)
year2007	575.2***	888.4***
	(117.8)	(114.1)
year2008	375.1***	444.1***
	(76.47)	(73.93)
year2009	201.0***	207.5***
	(37.78)	(36.52)
q1	150.3***	182.8***
	(29.89)	(28.90)
q2	100.6***	132.1***
	(20.05)	(19.40)
q3	48.54***	72.50***
	(10.21)	(9.887)
mhincome	0.0118***	0.0182***
	(0.00353)	(0.00342)
Large	13.63**	15.16***
	(5.582)	(5.396)
Small	15.68***	19.67***
	(5.318)	(5.141)
bedsmore	5.528***	7.708***
	(1.953)	(1.888)
bathsmore	9.251**	10.66***
	(3.934)	(3.803)
invMills		-210.0***
		(5.296)
Constant	-16,061***	-17,891***
	(2,938)	(2,840)
Observations	22,362	22,362
R-squared	0.123	0.181

Table B-5 Heckman Self Selection

	ln(sale price)			Distress		
		Std. Err.	P>z		Std. Err.	P>z
ln(sqft)	0.97	0.03	0.00	-0.42	0.06	0.00
age	0.00	0.00	0.00	0.00	0.00	0.00
TOM	0.00	0.00	0.00	0.00	0.00	0.00
Govt	0.03	0.03	0.00	-0.55	0.03	0.00
Cash	-0.28	0.02	0.00	0.32	0.03	0.00
vacant	-0.27	0.04	0.00	0.71	0.03	0.00
pool	-0.01	0.01	0.52	0.14	0.03	0.00
stories	-0.15	0.02	0.00	0.20	0.03	0.00
wood	0.00	0.01	0.85	-0.13	0.03	0.00
bedrooms	-0.03	0.01	0.00	0.05	0.02	0.01
fireplaces	0.05	0.01	0.00	-0.05	0.02	0.00
bathrooms	0.06	0.01	0.00	0.06	0.03	0.03
garage_spaces	0.00	0.00	0.78	0.00	0.01	0.63
longitude	0.65	0.07	0.00	-0.81	0.15	0.00
latitude	2.09	0.23	0.00	-2.59	0.49	0.00
zip_93701	-0.39	0.05	0.00	-0.10	0.12	0.43
zip_93702	-0.30	0.03	0.00	0.04	0.09	0.64
zip_93703	-0.25	0.03	0.00	0.02	0.09	0.79
zip_93704	0.04	0.04	0.30	-0.26	0.09	0.00
zip_93705	-0.15	0.03	0.00	-0.03	0.08	0.72
zip_93706	-0.32	0.04	0.00	-0.14	0.10	0.14
zip_93710	-0.05	0.04	0.16	0.10	0.09	0.29
zip_93711	0.18	0.04	0.00	-0.24	0.09	0.01
zip_93720	0.11	0.04	0.00	0.11	0.09	0.24
zip_93722	-0.09	0.03	0.01	0.29	0.07	0.00
zip_93725	-0.15	0.04	0.00	0.21	0.10	0.03
zip_93726	-0.18	0.03	0.00	0.10	0.08	0.24
zip_93727	-0.06	0.03	0.03	0.02	0.07	0.78
zip_93728	-0.08	0.04	0.03	-0.15	0.09	0.11
zip_93730	0.27	0.05	0.00	-0.18	0.11	0.10
year2006	1.79	0.19	0.00	-2.76	0.08	0.00
year2007	1.03	0.09	0.00	-1.47	0.04	0.00
year2008	0.21	0.01	0.00	-0.06	0.03	0.03
year2009	-0.07	0.01	0.00	0.20	0.03	0.00
q1	0.10	0.01	0.00	-0.06	0.03	0.03
q2	0.09	0.01	0.00	-0.11	0.03	0.00
q3	0.08	0.01	0.00	-0.11	0.03	0.00
_cons	5.57	0.18	0.00	1.08	0.42	0.01
mills lambda	-0.47	0.09	0.00			

Table B-6 Sales – 2006 to 2012

Year	Sales	Foreclosure		Short Sale	
		Number	Percent	Number	Percent
2006	3961	16	0.00	11	0.00
2007	2803	289	0.10	26	0.01
2008	4077	2214	0.54	225	0.06
2009	5617	3279	0.58	616	0.11
2010	4949	2121	0.43	832	0.17
2011	5270	2096	0.40	1014	0.19
2012	5207	1549	0.30	1283	0.25
Total	31884	11564	2.35	4007	0.79

Table B-7 Variable Description (2008-2012)

Variable	Description
LSales	Natural logarithm of sales price
Foreclosure	Dummy variable equal to 1 if property status is "foreclosure"
Shortsale	Dummy variable equal to 1 if property status is "short-sales"
Distress	Dummy variable equal to 1 if property status is either "foreclosure" or "short-sales"
Foreclosure2008	Dummy variable equal to 1 if property status is "foreclosure" in year 2008
Foreclosure2009	Dummy variable equal to 1 if property status is "foreclosure" in year 2009
Foreclosure2010	Dummy variable equal to 1 if property status is "foreclosure" in year 2010
Foreclosure2011	Dummy variable equal to 1 if property status is "foreclosure" in year 2011
Foreclosure2012	Dummy variable equal to 1 if property status is "foreclosure" in year 2012
Shortsale2008	Dummy variable equal to 1 if property status is "shortsale" in year 2008
Shortsale2009	Dummy variable equal to 1 if property status is "shortsale" in year 2009
Shortsale2010	Dummy variable equal to 1 if property status is "shortsale" in year 2010
Shortsale2011	Dummy variable equal to 1 if property status is "shortsale" in year 2011
Shortsale2012	Dummy variable equal to 1 if property status is "shortsale" in year 2012
LSqft)	Natural logarithm of square footage
Age	Property age
Agesq	Square of property age
ForeclosureTOM	Time on market for a property with a "foreclosure" status
ShortsaleTOM	Time of market for a for a property with a "shortsale" status
DOM	Time on market
FHA	Dummy variable equal to 1 if property is financed using FHA loan
VA	Dummy variable equal to 1 if property is financed using VA loan
Private	Dummy variable equal to 1 if property is privately financed
Cash	Dummy variable equal to 1 if property is financed using cash
Cash2008	Dummy variable equal to 1 if property is financed using cash in year 2008
Cash2009	Dummy variable equal to 1 if property is financed using cash in year 2009
Cash2010	Dummy variable equal to 1 if property is financed using cash in year 2010
Cash2011	Dummy variable equal to 1 if property is financed using cash in year 2011
Cash2012	Dummy variable equal to 1 if property is financed using cash in year 2012
Conv	Dummy variable equal to 1 if property is financed using conventional loan
Vacant	Dummy variable equal to 1 if property is vacant
Pool	Dummy variable equal to 1 if pool is present
Stories	Dummy variable equal to 1 if stories=2
Floor	Dummy variable equal to 1 if property has wood flooring
Bedrooms	Number of bedrooms
FireplacesNumber	Number of fireplaces
CarportSpaces	Number of carport spaces
Bathrooms	Number of bathrooms
GarageSpaces	Number of garage spaces

Table B.7 – *Continued*

Basement	Dummy variable equal to 1 if basement is present
Large	Dummy variable equal to 1 if size of property is more than 1percentile of the sample
Small	Dummy variable equal to 1 if size of property is less than 1percentile of the sample
Bedsmore	Dummy variable equal to 1 if bedrooms is more than 4
Bathsmore	Dummy variable equal to 1 if bathrooms is more than 3
Oldhomes	Dummy variable equal to 1 if age of property is more than 1percentile of the sample
Newhomes	Dummy variable equal to 1 if age of property is less than 1percentile of the sample
Longitude	Longitude of the property
Latitude	Square of Latitude of the property
Latitudesq	Square of Longitude of the property
Longitudesq	Latitude of the property
Zip92727	Dummy variable equal to 1 if property is located in the zip code 92727
Zip93701	Dummy variable equal to 1 if property is located in the zip code 93701
Zip93702	Dummy variable equal to 1 if property is located in the zip code 93702
Zip93703	Dummy variable equal to 1 if property is located in the zip code 93703
Zip93704	Dummy variable equal to 1 if property is located in the zip code 93704
Zip93705	Dummy variable equal to 1 if property is located in the zip code 93705
Zip93706	Dummy variable equal to 1 if property is located in the zip code 93706
Zip93710	Dummy variable equal to 1 if property is located in the zip code 93710
Zip93711	Dummy variable equal to 1 if property is located in the zip code 93711
Zip93720	Dummy variable equal to 1 if property is located in the zip code 93720
Zip93721	Dummy variable equal to 1 if property is located in the zip code 93721
Zip93722	Dummy variable equal to 1 if property is located in the zip code 93722
Zip93723	Dummy variable equal to 1 if property is located in the zip code 93723
Zip93725	Dummy variable equal to 1 if property is located in the zip code 93725
Zip93726	Dummy variable equal to 1 if property is located in the zip code 93726
Zip93727	Dummy variable equal to 1 if property is located in the zip code 93727
Zip93728	Dummy variable equal to 1 if property is located in the zip code 93728
Zip93730	Dummy variable equal to 1 if property is located in the zip code 93730
Zip93737	Dummy variable equal to 1 if property is located in the zip code 93737
Year2008	Dummy variable equal to 1 if property is sold in year 2008
Year2009	Dummy variable equal to 1 if property is sold in year 2009
Year2010	Dummy variable equal to 1 if property is sold in year 2010
Year2011	Dummy variable equal to 1 if property is sold in year 2011
Year2012	Dummy variable equal to 1 if property is sold in year 2012
Q1	Dummy variable equal to 1 if property is sold in quarter 1
Q2	Dummy variable equal to 1 if property is sold in quarter 2
Q3	Dummy variable equal to 1 if property is sold in quarter 3
Q4	Dummy variable equal to 1 if property is sold in quarter 4

Table B-8 Descriptive Statistics (2008-2012)

Variables	Observations	Mean	Std. Dev	Min	Max
Lsales	25120	11.83	0.63	8.70	14.73
Foreclosure	25120	0.45	0.50	0.00	1.00
Shortsale	25120	0.16	0.36	0.00	1.00
Foreclosure2008	25120	0.09	0.28	0.00	1.00
Foreclosure2009	25120	0.13	0.34	0.00	1.00
Foreclosure2010	25120	0.08	0.28	0.00	1.00
Foreclosure2011	25120	0.08	0.28	0.00	1.00
Foreclosure2012	25120	0.06	0.24	0.00	1.00
Shortsale2008	25120	0.01	0.09	0.00	1.00
Shortsale2009	25120	0.02	0.15	0.00	1.00
Shortsale2010	25120	0.03	0.18	0.00	1.00
Shortsale2011	25120	0.04	0.20	0.00	1.00
Shortsale2012	25120	0.05	0.22	0.00	1.00
LSqft	25120	7.38	0.34	6.06	9.21
Age	25120	33.88	24.86	0.00	99.00
Agesq	25120	1765.46	2025.96	0.00	9801.00
DOM	25120	64.16	79.27	0.00	1008.00
ForeclosureTOM	25120	21.88	44.08	0.00	663.00
ShortsaleTOM	25120	17.86	58.99	0.00	1008.00
Bathrooms	25120	2.00	0.64	1.00	7.00
Bedrooms	25120	3.25	0.79	1.00	20.00
CarportSpaces	25120	0.03	0.22	0.00	4.00
Cash	25120	0.28	0.45	0.00	1.00
Cash2008	25120	0.03	0.16	0.00	1.00
Cash2009	25120	0.07	0.25	0.00	1.00
Cash2010	25120	0.06	0.23	0.00	1.00
Cash2011	25120	0.07	0.25	0.00	1.00
Cash2012	25120	0.07	0.25	0.00	1.00
FHA	25120	0.33	0.47	0.00	1.00
VA	25120	0.02	0.15	0.00	1.00
Private	25120	0.02	0.12	0.00	1.00
Stories	25120	0.85	0.36	0.00	1.00
GarageSpaces	25120	1.58	0.97	0.00	10.00
Vacant	25120	0.75	0.43	0.00	1.00
Pool	25120	0.20	0.40	0.00	1.00

Table B.8 – *Continued*

FireplacesNumber	25120	0.62	0.60	0.00	5.00
Basement	25120	0.02	0.15	0.00	1.00
Floor	25120	0.67	0.47	0.00	1.00
Q1	25120	0.21	0.41	0.00	1.00
Q2	25120	0.27	0.44	0.00	1.00
Q3	25120	0.26	0.44	0.00	1.00
Q4	25120	0.26	0.44	0.00	1.00
Y2008	25120	0.16	0.37	0.00	1.00
Y2009	25120	0.22	0.42	0.00	1.00
Y2010	25120	0.20	0.40	0.00	1.00
Y2011	25120	0.21	0.41	0.00	1.00
Y2012	25120	0.21	0.41	0.00	1.00
Longitude	25120	-118.85	10.54	-120.00	0.00
Latitude	25120	36.50	3.24	35.81	36.92
Latitudesq	25120	1342.96	119.15	1282.36	1363.25
Longitudesq	25120	14237.23	1262.66	14400	14399.70
Zip93737	25120	0.00	0.06	0.00	1.00
Zip93723	25120	0.02	0.14	0.00	1.00
Zip93721	25120	0.00	0.05	0.00	1.00
Zip92727	25120	0.00	0.04	0.00	1.00
Zip93701	25120	0.01	0.10	0.00	1.00
Zip93702	25120	0.05	0.22	0.00	1.00
Zip93703	25120	0.05	0.22	0.00	1.00
Zip93704	25120	0.05	0.22	0.00	1.00
Zip93705	25120	0.06	0.25	0.00	1.00
Zip93706	25120	0.03	0.18	0.00	1.00
Zip93710	25120	0.04	0.20	0.00	1.00
Zip93711	25120	0.06	0.24	0.00	1.00
Zip93720	25120	0.10	0.30	0.00	1.00
Zip93725	25120	0.03	0.17	0.00	1.00
Zip93726	25120	0.07	0.25	0.00	1.00
Zip93727	25120	0.15	0.36	0.00	1.00
Zip93728	25120	0.03	0.17	0.00	1.00
Zip93730	25120	0.03	0.17	0.00	1.00

Table B-9 Descriptive Statistics between Traditional, Foreclosure and Shortsale Sales (Mean)

Variables	**Traditional**	**Foreclosure**	**Shortsale**
Lsales	12.07	11.63	11.79
Foreclosure		11259.00	
Shortsale			3970.00
Foreclosure2008		2214.00	
Foreclosure2009		3279.00	
Foreclosure2010		2121.00	
Foreclosure2011		2096.00	
Foreclosure2012		1549.00	
Shortsale2008			225.00
Shortsale2009			616.00
Shortsale2010			832.00
Shortsale2011			1014.00
Shortsale2012			1283.00
LSqft	7.45	7.33	7.39
Age	31.43	36.80	31.70
Agesq	1588.52	1974.60	1615.20
DOM	62.10	48.83	113.01
ForeclosureTOM		48.83	
ShortsaleTOM		0.26	113.01
Bathrooms	2.08	1.91	2.01
Bedrooms	3.31	3.19	3.24
CarportSpaces	382.00	0.02	0.03
Cash	1778.00	4339.00	1023.00
Cash2008	160.00	461.00	25.00
Cash2009	251.00	1317.00	89.00
Cash2010	355.00	891.00	170.00
Cash2011	466.00	922.00	302.00
Cash2012	546.00	748.00	437.00
FHA	3850.00	2950.00	1408.00
VA	348.00	137.00	66.00
Private	130.00	213.00	49.00
Stories	8420.00	0.86	0.84
GarageSpaces	1.65	1.53	1.54
Vacant	6572.00	11084.00	1222.00
Pool	2356.00	1858.00	785.00
FireplacesNumber	0.70	6186.00	0.64

Table B.9 – *Continued*

Basement	252.00	220.00	99.00
Floor	6741.00	7275.00	2811.00
Q1	1799.00	2755.00	800.00
Q2	2750.00	3061.00	986.00
Q3	2760.00	2716.00	1077.00
Q4	6444.00	2727.00	1107.00
Y2008	4077.00	2214.00	225.00
Y2009	1724.00	3279.00	616.00
Y2010	1997.00	2121.00	832.00
Y2011	2167.00	2096.00	1014.00
Y2012	2381.00	1549.00	1283.00
Longitude	-117.59	-119.69	-119.64
Latitude	36.12	36.75	36.75
Latitudesq	1329.33	1351.82	1351.99
Longitudesq	14085.59	14337.88	14331.77
Zip93737	50.00	25.00	27.00
Zip93723	196.00	169.00	102.00
Zip93721	12.00	34.00	11.00
Zip92727	49.00	0.00	0.00
Zip93701	63.00	166.00	32.00
Zip93702	326.00	815.00	174.00
Zip93703	420.00	724.00	163.00
Zip93704	623.00	533.00	183.00
Zip93705	619.00	790.00	221.00
Zip93706	231.00	495.00	115.00
Zip93710	451.00	399.00	180.00
Zip93711	948.00	425.00	229.00
Zip93720	1225.00	772.00	434.00
Zip93725	247.00	418.00	121.00
Zip93726	584.00	822.00	254.00
Zip93727	1475.00	1783.00	591.00
Zip93728	264.00	373.00	134.00
Zip93730	496.00	182.00	114.00

Table B-10 Ordinary Least Squares, Two-Stage Least Squares and Three-Stage Least Squares

Estimation of the Log of Selling Price (with yearly foreclosure and shortsales variables)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	OLS1	OLS2	2SLS	3SLS1	3SLS2
Foreclosure2008	-0.147***	-0.145***	-0.146***	-0.149***	-0.149***
	(0.00765)	(0.00763)	(0.00959)	(0.00740)	(0.00741)
Foreclosure2009	-0.202***	-0.199***	-0.202***	-0.203***	-0.203***
	(0.00720)	(0.00722)	(0.00962)	(0.00688)	(0.00689)
Foreclosure2010	-0.165***	-0.164***	-0.168***	-0.166***	-0.167***
	(0.00709)	(0.00709)	(0.00837)	(0.00711)	(0.00712)
Foreclosure2011	-0.155***	-0.154***	-0.156***	-0.156***	-0.156***
	(0.00676)	(0.00677)	(0.00789)	(0.00693)	(0.00695)
Foreclosure2012	-0.151***	-0.150***	-0.150***	-0.152***	-0.152***
	(0.00801)	(0.00802)	(0.00820)	(0.00745)	(0.00746)
Shortsale2008	-0.0812***	-0.0850***	-0.0808***	-0.0822***	-0.0824***
	(0.0153)	(0.0152)	(0.0195)	(0.0157)	(0.0157)
Shortsale2009	-0.138***	-0.145***	-0.140***	-0.138***	-0.139***
	(0.00947)	(0.00923)	(0.0220)	(0.0105)	(0.0105)
Shortsale2010	-0.136***	-0.143***	-0.140***	-0.135***	-0.136***
	(0.00849)	(0.00826)	(0.0226)	(0.00931)	(0.00932)
Shortsale2011	-0.146***	-0.151***	-0.147***	-0.146***	-0.146***
	(0.00824)	(0.00815)	(0.0165)	(0.00866)	(0.00867)
Shortsale2012	-0.169***	-0.173***	-0.172***	-0.167***	-0.168***
	(0.00829)	(0.00814)	(0.0150)	(0.00785)	(0.00786)
LSqft	0.877***	0.875***	0.896***	0.875***	0.875***
	(0.00995)	(0.00993)	(0.0108)	(0.00810)	(0.00811)
Age	-0.00888***	-0.00890***	-0.00857***	-0.00872***	-0.00871***
	(0.000275)	(0.000275)	(0.000263)	(0.000248)	(0.000248)
Agesq	6.38e-05***	6.40e-05***	6.06e-05***	6.19e-05***	6.17e-05***
	(3.88e-06)	(3.88e-06)	(3.09e-06)	(2.97e-06)	(2.97e-06)
DOM	-8.62e-05***				
	(2.24e-05)				
Bathrooms	0.0745***	0.0742***	0.0775***	0.0751***	0.0750***
	(0.00524)	(0.00524)	(0.00431)	(0.00412)	(0.00412)
Bedrooms	-0.0196***	-0.0193***	-0.0225***	-0.0200***	-0.0199***
	(0.00314)	(0.00314)	(0.00280)	(0.00258)	(0.00258)
CarportSpaces	-0.0722***	-0.0727***	-0.0691***	-0.0730***	-0.0732***
	(0.0146)	(0.0147)	(0.00678)	(0.00645)	(0.00646)
Cash	-0.201***	-0.201***	-0.201***	-0.201***	-0.201***
	(0.00467)	(0.00467)	(0.00404)	(0.00392)	(0.00393)
FHA	0.0255***	0.0256***	0.0234***	0.0241***	0.0239***
	(0.00310)	(0.00310)	(0.00370)	(0.00359)	(0.00359)
VA	0.0309***	0.0302***	0.0373***	0.0316***	0.0308***
	(0.00688)	(0.00687)	(0.0103)	(0.00983)	(0.00986)
Private	-0.0478***	-0.0483***	-0.0434***	-0.0472***	-0.0470***
	(0.0154)	(0.0154)	(0.0120)	(0.0115)	(0.0116)
Stories	0.124***	0.124***	0.122***	0.125***	0.124***

Table B.10 – *Continued*

	(0.00469)	(0.00469)	(0.00487)	(0.00466)	(0.00467)
GarageSpaces	0.0337***	0.0338***	0.0332***	0.0340***	0.0341***
	(0.00188)	(0.00188)	(0.00178)	(0.00170)	(0.00170)
Vacant	-0.0576***	-0.0584***	-0.0512***	-0.0578***	-0.0573***
	(0.00419)	(0.00418)	(0.00477)	(0.00402)	(0.00402)
Pool	0.0375***	0.0373***	0.0408***	0.0397***	0.0396***
	(0.00449)	(0.00450)	(0.00407)	(0.00395)	(0.00395)
Fireplaces_number	0.0384***	0.0385***	0.0390***	0.0393***	0.0392***
	(0.00276)	(0.00276)	(0.00270)	(0.00262)	(0.00262)
Basement	0.0834***	0.0832***	0.0830***	0.0814***	0.0812***
	(0.0140)	(0.0140)	(0.0105)	(0.0102)	(0.0102)
Floor	-0.0122**	-0.0125**	-0.00879*	-0.0112***	-0.0110**
	(0.00580)	(0.00580)	(0.00452)	(0.00432)	(0.00432)
Q1	0.0426***	0.0415***	0.0519***	0.0419***	0.0420***
	(0.00424)	(0.00423)	(0.00542)	(0.00418)	(0.00418)
Q2	0.0361***	0.0355***	0.0419***	0.0355***	0.0354***
	(0.00389)	(0.00388)	(0.00449)	(0.00389)	(0.00389)
Q3	0.0166***	0.0166***	0.0173***	0.0163***	0.0163***
	(0.00400)	(0.00400)	(0.00402)	(0.00390)	(0.00391)
Y2009	-0.163***	-0.162***	-0.175***	-0.163***	-0.163***
	(0.00808)	(0.00806)	(0.00877)	(0.00766)	(0.00767)
Y2010	-0.177***	-0.174***	-0.203***	-0.176***	-0.176***
	(0.00785)	(0.00781)	(0.0118)	(0.00747)	(0.00748)
Y2011	-0.278***	-0.275***	-0.301***	-0.277***	-0.278***
	(0.00764)	(0.00762)	(0.0109)	(0.00737)	(0.00738)
Y2012	-0.254***	-0.250***	-0.288***	-0.253***	-0.253***
	(0.00782)	(0.00772)	(0.0137)	(0.00723)	(0.00724)
Longitude	-12.88***	-12.97***	0.552***	-0.449***	-0.450***
	(1.245)	(1.245)	(0.0858)	(0.0753)	(0.0754)
Latitude	-42.01***	-42.29***	2.728***		
	(4.148)	(4.148)	(0.547)		
Latitudesq	0.592***	0.596***	-0.0253***	0.0133***	0.0133***
	(0.0570)	(0.0570)	(0.00737)	(0.000790)	(0.000791)
Longitudesq	-0.0556***	-0.0560***		-0.00500***	-0.00501***
	(0.00516)	(0.00516)		(0.000640)	(0.000641)
Zip93737	0.112***	0.112***	0.0647**	0.0287	0.0285
	(0.0273)	(0.0272)	(0.0293)	(0.0279)	(0.0279)
Zip93723	0.0950***	0.0948***	0.103***	0.105***	0.105***
	(0.0109)	(0.0109)	(0.0115)	(0.0111)	(0.0111)
Zip93721	-0.264***	-0.264***	-0.318***	-0.331***	-0.331***
	(0.0351)	(0.0354)	(0.0320)	(0.0309)	(0.0309)
Zip92727	0.0165	0.0173	-0.0562	-0.0733**	
	(0.0185)	(0.0185)	(0.0357)	(0.0343)	
Zip93701	-0.417***	-0.418***	-0.450***	-0.469***	-0.469***
	(0.0225)	(0.0225)	(0.0184)	(0.0175)	(0.0175)
Zip93702	-0.234***	-0.235***	-0.280***	-0.304***	-0.304***
	(0.0163)	(0.0163)	(0.0141)	(0.0129)	(0.0129)
Zip93703	-0.142***	-0.142***	-0.171***	-0.195***	-0.196***
	(0.0147)	(0.0147)	(0.0133)	(0.0123)	(0.0123)
Zip93704	0.120***	0.119***	0.111***	0.0914***	0.0909***

Table B.10 – *Continued*

	(0.0127)	(0.0127)	(0.0110)	(0.0102)	(0.0102)
Zip93705	-0.0504***	-0.0509***	-0.0629***	-0.0758***	-0.0762***
	(0.00958)	(0.00958)	(0.00896)	(0.00837)	(0.00838)
Zip93706	-0.262***	-0.263***	-0.316***	-0.330***	-0.330***
	(0.0159)	(0.0159)	(0.0120)	(0.0110)	(0.0110)
Zip93710	0.0340**	0.0335**	0.0337**	0.00994	0.00955
	(0.0142)	(0.0142)	(0.0136)	(0.0130)	(0.0130)
Zip93711	0.201***	0.200***	0.217***	0.200***	0.199***
	(0.00852)	(0.00852)	(0.00886)	(0.00810)	(0.00811)
Zip93720	0.129***	0.128***	0.153***	0.124***	0.123***
	(0.0156)	(0.0156)	(0.0133)	(0.0128)	(0.0128)
Zip93725	-0.0881***	-0.0881***	-0.161***	-0.181***	-0.181***
	(0.0182)	(0.0182)	(0.0153)	(0.0140)	(0.0140)
Zip93726	-0.0694***	-0.0696***	-0.0898***	-0.111***	-0.111***
	(0.0138)	(0.0137)	(0.0125)	(0.0118)	(0.0118)
Zip93727	-0.0104	-0.0106	-0.0657***	-0.0950***	-0.0954***
	(0.0184)	(0.0183)	(0.0160)	(0.0146)	(0.0147)
Zip93728	-0.0591***	-0.0597***	-0.0858***	-0.102***	-0.102***
	(0.0173)	(0.0173)	(0.0126)	(0.0118)	(0.0118)
Zip93730	0.216***	0.215***	0.265***	0.230***	0.229***
	(0.0171)	(0.0171)	(0.0156)	(0.0149)	(0.0149)
Constant	5.660***	5.670***	5.587***	5.684***	5.681***
	(0.0683)	(0.0682)	(0.0667)	(0.0569)	(0.0570)
Observations	25,120	25,120	25,120	25,120	25,071
R-squared	0.877	0.877	0.869	0.876	0.876

Table B-11 Summary of Findings for Foreclosure and Short Sales

Year	Foreclosure Discount	Short Sale Discount	Spread (Foreclosure – Short Sale)
2006-2010	21%	14%	7%
2008	17%	11%	6%
2009	22%	15%	7%
2010	17%	14%	3%
2008-2010	19%	14%	5%

Table B-12 Ordinary Least Squares, Two-Stage Least Squares and Three-Stage Least Squares Estimation of the Log of Selling Price (with yearly foreclosure, shortsales and cash variables)

VARIABLES	(1) OLS1	(2) OLS2	(3) 2SLS	(4) 3SLS1	(5) 3SLS2
Foreclosure2008	-0.148***	-0.146***	-0.145***	-0.150***	-0.150***
	(0.00769)	(0.00767)	(0.00975)	(0.00747)	(0.00747)
Foreclosure2009	-0.195***	-0.193***	-0.203***	-0.197***	-0.197***
	(0.00757)	(0.00759)	(0.00965)	(0.00705)	(0.00705)
Foreclosure2010	-0.165***	-0.164***	-0.166***	-0.166***	-0.167***
	(0.00743)	(0.00743)	(0.00839)	(0.00727)	(0.00728)
Foreclosure2011	-0.155***	-0.154***	-0.155***	-0.156***	-0.156***
	(0.00707)	(0.00707)	(0.00792)	(0.00705)	(0.00706)
Foreclosure2012	-0.157***	-0.156***	-0.154***	-0.158***	-0.157***
	(0.00848)	(0.00849)	(0.00826)	(0.00760)	(0.00761)
Shortsale2008	-0.0811***	-0.0848***	-0.0851***	-0.0820***	-0.0822***
	(0.0153)	(0.0152)	(0.0194)	(0.0156)	(0.0157)
Shortsale2009	-0.138***	-0.145***	-0.131***	-0.138***	-0.139***
	(0.00952)	(0.00929)	(0.0219)	(0.0105)	(0.0105)
Shortsale2010	-0.136***	-0.143***	-0.136***	-0.135***	-0.136***
	(0.00852)	(0.00828)	(0.0225)	(0.00930)	(0.00932)
Shortsale2011	-0.146***	-0.151***	-0.142***	-0.146***	-0.146***
	(0.00834)	(0.00826)	(0.0164)	(0.00866)	(0.00868)
Shortsale2012	-0.171***	-0.175***	-0.169***	-0.170***	-0.170***
	(0.00842)	(0.00827)	(0.0149)	(0.00787)	(0.00788)
Cash2008	-0.195***	-0.196***	-0.198***	-0.194***	-0.194***
	(0.0122)	(0.0122)	(0.0103)	(0.00976)	(0.00976)
Cash2009	-0.228***	-0.228***	-0.228***	-0.227***	-0.227***
	(0.00851)	(0.00853)	(0.00727)	(0.00711)	(0.00712)
Cash2010	-0.200***	-0.200***	-0.202***	-0.200***	-0.200***
	(0.00904)	(0.00905)	(0.00781)	(0.00761)	(0.00762)
Cash2011	-0.201***	-0.201***	-0.202***	-0.201***	-0.200***
	(0.00793)	(0.00793)	(0.00729)	(0.00713)	(0.00714)
Cash2012	-0.179***	-0.179***	-0.181***	-0.180***	-0.179***
	(0.00873)	(0.00873)	(0.00729)	(0.00712)	(0.00713)
LSqft	0.877***	0.875***	0.893***	0.876***	0.875***
	(0.00994)	(0.00992)	(0.0107)	(0.00810)	(0.00810)
Age	-0.00886***	-0.00888***	-0.00857***	-0.00870***	- 0.00869***
	(0.000275)	(0.000275)	(0.000261)	(0.000248)	(0.000248)
Agesq	6.38e-05***	6.40e-05***	6.08e-05***	6.19e-05***	6.17e- 05***
	(3.88e-06)	(3.88e-06)	(3.07e-06)	(2.96e-06)	(2.97e-06)
DOM	-8.63e-05***				
	(2.24e-05)				
Bathrooms	0.0747***	0.0744***	0.0774***	0.0752***	0.0752***
	(0.00524)	(0.00524)	(0.00427)	(0.00411)	(0.00412)
Bedrooms	-0.0196***	-0.0193***	-0.0221***	-0.0200***	-0.0199***
	(0.00314)	(0.00314)	(0.00277)	(0.00258)	(0.00258)
CarportSpaces	-0.0742***	-0.0747***	-0.0715***	-0.0749***	-0.0751***

Table B.12 – *Continued*

	(0.0146)	(0.0147)	(0.00675)	(0.00647)	(0.00647)
FHA	0.0257***	0.0258***	0.0234***	0.0243***	0.0241***
	(0.00310)	(0.00310)	(0.00369)	(0.00361)	(0.00361)
VA	0.0319***	0.0312***	0.0371***	0.0324***	0.0317***
	(0.00687)	(0.00685)	(0.0102)	(0.00983)	(0.00987)
Private	-0.0457***	-0.0461***	-0.0422***	-0.0452***	-0.0449***
	(0.0154)	(0.0154)	(0.0119)	(0.0115)	(0.0116)
Stories	0.124***	0.124***	0.123***	0.125***	0.125***
	(0.00469)	(0.00469)	(0.00483)	(0.00466)	(0.00467)
GarageSpaces	0.0337***	0.0338***	0.0333***	0.0341***	0.0341***
	(0.00187)	(0.00187)	(0.00177)	(0.00170)	(0.00170)
Vacant	-0.0575***	-0.0583***	-0.0520***	-0.0577***	-0.0572***
	(0.00420)	(0.00419)	(0.00473)	(0.00402)	(0.00402)
Pool	0.0374***	0.0372***	0.0407***	0.0396***	0.0395***
	(0.00448)	(0.00449)	(0.00404)	(0.00394)	(0.00395)
Fireplaces_number	0.0383***	0.0384***	0.0390***	0.0392***	0.0391***
	(0.00276)	(0.00276)	(0.00268)	(0.00262)	(0.00262)
Basement	0.0831***	0.0829***	0.0825***	0.0811***	0.0809***
	(0.0139)	(0.0140)	(0.0104)	(0.0102)	(0.0102)
Floor	-0.0122**	-0.0125**	-0.00912**	-0.0112***	-0.0110**
	(0.00581)	(0.00581)	(0.00448)	(0.00432)	(0.00432)
Q1	0.0428***	0.0416***	0.0508***	0.0420***	0.0422***
	(0.00423)	(0.00422)	(0.00540)	(0.00418)	(0.00418)
Q2	0.0364***	0.0357***	0.0414***	0.0357***	0.0357***
	(0.00389)	(0.00388)	(0.00447)	(0.00389)	(0.00389)
Q3	0.0167***	0.0167***	0.0174***	0.0164***	0.0164***
	(0.00400)	(0.00400)	(0.00399)	(0.00390)	(0.00391)
Y2009	-0.159***	-0.158***	-0.168***	-0.158***	-0.158***
	(0.00792)	(0.00790)	(0.00870)	(0.00778)	(0.00779)
Y2010	-0.177***	-0.174***	-0.198***	-0.176***	-0.176***
	(0.00766)	(0.00761)	(0.0115)	(0.00764)	(0.00766)
Y2011	-0.277***	-0.275***	-0.297***	-0.277***	-0.277***
	(0.00745)	(0.00742)	(0.0107)	(0.00757)	(0.00759)
Y2012	-0.259***	-0.255***	-0.287***	-0.257***	-0.257***
	(0.00758)	(0.00749)	(0.0135)	(0.00745)	(0.00746)
Longitude	-12.93***	-13.01***	0.561***	-0.451***	-0.453***
	(1.244)	(1.244)	(0.0851)	(0.0752)	(0.0754)
Latitude	-42.16***	-42.44***	2.780***		
	(4.147)	(4.146)	(0.543)		
Latitudesq	0.594***	0.598***	-0.0259***	0.0133***	0.0133***
	(0.0570)	(0.0570)	(0.00731)	(0.000790)	(0.000791)
Longitudesq	-0.0558***	-0.0562***		-0.00502***	-0.00503***
	(0.00516)	(0.00516)		(0.000640)	(0.000641)
Zip93737	0.115***	0.115***	0.0659**	0.0306	0.0304
	(0.0272)	(0.0271)	(0.0291)	(0.0279)	(0.0279)
Zip93723	0.0960***	0.0958***	0.104***	0.106***	0.106***
	(0.0109)	(0.0109)	(0.0114)	(0.0111)	(0.0111)
Zip93721	-0.267***	-0.267***	-0.321***	-0.334***	-0.334***
	(0.0352)	(0.0355)	(0.0318)	(0.0309)	(0.0309)
Zip92727	0.0174	0.0182	-0.0554	-0.0728**	
	(0.0185)	(0.0185)	(0.0354)	(0.0343)	

Table B.12 – *Continued*

Zip93701	-0.417***	-0.418***	-0.451***	-0.469***	-0.469***
	(0.0225)	(0.0225)	(0.0183)	(0.0175)	(0.0175)
Zip93702	-0.234***	-0.235***	-0.281***	-0.304***	-0.304***
	(0.0163)	(0.0163)	(0.0140)	(0.0129)	(0.0129)
Zip93703	-0.142***	-0.142***	-0.172***	-0.196***	-0.196***
	(0.0147)	(0.0147)	(0.0132)	(0.0123)	(0.0123)
Zip93704	0.119***	0.119***	0.109***	0.0907***	0.0902***
	(0.0127)	(0.0127)	(0.0109)	(0.0102)	(0.0102)
Zip93705	-0.0508***	-0.0514***	-0.0642***	-0.0764***	-0.0768***
	(0.00959)	(0.00959)	(0.00889)	(0.00837)	(0.00838)
Zip93706	-0.262***	-0.263***	-0.318***	-0.330***	-0.331***
	(0.0159)	(0.0159)	(0.0119)	(0.0110)	(0.0110)
Zip93710	0.0332**	0.0327**	0.0323**	0.00909	0.00870
	(0.0142)	(0.0142)	(0.0135)	(0.0130)	(0.0130)
Zip93711	0.200***	0.199***	0.215***	0.200***	0.199***
	(0.00851)	(0.00851)	(0.00878)	(0.00810)	(0.00811)
Zip93720	0.129***	0.128***	0.152***	0.124***	0.123***
	(0.0156)	(0.0156)	(0.0132)	(0.0128)	(0.0128)
Zip93725	-0.0882***	-0.0882***	-0.162***	-0.182***	-0.182***
	(0.0182)	(0.0182)	(0.0152)	(0.0140)	(0.0140)
Zip93726	-0.0704***	-0.0706***	-0.0913***	-0.112***	-0.112***
	(0.0138)	(0.0137)	(0.0124)	(0.0118)	(0.0118)
Zip93727	-0.0107	-0.0109	-0.0670***	-0.0957***	-0.0960***
	(0.0184)	(0.0183)	(0.0159)	(0.0146)	(0.0147)
Zip93728	-0.0593***	-0.0599***	-0.0870***	-0.102***	-0.102***
	(0.0173)	(0.0173)	(0.0126)	(0.0118)	(0.0118)
Zip93730	0.216***	0.215***	0.264***	0.230***	0.229***
	(0.0172)	(0.0171)	(0.0155)	(0.0149)	(0.0149)
Constant	5.658***	5.668***	5.598***	5.682***	5.679***
	(0.0683)	(0.0682)	(0.0662)	(0.0569)	(0.0570)
Observations	25,120	25,120	25,120	25,120	25,071
R-squared	0.877	0.877	0.871	0.876	0.876

Table B-13 Descriptive Statistics between Lower, Medium and Higher Sub-markets (Mean)

Variables	Lower <100K	Medium 1 100-200K	Medium 2 200-400K	Higher >400K
Lsales	11.05	11.88	12.45	13.24
Foreclosure	4534.00	4857.00	1738.00	130.00
Shortsale	1128.00	1945.00	809.00	88.00
Foreclosure2008	497.00	1120.00	559.00	38.00
Foreclosure2009	1537.00	1233.00	476.00	33.00
Foreclosure2010	826.00	944.00	329.00	22.00
Foreclosure2011	988.00	891.00	201.00	16.00
Foreclosure2012	686.00	669.00	173.00	21.00
Shortsale2008	9.00	105.00	97.00	14.00
Shortsale2009	136.00	312.00	155.00	13.00
Shortsale2010	216.00	399.00	192.00	25.00
Shortsale2011	366.00	476.00	157.00	15.00
Shortsale2012	401.00	653.00	208.00	21.00
LSqft	7.07	7.36	7.68	8.14
Age	55.63	29.72	18.21	17.60
Agesq	3506.89	1342.26	654.23	577.87
DOM	59.48	61.24	69.44	100.84
ForeclosureTOM	30.52	21.94	13.89	6.85
ShortsaleTOM	16.73	20.09	16.08	12.00
Bathrooms	1.47	1.99	2.43	3.27
Bedrooms	2.78	3.23	3.68	4.20
CarportSpaces	0.07	0.02	0.01	0.02
Cash	4518.00	1769.00	706.00	141.00
Cash2008	323.00	176.00	120.00	25.00
Cash2009	1174.00	317.00	140.00	24.00
Cash2010	884.00	354.00	143.00	35.00
Cash2011	1124.00	414.00	118.00	33.00
Cash2012	1013.00	508.00	185.00	24.00
FHA	1145.00	4983.00	2055.00	18.00
VA	19.00	279.00	246.00	5.00
Private	142.00	159.00	80.00	11.00
Stories	6797.00	9829.00	4219.00	543.00
GarageSpaces	1.04	1.65	1.92	2.65
Vacant	5969.00	8490.00	4007.00	396.00
Pool	658.00	1796.00	1942.00	595.00
FireplacesNumber	0.35	0.63	0.82	1.33
Basement	271.00	171.00	96.00	29.00
Floor	2934.00	7690.00	5346.00	835.00
Q1	1731.00	2180.00	1254.00	181.00
Q2	1880.00	2965.00	1666.00	277.00
Q3	1738.00	2896.00	1696.00	212.00
Q4	1830.00	2865.00	1516.00	233.00
Y2008	606.00	1681.00	1547.00	243.00
Y2009	1948.00	2160.00	1342.00	167.00
Y2010	1359.00	2233.00	1187.00	170.00
Y2011	1780.00	2395.00	957.00	138.00

Table B.13 – *Continued*

Y2012	1486.00	2437.00	1099.00	185.00
Longitude	-119.68	-119.37	-116.83	-119.79
Latitude	36.73	36.66	35.91	36.85
Latitudesq	1350.37	1348.49	1322.21	1358.27
Longitudesq	14336.39	14299.54	13993.93	14348.59
Zip93737	0.00	42.00	57.00	3.00
Zip93723	6.00	155.00	282.00	24.00
Zip93721	47.00	10.00	0.00	0.00
Zip92727	0.00	49.00	0.00	0.00
Zip93701	235.00	26.00	0.00	0.00
Zip93702	1141.00	164.00	8.00	1.00
Zip93703	899.00	404.00	4.00	0.00
Zip93704	397.00	575.00	322.00	44.00
Zip93705	881.00	709.00	35.00	0.00
Zip93706	654.00	147.00	39.00	0.00
Zip93710	71.00	779.00	179.00	0.00
Zip93711	46.00	484.00	842.00	228.00
Zip93720	22.00	609.00	1607.00	192.00
Zip93725	325.00	416.00	41.00	3.00
Zip93726	713.00	921.00	23.00	0.00
Zip93727	616.00	1955.00	1230.00	41.00
Zip93728	513.00	227.00	26.00	3.00
Zip93730	0.00	63.00	423.00	306.00

Table B-14 Three-Stage Least Squares Estimation of the Log of Selling Price for Submarkets

VARIABLES	(1) Lower (<100K)	(2) Medium (100-200K)	(3) Medium (200-400K)	(4) Higher (>400K)
Foreclosure	-0.0463***	-0.0977***	-0.104***	-0.169***
	(0.00709)	(0.00301)	(0.00384)	(0.0191)
Shortsale	-0.0239**	-0.0916***	-0.0940***	-0.146***
	(0.00969)	(0.00391)	(0.00456)	(0.0206)
LSqft	0.373***	0.496***	0.581***	0.893***
	(0.0154)	(0.00822)	(0.0103)	(0.0425)
Age	-0.00218***	-0.00930***	-0.00506***	-0.0105***
	(0.000641)	(0.000244)	(0.000323)	(0.00149)
Agesq	7.14e-07	9.09e-05***	7.14e-05***	0.000132***
	(5.87e-06)	(3.38e-06)	(5.05e-06)	(2.43e-05)
Bathrooms	0.0392***	0.0126***	0.0185***	0.0435***
	(0.00749)	(0.00441)	(0.00410)	(0.0116)
Bedrooms	0.0462***	-0.0219***	-0.0208***	-0.0888***
	(0.00453)	(0.00241)	(0.00270)	(0.0102)
CarportSpaces	-0.0788***	-0.00571	0.00166	0.0551
	(0.00885)	(0.00697)	(0.00895)	(0.0346)
Cash	-0.174***	-0.0729***	-0.0247***	0.0569***
	(0.00699)	(0.00377)	(0.00476)	(0.0166)
FHA	0.113***	0.00838***	-0.0176***	-0.136***
	(0.00893)	(0.00288)	(0.00339)	(0.0427)
VA	0.0603	0.0409***	-0.0121	-0.0591
	(0.0506)	(0.00799)	(0.00753)	(0.0789)
Private	-0.0747***	0.0160	0.00637	0.0476
	(0.0195)	(0.0104)	(0.0127)	(0.0538)
Stories	0.101***	0.0383***	0.0592***	0.0932***
	(0.0122)	(0.00468)	(0.00402)	(0.0140)
GarageSpaces	0.0371***	0.0115***	0.00743***	0.0137**
	(0.00337)	(0.00158)	(0.00160)	(0.00544)
Vacant	-0.00785	-0.0281***	-0.0295***	-0.0569***
	(0.00919)	(0.00362)	(0.00360)	(0.0141)
Pool	-0.0823***	0.0304***	0.0548***	0.0292**
	(0.00975)	(0.00350)	(0.00354)	(0.0139)
Fireplaces_number	0.0536***	0.0101***	0.00166	0.0144**
	(0.00565)	(0.00243)	(0.00238)	(0.00709)
Basement	0.0446***	0.00886	0.0150	-0.0567
	(0.0143)	(0.0110)	(0.0142)	(0.0441)
Floor	-0.00969	-0.0193***	0.0193***	-0.0881***
	(0.00659)	(0.00390)	(0.00591)	(0.0294)
Q1	0.0276***	0.0305***	0.0251***	0.0327*
	(0.00764)	(0.00367)	(0.00432)	(0.0176)
Q2	0.0259***	0.0241***	0.0194***	0.0229
	(0.00740)	(0.00335)	(0.00400)	(0.0157)
Q3	0.0202***	0.0140***	0.00616	0.0155
	(0.00742)	(0.00336)	(0.00398)	(0.0169)
Y2009	-0.150***	-0.120***	-0.0774***	-0.0813***
	(0.0107)	(0.00431)	(0.00432)	(0.0180)

Table B.14 – *Continued*

Y2010	-0.110***	-0.130***	-0.0996***	-0.0610***
	(0.0112)	(0.00438)	(0.00456)	(0.0185)
Y2011	-0.168***	-0.193***	-0.149***	-0.113***
	(0.0111)	(0.00450)	(0.00498)	(0.0195)
Y2012	-0.146***	-0.180***	-0.141***	-0.117***
	(0.0117)	(0.00454)	(0.00491)	(0.0183)
Longitude	-0.597***	-0.00435	-0.221***	2.831***
	(0.205)	(0.0800)	(0.0603)	(0.501)
Latitudesq	0.0162***	0.0163***	0.00582***	0.0486***
	(0.00272)	(0.000818)	(0.000604)	(0.00702)
Longitudesq	-0.00652***	-0.00158**	-0.00240***	0.0195***
	(0.00165)	(0.000660)	(0.000528)	(0.00392)
Zip93737		0.0535**	0.0392*	0.823***
		(0.0265)	(0.0208)	(0.164)
Zip93723	0.106	0.0472***	0.0654***	-0.0272
	(0.0908)	(0.0108)	(0.00784)	(0.0467)
Zip93721	-0.208***	-0.128***		
	(0.0395)	(0.0413)		
Zip93701	-0.311***	-0.238***		
	(0.0263)	(0.0268)		
Zip93702	-0.219***	-0.174***	-0.103**	0.377*
	(0.0273)	(0.0149)	(0.0418)	(0.197)
Zip93703	-0.131***	-0.118***	-0.102*	
	(0.0244)	(0.0125)	(0.0571)	
Zip93704	-0.0218	0.0496***	0.0588***	0.307***
	(0.0203)	(0.00933)	(0.0111)	(0.0651)
Zip93705	-0.0345**	-0.0392***	-0.0147	
	(0.0148)	(0.00749)	(0.0204)	
Zip93706	-0.317***	0.0287**	0.0850***	
	(0.0232)	(0.0134)	(0.0191)	
Zip93710	-0.00654	0.0307***	-0.0412***	
	(0.0335)	(0.0112)	(0.0139)	
Zip93711	0.0837**	0.0725***	0.0920***	0.184***
	(0.0347)	(0.00725)	(0.00742)	(0.0372)
Zip93720	-0.322***	0.123***	0.0788***	0.0953
	(0.0536)	(0.0120)	(0.0114)	(0.0636)
Zip93725	-0.212***	-0.0241*	0.00838	1.149***
	(0.0330)	(0.0144)	(0.0198)	(0.171)
Zip93726	-0.0639***	-0.0629***	-0.117***	
	(0.0237)	(0.0110)	(0.0255)	
Zip93727	-0.142***	0.00851	-0.0462***	0.559***
	(0.0331)	(0.0151)	(0.0127)	(0.115)
Zip93728	-0.0402**	-0.0317**	-0.101***	-0.0460
	(0.0198)	(0.0123)	(0.0257)	(0.130)
Zip93730		0.157***	0.141***	0.165***
		(0.0196)	(0.0124)	(0.0634)
Constant	8.613***	8.568***	8.086***	
	(0.140)	(0.0599)	(0.0709)	
Observations	7,179	10,857	6,132	903
R-squared	0.569	0.572	0.597	0.659

Table B-15 Three-Stage Least Squares Estimation of the Log of Selling Price for Submarkets

(with yearly foreclosure and shortsales variables)

VARIABLES	(1) Lower (<100K)	(2) Medium (100-200K)	(3) Medium (200-400K)	(4) Higher (>400K)
Foreclosure2008	-0.0589**	-0.104***	-0.0946***	-0.138***
	(0.0239)	(0.00700)	(0.00632)	(0.0325)
Foreclosure2009	-0.0415***	-0.134***	-0.113***	-0.177***
	(0.0146)	(0.00643)	(0.00698)	(0.0357)
Foreclosure2010	-0.0617***	-0.0832***	-0.129***	-0.219***
	(0.0148)	(0.00605)	(0.00782)	(0.0417)
Foreclosure2011	-0.0491***	-0.0792***	-0.0974***	-0.195***
	(0.0128)	(0.00590)	(0.00931)	(0.0479)
Foreclosure2012	-0.0251*	-0.0898***	-0.0753***	-0.137***
	(0.0142)	(0.00633)	(0.00970)	(0.0423)
Shortsale2008	-0.0579	-0.0456***	-0.0581***	-0.172***
	(0.0755)	(0.0135)	(0.0119)	(0.0494)
Shortsale2009	0.0203	-0.101***	-0.101***	-0.138***
	(0.0233)	(0.00889)	(0.00998)	(0.0507)
Shortsale2010	-0.0310	-0.0698***	-0.101***	-0.172***
	(0.0197)	(0.00788)	(0.00932)	(0.0389)
Shortsale2011	-0.0384**	-0.0872***	-0.0912***	-0.157***
	(0.0164)	(0.00731)	(0.0102)	(0.0485)
Shortsale2012	-0.0191	-0.111***	-0.107***	-0.104**
	(0.0160)	(0.00650)	(0.00893)	(0.0407)
LSqft	0.373***	0.497***	0.582***	0.900***
	(0.0154)	(0.00819)	(0.0102)	(0.0426)
Age	-0.00219***	-0.00926***	-0.00508***	-0.0106***
	(0.000641)	(0.000243)	(0.000322)	(0.00150)
Agesq	7.37e-07	9.03e-05***	7.21e-05***	0.000134***
	(5.88e-06)	(3.37e-06)	(5.04e-06)	(2.44e-05)
Bathrooms	0.0392***	0.0123***	0.0190***	0.0433***
	(0.00749)	(0.00439)	(0.00409)	(0.0117)
Bedrooms	0.0460***	-0.0219***	-0.0211***	-0.0891***
	(0.00453)	(0.00240)	(0.00269)	(0.0102)
CarportSpaces	-0.0779***	-0.00529	0.00213	0.0575*
	(0.00887)	(0.00695)	(0.00893)	(0.0345)
Cash	-0.174***	-0.0723***	-0.0249***	0.0582***
	(0.00699)	(0.00376)	(0.00475)	(0.0166)
FHA	0.112***	0.00821***	-0.0184***	-0.134***
	(0.00894)	(0.00287)	(0.00339)	(0.0427)
VA	0.0609	0.0399***	-0.0135*	-0.0574
	(0.0506)	(0.00797)	(0.00752)	(0.0787)
Private	-0.0745***	0.0127	0.00680	0.0516
	(0.0195)	(0.0104)	(0.0127)	(0.0538)
Stories	0.101***	0.0378***	0.0583***	0.0957***
	(0.0122)	(0.00466)	(0.00402)	(0.0141)
GarageSpaces	0.0373***	0.0119***	0.00783***	0.0136**
	(0.00337)	(0.00158)	(0.00160)	(0.00543)

Table B.15 – *Continued*

Vacant	-0.00923	-0.0274***	-0.0299***	-0.0575***
	(0.00923)	(0.00361)	(0.00360)	(0.0141)
Pool	-0.0821***	0.0304***	0.0549***	0.0288**
	(0.00976)	(0.00349)	(0.00354)	(0.0139)
Fireplaces_number	0.0537***	0.00968***	0.00163	0.0134*
	(0.00565)	(0.00243)	(0.00238)	(0.00717)
Basement	0.0446***	0.00850	0.0125	-0.0551
	(0.0143)	(0.0110)	(0.0142)	(0.0443)
Floor	-0.0105	-0.0195***	0.0202***	-0.0904***
	(0.00659)	(0.00388)	(0.00589)	(0.0295)
Q1	0.0276***	0.0317***	0.0258***	0.0328*
	(0.00769)	(0.00367)	(0.00433)	(0.0176)
Q2	0.0258***	0.0247***	0.0199***	0.0219
	(0.00744)	(0.00335)	(0.00400)	(0.0157)
Q3	0.0202***	0.0143***	0.00641	0.0128
	(0.00742)	(0.00335)	(0.00397)	(0.0170)
Y2009	-0.168***	-0.0996***	-0.0677***	-0.0776***
	(0.0254)	(0.00782)	(0.00572)	(0.0207)
Y2010	-0.111***	-0.141***	-0.0859***	-0.0479**
	(0.0251)	(0.00736)	(0.00591)	(0.0208)
Y2011	-0.174***	-0.202***	-0.146***	-0.106***
	(0.0244)	(0.00728)	(0.00619)	(0.0219)
Y2012	-0.169***	-0.178***	-0.138***	-0.123***
	(0.0246)	(0.00716)	(0.00595)	(0.0203)
Longitude	-0.600***	-0.00767	-0.214***	2.829***
	(0.205)	(0.0797)	(0.0602)	(0.502)
Latitudesq	0.0162***	0.0162***	0.00570***	0.0493***
	(0.00272)	(0.000815)	(0.000602)	(0.00702)
Longitudesq	-0.00653***	-0.00159**	-0.00233***	0.0194***
	(0.00165)	(0.000658)	(0.000527)	(0.00393)
Zip93737		0.0538**	0.0428**	0.831***
		(0.0264)	(0.0208)	(0.164)
Zip93723	0.108	0.0474***	0.0660***	-0.0265
	(0.0907)	(0.0107)	(0.00782)	(0.0471)
Zip93721	-0.207***	-0.128***		
	(0.0395)	(0.0412)		
Zip93701	-0.311***	-0.240***		
	(0.0263)	(0.0267)		
Zip93702	-0.218***	-0.172***	-0.103**	0.348*
	(0.0273)	(0.0149)	(0.0417)	(0.198)
Zip93703	-0.131***	-0.118***	-0.0950*	
	(0.0244)	(0.0125)	(0.0570)	
Zip93704	-0.0216	0.0488***	0.0592***	0.302***
	(0.0203)	(0.00930)	(0.0111)	(0.0654)
Zip93705	-0.0342**	-0.0406***	-0.0164	
	(0.0148)	(0.00747)	(0.0204)	
Zip93706	-0.316***	0.0290**	0.0860***	
	(0.0232)	(0.0133)	(0.0190)	
Zip93710	-0.00607	0.0301***	-0.0399***	
	(0.0335)	(0.0112)	(0.0139)	
Zip93711	0.0833**	0.0713***	0.0926***	0.181***
	(0.0347)	(0.00722)	(0.00740)	(0.0374)

Table B.15 – *Continued*

Zip93720	-0.319***	0.122***	0.0807***	0.0899
	(0.0537)	(0.0120)	(0.0113)	(0.0639)
Zip93725	-0.211***	-0.0240*	0.0105	1.153***
	(0.0330)	(0.0144)	(0.0198)	(0.171)
Zip93726	-0.0634***	-0.0632***	-0.115***	
	(0.0237)	(0.0110)	(0.0254)	
Zip93727	-0.141***	0.00801	-0.0452***	0.554***
	(0.0331)	(0.0151)	(0.0126)	(0.115)
Zip93728	-0.0399**	-0.0327***	-0.0985***	-0.0449
	(0.0198)	(0.0123)	(0.0257)	(0.130)
Zip93730		0.156***	0.143***	0.158**
		(0.0195)	(0.0124)	(0.0637)
Constant	8.622***	8.559***	8.070***	
	(0.141)	(0.0599)	(0.0709)	
Observations	7,179	10,857	6,132	903
R-squared	0.570	0.575	0.600	0.661

Table B-16 Three-Stage Least Squares Estimation of the Log of Selling Price for Submarkets

(with yearly foreclosure, shortsales and cash variables)

VARIABLES	(1) Lower <100K	(2) Medium 100-200K	(3) Medium 200-400K	(4) Higher >400K
Foreclosure2008	-0.0559**	-0.103***	-0.0946***	-0.138***
	(0.0240)	(0.00702)	(0.00632)	(0.0324)
Foreclosure2009	-0.0433***	-0.133***	-0.114***	-0.175***
	(0.0147)	(0.00647)	(0.00700)	(0.0359)
Foreclosure2010	-0.0605***	-0.0826***	-0.129***	-0.225***
	(0.0151)	(0.00607)	(0.00784)	(0.0418)
Foreclosure2011	-0.0474***	-0.0795***	-0.0971***	-0.195***
	(0.0129)	(0.00590)	(0.00931)	(0.0479)
Foreclosure2012	-0.0287**	-0.0915***	-0.0755***	-0.138***
	(0.0144)	(0.00635)	(0.00971)	(0.0424)
Shortsale2008	-0.0550	-0.0456***	-0.0582***	-0.170***
	(0.0755)	(0.0135)	(0.0120)	(0.0494)
Shortsale2009	0.0214	-0.101***	-0.101***	-0.139***
	(0.0233)	(0.00889)	(0.00997)	(0.0507)
Shortsale2010	-0.0310	-0.0698***	-0.101***	-0.172***
	(0.0197)	(0.00787)	(0.00932)	(0.0389)
Shortsale2011	-0.0381**	-0.0872***	-0.0910***	-0.156***
	(0.0164)	(0.00730)	(0.0102)	(0.0484)
Shortsale2012	-0.0203	-0.111***	-0.107***	-0.103**
	(0.0160)	(0.00650)	(0.00893)	(0.0406)
Cash2008	-0.196***	-0.0935***	-0.0200*	0.0290
	(0.0180)	(0.0102)	(0.0107)	(0.0370)
Cash2009	-0.165***	-0.0838***	-0.0196*	0.0394
	(0.0111)	(0.00795)	(0.0102)	(0.0386)
Cash2010	-0.177***	-0.0787***	-0.0235**	0.104***
	(0.0139)	(0.00764)	(0.0102)	(0.0335)
Cash2011	-0.183***	-0.0680***	-0.0426***	0.0637*
	(0.0120)	(0.00712)	(0.0111)	(0.0347)
Cash2012	-0.157***	-0.0541***	-0.0219**	0.0415
	(0.0134)	(0.00661)	(0.00919)	(0.0389)
LSqft	0.374***	0.497***	0.583***	0.899***
	(0.0154)	(0.00819)	(0.0102)	(0.0426)
Age	-0.00219***	-0.00927***	-0.00509***	-0.0104***
	(0.000641)	(0.000243)	(0.000322)	(0.00151)
Agesq	6.93e-07	9.04e-05***	7.21e-05***	0.000131***
	(5.87e-06)	(3.37e-06)	(5.04e-06)	(2.44e-05)
Bathrooms	0.0391***	0.0120***	0.0189***	0.0426***
	(0.00749)	(0.00439)	(0.00409)	(0.0117)
Bedrooms	0.0460***	-0.0218***	-0.0211***	-0.0891***
	(0.00453)	(0.00240)	(0.00269)	(0.0103)
CarportSpaces	-0.0785***	-0.00555	0.00211	0.0587*
	(0.00888)	(0.00695)	(0.00892)	(0.0346)
FHA	0.113***	0.00879***	-0.0185***	-0.131***
	(0.00904)	(0.00288)	(0.00340)	(0.0427)

Table B.16 – *Continued*

VA	0.0617	0.0409***	-0.0137*	-0.0563
	(0.0506)	(0.00797)	(0.00752)	(0.0786)
Private	-0.0729***	0.0143	0.00673	0.0517
	(0.0196)	(0.0104)	(0.0127)	(0.0537)
Stories	0.100***	0.0376***	0.0584***	0.0947***
	(0.0122)	(0.00466)	(0.00402)	(0.0141)
GarageSpaces	0.0373***	0.0118***	0.00783***	0.0143***
	(0.00337)	(0.00158)	(0.00160)	(0.00545)
Vacant	-0.00884	-0.0273***	-0.0299***	-0.0570***
	(0.00923)	(0.00361)	(0.00360)	(0.0142)
Pool	-0.0827***	0.0304***	0.0550***	0.0282**
	(0.00976)	(0.00348)	(0.00354)	(0.0140)
Fireplaces_number	0.0539***	0.00957***	0.00169	0.0135*
	(0.00565)	(0.00242)	(0.00238)	(0.00716)
Basement	0.0444***	0.00879	0.0127	-0.0570
	(0.0143)	(0.0109)	(0.0142)	(0.0443)
Floor	-0.0106	-0.0197***	0.0203***	-0.0902***
	(0.00659)	(0.00388)	(0.00589)	(0.0294)
Q1	0.0282***	0.0319***	0.0259***	0.0319*
	(0.00770)	(0.00367)	(0.00433)	(0.0177)
Q2	0.0264***	0.0250***	0.0200***	0.0218
	(0.00744)	(0.00334)	(0.00400)	(0.0157)
Q3	0.0206***	0.0145***	0.00645	0.0136
	(0.00742)	(0.00335)	(0.00397)	(0.0170)
Y2009	-0.182***	-0.100***	-0.0677***	-0.0778***
	(0.0270)	(0.00788)	(0.00583)	(0.0217)
Y2010	-0.119***	-0.142***	-0.0857***	-0.0591***
	(0.0270)	(0.00745)	(0.00606)	(0.0219)
Y2011	-0.179***	-0.205***	-0.143***	-0.110***
	(0.0263)	(0.00738)	(0.00637)	(0.0236)
Y2012	-0.188***	-0.183***	-0.138***	-0.124***
	(0.0268)	(0.00727)	(0.00618)	(0.0213)
Longitude	-0.597***	-0.00865	-0.215***	2.773***
	(0.205)	(0.0797)	(0.0602)	(0.503)
Latitudesq	0.0162***	0.0163***	0.00569***	0.0486***
	(0.00272)	(0.000814)	(0.000602)	(0.00703)
Longitudesq	-0.00651***	-0.00161**	-0.00234***	0.0190***
	(0.00165)	(0.000657)	(0.000527)	(0.00394)
Zip93737		0.0531**	0.0427**	0.810***
		(0.0264)	(0.0208)	(0.165)
Zip93723	0.109	0.0482***	0.0656***	-0.0300
	(0.0907)	(0.0107)	(0.00783)	(0.0471)
Zip93721	-0.206***	-0.131***		
	(0.0395)	(0.0411)		
Zip93701	-0.311***	-0.240***		
	(0.0263)	(0.0266)		
Zip93702	-0.218***	-0.174***	-0.103**	0.337*
	(0.0273)	(0.0149)	(0.0417)	(0.197)
Zip93703	-0.131***	-0.118***	-0.0948*	
	(0.0244)	(0.0125)	(0.0570)	
Zip93704	-0.0211	0.0483***	0.0587***	0.300***
	(0.0203)	(0.00929)	(0.0111)	(0.0655)

Table B.16 – *Continued*

Zip93705	-0.0341**	-0.0407***	-0.0164	
	(0.0148)	(0.00746)	(0.0204)	
Zip93706	-0.315***	0.0285**	0.0858***	
	(0.0232)	(0.0133)	(0.0190)	
Zip93710	-0.00556	0.0300***	-0.0400***	
	(0.0335)	(0.0112)	(0.0139)	
Zip93711	0.0834**	0.0711***	0.0924***	0.177***
	(0.0347)	(0.00722)	(0.00740)	(0.0375)
Zip93720	-0.318***	0.121***	0.0805***	0.0837
	(0.0537)	(0.0120)	(0.0113)	(0.0640)
Zip93725	-0.211***	-0.0243*	0.0108	1.128***
	(0.0330)	(0.0143)	(0.0198)	(0.172)
Zip93726	-0.0633***	-0.0634***	-0.115***	
	(0.0237)	(0.0110)	(0.0254)	
Zip93727	-0.141***	0.00759	-0.0455***	0.538***
	(0.0331)	(0.0151)	(0.0126)	(0.116)
Zip93728	-0.0401**	-0.0335***	-0.0991***	-0.0477
	(0.0198)	(0.0123)	(0.0257)	(0.130)
Zip93730		0.156***	0.143***	0.154**
		(0.0195)	(0.0124)	(0.0637)
Constant	8.633***	8.558***	8.066***	
	(0.141)	(0.0599)	(0.0709)	
Observations	7,179	10,857	6,132	903
R-squared	0.570	0.576	0.600	0.662

Table B-17 Three-Stage Least Squares Estimation of the Log of Selling Price for Submarkets with TOM interaction with Foreclosure and Shortsale (with yearly foreclosure and shortsales variables)

VARIABLES	(1) All	(2) Lower <100K	(3) Medium 100-200K	(4) Medium 200-400K	(5) Higher >400K
Foreclosure2008	-0.116***	-0.0478**	-0.0843***	-0.0782***	-0.126***
	(0.00783)	(0.0243)	(0.00737)	(0.00697)	(0.0375)
Foreclosure2009	-0.177***	-0.0300**	-0.121***	-0.100***	-0.164***
	(0.00714)	(0.0149)	(0.00661)	(0.00733)	(0.0401)
Foreclosure2010	-0.146***	-0.0553***	-0.0717***	-0.116***	-0.211***
	(0.00727)	(0.0149)	(0.00620)	(0.00814)	(0.0436)
Foreclosure2011	-0.133***	-0.0414***	-0.0645***	-0.0842***	-0.187***
	(0.00717)	(0.0130)	(0.00616)	(0.00960)	(0.0496)
Foreclosure2012	-0.135***	-0.0190	-0.0794***	-0.0626***	-0.132***
	(0.00757)	(0.0143)	(0.00645)	(0.00999)	(0.0435)
Shortsale2008	-0.0734***	-0.0672	-0.0462***	-0.0470***	-0.214***
	(0.0162)	(0.0760)	(0.0140)	(0.0127)	(0.0580)
Shortsale2009	-0.134***	0.00612	-0.104***	-0.0900***	-0.176***
	(0.0116)	(0.0251)	(0.00971)	(0.0114)	(0.0575)
Shortsale2010	-0.133***	-0.0472**	-0.0730***	-0.0917***	-0.212***
	(0.0103)	(0.0216)	(0.00867)	(0.0104)	(0.0482)
Shortsale2011	-0.142***	-0.0492***	-0.0892***	-0.0824***	-0.178***
	(0.00943)	(0.0177)	(0.00796)	(0.0110)	(0.0507)
Shortsale2012	-0.165***	-0.0283*	-0.113***	-0.101***	-0.126***
	(0.00843)	(0.0170)	(0.00700)	(0.00949)	(0.0435)
Cash	-0.201***	-0.174***	-0.0725***	-0.0252***	0.0579***
	(0.00392)	(0.00699)	(0.00375)	(0.00474)	(0.0167)
ForeclosureTOM	-0.000462***	-0.000153***	-0.000281***	-0.000270***	-0.000227
	(3.87e-05)	(5.68e-05)	(3.56e-05)	(5.27e-05)	(0.000325)
ShortsaleTOM	-8.80e-05***	7.05e-05	-1.40e-05	-8.94e-05**	0.000268
	(3.38e-05)	(6.46e-05)	(2.79e-05)	(3.56e-05)	(0.000189)
LSqft	0.877***	0.374***	0.499***	0.585***	0.901***
	(0.00810)	(0.0154)	(0.00819)	(0.0102)	(0.0426)
Age	-0.00867***	-0.00217***	-0.00926***	-0.00503***	-0.0103***
	(0.000248)	(0.000641)	(0.000243)	(0.000321)	(0.00151)
Agesq	6.12e-05***	5.98e-07	9.04e-05***	7.14e-05***	0.000130***
	(2.96e-06)	(5.87e-06)	(3.36e-06)	(5.03e-06)	(2.44e-05)
Bathrooms	0.0745***	0.0391***	0.0123***	0.0186***	0.0433***
	(0.00411)	(0.00749)	(0.00438)	(0.00408)	(0.0116)
Bedrooms	-0.0199***	0.0460***	-0.0221***	-0.0212***	-0.0892***
	(0.00258)	(0.00453)	(0.00240)	(0.00268)	(0.0102)
CarportSpaces	-0.0738***	-0.0778***	-0.00543	0.00187	0.0568*
	(0.00644)	(0.00887)	(0.00694)	(0.00891)	(0.0345)
FHA	0.0245***	0.112***	0.00840***	-0.0180***	-0.133***
	(0.00359)	(0.00894)	(0.00286)	(0.00338)	(0.0427)
VA	0.0323***	0.0641	0.0408***	-0.0130*	-0.0587
	(0.00984)	(0.0506)	(0.00795)	(0.00751)	(0.0786)

Table B.17 – *Continued*

Private	-0.0471***	-0.0745***	0.0123	0.00944	0.0538
	(0.0115)	(0.0195)	(0.0104)	(0.0127)	(0.0538)
Stories	0.124***	0.102***	0.0373***	0.0575***	0.0947***
	(0.00466)	(0.0122)	(0.00465)	(0.00401)	(0.0141)
GarageSpaces	0.0336***	0.0372***	0.0116***	0.00760***	0.0136**
	(0.00170)	(0.00337)	(0.00158)	(0.00159)	(0.00542)
Vacant	-0.0582***	-0.0113	-0.0281***	-0.0299***	-0.0576***
	(0.00402)	(0.00924)	(0.00362)	(0.00360)	(0.0141)
Pool	0.0400***	-0.0817***	0.0309***	0.0549***	0.0267*
	(0.00394)	(0.00977)	(0.00348)	(0.00353)	(0.0140)
Fireplaces_number	0.0390***	0.0539***	0.00953***	0.00161	0.0136*
	(0.00261)	(0.00565)	(0.00242)	(0.00237)	(0.00717)
Basement	0.0818***	0.0447***	0.00941	0.0129	-0.0555
	(0.0102)	(0.0143)	(0.0109)	(0.0142)	(0.0443)
Floor	-0.0116***	-0.0110*	-0.0195***	0.0198***	-0.0914***
	(0.00431)	(0.00659)	(0.00387)	(0.00588)	(0.0295)
Q1	0.0435***	0.0279***	0.0326***	0.0264***	0.0339*
	(0.00418)	(0.00771)	(0.00367)	(0.00432)	(0.0177)
Q2	0.0365***	0.0258***	0.0255***	0.0205***	0.0233
	(0.00389)	(0.00744)	(0.00334)	(0.00400)	(0.0157)
Q3	0.0163***	0.0202***	0.0144***	0.00650	0.0151
	(0.00390)	(0.00742)	(0.00334)	(0.00396)	(0.0171)
Y2009	-0.162***	-0.171***	-0.0991***	-0.0672***	-0.0774***
	(0.00765)	(0.0254)	(0.00780)	(0.00570)	(0.0207)
Y2010	-0.173***	-0.110***	-0.140***	-0.0853***	-0.0480**
	(0.00746)	(0.0250)	(0.00734)	(0.00590)	(0.0208)
Y2011	-0.276***	-0.175***	-0.202***	-0.145***	-0.106***
	(0.00737)	(0.0244)	(0.00727)	(0.00618)	(0.0219)
Y2012	-0.251***	-0.169***	-0.178***	-0.137***	-0.123***
	(0.00722)	(0.0246)	(0.00714)	(0.00594)	(0.0203)
Longitude	-0.451***	-0.606***	-0.00834	-0.216***	2.806***
	(0.0752)	(0.205)	(0.0796)	(0.0601)	(0.501)
Latitudesq	0.0133***	0.0162***	0.0164***	0.00571***	0.0494***
	(0.000789)	(0.00272)	(0.000813)	(0.000601)	(0.00701)
Longitudesq	-0.00502***	-0.00659***	-0.00162**	-0.00234***	0.0192***
	(0.000640)	(0.00165)	(0.000656)	(0.000526)	(0.00393)
Zip93737	0.0287		0.0526**	0.0424**	0.821***
	(0.0279)		(0.0263)	(0.0207)	(0.164)
Zip93723	0.105***	0.110	0.0486***	0.0651***	-0.0272
	(0.0111)	(0.0907)	(0.0107)	(0.00781)	(0.0471)
Zip93721	-0.332***	-0.207***	-0.130***		
	(0.0309)	(0.0395)	(0.0411)		
Zip93701	-0.470***	-0.311***	-0.245***		
	(0.0175)	(0.0263)	(0.0266)		
Zip93702	-0.304***	-0.219***	-0.173***	-0.102**	0.331*
	(0.0129)	(0.0273)	(0.0148)	(0.0416)	(0.198)
Zip93703	-0.195***	-0.131***	-0.118***	-0.0950*	
	(0.0123)	(0.0244)	(0.0125)	(0.0569)	
Zip93704	0.0918***	-0.0216	0.0493***	0.0594***	0.301***
	(0.0102)	(0.0203)	(0.00927)	(0.0111)	(0.0653)
Zip93705	-0.0753***	-0.0342**	-0.0397***	-0.0181	
	(0.00836)	(0.0148)	(0.00745)	(0.0204)	

Table B.17 – *Continued*

Zip93706	-0.329***	-0.316***	0.0289**	0.0863***	
	(0.0110)	(0.0232)	(0.0133)	(0.0190)	
Zip93710	0.0103	-0.00550	0.0298***	-0.0400***	
	(0.0130)	(0.0335)	(0.0112)	(0.0139)	
Zip93711	0.200***	0.0839**	0.0730***	0.0929***	0.178***
	(0.00809)	(0.0347)	(0.00721)	(0.00739)	(0.0374)
Zip93720	0.124***	-0.319***	0.122***	0.0810***	0.0839
	(0.0128)	(0.0537)	(0.0120)	(0.0113)	(0.0639)
Zip93725	-0.182***	-0.213***	-0.0232	0.0103	1.161***
	(0.0140)	(0.0330)	(0.0143)	(0.0198)	(0.171)
Zip93726	-0.111***	-0.0644***	-0.0637***	-0.116***	
	(0.0118)	(0.0237)	(0.0110)	(0.0254)	
Zip93727	-0.0954***	-0.142***	0.00798	-0.0456***	0.549***
	(0.0146)	(0.0331)	(0.0150)	(0.0126)	(0.115)
Zip93728	-0.101***	-0.0403**	-0.0333***	-0.0981***	-0.0446
	(0.0118)	(0.0198)	(0.0123)	(0.0256)	(0.130)
Zip93730	0.230***		0.156***	0.144***	0.153**
	(0.0149)		(0.0195)	(0.0123)	(0.0637)
Constant	5.672***	8.617***	8.547***	8.054***	
	(0.0569)	(0.141)	(0.0599)	(0.0708)	
Observations	25,071	7,179	10,857	6,132	903
R-squared	0.877	0.571	0.577	0.601	0.662

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Appendix C

Tables for Chapter 4: Information Symmetry, Credit Ratings and REIT Returns

Table C-1 Descriptive statistics for REIT senior unsecured and long-term debt rating actions by year

Rating Changes	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Total
Remove	0	1	2	1	5	0	2	6	7	5	4	3	3	2	41
Affirm	20	52	66	46	46	65	108	28	34	56	74	65	67	23	750
Initiate	2	16	7	7	9	12	11	5	2	5	4	14	7	7	108
Upgrade	6	7	2	7	9	8	14	13	0	3	10	14	13	8	114
Downgrade	13	14	16	9	2	3	8	8	51	40	20	9	11	4	208
Total	41	90	93	70	71	88	143	60	94	109	112	105	101	44	1221

Table C-2 Descriptive statistics for REIT senior unsecured and long-term debt upgrades and downgrades by year and rating agency

Upgrades														
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Total
S&P	3	4	2	3	5	2	3	2	0	1	3	6	2	3	39
Moody's	1	3	0	4	4	6	9	7	0	2	6	5	10	4	61
Fitch	2	0	0	0	0	0	2	0	0	0	0	3	0	1	8
DBRS	0	0	0	0	0	0	0	4	0	0	1	0	1	0	6
Total	6	7	2	7	9	8	14	13	0	3	10	14	13	8	114
Downgrades															
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Total
S&P	10	10	8	3	2	1	3	3	24	15	9	7	4	1	100
Moody's	3	4	7	5	0	1	5	5	18	16	3	2	5	2	76
Fitch	0	0	1	1	0	1	0	0	9	9	8	0	2	1	32
DBRS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	13	14	16	9	2	3	8	8	51	40	20	9	11	4	208

Table C-3 Variable Descriptions

VARIABLES	DESCRIPTION
CAAR	Cumulative average abnormal return for the window (-1,+1)
MarketReturn	Average value weighted return for the past 6 months
Downgrade	Dummy variable equal to 1 if a downgrade
Upgrade	Dummy variable equal to 1 if an upgrade
Sellpct	Percentage of SELL recommendations made by analysts
Buypct	Percentage of BUY recommendations made by analysts
NPR	Net purchase ratio calculated as (Insider Purchase-Insider Sale)/(Insider Purchase+ Insider Sale) between 90 and 10 days prior to credit rating announcements
DowngradeNPR	Net purchase Ratio for downgrades calculated as Downgrade*NPR
UpgradeNPR	Net purchase Ratio for upgrades calculated as Upgrade*NPR
BidAskSpread	Average bid ask spread calculated as 2*(Ask price-Bid price)/(Ask price+ Bid price) in the last fiscal quarter
Analyst	Number of analyst recommendations in the last fiscal quarter
Stdev	Standard deviation of analyst recommendations in the last fiscal quarter
LTA	Natural logarithm of total assets in the last fiscal quarter
DE	Debt equity ratio calculated as the ratio of long term debt to total equity in the last fiscal quarter
VOL	Average trading volume in the last fiscal quarter
NI	Net Income scaled by total assets in the last fiscal quarter

Table C.3 – *Continued*

SIZE	Market Capitalization in the last fiscal quarter
DowngradeCrisis	Dummy variable equal to 1 if a downgrade during the liquidity crisis
UpgradeCrisis	Dummy variable equal to 1 if an upgrade during the liquidity crisis
DMC	Average value weighted return for the past 6 months for a downgraded firm before liquidity crisis
UMC	Average value weighted return for the past 6 months for an upgraded firm during liquidity crisis
BoardSize	Number of Board members
BoardTenure	Average number of years of tenure for the board members
BoardIndependence	Number of independent board members scaled by number of total board members
BoardBusyness	Number of other outside boards that the members serve in
CEODuality	Dummy variable equals one if CEO is not the Board Chairman
BoardSizeDummy	Dummy variable equals one if BoardSize is above median BoardSize value.
BoardTenureDummy	Dummy variable equals one if BoardTenure is above median BoardTenure value.
BoardIndependenceDummy	Dummy variable equals one if BoardIndependence is above median BoardIndependence value.
BoardBusynessDummy	Dummy variable equals one if BoardBusyness is below median BoardBusyness value.
GovernanceIndex	Index variable that is the sum of the above 5 governance dummy variables and this index takes a value between 0 and 5.
Governance	Dummy variable equals one if GovernanceIndex is above median GovernanceIndex value.

Table C-4 Descriptive Statistics

VARIABLES	N	Mean	Std. Dev
CAAR	200	0.37	1.70
MarketReturn	200	0.00	0.06
Downgrade	200	0.64	0.48
Upgrade	200	0.36	0.48
Sellpct	200	10.81	15.28
Buypct	200	39.58	26.82
NPR	74	0.08	0.67
DowngradeNPR	74	-0.04	0.31
UpgradeNPR	74	0.11	0.58
BidAskSpread	74	0.41	3.11
Analyst	200	11.29	5.82
Stdev	200	0.80	0.28
LTA	200	8.12	1.02
DE	200	0.64	0.18
VOL	200	334597	465760
NI	200	15.17	149.70
SIZE	200	3419013	4478380
DowngradeCrisis	200	0.41	0.49
UpgradeCrisis	200	0.17	0.38
DMC	200	-7.75E-06	0.02
UMC	200	0.00	0.04
BoardSize	50	9.78	1.58
BoardTenure	50	12.43	4.58
BoardIndependence	50	13.53	5.09
BoardBusyness	50	623.10	112.24
CEODuality	50	0.32	0.47
BoardSizeDummy	50	0.54	0.50
BoardTenureDummy	50	0.32	0.47
BoardIndependenceDummy	50	0.46	0.50
BoardBusynessDummy	50	0.72	0.45
GovernanceIndex	50	2.36	0.96
Governance	50	0.46	0.50

Table C-5 Market model mean abnormal return and precision weighted cumulative average abnormal return (CAAR) for credit rating upgrade changes

This table presents the market model cumulative average abnormal return for a sample of REIT rating actions from 2000 through 2013 in the first panel and 2000 to 2007 in the second panel and 2007-2013 in the third panel. Parameters for the market model are estimated using CRSP daily REIT prices, and the estimation period associated with the event is (-46,-255). The CRSP value-weighted index is included as the market proxy. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively, for a two-tailed Patell test. The symbols $, $$, $$$ indicate significance at 10%, 5%, and 1% levels, respectively for the Rank test. The symbols &, &&, &&& indicate significance at 10%, 5%, and 1% levels, respectively for the generalized sign test

Market Adjusted Returns, Value Weighted Index						
	Window	CAR	Rank	Precision Weighted CAAR	% of Positive	Generalized Sign Test
2000-2013	(-20,-10)	0.0177	0.277	0.0086	0.61	1.825*
	(-10,-4)	0.0007	-0.072	-0.0004	0.53	0.349
	(-4,0)	0.0021	-0.503	0.0011	0.54	0.559
	(0,+4)	0.0056	-0.232	0.0011	0.47	-0.917
	(+4,+10)	0.0113	0.639	0.0093	0.62	2.036*
	(+10,+20)	0.0014	-0.212	-0.0015	0.48	-0.706
	Window	CAR	Rank	Precision Weighted CAAR	% of Positive	Generalized Sign Test
2000-2006	(-20,-10)	0.0136	0.708	0.0144	0.67	2.251*
	(-10,-4)	-0.0009	0.229	-0.0001	0.51	-0.178
	(-4,0)	0.0058	0.443	0.0043	0.60	1.172
	(0,+4)	0.0069	0.018	0.0016	0.55	0.188
	(+4,+10)	0.0127	0.36	0.0098	0.67	2.251*
	(+10,20)	-0.0024	0.232	-0.0002	0.49	-0.448
	Window	CAR	Rank	Precision Weighted CAAR	% of Positive	Generalized Sign Test
2008-2013	(-20,-10)	0.0765	1.005	0.0683	0.89	2.309*
	(-10,-4)	0.0276*	1.312*	0.0207**	0.89	2.309*
	(-4,0)	0.0002*	1.832**	0.0036*	0.67	0.358
	(0,+4)	0.0269***	1.018	0.0267***	0.67	0.309
	(+4,+10)	0.0204	0.331	0.0154	0.67	0.309
	(+10,+20)	0.0437	0.066	0.0219	0.67	0.309

Table C-6 Market model mean abnormal return and precision weighted cumulative average abnormal return (CAAR) for credit rating downgrade changes

This table presents the market model cumulative average abnormal return for a sample of REIT rating actions from 2000 through 2013 in the first panel and 2000 to 2007 in the second panel and 2007-2013 in the third panel. Parameters for the market model are estimated using CRSP daily REIT prices, and the estimation period associated with the event is (-46,-255). The CRSP value-weighted index is included as the market proxy. *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively, for a two-tailed Patell test. The symbols $, $$, $$$ indicate significance at 10%, 5%, and 1% levels, respectively for the rank test. The symbols &, &&, &&& indicate significance at 10%, 5%, and 1% levels, respectively for the generalized sign test.

Market Adjusted Returns, Value Weighted Index						
	Window	CAR	Rank	Precision Weighted CAAR	% of Negative	Generalized Sign Test
2000-2013	(-20,-10)	0.0058	0.0067	0.0045	0.49	0.748
	(-10,-4)	-0.014***	-0.026**	-0.0092**	0.54	-0.547
	(-4,0)	-0.0177*	-0.0108*	-0.0133**	0.54	-0.547
	(0,+4)	-0.0012	-0.006	-0.0045	0.52	-0.517
	(+4,+10)	0.0165	0.0145	0.0212	0.49	0.666
	(+10,+20)	0.0186	0.0137	0.0193	0.43	2.204*
	Window	CAR	Rank	Precision Weighted CAAR	% of Negative	Generalized Sign Test
2000-2006	(-20,-10)	0.0001	0.011	0.0009	0.51	-0.047
	(-10,-4)	-0.0469**	-2.228*	-0.0454***	0.57	-0.904
	(-4,0)	-0.0462***	-2.003*	-0.0148**	0.53	-0.333
	(0,+4)	-0.0012**	-1.656*	-0.0008**	0.47	-0.524
	(+4,+10)	0.0130	1.056	0.013	0.43	1.096
	(+10,20)	0.0376	1.139	0.0298	0.37	1.953*
	Window	CAR	Rank	Precision Weighted CAAR	% of Negative	Generalized Sign Test
2008-2013	(-20,-10)	0.0121	-0.039	0.0175	0.47	0.749
	(-10,-4)	-0.0028	-0.06	-0.0258	0.57	-0.713
	(-4,0)	-0.0023	-0.931	-0.0088	0.53	-0.295
	(0,+4)	0.0034	-0.409	-0.0077	0.55	-1.037
	(+4,+10)	0.0214	-0.933	0.0176	0.56	-0.618
	(+10,+20)	0.011	-0.132	0.0013	0.48	1.376$

Table C-7 Regressions to examine residual CARs on possible explanatory variables

VARIABLES	(1) All	(2) All	(3) Downgrade	(4) Upgrade
BidAskSpread	0.992**	0.901**	0.827**	-2.690
	(0.433)	(0.379)	(0.387)	(1.782)
Analyst	-0.171	-0.0643	0.0129	-0.390
	(0.307)	(0.267)	(0.345)	(0.316)
Stdev	0.811*	0.903**	1.623***	-0.00566
	(0.460)	(0.401)	(0.547)	(0.462)
LTA	-0.157	-0.0102	-0.262	-0.216
	(0.166)	(0.139)	(0.164)	(0.218)
Sellpct	-0.0218**	-0.0212**	-0.0314***	-0.0266
	(0.0103)	(0.00896)	(0.0107)	(0.0199)
Buypct	0.000482	-0.00460	-0.0108	0.00102
	(0.00532)	(0.00462)	(0.00725)	(0.00451)
DE	0.00414**	0.00316*	0.00337*	0.00165
	(0.00197)	(0.00171)	(0.00173)	(0.0246)
VOL	0.150***	0.162***	0.160***	0.141
	(0.0485)	(0.0421)	(0.0475)	(0.118)
NI	0.217	-0.261	-0.0295	-0.892**
	(0.282)	(0.247)	(0.287)	(0.381)
SIZE	-8.60e-09	-2.81e-08	3.47e-08	1.93e-09
	(3.63e-08)	(3.06e-08)	(4.30e-08)	(3.64e-08)
DMC		-1.622***	-2.342***	
		(0.270)	(0.283)	
UMC		1.137***		2.135***
		(0.282)		(0.235)
Downgrade	0.136			
	(0.274)			
Constant	0.520	-0.00751	1.974	1.688
	(1.324)	(1.148)	(1.380)	(1.669)
Observations	200	200	127	73
R-squared	0.153	0.366	0.474	0.658

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C-8 Information Asymmetry and Insider Trading

VARIABLES	(1) All	(2) All	(3) All	(4) All	(5) All
BidAskSpread	0.851**	0.862**	0.863**	0.575	0.540
	(0.382)	(0.383)	(0.382)	(0.532)	(0.518)
Analyst	-0.106	-0.0960	-0.0892	-0.179	0.00484
	(0.268)	(0.269)	(0.269)	(0.505)	(0.424)
Stdev	0.478	0.485	0.479	-0.153	-0.0861
	(0.361)	(0.362)	(0.362)	(0.493)	(0.481)
LTA	-0.0240	-0.0306	-0.0223	0.314	0.200
	(0.140)	(0.140)	(0.140)	(0.217)	(0.211)
DE	0.00275	0.00277	0.00269	0.0232	0.0312
	(0.00172)	(0.00172)	(0.00172)	(0.0265)	(0.0256)
VOL	0.158***	0.161***	0.157***	0.0784	0.0418
	(0.0419)	(0.0423)	(0.0424)	(0.0589)	(0.0596)
NI	-0.223	-0.199	-0.214	0.0714	0.183
	(0.248)	(0.252)	(0.252)	(0.328)	(0.325)
SIZE	-1.43e-08	-1.46e-08	-1.63e-08	-4.19e-08	-5.21e-08
	(3.04e-08)	(3.04e-08)	(3.04e-08)	(3.52e-08)	(3.45e-08)
DMC	-1.581***	-1.567***	-1.576***	-1.525***	-1.607***
	(0.271)	(0.273)	(0.273)	(0.341)	(0.335)
UMC	1.214***	1.199***	1.176***	1.252***	1.194***
	(0.281)	(0.283)	(0.283)	(0.425)	(0.414)
DowngradeNPR			0.0197	0.186	0.0602
			(0.290)	(0.262)	(0.262)
UpgradeNPR			-0.725**	-0.602	-0.479
			(0.514)	(0.480)	(0.470)
NPR		-0.149			
		(0.257)			
HighAnalyst				-0.381*	
				(0.210)	
HighInfoAssy					0.768**
					(0.375)
Constant	-0.0305	-0.00652	-0.0535	-.0535	-0.0786
	(1.157)	(1.160)	(1.159)	(1.728)	(1.683)
Observations	200	200	200	200	200
R-squared	0.346	0.347	0.353	0.454	0.483

Table C-9 Insider Trading and Corporate Governance

VARIABLES	(1) Allgov	(2) Allgov	(3) Highgov	(4) Highgov
BidAskSpread	0.862	-0.872	0.588	-0.874
	(0.757)	(0.958)	(0.754)	(0.958)
Analyst	-0.0395	-0.00680	-0.0590	-0.0292
	(0.0390)	(0.0385)	(0.0391)	(0.0395)
Stdev	0.526	0.520	-0.0561	-0.0629
	(0.578)	(0.543)	(0.655)	(0.624)
LTA	0.341	0.358	0.218	0.217
	(0.293)	(0.276)	(0.290)	(0.276)
DE	1.153	-0.359	1.583	0.207
	(1.304)	(1.346)	(1.318)	(1.391)
VOL	5.26e-07	4.10e-07	7.06e-07**	5.78e-07*
	(3.38e-07)	(3.20e-07)	(3.32e-07)	(3.21e-07)
NI	0.0959	0.108	0.286	0.265
	(0.314)	(0.295)	(0.315)	(0.300)
SIZE	-7.17e-08	-7.97e-08*	-6.14e-08	-7.50e-08*
	(4.43e-08)	(4.17e-08)	(4.49e-08)	(4.32e-08)
DowngradeNPR	-0.00197	-0.0572	0.233	0.166
	(0.282)	(0.265)	(0.279)	(0.267)
UpgradeNPR	-0.959*	-0.938**	-1.268**	-1.201**
	(0.483)	(0.454)	(0.481)	(0.459)
DMC	-1.655***	-1.655***	-1.712***	-1.719***
	(0.315)	(0.296)	(0.324)	(0.308)
UMC	0.571	0.694	0.692	0.880*
	(0.472)	(0.446)	(0.478)	(0.463)
BoardSizeDummy			-1.200**	-0.883*
			(0.475)	(0.473)
BoardIndependenceDummy			0.623	0.496
			(0.452)	(0.434)
BoardTenureDummy			-1.063**	-0.910*
			(0.521)	(0.501)
BoardBusynessDummy			-1.424***	-1.306***
			(0.462)	(0.443)
CEODuality			-0.612*	-0.449
			(0.362)	(0.352)
Governance	-0.899**	-0.783**		
	(0.400)	(0.379)		
High Info Assy		1.191***		1.034**
		(0.441)		(0.449)
Constant	-2.499	-1.018	0.0561	1.337
	(2.353)	(2.277)	(2.538)	(2.483)
Observations	61	61	61	61
R-squared	0.591	0.647	0.655	0.694

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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