Essays in Corporate Finance:

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ESSAYS IN CORPORATE FINANCE

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A dissertation

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ABSTRACT

The dissertation aims to investigate the role of asymmetric information in capital structure, investment, compensation of mortgage servicers, and bond and equity returns. Specifically, I evaluate the impact of credit ratings on debt issuance and investment of private and public firms, as well as the effect of asymmetric information on compensation of loan servicers in the mortgage backed securities market. Further, I study the relationship between ratings issued by investor and issuer-paid credit rating agencies and equity analyst recommendations. Finally, I evaluate the effect of the aforementioned signals on bond and equity returns as well as firm leverage and investment decisions.

Chapter one in the dissertation is the first study to empirically evaluate the effect of credit ratings on capital structure and investment for private U.S. firms, relative to equivalent public firms. I find that private firms constrain debt issuance and investment by 4.5 and 6.5 percentage points more than public firms, respectively, when their credit ratings are on upgrade or downgrade thresholds. Consistent with these results, private firms that become public through an IPO constrain debt issuance by 10 percentage points before going public, if their ratings are on an upgrade or downgrade boundary.

The second chapter studies the impact of asymmetric information between mortgage sellers and servicers on mortgage servicer compensation. We proxy for asymmetric information using the decision to retain mortgage servicing rights, which creates a principal-agent problem between sellers and servicers. Using loan-level data on Fannie Mae-insured, full documentation mortgages, we first find that loans in which sellers retain servicing rights default and foreclose at a significantly lower rate, and lose less in foreclosure than those in which they are not retained. Since it is more costly to service non-performing loans, these ex-post differences in default rates should be reflected in servicer compensation. However, using Fannie Mae MBS pool-level data, we find no difference in servicing fees for pools in which servicing rights are retained relative to pools in which they are not retained. In order to identify the impact of seller/servicer affiliation on servicing fees, we exploit a post-crisis regulatory change which altered the incentive to retain servicing rights for small sellers of MBS relative to large sellers.

Finally, in the third chapter, we evaluate the information flows to the stock and bond markets of issuer versus investor-paid rating agencies and equity analysts. Equity analysts' forecasts and ratings assigned by issuer-paid credit rating agencies such as Standard and Poor's (S&P) and by investor-paid rating agencies such as Egan and Jones (EJR) all involve information production about the same underlying set of firms, even though equity analysts focus on cash flows to equity and bond ratings focus on cash flows to bonds. Further, the two types of credit rating agencies differ in their incentives to produce and report accurate information signals. Given this setting, we empirically analyze the timeliness and accuracy of the information signals provided by each of the above three types of financial intermediary to their investor clienteles and the information flows between these intermediaries. We find that the information signals produced by EJR are the most timely (on average), and seem to anticipate the information signals produced by equity analysts as well as by S&P. We find that changes in leverage are associated with lower EJR ratings but higher equity analysts' recommendations;

further, credit rating changes by EJR have the largest impact on firms' investment levels. We also document an "investor attention" effect (in the sense of Merton, 1987) among stock and bond market investors in the sense that changes in equity analyst recommendations have a higher impact than either EJR or S&P ratings changes on the excess returns on firm equity, while EJR rating changes have a higher impact on bond yield spreads than either S&P ratings changes or changes in equity analyst recommendations. Finally, we analyze differences in bond ratings assigned to a given firm by EJR and S&P, and find that these differences are positively related to the standard proxies for disagreement among stock market investors.

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ACKNOWLEDGMENTS

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1.0 CHAPTER 1

CREDIT RATINGS AND DEBT ISSUANCE:
HOW DO PRIVATE FIRMS DIFFER FROM PUBLIC FIRMS?

1.1 INTRODUCTION

Private firms represent a major part of the economy. Many receive credit ratings and rely heavily on public debt markets to raise capital. The aggregated revenue in 2015 for private firms that issued bonds to public investors accounted for more than seven percent of the U.S. Gross Domestic Product. Moreover, over 40 percent of all private firms with more than one billion dollars in revenue issued bonds to public investors[1].

This paper documents differences between private and public firms and evaluates their implications for firm capital structure and investment decisions. Despite the large economic importance of private firms, in studying the relationship between credit ratings and capital structure, the literature has predominantly focused on public firms. Kisgen (2006) documents that public firms near a credit rating upgrade or downgrade issue less debt relative to equity than firms not near a change in rating. Moreover, Kisgen (2009) outlines that firms reduce leverage following credit rating downgrades, while rating upgrades do not affect firms' capital structure. Michelsen and Klein (2011) find that companies near a rating change issue 1.8% less net debt relative to net equity as a percentage of total assets than firms not near a rating change. For private U.S. firms, the evidence on the effect of ratings on investment and capital structure remains scarce.

The contribution made by this paper is three-fold. First, this study is the first to document how private U.S. firms adjust their capital structure and investment

[1] Information for private firms with credit ratings is reported from Bloomberg and Capital IQ.

differently from public firms when they are concerned about rating changes that may impact their cost of debt. Second, this study outlines differences in leverage patterns and credit ratings between private and public U.S. firms that issue bonds to public investors. Third, this study shows how the aforementioned differences between private and public firms are consistent with theories of capital structure such as the Pecking Order Theory (Myers and Majluf 1984), Trade-Off Theory (Myers 1984), and the CR-CS theory (Kisgen 2006).

Investors generally have less information about private firms than they do about public firms. Private firms with credit ratings are required to file 10K reports. However, investors cannot track the evolution of private firms' share values, as they can for public firms, and thus must rely on less timely information when evaluating investment opportunities. Further, private firms are not required to file some of the financial reports that public firms are mandated to file with the Securities and Exchange Commission[2]. As evidence for the larger information asymmetry for private firms, I find that credit rating agencies disagree more frequently about ratings assigned to private firms than those assigned to equivalent public firms (section 1.5.1).

The direct implication of the larger information asymmetry for private firms between firm management and outsiders is that investors observe less information about private firms than they do about public firms. Therefore, investors must rely more heavily on private firms' publicly available credit ratings. Internalizing that as a result, investors in private firms are expected to be highly sensitive to credit rating changes, private firms should be more responsive than public firms to credit rating fluctuations, particularly when their ratings are on upgrade/downgrade thresholds where shifts in credit ratings give rise to large changes in the cost of debt.

The indirect implication of the larger asymmetric information for private firms

[2]For instance, private firms do not file form 14A. This document constitutes a financial disclosure that public firms are required to file before shareholders' meetings.

is based on the Myers and Majluf (1984) pecking order theory, which suggests that the cost of financing increases with asymmetric information. Since investors in private firms face greater information asymmetry relative to investors in public firms, it follows that the discrepancy between the cost of debt and equity is greater for private firms relative to public firms. Therefore, debt issuance is a particularly attractive channel for private firms to raise funds. Indeed, I find that the average level of debt, as a share of assets, is 56% for private firms, following their first access to the public debt market. This measure of leverage is significantly larger than that of equivalent public firms – a mere 25%. As private firms utilize heavily the public debt channel of financing, it follows that they would be more sensitive to concerns of credit rating changes that would affect their cost of debt. I find that even after controlling for the leverage level, private firms are more responsive than public firms to rating changes when their ratings are on boundaries where rating fluctuations have a major impact on the cost of debt.

The aforementioned rating boundaries refer to credit ratings where upgrades or downgrades lead to new ratings of different letter bins. Specifically, I define upgrade and downgrade thresholds similarly to Kisgen (2006), as ratings with positive or negative signs (respectively). Kisgen (2006) argues that rating changes on these boundaries lead to large changes in the cost of debt. The rationale is that shifts in the cost of debt are going to be larger when an upgrade or downgrade will yield a rating of a different letter. Put differently, firms incur distinct costs from a downgrade (benefits from an upgrade) particularly when the rating downgrade (upgrade) results in a letter change. For instance, a downgrade from a B- to CCC+ would yield a larger increase in the cost of debt, relative to a rating downgrade from B to B-. Similarly, the decrease in cost of debt will be larger given a credit rating upgrade from B+ to BB-, than from B to B+.

Constraining debt issuance when firms' ratings are on upgrade/downgrade thresholds is likely to increase the probability of getting rating upgrades or avoiding downgrades. In particular, when firms' ratings are at a downgrade threshold, firms internalize that a downgrade would yield a significant increase in the cost of debt. Thus, they send a favorable signal to the credit rating agencies by constraining their debt issuance and thereby boosting cash flow to equity holders. Similarly, when a firm's credit rating has a plus sign, firms know that an upgrade would significantly reduce the cost of debt. Therefore, firms constrain debt issuance to signal that they have sufficient cash flow available after repayment of their debt obligations. This in turn makes investment in these firms less risky and can increase the likelihood of a rating upgrade. Given that private firms disclose less information to public investors and have fewer channels to raise capital, they are more sensitive to credit rating fluctuations relative to public firms. Consequently, I hypothesize that private firms constrain debt issuance more than public firms when their ratings are on upgrade or downgrade thresholds. Alternatively, when private firms' ratings are not at upgrade/downgrade boundaries, I expect them to issue more debt as a share of assets relative to public firms. This is because equity financing is more costly for private firms as they cannot access the public equity market, and have greater information asymmetry between investors and firm insiders, which increases the discrepancy between the cost of debt and equity. This makes debt issuance an attractive channel of financing for private firms.

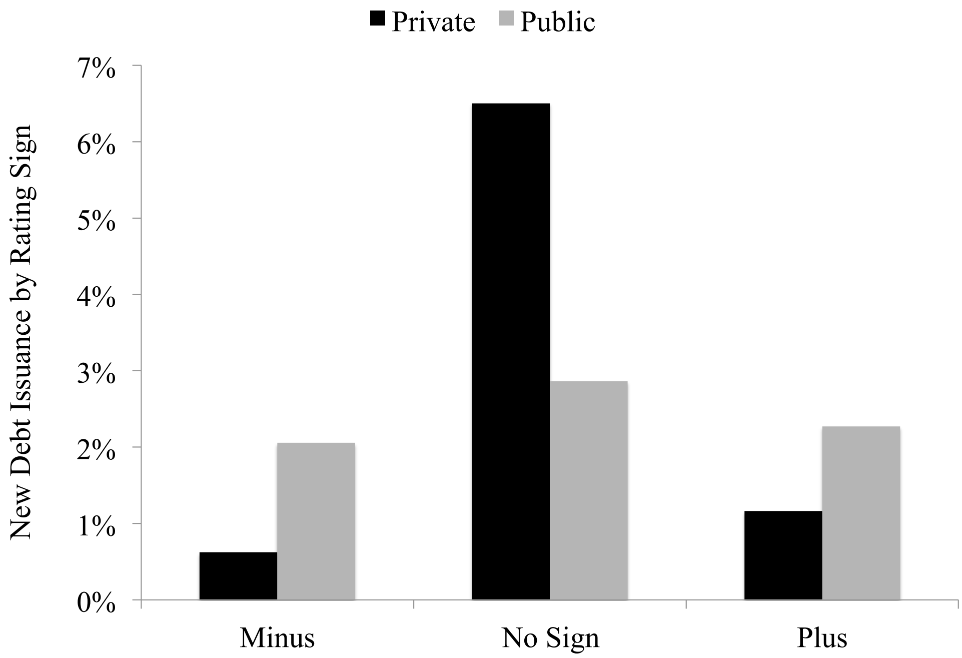
My results confirm this hypothesis. I find that private firms constrain debt issuance at least 4.5 percentage points more than public firms when their ratings are on upgrade or downgrade thresholds. However, when their credit ratings do not have plus or minus signs, private firms issue substantially more debt, as a share of assets, than equivalent public firms (section 1.5.2). Figure 1 depicts the change in annual debt issuance as a share of assets ($\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$) averaged by credit rating sign categories[3]. The average change in debt issuance is calculated for private and public firms across all firm-year observations that have credit ratings with

[3]The credit rating sign categories include ratings with minus signs, ratings with no signs, and ratings with plus signs.

plus, minus, and no signs. The black bars represent levels of new debt issuance for private firms, while the gray bars represent the average new debt issuance for public firms. Figure 1 suggests that private firms reduce new debt issuance from an average of 6.5%, when their ratings do not have a plus or minus sign, to 0.62% when their ratings have minus signs, and to 1.16% when their ratings have plus signs. These summary statistics indicate that private firms constrain new debt issuance by 5.88% when their ratings are on a downgrade threshold, and by 5.34% when their ratings are on an upgrade threshold. However, public firms constrain new debt issuance from 2.86% to 2.06% when their ratings have negative signs and from 2.86% to 2.27% when their credit ratings have positive signs. This constitutes a decrease of only 0.8% in new debt issuance when public firms' ratings are on downgrade thresholds and a reduction of 0.59% when their ratings are on upgrade thresholds. On the other hand, when their ratings are not on the upgrade/downgrade boundaries, private firms issue substantially more new debt as a share of assets (6.5%) relative to public firms (2.86%).

Figure 1
Debt Issuance for Private and Public Firms

Figure 1 depicts the average annual change in debt issuance for public and private firms by credit rating signs. The vertical axis represents the change in debt issuance between year $t-1$ and t over assets in year $t-1$ defined as $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$. The horizontal axis represents ratings with minus signs, no signs, and plus signs. The black bar refers to average new debt issuance for private firms, while the gray bar represents the average new debt issuance for public firms.



While I demonstrate that private firms constrain debt issuance when their ratings are on upgrade/downgrade boundaries, I also find that they turn to equity, as a substitute for debt in order to raise capital. However, the reduction in debt issuance more than offsets the increase in equity issuance[4]. Thus, it appears that raising capital is less cost effective for private firms, particularly when their ratings are at a boundary. As a result, I hypothesize that firms reduce capital expenditure when their ratings are on upgrade/downgrade threshold. Indeed, I find that private firms constrain investment, defined as capital expenditure as a share of assets, by at least 6.5 percentage points more than public firms, when their credit ratings are on an upgrade/downgrade boundary (section 1.5.6).

[4]Figure 2 demonstrates that the debt net of equity issuance is negative since the fall in debt issuance more than offsets the increase in equity issuance.

Next, I evaluate how bond issuance patterns change as private firms become public through IPOs. Figure 3 depicts the change in debt net of equity issuance averaged by rating sign categories during years prior to IPOs. As hypothesized, the summary statistics suggest that these firms constrain debt issuance when their ratings have positive or negative signs. Interestingly, as firms get closer to the public offering, in addition to constraining debt issuance on rating boundaries, they also reduce overall leverage, presumably to get higher valuation of their publicly offered equity. When firms that file for IPOs turn public, in contrast to pre-IPO years, there is no clear pattern of capital structure or bond issuance (section 1.5.5). Moreover, my regression results suggest that private firms that become public through IPOs constrain their debt issuance at least 10 percentage points more during pre-IPO years if their ratings are on upgrade/downgrade boundaries, relative to years after they turn public.

The aforementioned discrepancy in debt issuance between private and public firms disappears when I consider private firms that are backed by private equity funds (section 1.5.3). This result reinforces the intuition that private firms' capital structure behavior is partly driven by their reliance on the public debt market as a cost effective channel to raise capital. Private equity support also sends a signal to the market about the quality of the financed firms, thereby reducing the information asymmetry between firm insiders and outside investors. Consistently, private and public firms exhibit similar capital structure patterns when public firms issue more bonds than the median number of bonds issued by firms in the given industry (section 1.5.4).

Lastly, I evaluate leverage trends for private and public firms prior and following their first access to public debt (section 1.5.7). Since private firms do not have access to the public equity market as a channel to raise capital, they are likely to rely more heavily than public firms on issuance of bonds to public investors to raise funds. I demonstrate that equivalent private and public firms have similar levels of leverage prior to their initial access to public debt[5]. However, following their first credit rating, the leverage for private firms is significantly higher (an average of 56%) and upward trending while the leverage for public firms is lower (an average of 25%) and downward sloping. These results confirm the intuition that private firms utilize the opportunity to raise capital by issuing bonds to public investors since they have fewer cost effective channels to raise funds, relative to public firms[6].

The rest of this paper is organized as follows. Section 2 describes the closely related literature. In section 3, I briefly outline the theoretical background and develop testable hypothesis. In section 4, I describe the data, sample selection, and my matching methodology of private and public firms. Section 5 presents my regression models and empirical results that address the testable hypothesis $H1 - H7$. Section 6 concludes.

[5]Figure 6 shows the average annual leverage for private and public firms for years relative to first year of getting a credit rating.

[6]Faulkender & Petersen (2006) argue that public firms have higher leverage following their first credit rating, which they define as first access to public debt. My results confirm their conclusion for public firms, but show a more pronounced positive leverage trajectory for private firms.

1.2 RELATED LITERATURE

1.2.1 Capital structure literature

Evidence that debt issuance can raise firm value was first introduced by Modigliani and Miller (1963). They demonstrate that the market value of levered firms can be higher than that of non-levered firms due to the tax benefits of debt. Modigliani and Miller's idea has contributed to the rise of the trade-off theory (Myers 1984), which suggests that firms balance the cost of financial distress due to the risk of bankruptcy with the benefit from tax shield on interest from debt issuance, when determining the optimal level of leverage. Subsequently, Jensen and Meckling (1976) and Jensen (1986) incorporate debt and equity agency costs into the trade-off theory by documenting costs that stem from conflicts of interest between different stakeholders in firms where asymmetric information is prevalent between firm insiders and outsiders. They mention that one of the benefits of debt issuance beyond the tax shield on interest is that the need to pay interest will reduce wasteful spending by firm insiders and thus will have monitoring effect on cash flow. Therefore, this theory suggests that firms would adjust their capital structure to ultimately converge towards an optimal leverage ratio while balancing the costs of bankruptcy with the benefits of the tax shield on interest from debt issuance, as well as trade-offs between agency costs that stem from debt and equity issuance. Moreover, Graham (2000) shows that a typical firm could double tax benefits by issuing debt until the marginal tax benefit begins to decline.

Consistently, Brennan and Schwartz (1984) and Kane, Lee, and Marcus (1984) construct dynamic models of firm leverage decisions in a multi-period framework. They consider the trade-off between tax savings and bankruptcy costs and demonstrate that it is beneficial for firms to maintain high levels of debt in order to take advantage of the debt financing tax savings. Likewise, additional studies of dynamic trade-off theory highlight the benefit for firms to minimize transaction costs by adjusting financing only periodically. They suggest that firms would deviate from optimal leverage ratios since they can decrease leverage in one period knowing that they may raise their leverage in following periods [Goldstein, Ju, and Leland (2001), Strebulaev (2007), Fischer et al. (1989)].

An alternative approach to explain how firms target optimal capital structure was introduced by Myers and Majluf's (1984) pecking order theory. This theory states that the cost of financing increases with asymmetric information. They argue that firms prefer to use internal financing over debt or equity issuance to raise capital. In case internal financing is depleted, firms prefer to issue debt over equity since issuing debt sends a favorable signal about the quality of the firm to outside investors which in-turn reduces the cost of debt relative to equity financing. Put differently, investors seek greater compensation when they purchase firm equity since they perceive firms that raise capital by issuing equity rather than debt to be riskier. This idea is consistent with costs of asymmetric information outlined by Akerlof (1970). He suggests that the quality of goods traded in a market can degrade in the presence of information asymmetry between buyers and sellers. Subsequently, Leland and Pyle (1977) suggest that one way to mitigate such information asymmetry between firm insiders and outside investors is to have an intermediary send an informed signal about the quality of the firm by investing its wealth in firms' assets about which it has special knowledge. Moreover, Shyam-Sunder and Myers (1999) explain that unlike the trade-off theory, the pecking order theory does not specify an optimal debt ratio, but rather as Frank and Goyal (2003) suggest, firms will inevitably raise debt issuance when internal financing is depleted.

In contrast, the market timing theory of capital structure argues that firms issue new stocks when the equity prices are perceived to be overvalued, and buy back own shares when their equity is undervalued. Baker and Wurgler (2002) argue that managers issue equity when they believe its cost is irrationally low and repurchase equity when they think its cost is irrationally high. They find that leverage changes are strongly and positively related to their market timing measure. Further, Graham and Harvey (2001) document managers disclosing that they try to time the equity market when issuing shares. Managers assert that whether the firms' stock was undervalued or overvalued played an important role in their equity issuance decisions.

Finally, Kisgen (2006) outlined the Credit Rating–Capital Structure hypothesis (CR-CS). This hypothesis states that ratings on downgrade or upgrade thresholds are associated with discrete costs or benefits (respectively) that cause managers to balance considerations of discrete changes in the cost of debt around upgrade or downgrade rating thresholds with trade-off theory considerations. For instance, it is plausible that it is optimal according to the trade-off theory for a firm to issue additional debt to increase its leverage. However, according to CR-CS theory such increases in leverage will trigger discrete increases in the cost of debt when the credit rating is on a downgrade boundary. Thus, the optimal leverage equilibrium in this instance should not increase to avoid a large rise in the cost of debt financing.

1.2.2 Empirical literature on credit ratings and capital structure

While there exists vast literature on credit ratings for public firms, the literature on credit ratings for private firms remains scarce. The most closely related empirical literature includes papers that evaluate the effect of credit ratings on capital structure for public firms. Kisgen (2006) provides evidence that public firms constrain debt issuance when their credit ratings are on upgrade or downgrade thresholds, and issue more debt when their ratings are not near those boundaries. He defines ratings being close to upgrade or downgrade thresholds as ratings with plus or minus signs, and argues that firm behavior is consistent with existence of distinct costs from downgrades or benefits from upgrade particularly when rating downgrades or upgrades yield letter changes. For instance, for a firm with B- rating, a downgrades will yield a CCC+ rating which will constitute a letter change. According to Kisgen's CR-CS theory, a drop in credit rating from B- to CCC+ would yield higher change in cost of debt than a decrease of credit score within a letter group such as from CCC+ to CCC or B to B-. In a subsequent paper, Kisgen (2009) documents that firms reduce leverage following credit rating downgrades, while rating upgrades do not affect firms' capital structure.

Michelsen and Klein (2011) evaluate the impact of credit ratings on capital structure for international firms. They find that companies near a rating change issue 1.8% less net debt relative to net equity as a percentage of total assets than firms not near a rating change. They conclude that the negative effect on debt issuance is pronounced for US firms particularly in times when access to the commercial paper market is at risk. On the other hand, Drobetz and Heller (2014) document that changes in the capital structure and financing choices of creditworthy privately-held firms in Germany are independent from credit rating changes. Further, Kisgen and Strahan (2010) show that credit rating regulations have an important role for cost of capital. They demonstrate that following DBRS certification, bond yields change in the direction implied by the firm's DBRS rating. Consistently, Kisgen (2012) provides evidence emphasizing the impact of credit rating adjustments on capital structure and investment decisions. He concludes that when Moody's changes the adjustments it makes to GAAP leverage for determining its ratings, firms react in both their financing and investment decisions. If the change in adjustment results in an improvement in a firm's rating status, the firm is then more likely to issue debt and grow assets the following year. Moreover, Binsbergen, Graham, and Yang (2010) highlight that the cost of being overlevered is asymmetrically higher than the cost of being underlevered and that expected default costs constitute approximately half of the total ex ante cost of debt. Finally, Rauh and Sufi (2010) demonstrate the importance of heterogeneous debt structure where low-credit-quality firms are more likely to have a multi-tiered capital structure consisting of both secured bank debt with tight covenants and subordinated non-bank debt with loose covenants.

In addition to studying the impact of credit ratings on changes in debt issuance, recent empirical literature has documented how public firms optimize their level of leverage. Faulkender and Petersen (2006) evaluate the changes in leverage for public firms prior and following first credit rating. They find that firms that have access to the public bond markets, as measured by having a bond credit rating, have higher leverage[7]. Faulkender and Petersen argue that after controlling for firms characteristics, firms with access to public debt have 35% more debt as a share of assets.

Finally, the literature has addressed the impact of credit default swaps on loans and debt issuance of public firms. Intuitively, CDSs create new hedging opportunities and could lead to a reduction in the cost of debt by revealing new information about firms. Consistently, Hull, Predescu, and White (2004) evaluate credit default swap changes conditional on rating announcement as well as rating announcements conditional on credit default changes. They find that the credit default swap market anticipates credit rating events. This may in-turn contributes to reduction in the cost of debt by lowering the rents that banks extract from borrowers as compensation for information asymmetry between investors and firm insiders (Santos and Winton (2008) and Hale and Santos (2009)). In contrast, Ashcraft and Santos (2009) find no evidence that the onset of CDS trading lowers the cost of debt financing for the average borrowers, but rather find economically adverse effects on risky and informationally opaque firms.

This paper is the first to document how private U.S. firms adjust their capital structure and investment differently from public firms when they are concerned about rating changes that may impact their cost of debt. It also outlines differences in leverage patterns and credit ratings between private and public U.S. firms that issue bonds to public investors.

[7]Faulkender and Petersen (2006) define leverage as book value of debt as a share of assets

1.3 THEORY AND HYPOTHESIS

In this section, I briefly discuss the underlying theory and develop hypotheses for my empirical tests. First, I evaluate whether private firms have greater information asymmetry between firm insiders and outside investors, relative to equivalent public firms. I anticipate this to be the case since private firms do not have publicly traded shares that allow investors to get the most updated information about firm performance, as well as private firms are not required to file the same financial disclosures that public firms are mandated to file[8].

Consequently, I test whether *credit rating agencies disagree more frequently about ratings assigned to private firms (H1).* If there exists grater information asymmetry between firm insiders and outside investors for private firms, one would expect the credit rating agencies to have a more difficult task of assessing the default risk of private firms. I find statistically significant evidence that rating agencies disagree more frequently about rating scores assigned to private firms than to equivalent public firms. This reinforces the intuition that private firms have greater asymmetric information between firm insiders and outside investors.

Myers and Majluf's (1984) pecking order theory implies that as information asymmetry increases between firm insiders and investors, so does the cost of external capital. They argue that debt issuance is a preferable source of financing to equity since issuing equity sends a signal to investors that firm management perceives the equity to be overvalued. Therefore, investors demand a higher return when they purchase firm equity, which in-turn makes equity more expensive channel to raise capital. Thus, the greater information asymmetry between firm insiders and outside investors for private firms, leads to greater discrepancy be-

[8]For instance, private firms do not file form 14A. This document constitutes a financial disclosure that public firms are required to file before shareholders' meetings.

tween cost of debt and equity for private relative to public firms[9]. Consequently, debt issuance becomes more cost effective channel for private firms to raise capital. As private firms rely heavily on debt financing, they are likely to be more sensitive than public firms to credit rating changes that shift their cost of debt.

Additional explanation for why private firms are more responsive to credit rating fluctuations is that they disclose less information to public investors than public firms do. Consequently, investors have limited information about the performance of private firms, and thus are more responsive to the publicly posted credit rating changes. Consistently, I develop testable hypothesis to evaluate whether *private firms constrain debt issuance more than public firms when their credit ratings are on upgrade/downgrade thresholds (H2)*. Intuitively, I expect private firms to constrain debt issuance, and thus send a favorable signal to the rating agencies in order to avoid rating downgrades when they have ratings with minus signs, or achieve rating upgrades when their ratings have plus signs. This is due to the large costs associated with rating downgrades and the significant benefits from rating upgrades at those respective boundaries. While this logic applies to public firms as well, public firms are less sensitive to credit rating fluctuations since investors have a better understanding of the firms' financial performance, partly due to availability of their financial statements and equity trading information.

Similarly, I evaluate if *private firms that are backed by private equity funds constrain debt issuance similarly to public firms when their credit ratings are on upgrade/downgrade thresholds (H3)*. This unique set of private firms is different along two important dimensions, from private firms that do not have external financial support. First, private equity backed private firms are less dependant on the bond market for raising capital. Second, the support of private equity funds sends a positive signal to the market about growth opportunities of the firms that they support, which in-turn reduces the asymmetric information between

[9] I refer to the management of the firm as firm insiders since they have full information about the state of the firm. I consider public investors to be firm outsiders since they are not privy to all information about the financial performance of the firm.

firm management and outsiders for those firms. Therefore, I expect private equity backed private firms to be less sensitive to credit rating fluctuations, and hence less likely to adjust their capital structure to avoid rating changes.

In addition to matching private firms with equivalent public firms, I study how capital structure changes for the same firms before and after they turn public. To that end, I evaluate whether *firms that file for IPOs constrain debt issuance when their ratings have positive or negative signs only prior to becoming public (H4)* when their ratings are on upgrade/downgrade boundaries. This difference-in-difference analysis is a useful robustness check since it allows differencing unobserved firm characteristics that do not change prior and following the IPOs. Next, I move on to test whether *public firms that issue more bonds than industry median number of bonds per firm, have similar debt issuance patterns to private firms (H5).* I hypothesize that public firms that issue large number of bonds are highly sensitive to credit rating fluctuations and thus constrain debt issuance when their ratings are on the boundaries, similarly to private firms.

In summary, hypothesis $H1$ tests whether there exists greater information asymmetry for private firms relative to equivalent public firms by evaluating if credit rating agencies disagree more frequently about credit ratings assigned to private firms. Testable hypotheses $H2$-$H5$ examine the implications of greater aforementioned information asymmetry between firm insiders and outside investors for private firms. As a result, if private firms constrain debt financing when their ratings are on the upgrade or downgrade thresholds, they might have less available funds to invest in new projects. Thus, I test whether *private firms constrain investment more than public firms following years when their ratings were on upgrade/downgrade thresholds (H6).* I expect private firms to restrict their capital expenditure more than public firms around the rating boundaries since they do not raise enough funds on the private equity market to compensate for the insufficient capital raised on the public debt market when their ratings have plus or minus signs (figure 2).

Finally, I analyze the discrepancy in leverage trends, defined as debt as a share of assets, for private and public firms prior and following first access to public debt. Similarly to Faulkender & Petersen 2006, I define first year of having access to public debt as the first year when firms get credit ratings. Private firms do not have access to public equity and thus rely more heavily on public bond issuance when given access to the public debt market. Therefore, I evaluate whether *leverage is higher for private firms relative to public firms following first access to the public debt market (H7).* I find that private firms have similar leverage levels to public firms before their first credit rating. However, when given access to public debt market, private firms have higher (56% on average) levels of leverage relative to equivalent public firms (25% on average). In summary, the hypotheses tested in this study include:

H1: Credit rating agencies disagree more frequently about ratings assigned to private firms

H2: Private firms constrain debt issuance more than public firms when their credit ratings are on upgrade/downgrade thresholds

H3: Private firms that are backed by private equity funds constrain debt issuance similarly to public firms when their credit ratings are on upgrade/downgrade thresholds

H4: Firms that file for IPOs constrain debt issuance when their ratings have positive or negative signs only prior to becoming public

H5: Public firms that issue more bonds than industry median number of bonds per firm, have similar debt issuance patterns to private firms

H6: Private firms constrain investment more than public firms when their credit ratings are on upgrade/downgrade thresholds

H7: Leverage is higher for private firms relative to public firms following first access to the public debt market

1.4 DATA AND SAMPLE SELECTION

1.4.1 Sample of private and public firms with credit ratings

I construct a panel dataset over 1990-2014 of 257 private firms that issue bonds to public investors. I incorporate in my data private firms with credit ratings that are included in the 2014 Forbes list of largest American private firms, as well as all private firms with credit ratings in the Bloomberg Terminal that have more than one billion dollars in revenue. The aggregate annual revenue for the private firms included in the sample accounts for more than 7% of U.S. GDP in 2014. Subsequently, I turn to the Bloomberg Terminal and Capital IQ to obtain credit ratings and firm characteristics for each of the private firms in my sample.

The credit rating data for private firms in my sample includes long and short term bond products issued by all rating agencies available on Bloomberg such as Standard & Poor, Moody's, Fitch, DBRS, EJR, A. M. Best, and Duff & Phelps. In this paper, I primarily focus on long term bond ratings issued by Standard & Poor. This is because the data reported for S&P is highly detailed and is available for all firms in my sample. For each bond, Bloomberg reports the dates of the rating changes. This allows me to construct a daily time series of credit ratings for each firm, which I aggregate monthly or annually by firm given the context of my analyses. Next, I match firm specific credit ratings with annual firm characteristics that I obtain from Bloomberg and Capital IQ. I observe on average about 9 years of financial data for each of the 257 private firms that issue bonds to investors in my sample.

Subsequently, I construct a sample of public firms to compare the impact of rating changes on capital structure and investment for private versus public firms. To that end, I obtain S&P monthly ratings and annual firm characteristics from the Wharton Research Data Services over the time period of 1970-2014. The sample includes 33,177 distinct public firms with about 8 years of data available on average per firm. Finally, I employ nearest neighbor matching of private and public firms within the same industry, and across assets, sales, and profitability. This allows me to compare the capital structure and investment behavior of equivalent private and public firms.

Table one provides summary statistics of my raw and matched data of public and private firms. Noticeably, the leverage for private firms with credit ratings following access to the public debt market is about 56%.This is substantially higher than the average leverage for public firms - a mere 25%[10]. This summary statistic confirms the intuition that since private firms do not have access to the public equity market, they rely more heavily on bond issuance to public investors as a channel to raise capital.

Moreover, the mean and median credit ratings are higher for public firms than for private firms. This discrepancy can be explained by the fact that private firms have substantially higher leverage and thus may be perceived as more risky. Finally, the mean annual sales, cash as a share of assets, revenues, assets and other firm characteristics in table one are comparable across public and private firms. It suggests that a comparison between private and public firms on these variables seems appropriate.

1.4.2 Identification, matching private and public firms

A potential identification challenge when comparing the impact of credit ratings on capital structure and investment of private and public firms is that private firms that choose to issue bonds to public investors may inherently be different from public firms. For instance, if the private firms in my sample exhibit rapid growth, they may be more sensitive to credit rating fluctuations than public firms, and thus adjust their capital stricture more than public firms, when their ratings are on downgrade/upgrade thresholds. Hence, a potential concern is that my findings that private firms constrain debt issuance more than public firms when

[10]Leverage is defined as debt over assets for each firm-year cell.

their ratings are on the boundaries are driven by sample selection.

To address the aforementioned self selection challenge, I employ nearest neighbor matching to match for each private firm in my data, a public firm within the same industry 4 digit sic code, with the closest assets, sales, and profitability. The matching methodology is graphically described in figure 7. The large sample of public firms (33,177) allows me to find highly equivalent public firms for each of the private firms in my data. I choose to match private and public firms based on the first year that I observe financials for both types of firms in the data to avoid matching based on endogenous growth of these companies over their lifespan in my data. However, to make sure my results are not driven by the choice of my matching approach, I performed multiple robustness checks of matching private and public firms based on first year of access to public debt, average annual firm characteristics, as well as matching on different observables within the same industry. The results are highly robust to my choice of the matching methodology. This suggests that if a private firm in my sample is growing rapidly, so would an equivalent matched public firms within the same industry. Hence, the difference in firms' responses to credit ratings is not likely to be driven by sample selection. Moreover, the industry, firm, and year fixed effects that I include in my regressions can also mitigate potential challenges of self selection.

Further, I regress the change in debt net of equity issuance on lagged dummy variables for ratings with positive and negative signs rather then regressing the change in debt issuance on the rating level itself. This is done to avoid concerns of reverse causality or simultaneity bias. Thus, this methodology allows me to evaluate causal effects of ratings on capital structure and investment of private and public firms, rather then merely documenting correlations.

After constructing my sample of private and public firms, I turn to adjusting my data for econometric analysis. My guiding principle is to keep data cleaning to the minimum needed. For all regressions, I drop observations where any of my dependent variables or controls are missing in the data. For instance, in my regression specifications for *H2-H4*, I define debt net of equity issuance as the change in the debt minus the change in equity level for each firm from year $t-1$ to year t over total assets in period $t-1$. This requires that private firms in my data disclose debt and equity issuance for at least two consecutive years. Lastly, as a robustness check, I truncate the distribution of debt net of equity issuance below the 1^{st} and above the 99^{th} percentile. This does not have any meaningful impact on my results.

1.5 EMPIRICAL MODELS AND REGRESSION RESULTS

1.5.1 Disagreement between credit rating agencies about ratings assigned to private and public firms

The first aim of my regression analysis is to test whether there exists greater asymmetric information between firm insiders and outside investors for private versus public firms. To that end, I evaluate if credit rating agencies disagree more frequently about ratings assigned to private than public firms. Unlike private firms, public firms have traded shares which allow the credit rating agencies and investors to get updated information about public firms' performance at any point in time. Consequently, the rating agencies may have a more difficult task of assessing the riskiness of default of private firms, and thus may disagree more frequently about the rating scores that they assign to private firms as apposed to public firms.

Therefore, I test whether there exists greater information asymmetry for private firms between firm insiders and investors by evaluating if credit rating agencies disagree more frequently about the ratings that they assigns to private firms relative to public firms. I create two different measures for disagreement between credit rating agencies for ratings assigned to the same firm within each year where I observe S&P and Moody's ratings in the data. The first measure of disagreement is the absolute value of the difference between average S&P and Moody's ratings $|S\&P_{i,t} - Moodys_{i,t}|$ for each firm-year combination. The second measure is the squared difference between the average S&P and Moody's ratings $(S\&P_{i,t} - Moodys_{i,t})^2$.

I hypothesis that the credit rating agencies disagree more frequently about ratings assigned to private firms as apposed to public firms. Indeed, my regression results in table 2 confirm this intuition. The dependent variable in model (1) of table 2 is $|S\&P_{i,t} - Moodys_{i,t}|$. I regress this dependent variable on a dummy variable for private firms ($Private_i$) and industry and year fixed effects. The positive and highly significant coefficient on the dummy variable for private firms indicates that the discrepancy between S&P and Moody's ratings is larger for private firms. The regression specification in model (2) is similar to model (1), but also controls for profitability, assets, and log of sales in addition to industry and year fixed effects. The coefficient on $Private_i$ is still positive, highly significant, and of similar magnitude to model (1). This suggests that my finding that credit rating agencies disagree more about ratings assigned to private firms is robust for controlling for firm characteristics. Finally, models (3) and (4) in table 2 have similar regression specifications to models (1) and (2), however, the measure for discrepancy between S&P and Moody's ratings in this case is the squared difference between the two ratings. My positive and significant coefficients on the dummies for private firms in those models reinforce the intuition that credit rating agencies may have a more difficult task of assessing the riskiness of default for private firms due to the greater information asymmetry between firm insiders, CRAs, and outside investors for private firms.

1.5.2 Effect of credit rating thresholds on debt issuance of private versus public firms

The greater information asymmetry for private firms between investors and firm insiders makes investors in those firms more sensitive to publicly available information such credit ratings. This in-turn suggests that private firms are expected to be more responsive to rating changes, particularly on thresholds when those rating adjustments have major implications for the cost of debt. Consequently, I evaluate whether private firms constrain debt issuance more than public firms do, when their ratings are on upgrade/downgrade thresholds, in order to send a favorable signal to the rating agencies and thereby avoid a rating downgrade or achieve an upgrade.

Similarly to Kisgen (2006), I define rating upgrade thresholds as ratings with a positive signs next to the letter grades, and downgrade thresholds as ratings that have negative signs. Thus, the dummy variable $Plus_{i,t-1} = 1$ in table 3 when the majority of the monthly ratings for firm i during year $t-1$ have plus signs. Similarly, $Minus_{i,t-1} = 1$ when the majority of the ratings for firm i during year $t-1$ have minus signs. $Rating_{i,t-1}$ refers to the level of Standard and Poor's long term issuer credit ratings for firm i in year $t-1$. I assign for each S&P rating a number between 1-23 such that higher assigned levels represents ratings for bonds with low probability of default. For instance, the highest grade of 23 is assigned to AAA rating. Furthermore, the Bloomberg data allows me to observe when the rating agencies disclose that firms' ratings have positive or negative outlooks. These outlooks represent potential future rating upgrade or downgrade. Therefore, $NegativeOutlook_{i,t-1} = 1$ and $PositiveOutlook_{i,t-1} = 1$ when the majority of the monthly ratings for firm i during year $t-1$ have positive or negative outlooks (respectively).

In table 3, I evaluate how private firms adjust their capital structure when their credit ratings are on upgrade/downgrade thresholds. In models (1) and (2), I regress the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$ on a dummy for ratings with plus signs ($Plus_{i,t-1}$), a dummy for ratings with minus signs ($Minus_{i,t-1}$), rating level for firm i in year $t-1$ ($Rating_{i,t-1}$), dummy variables for negative and positive rating outlooks ($NegativeOutlook_{i,t-1}$, $PositiveOutlook_{i,t-1}$), and firm and year fixed effects. In model (2) I also add firm controls that include $Profitability_{i,t-1}$, $Log(Sales_{i,t-1})$, and $\frac{CashFlow_{i,t-1}}{Assets_{i,t-1}}$. I adjust my regression models 3 and 4 in table 3 to account for the fact that when ratings are on upgrade or downgrade thresholds, while firms constrain their debt issuance, they may turn to alternative channels to raise capital such as private equity issuance. Thus, models 3 and 4 have similar specifications to models 1 and 2 (respectively), however the dependant variable is the change in debt net of equity over assets defined as

$\frac{[Debt_{i,t} - Debt_{i,t-1}] - [Equity_{i,t} - Equity_{i,t-1}]}{Assets_{i,t-1}}$.

Thus, the regression specification of model (4) in table 3 is depicted in equation (1) where the variable $K_{i,t-1}$ represents firm controls $Profitability_{i,t-1}$, $Log(Sales_{i,t-1})$, and $\frac{CashFlow_{i,t-1}}{Assets_{i,t-1}}$ while γ_i and γ_t represent firm and year fixed effects.

$$\frac{\triangle Debt_{i,t} - \triangle Equity_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_0 Minus_{i,t-1} + \beta_1 Plus_{i,t-1} + \beta_2 Rating_{i,t-1} + \beta_3 NegativeOutlook_{i,t-1} + \beta_4 PositiveOutlook_{i,t-1} + \gamma_i + \gamma_t + \phi K_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

The negative and highly significant coefficients on the $Minus_{i,t-1}$ and $Plus_{i,t-1}$ dummy variables in all models in table 3 suggest that private firms constrain debt issuance when their ratings are on upgrade or downgrade thresholds. The fact that the magnitude of the coefficients on the plus and minus dummies is similar across regression specification suggests the change in debt issuance rather than equity issuance drives these results, which are robust for inclusion of controls. Moreover, the coefficients on $Minus_{i,t-1}$ and $Plus_{i,t-1}$ are also similar in magnitude. This implies that firms' decisions to constrain debt issuance are symmetric around both the upgrade and downgrade thresholds. Further, the insignificant coefficients on the rating variable across models suggests that the change in debt issuance is not driven by the level of the rating, but rather by the fact that the ratings are on upgrade or downgrade thresholds. Lastly, mostly insignificant coefficients on $NegativeOutlook_{i,t-1}$ and $PositiveOutlook_{i,t-1}$ suggests that having a positive or negative rating outlook is not sufficient to motivate firms to adjust their capital stricture. Firms constrain debt issuance when they have ratings with plus or minus signs because they may face significant changes in the cost of debt if their rating upgrades or downgrades would lead to new ratings within a different letter bin. However, since rating outlooks may not necessary imply a meaningful change in the cost of debt, they are less likely to trigger a change capital structure.

Note that my coefficients in table 3 for private firms on the $Minus_{i,t-1}$ and

$Plus_{i,t-1}$ dummy variables are larger in magnitude than the respective coefficients in a similar model for public firms that are reported in Kisgen (2006). Specifically, Kisgen (2006) reports a coefficient of -0.0064 for credit rating with plus signs and -0.0051 for ratings with minus signs. However, I report the coefficient of -0.128 on the plus dummy and -0.0972 on the minus dummy for private firms in model (4) of table 3. These discrepancies in the size of the coefficients suggest that private firms are more sensitive to credit rating changes and constrain debt issuance significantly more than public firms when their ratings are on upgrade/downgrade thresholds.

Next, in tables 4, I include both private and public firms to evaluate the discrepancy in debt issuance of these types of firms when their ratings are on upgrade or downgrade thresholds. The dependent variable in models (1) and (2) is the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$. The dependent variable in models (3) and (4) is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in firm debt issuance [models (1)] and debt net of equity issuance [models (3)] on a dummy for ratings with plus signs ($Plus_{i,t-1}$), a dummy for ratings with minus signs ($Minus_{i,t-1}$), interaction term of a dummy variable for private firms with a dummy for ratings with plus signs ($Plus_{i,t-1} * Private_i$), interaction term of a dummy variable for private firms with a dummy for ratings with minus signs ($Minus_{i,t-1} * Private_i$) , and controls such as lagged rating level, leverage, profitability, log of sales, and year and industry fixed effects. Models 2 and 4 have similar regression specifications to models 1 and 3, however I replace the dummy variables for ratings with minus and plus signs ($Minus_{i,t-1}$, $Plus_{i,t-1}$), with a single dummy variable $Minus_{i,t-1}\&Plus_{i,t-1}$ that turns on when the majority of the monthly ratings within a year have positive or negative signs. Thus, regression model (3) in table 4 can be described in equation 2, while model (4) is depicted in equation 3. Vector $K_{i,t-1}$ represents firm controls such as $Profitability_{i,t-1}$, $Log(Sales_{i,t-1})$, and $Leverage_{i,t-2}$ while γ_i and γ_t represent industry and year fixed effects.

$$\frac{\triangle Debt_{i,t} - \triangle Equity_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_0 Minus_{i,t-1} + \beta_1 Plus_{i,t-1} + \beta_2 Minus_{i,t-1} * Private_i$$
$$+\beta_3 Plus_{i,t-1} * Private_i + \beta_4 Private_i + \beta_5 Rating_{i,t-1} + \gamma_i + \gamma_t + \phi K_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

$$\frac{\triangle Debt_{i,t} - \triangle Equity_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_0 Minus_{i,t-1} \& Plus_{i,t-1} + \beta_1 Private_i$$
$$+\beta_2 (Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i + \beta_3 Rating_{i,t-1} + \gamma_i + \gamma_t + \phi K_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

My coefficients on the $Minus_{i,t-1}$ and $Plus_{i,t-1}$ dummy variables in table 4 are negative and highly significant. This implies that public firms constrain their debt issuance when their credit ratings have plus or minus signs. These results are highly consistent with Kisgen (2006) as he reports coefficients of -0.0064 for credit rating with plus signs and -0.0051 for ratings with minus signs, while I report -0.0071 and -0.00655 for the respective coefficients in model (1) of table 4[11].

The coefficients on interaction terms $Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$, and $(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$ are my primary coefficients of interest as they outline the discrepancy in debt issuance between public and private firms when their ratings have plus or minus signs. The magnitude of the negative and highly significant coefficients on the interaction terms suggest that private firms constrain debt issuance at least 4.5 percentage points more than public firms do when their ratings are on upgrade/downgrade thresholds (model 3). Finally, the positive and significant coefficients on the dummy variable for private firms indicates that, on average, private firms issue more new debt relative to public firms. This result is consistent with the intuition that since private firms do not

[11] My regression specification is similar but not identical to Kisgen (2006) due to data limitations for private firms

have access to the public equity market, they have less channels to raise capital, and thus will rely heavily on issuing bonds to public investors to raise funds.

Finally, I use the same regression specifications in table 5 as in table 4, however in table 5, I match for each private firm, an equivalent public firm within the same industry that has similar profitability, assets, and sales in the first year it is observed in the data. The results on the interaction terms $Plus_{i,t-1} * Private_i$ and $Minus_{i,t-1} * Private_i$ are negative and highly significant. This implies that for a matched set of private and public firms, private firms constrain debt issuance more than public firms when their ratings are on upgrade or downgrade thresholds.

1.5.3 Effect of rating thresholds on debt issuance of firms that receive financing from private equity funds

After documenting the discrepancies in capital structure of private and equivalent public firms, I turn to evaluating whether private firms that receive financing from private equity funds constrain debt issuance more than public firms, when their credit ratings are on upgrade or downgrade thresholds. Intuitively, private firms that have alternative source of financing such as private equity funds, are not as sensitive to credit rating fluctuations since they depend less on the public debt market for financing. Moreover, the fact that private equity firms are willing to provide financial support to particular private firms sends a signal to the market that those firms have good growth prospects. This in-turn reduces the information asymmetry between insiders and public investors for these firms.

Consequently, I expect private firms that are backed by private equity funds to be less sensitive to rating fluctuations and thus have similar debt issuance patterns to public firms. Specifically, I hypothesis that private firms that get support from private equity funds do not constrain debt issuance more than public firms when their ratings have positive or negative signs.

My regression models in table 6 have similar specifications to the regressions in tables 4 and 5. However, the data for table 6 is limited to information about private firms that are supported by private equity funds along with public firms. Thus, the coefficients on interaction terms $Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$, and $(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$ outline the discrepancy in debt issuance between public firms and private firms that are backed by private equity funds when their ratings have plus or minus signs. Hence, the fact that the coefficients are statistically insignificant on $Minus_{i,t-1} * Private_i$ and $Plus_{i,t-1} * Private_i$ in models (1) and (3), and on $(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$ for models (2) and (4), implies that private and public firms constrain debt issuance to a similar extent when their credit ratings are on upgrade or downgrade thresholds. Note, however, that the coefficients on $Minus_{i,t-1}$ and $Plus_{i,t-1}$ for models (1) and (3), and $Minus_{i,t-1} \& Plus_{i,t-1}$ for models (2) and (4), are negative and highly significant. This implies that both public firms and private firms that are backed by equity funds constrain their debt issuance when their ratings are on the aforementioned boundaries.

1.5.4 Effect of rating thresholds on debt issuance of firms with median ratings above investment grade, and firms that issue abnormally large number of bonds

The tradeoff theory of capital structure suggests that firms balance the benefits of debt issuance such as the value of interest tax shields against the costs of bankruptcy. Thus, a potential concern is that my results, that private firms constrain debt issuance more than public firms when their ratings are on upgrade/downgrade boundaries, are primarily driven by low quality firms for which investors are concerned about default risk.

To address this concern, I rerun all the regression models specified in equations (2) and (3) for private and public firms with median S&P credit ratings above investment grade. The coefficients reported in table 7 reinforce my results in table 4 for firms with low default risk. This suggests that the gap in debt issuance between private and public firms is not driven by concerns about firms' default risks that elevate their sensitivity to rating changes. Instead, the results reinforce the intuition that private firms have limited information available for investors, and thus are more sensitive to the publicly available credit rating fluctuations, in comparison with public firms.

Next, I move on to evaluate whether private firms adjust their debt issuance similarly to public firms that issue abnormally large number of bonds, when their credit ratings are on upgrade/downgrade thresholds. The rationale is that public firms that issue large number of bonds are relying heavily on the bond market as a channel to raise capital, and thus are more sensitive to credit rating changes. Consequently, their debt issuance response to credit ratings being on upgrade/downgrade boundaries is likely to be similar to that of private firms.

Table 8 includes data for private and public firms with number of bonds issued that exceeds the median number of bonds issued by firms in the same industry. Similarly to table 7, the dependent variable in models (1) and (2) is the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$. The dependent variable in models (3) and (4) is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in firm debt issuance [models (1),(2)] and debt net of equity issuance [models (3),(4)] on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), interaction terms of a dummy variable for private firms with plus and minus coefficients ($Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$), and controls such as lagged rating level, leverage, profitability, log of sales, and year and industry fixed effects. The statistically insignificant coefficients on interaction terms $Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$, and $(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$ outline that there is no discrepancy in debt issuance between private firms and public firms that issue abnormally large number of bonds, when their ratings are on downgrade or upgrade thresholds. This reinforces the intuition that when public firms issue large number of bonds, they become highly sensitive to credit rating fluctuations as they rely heavily on the public debt market to raise capital.

1.5.5 Effect of credit rating thresholds on debt issuance prior and following firms' IPOs

After evaluating the impact of ratings on upgrade/downgrade thresholds on debt issuance for private, public, and firms that receive financing from private equity funds, I turn to analyzing the effect on debt issuance for private firms that became public through an IPO[12]. To that end, I construct a sample from Nasdaq.com of all firms that filed for initial public offering on NYSE or NASDAQ with more than $150,000 of equity offerings. Then, I construct a time series of credit ratings from Bloomberg for each of those firms. I limit the analysis to Standard and Poor's long term bond ratings since those ratings have frequent updates and are available for all firms in my sample. Consistently with the literature, I assign for each rating a number between 1 and 23 where bonds with low default risk get high rating numbers, while bonds with high default risk are assigned low rating numbers[13]. Subsequently, I limit my sample to firms that were issued credit ratings prior and following their IPOs, and merge firm characteristics and credit ratings for those firms from Capital IQ and Bloomberg. Finally, I add firms' IPO years from Nasdaq.com and the number of years each firm has been in business as well as industry sic classifications from firms' websites and Nasdaq.com. Consequently, I end up constructing a panel dataset for 155 firms with credit ratings prior and following to their IPOs.

Figure 4 shows summary statistics of the average new debt net of equity is-

[12]This analysis focuses on firms that filed for initial public offering, and exclude firms that had secondary offerings.

[13]For example, AAA rating gets a level of 23, while AA+ ratings get 22, and so forth.

suance prior and following firms' IPOs by credit rating signs[14]. The top figure (Prior to IPO) suggests that firms constrain their debt net of equity issuance prior to their IPOs when their ratings have plus or minus signs, in contrast to years when firms' credit ratings were not on the boundaries. However, the pattern of restricting debt issuance when ratings are on upgrade/downgrade thresholds disappears following firms' IPOs, as depicted in the figure at the bottom (Following IPO). This result reinforces the intuition that public firms are less responsive to credit rating fluctuations since they disclose more information to public investors relative to private firms and thus reduce information asymmetry between firm insiders and outside investors. Figure 3 suggests that the pattern of constraining debt net of equity issuance when ratings are on upgrade/downgrade boundaries is consistent for more than 2 years prior to firms' IPOs as well as within 2 years prior to IPOs. However, firms tend to reduce overall debt issuance as they get closer to initial public offering.

I test the implications of my summary statistics in figure 4 with a regression analysis outlined in table 9. Model (1) of table 9 limits the data sample only for years prior to the firms' initial public offerings. I regress debt net of equity issuance which is defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$ on lagged firm plus and minus dummy variables and controls. I include revenue growth, firm age, and number of years following IPOs, as well as lagged controls for firm ratings, cash over assets, profitability, leverage, and firm and year fixed effects to adjust for potential evolution in firm's business following initial public offering. Thus, the regression specification for model (1) in table 9 is specified in equation 4.

[14]New debt net of equity issuance is defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$

$$\frac{\triangle Debt_{i,t} - \triangle Equity_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_0 Minus_{i,t-1} + \beta_1 Plus_{i,t-1} + \beta_2 S\&P_{i,t-1}$$
$$+\beta_3 RevenueGrowth_{i,t-1} + \beta_4 FirmAge_{i,t-1} + \beta_5 YearsRelativeToIPO_{i,t} \tag{4}$$
$$+\beta_6 Profitability_{i,t-1} + \beta_7 \frac{Cash_{i,t-1}}{Assets_{i,t-1}} + \beta_8 Leverage_{i,t-2} + \gamma_i + \gamma_t + \varepsilon_{i,t}$$

The results of model (1) are consistent with my results in table 3, that suggest that when private firms have credit ratings with plus or minus signs, they constrain debt net of equity issuance. The negative coefficients on $Minus_{i,t-1}$ and $Plus_{i,t-1}$ dummies have similar magnitudes. This implies that firms respond to concerns of downgrades that may lead to ratings of lower letter bins in a similar way that they respond to the possibility of upgrades that may lead to ratings of higher letter bins. Further, the magnitude of the coefficients on $Minus_{i,t-1}$ and $Plus_{i,t-1}$ in table 9 is lager than the magnitude for the respective coefficients in model (4) of table 3. This discrepancy can be driven by the fact that when firms anticipate to file for IPOs, they may be particularly sensitive to credit rating fluctuations that would impact their valuation, and thus constrain debt issuance more in cases when their ratings are on upgrade/downgrade thresholds.

Finally, models (2) and (3) in table 9 include firms' data for years prior and following their IPOs[15]. The dependent variable and the controls are identical to model (1) however, I add a dummy variable for the time period prior to the IPO ($BeforeIPO_{i,t-1}$) as well as interaction terms of this dummy coefficient with plus and minus dummies ($BeforeIPO_{i,t-1} * Plus_{i,t-1}$ and $BeforeIPO_{i,t-1} * Minus_{i,t-1}$). Thus, regression model (2) in table 9 can be described in equation 5.

[15]Note that model (2) in table 9 includes year and firm fixed effects while model (3) on table 9 includes industry and firm fixed effects

$$\frac{\triangle Debt_{i,t} - \triangle Equity_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_0 Minus_{i,t-1} + \beta_1 Plus_{i,t-1} + \beta_2 BeforeIPO_{i,t-1}$$
$$+\beta_3 BeforeIPO_{i,t-1} * Minus_{i,t-1} + \beta_4 BeforeIPO_{i,t-1} * Plus_{i,t-1} + \beta_5 S\&P_{i,t-1}$$
$$+\beta_6 RevenueGrowth_{i,t-1} + \beta_7 FirmAge_{i,t-1} + \beta_8 YearsRelativeToIPO_{i,t}$$
$$+\beta_9 Profitability_{i,t-1} + \beta_{10} \frac{Cash_{i,t-1}}{Assets_{i,t-1}} + \beta_{11} Leverage_{i,t-2} + \gamma_i + \gamma_t + \varepsilon_{i,t} \tag{5}$$

My negative and statistically significant coefficients on the interaction terms (β_3 and β_4) suggest that firms constrain debt issuance at least 10 percentage points more prior to going public, when their ratings are on the upgrade/downgrade thresholds. In contrast, no such pattern is observed following initial public offerings. This result is consistent with the intuition that private firms are more responsive to rating fluctuations relatively to public firms and thus constrain debt issuance more when their ratings are close to upgrade or downgrade thresholds. Moreover, the positive coefficient on $BeforeIPO_{i,t-1}$ suggests that when ratings do not have a positive or negative signs, firms issue more debt net of equity prior to their IPOs. This result is consistent with the intuition that during the years when firms were private, they had larger information asymmetry between firm insiders and outside investors and thus had larger discrepancy between the cost of debt and equity, which incentivized them to issue more debt as a share of assets relative to years following their IPOs.

1.5.6 Effect of ratings on upgrade/downgrade thresholds on firm investment

Thus far, I have evaluated the impact of credit ratings on capital structure for private and public firms. I have demonstrated that firms constrain debt issuance when their ratings are on upgrade or downgrade boundaries. Thus, it appears that firms face greater costs of raising capital when their rating are on upgrade/downgrade thresholds since debt issuance becomes less cost effective, and alternative sources of financing such as equity issuance and bank loans are often more expensive.

Consequently, I test whether firms reduce their investment when their credit ratings are on upgrade or downgrade thresholds. I hypothesize that firms reduce their investment following periods when their ratings were on upgrade/downgrade boundaries since raising funds becomes less cost effective during those times. Indeed, I find that private firms constrain investment by 8.46 percentage points when their ratings have negative signs and reduce investment by 9.81 percentage points when their ratings have positive signs after controlling for firm characteristics as well as industry and year fixed effects[16].

Similarly to Blanchard, Lopez-de-Silanes, and Shleifer (1994), I define investment as capital expenditure over total assets. Figure 5 depicts the average change in private firms' investments defined as $\frac{CapitalExpenditure_{i,t} - CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}}$ for credit ratings with minus signs, no signs, and plus signs. The figure suggests that, on average, private firms decrease investment by approximately 6.37 percentage points during years when their credit ratings have negative signs relative to years when firms' credit ratings do not have a sign. Consistently, these firms decrease investment by 8.15 percentage points during years when their credit ratings have positive signs. Table 10 includes data for investment of private firms that issue bonds to public investors. In model (1), I regress the change in firm investment defined as $\frac{CapitalExpenditure_{i,t} - CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}}$ on dummy variables for ratings with plus signs ($Plus_{i,t-1}$) and a dummy variables for ratings with minus signs ($Minus_{i,t-1}$). In model (2), I also control for credit rating levels ($Rating_{i,t-1}$), a dummy for ratings outlooks ($RatingOutlook_{i,t-1}$), and firm controls such as leverage, sales, and profitability. Finally, in model (3), I also control for year and industry fixed effects. Consistently, the regression model in column (3) is specified in equation (6)

[16]Table 10, column (3)

$$\frac{CapitalExpenditure_{i,t} - CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}} = \alpha + \beta_1 Minus_{i,t-1} + \beta_2 Plus_{i,t-1}$$
$$+\beta_3 Rating_{i,t-1} + \beta_4 RatingOutlook_{i,t-1} + \beta_5 Leverage_{i,t-1} + \beta_6 Log(Sales_{i,t-1})$$
$$+\beta_7 Profitability_{i,t-1} + \gamma_i + \gamma_t + \varepsilon_{i,t} \tag{6}$$

All regression models in table 10 report negative and highly significant coefficients on $Minus_{i,t-1}$ and $Plus_{i,t-1}$ dummy variables ranging from -6.37 and -9.81 percentage points. These results suggest that private firms constrain investments by at least 6.37 percentage points when their ratings are on upgrade or downgrade thresholds.

Subsequently, I evaluate if private firms reduce investment more than public firms when their ratings are close to upgrade or downgrade thresholds. I hypothesize that since private firms are more sensitive to credit rating fluctuations, they decrease investment more than equivalent public firms when their credit ratings are on upgrade/downgrade boundaries. Table 11 includes data for investment of private and public firms that are issued credit ratings. Similarly to table 10, I define investment as capital expenditure over total assets. In models (1) and (3), I regress the change in firm investment defined as $\frac{CapitalExpenditure_{i,t} - CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}}$ on a dummy for ratings with minus signs ($Minus_{i,t-1}$), a dummy for ratings with plus signs ($Plus_{i,t-1}$), credit rating levels ($Rating_{i,t-1}$), a dummy for private firms ($Private_i$) as well as year and industry fixed effects. In models (2) and (4), I also control for firm leverage, sales, and profitability. Columns (3) and (4) report results for matched private and public firms within the same industry that have the closest assets, sales, and profitability. In summary, the regression models in columns (2) and (4) of table 11 are specified in equation (7)

$$\frac{CapitalExpenditure_{i,t} - CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}} = \alpha + \beta_1 Minus_{i,t-1} + \beta_2 Plus_{i,t-1}$$
$$+\beta_3 Minus_{i,t-1} * Private_i + \beta_4 Plus_{i,t-1} * Private_i + \beta_5 Rating_{i,t-1} + \beta_6 Private_i$$
$$+\beta_7 Leverage_{i,t-1} + \beta_8 Log(Sales_{i,t-1}) + \beta_9 Profitability_{i,t-1} + \gamma_i + \gamma_t + \varepsilon_{i,t} \quad (7)$$

The coefficients on the interaction terms of a dummy variable for private firms with dummies for ratings with negative and positive signs ($Minus_{i,t-1} * Private_i$ and $Plus_{i,t-1} * Private_i$) outline the relative impact of credit ratings on investment for private versus pubic firms. The negative and highly significant coefficients on these interaction terms (β_3 and β_4) suggest that private firms constrain investment more than public firms when their ratings are on upgrade or downgrade thresholds. Across regression models (1) to (4), the coefficients on the interaction terms range from -6.52 percentage points to -9.97 percentage points. This suggests that private firms constrain investment at least 6.52 percentage points more than public firms do, when their credit ratings are on the upgrade/downgrade boundaries. Note that the coefficients on the interaction terms (β_3 and β_4) in models (1) and (2) have similar magnitudes to the coefficients in columns (3) and (4). This implies that matching private and public firms does not change the results in a meaningful way.

1.5.7 Leverage for private and public firms prior and following first access to the public debt market

After analyzing how private and public firms adjust their capital structure and investment when their credit ratings are on upgrade/downgrade thresholds, I turn to evaluate the discrepancy in the leverage levels for these firms prior and following first access to public debt.

Private firms do not have access to the public equity market. Therefore, they are more likely to utilize public debt as a channel to raise funds. Figure 6 demonstrates that prior to first access to public debt, the leverage for private and public firms is very similar across years. However, following first credit rating, the leverage level for public firms (the dashed line) is downward sloping following an initial spike at the year of first issuance of bonds to public investors. However, following the first credit rating, leverage for private firms trends upward and diverges from the leverage level for public firms. Therefore, I evaluate the aforementioned gap between the leverage levels of private and public firms using the regression model specified in equation 8.

$$
\begin{aligned}
\frac{Debt_{i,t}}{Assets_{i,t}} &= \alpha + \beta_0(AccessToPublicDebt_{i,t}) * Private_i + \beta_1 AccessToPublicDebt_{i,t} \\
&+ \beta_2 Private_t + \beta_3 Profitability_{i,t} + \beta_4 Log(Sales_{i,t}) + \beta_5 \frac{Debt_{i,t-1}}{EBITDA_{i,t-1}} + \varepsilon_{i,t}
\end{aligned} \tag{8}
$$

The dependent variable of the regression is leverage for firm i in year t, defined as total debt as a share of assets. $Private_i = 1$ when firm i is private. $AccessToPublicDebt_{i,t} = 1$ for years following first credit ratings and 0 otherwise. Similarly to Faulkender & Petersen (2006), I use first credit rating as a signal for the first time a firm has access to public debt. Thus, the interaction term $(AccessToPublicDebt_{i,t}) * Private_i = 1$ for private firms during years when they have access to pubic debt, and 0 otherwise. The coefficient on this interaction term (β_0) is my primary object of interest since it outlines the relative impact for private versus public firms, of having access to the public debt market as a channel to raise capital, on firm leverage.

The data in table 12 includes matched private and public firms within the same industry with similar assets, sales, and profitability. The sample is limited to only private and public firms where I observe financials during years prior and following the first assigned credit ratings. This allows me to construct leverage level for equivalent private and public firms for years before and after first access to the public debt market. The results in table 12 confirm the findings of Faulkender & Petersen (2006) as my coefficients on $AccessToPublicDebt_{i,t}$ are positive and highly significant for all regression specifications. It implies that when public firms have access to the public bond market, their level of leverage rises[17]. However, the fact that coefficient β_0 on the interaction term $(AccessToPublicDebt_{i,t}) * Private_i$ is positive and highly significant implies that private firms increase their leverage level substantially more than equivalent public firms following first access to public debt[18]. Note that employing difference in difference methodology seems appropriate in this context since the leverage levels for private and public firms exhibit similar patterns across years prior to first credit rating[19].

[17] Note that in models (2)-(4) of table 12, I also control for profitability, log of sales, and lagged debt as a share of earning. However, it does not have a meaningful impact on the results.

[18] For the regression specifications in table 12, I match for each private firm, an equivalent public firm within the same industry that has similar profitability, assets, and sales in the first year it is observed in the data.

[19] As depicted in the non-shaded section of figure 6

1.6 CONCLUSIONS

This study is the first to evaluate the effect of credit ratings on capital structure and investment of private versus public U.S. firms. It contributes to the growing literature on discrepancies between private and public firms, as well as to the literature on credit ratings and capital structure. I find that credit rating agencies disagree more frequently about ratings assigned to private, as apposed to public firms. This result suggests that there is greater information asymmetry between firm insiders and outside investors, for private firms, which makes the rating agencies' task of assessing default risk more difficult for those firms. This finding is hardly surprising since less information about private firms is available in comparison to public firms. This is because private firms do not have publicly traded shares and are not required to file some financial disclosures that public firms are mandated to file. This limited information about private firms drives investors to pay closer attention to publicly posted credit ratings, which in turn makes private firms highly sensitive to rating fluctuations.

Consequently, I hypothesized that private firms constrain their debt issuance more than public firms when their ratings are on thresholds where rating changes yield large shifts in the cost of debt. This allows firms to boost cash flow to equity holders, and thereby send a favorable signal to rating agencies, in order to avoid a downgrade or possibly achieve a rating upgrade. Indeed, I find that when firms' ratings are on upgrade or downgrade boundaries, private firms constrain debt issuance at least 4.5 percentage points more than equivalent public firms. As a result, private firms reduce investment by more than 6.5 percentage points when their credit ratings are on upgrade/downgrade thresholds, since raising capital on the debt market becomes particularly costly in that instance, and alternative channels of financing are less cost effective than public debt financing.

Consistently, I demonstrate that private firms that file for IPOs constrain debt issuance at least 10 percentage points more, during years prior to going public, if their ratings are on upgrade/downgrade thresholds. Furthermore, my findings suggest that private firms that have access to alternative sources of financing, such as private equity funds, do not constrain debt issuance more than public firms, when their ratings are on a boundary. These results support the intuition that private firms are highly sensitive to rating changes due in part to the fact that they rely heavily on public debt as a channel to raise capital. Lastly, I document that private and public firms have similar leverage trajectories prior to their first access to the public debt market. However, following their first credit rating, private firms issue substantially more debt as a share of assets, relative to equivalent public firms[20]. This confirms that private firms utilize the public debt market as a channel to raise capital, more than public firms.

[20]Following first credit rating, private firms issue on average 56% debt as a share of assets relative to only 25% for public firms.

1.7 REFERENCES

[1] Modigliani, F., and M.H. Miller, 1963, Corporate income taxes and the cost of capital: A correction, *The American Economic Review*, 53, 433-443.

[2] Jensen, M.C., and W.H. Meckling, 1976, Theory of the firm: managerial behavior, agency costs and ownership structure, *Journal of Financial Economics* 3, 305-360.

[3] Jensen, M.C., 1986, Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers, *The American Economic Review* 76, 323-329.

[4] Graham, J.R., 2000, How Big Are the Tax Benefits of Debt?, *The Journal of Finance*, 55, 1901-1941.

[5] Brennan, M.J., and E.S. Schwartz, 1984, Optimal financial policy and firm valuation, *Journal of Finance*, 39.

[6] Kane, A., Lee Y.K., and A. Marcus, 1984, Earnings and Dividend Announcements: Is There a Corroboration Effect?, *Journal of Finance*, 39, 1091–1099.

[7] Goldstein, R., N. Ju, and H. Leland, 2001, An ebit-based model of dynamic capital structure, *Journal of Business*, 74, 483-512.

[8] Strebulaev, I. A., 2007, Do Tests of Capital Structure Theory Mean What They Say?, *Journal of Finance*, 62, 1747–1787.

[9] Fischer, E. O., Heinkel R., and Zechner J., 2007, Dynamic Capital Structure Choice: Theory and Tests, *Journal of Finance*, 44, 19-40.

[10] Myers, S. C. & Majluf, N. S. 1984, Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have, *Journal of Financial Economics*, 13, 187-221

[11] Myers, S. C. 1984, The Capital Structure Puzzle, *Journal of Finance*, 39, 575-592.

[12] Akerlof, G.A. 1970, The market for 'lemons': Quality uncertainty and the market mechanism, *The Quarterly Journal of Economics*, 84, 488-500.

[13] Leland, H.E., Pyle, D.H. 1977, Information Asymmetries, Financial Structure, and Financial Intermediation, *The Journal of Finance*, 32, 371-387.

[14] Shyam-Sunder, L., Myers, S. C. 1999. Testing static trade-off against pecking order models of capital structure. *Journal of Financial Economics*, 51, 219-244.

[15] Frank, M. Z., Goyal, V. K. 2003. Testing The Pecking Order Theory Of Capital Structure. *Journal of Financial Economics*, 67, 217-248.

[16] Baker, M., Wurgler, J., 2002, Market timing and capital structure *Journal of Finance*, 57.

[17] Graham, J.R., Harvey, C.R. 2001, The Theory and Practice of Corporate Finance: Evidence from the Field, *Journal of Financial Economics*, 60, 187-243.

[18] Kisgen, D. J. 2006, Credit Ratings and Capital Structure. *The Journal of Finance*, 61, 1035–1072

[19] Kisgen, D. J. 2009, Do Firms Target Credit Ratings or Leverage Levels? *The Journal of Financial and Quantitative Analysis*, 44, 1323-1344

[20] Michelsen & Klein 2011, The Relevance of External Credit Ratings in the Capital Structure Decision-Making Process, *University of Hohenheim*

[21] Drobetz, W. & Heller, S. 2014, The Impact of Credit Rating Changes on Capital Structure Decisions: Evidence from Non-listed Firms in Germany, *Working paper*

[22] Kisgen, D., Strahan, P. 2010, Do Regulations Based on Credit Ratings Affect a Firm's Cost of Capital? *The Review of Financial Studies*, 23, 4324-4347.

[23] Kisgen, D. 2012, The Real and Financial Effects of Credit Ratings: Evidence from Moody's Adjustments, *Boston College*, May 8, 2012, 1 – 40.

[24] Van Binsbergen, J.h., Graham, J.r., Yang, J., 2010, The Cost of Debt, *The Journal of Finance*, 65, 2089-2136.

[25] Rauh, J., Sufi, A. 2010, Capital Structure and Debt Structure *The Review of Financial Studies*, 23, 4242-4280.

[26] Faulkender, M., Petersen, M. A. 2006, Does the Source of Capital Affect Capital Structure? *The Review of Financial Studies*, 19, 45-79.

[27] Predescu, M., Hull, J. C., White, A., 2004, The Relationship between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements *Journal of Banking & Finance*, 28, 2789–2811.

[28] Santos, J.C., Winton, A., 2008, Bank loans, bonds, and information monopolies across the business cycle, *The Journal of Finance*, 63, 1315–1359.

[29] Hale, G., Santos, J. C., 2009, Do Banks Price Their Informational Monopoly? *Journal of Financial Economics*, 93, 185–206.

[30] Ashcraft, A. B, Santos, J. C., 2009, Has the CDS Market Lowered the Cost of Corporate Debt? *Federal Reserve Bank of New York Staff Report*, 1-44.

1.8 APPENDIX A: FIGURES

Figure 2
Debt, Equity, and Debt Net of Equity Issuance for Private Firms

The figure on the left (New Debt Issuance) depicts the change in annual debt issuance for private firms averaged by credit rating signs. The vertical axis represents the change in debt issuance between year $t-1$ and t over assets in year $t-1$ $[\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}]$. The horizontal axis represents ratings with minus signs, no signs, and plus signs. The figure on the right (New Equity Issuance) represents the change in equity issuance for private firms averaged by credit ratings signs. The vertical axis represents the change in private equity issuance between year $t-1$ and t over assets in year $t-1$ $[\frac{Equity_{i,t}-Equity_{i,t-1}}{Assets_{i,t-1}}]$. The horizontal axis represents ratings with minus signs, no signs, and plus signs. The figure at the bottom (Debt Net of Equity Issuance) depicts the average change in debt net of equity issuance for private firms averaged by credit rating signs. The vertical axis represents the change in debt net of equity issuance between year $t-1$ and t over assets in year $t-1$ $[\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}]$. The horizontal axis represents ratings with minus signs, no signs, and plus signs.

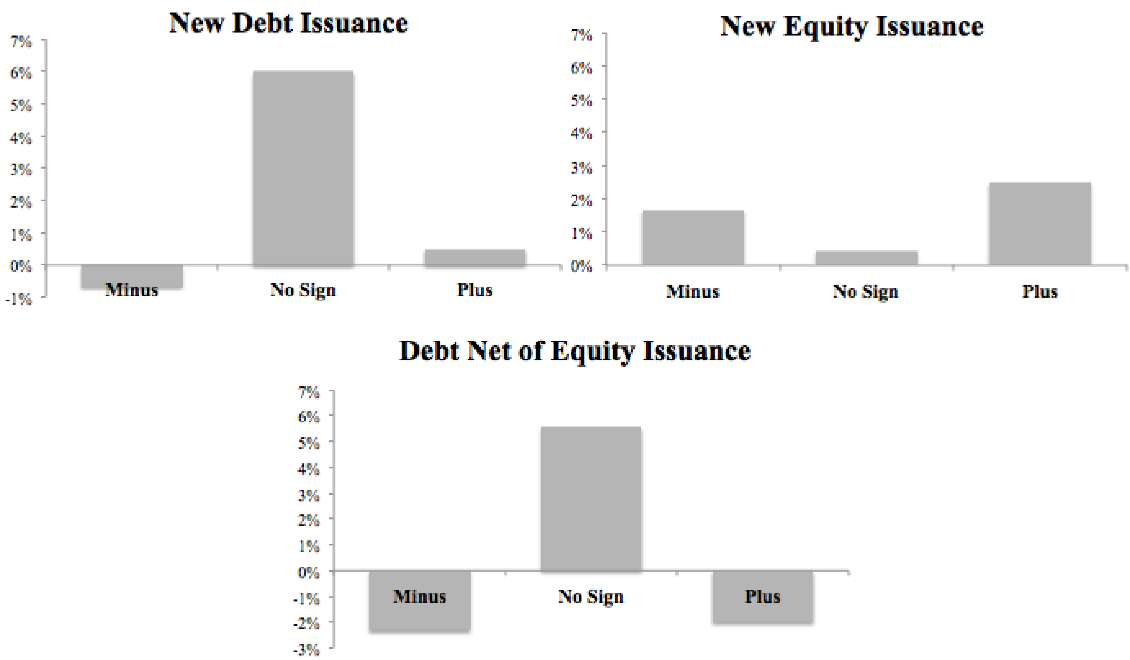
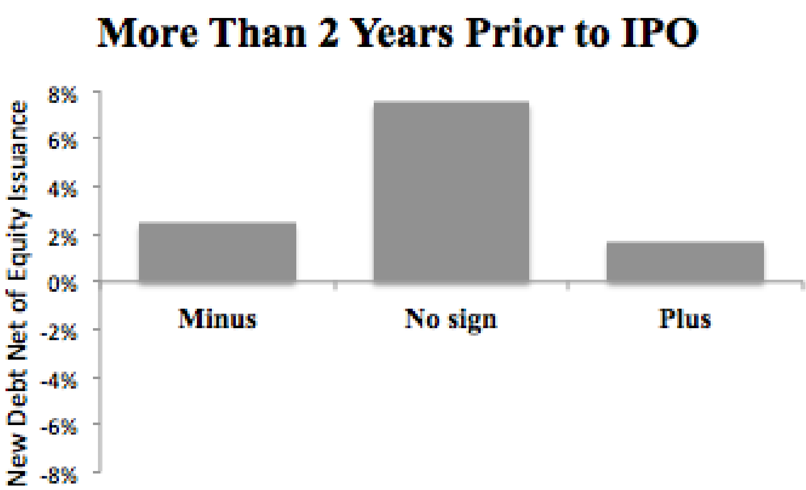


Figure 3
Debt Net of Equity Issuance
More Than and Within 2 Years Prior to IPOs

The figure on the top (More Than 2 Years Prior to IPO) depicts the change in debt net of equity issuance averaged by credit rating signs (rating signs include three categories: plus, minus, and no sign) for private firms more than 2 years prior to their IPOs. The vertical axis represents the change in debt net of equity issuance defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. The horizontal axis represents ratings with minus sings, no signs, and plus signs. The figure at the bottom (Within 2 Years Prior to IPO) depicts the change in debt net of equity issuance averaged by credit rating signs for private firms within 2 years prior to their IPOs. The vertical axis represents the change in debt net of equity issuance defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. The horizontal axis represents ratings with minus signs, no signs, and plus signs.



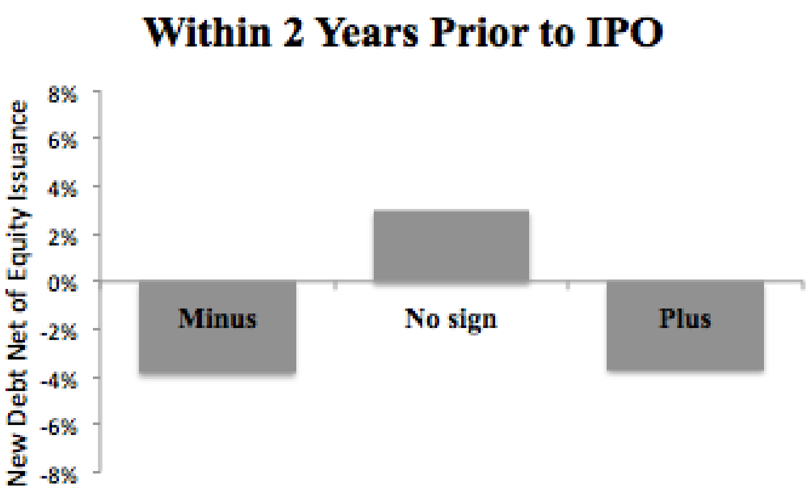
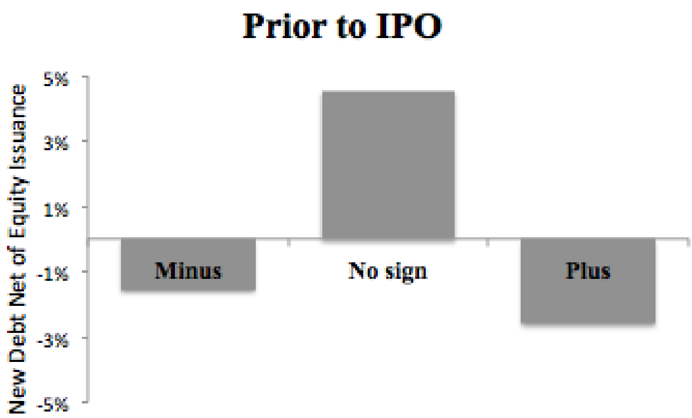


Figure 4
Debt Net of Equity Issuance
Prior and Following Firms' Initial Public Offerings

The figure on the top (Prior to IPO) depicts the change in debt net of equity issuance averaged by credit rating signs (rating signs include three categories: plus, minus, and no sign) for private firms during years prior to their initial public offerings. The vertical axis represents the change in debt net of equity issuance defined as $\frac{[Debt_{i,t} - Debt_{i,t-1}] - [Equity_{i,t} - Equity_{i,t-1}]}{Assets_{i,t-1}}$. The horizontal axis represents ratings with minus signs, no signs, and plus signs. The figure at the bottom (Following IPO) depicts the change in debt net of equity issuance averaged by credit rating signs for firms that turned public during years following their IPOs. The vertical axis represents the change in debt net of equity issuance defined as $\frac{[Debt_{i,t} - Debt_{i,t-1}] - [Equity_{i,t} - Equity_{i,t-1}]}{Assets_{i,t-1}}$. The horizontal axis represents ratings with minus signs, no signs, and plus signs.



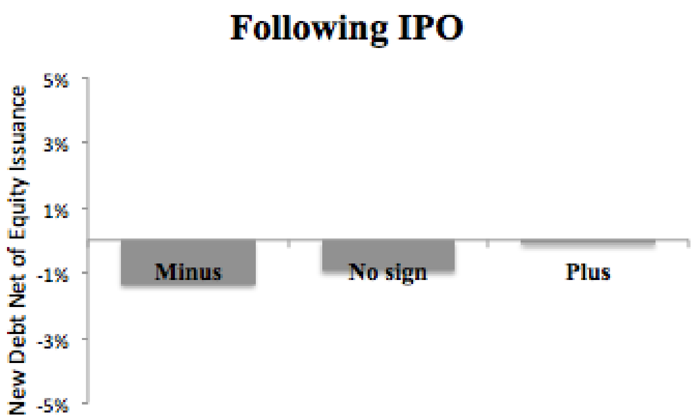


Figure 5
Private Firms' Investment when Credit Ratings are on Upgrade or Downgrade Thresholds

I define investment as capital expenditure over total assets similarly to Blanchard, Lopez-de-Silanes and Shleifer (1994). The figure depicts the average change in firm investment defined as $\frac{CapitalExpenditure_{i,t} - CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}}$ for credit ratings with minus signs, no signs, and plus signs. The figure suggests that, on average, firms decrease investment by approximately 6.37 percentage points during years when their credit ratings have negative signs relative to years when firms' credit ratings do not have plus or minus signs. Similarly, firms decrease investment by 8.15 percentage points during years when their credit ratings have positive signs relative to years when ratings do not plus or minus signs.

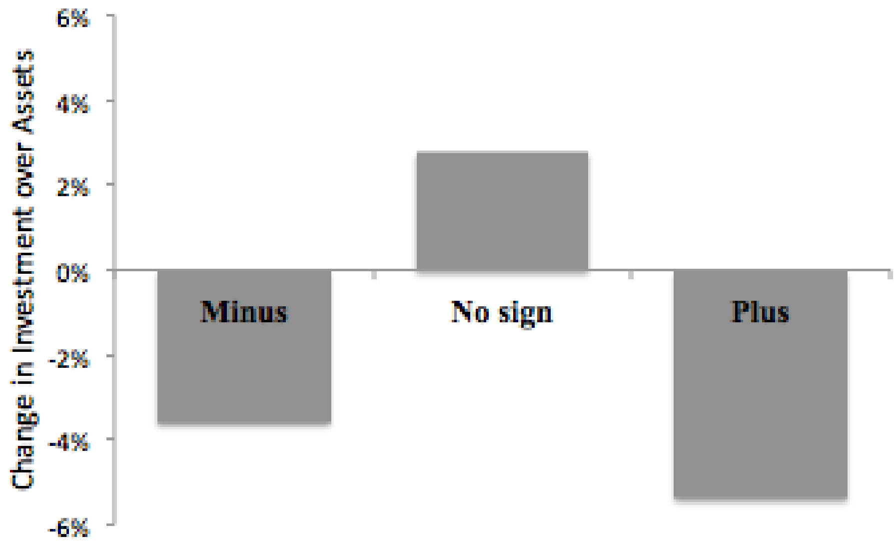


Figure 6
Private and Public Firms' Leverage
Prior and Following Access to Public Debt

The figure depicts average debt as a share of assets for private and public firms by year relative to first year of public debt issuance. The vertical axis represents the average level of leverage for private and public firms defined as $Leverage_{i,t} = \frac{Debt_{i,t}}{Assets_{i,t}}$. The horizontal axis represents years relative to first year of public debt issuance or first year of receiving credit ratings. For instance, year 0 represents the first year of access to the public debt market. Year $+3$ represents the third year for firm i following first year of public debt issuance. Similarly, year -5 represents five years prior to first year of receiving a credit rating. The solid (dashed) line represents the average debt as a share of assets for private (public) firms by year relative to first year of access to the public debt market. The shaded area represents years following first issued credit ratings when firms gained access to the public bond market.

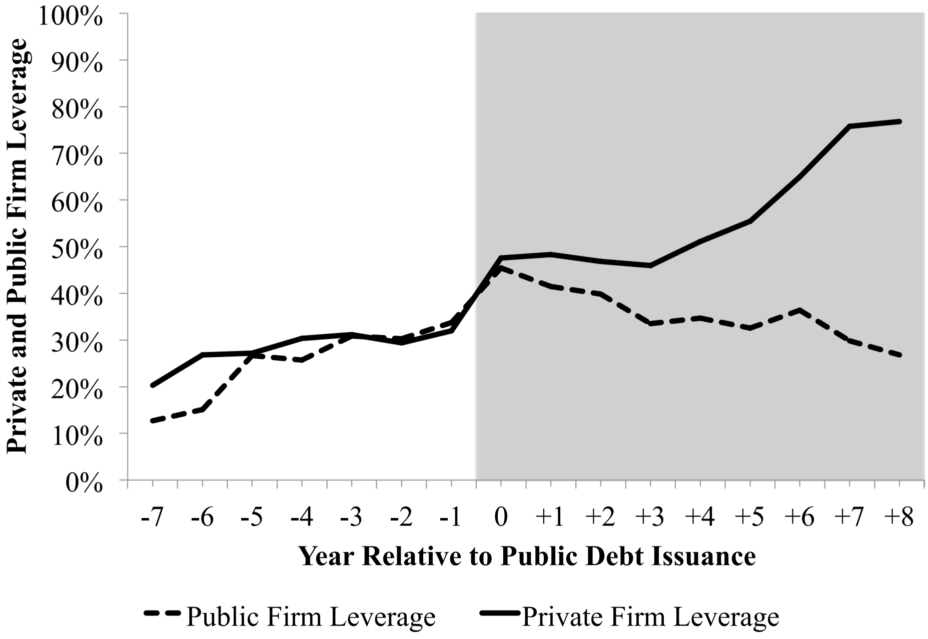
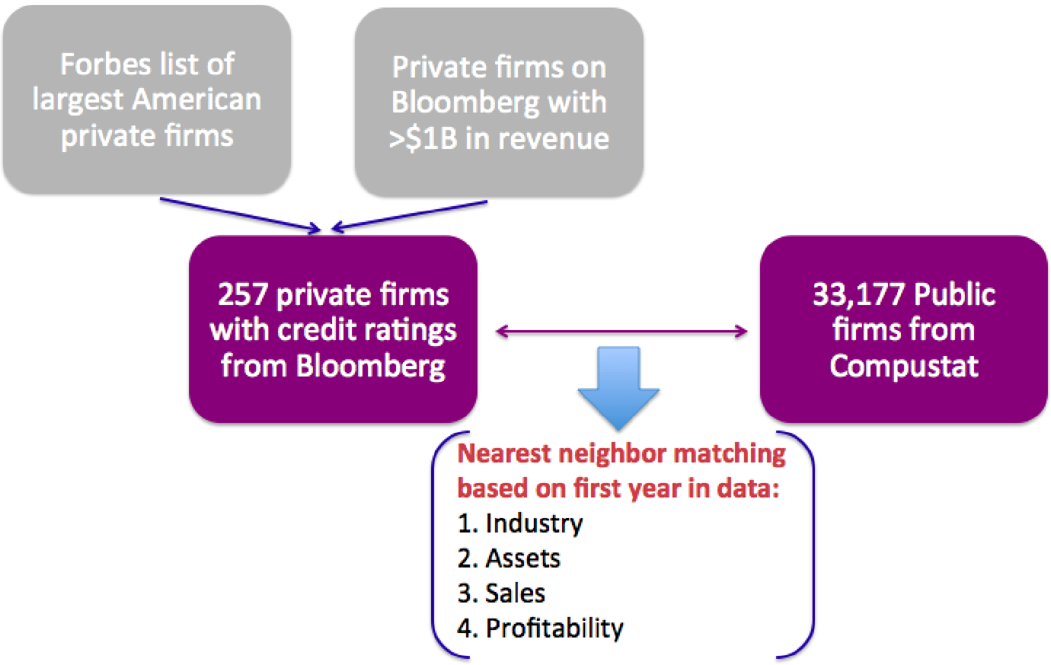


Figure 7
Data Construction and Matching Private and Public Firms

The figure describes the data construction and matching methodology of private and public firms in my sample. I obtain a list of private firms from the Forbes list of largest American private firms. I then supplement that list with private firms in Bloomberg with more than $1 Billion in revenue. Afterwards, I obtain credit ratings and firm characteristics from Bloomberg and Capital IQ for a total of 257 firms from the consolidated list of private firms. Next, I match the set of private firms with available credit ratings and firm characteristics with data from WRDS on 33,177 public firms. This allows me to match for each private firm in my sample, a public firm within the same industry with the closest assets, sales, and profitability. The matching is done based on the first year I observe public and private firms in the data.



1.9 APPENDIX B: TABLES

Table 1
Average Annual Firm Characteristics

Table 1 depicts summary statistics for 257 private firms, 33,177 public firms, and 257 public firms that are matched to private firms within the same industry, by assets, sales, and profitability. The sample of private firms consists of corporations that are assigned credit ratings and are included in the 2014 Forbes list of largest American private firms as well as all private firms with credit ratings on Bloomberg that have more than one Billion US dollars in revenue. The dataset is constructed over 1990-2014. The sample for private firms includes on average 9 years per firm as reported from Bloomberg and Capital IQ. The sample for public firms includes 8 years on average as reported from WRDS. The credit ratings sample focuses on long term bonds issued by Standard & Poor and Moody's. For each bond, I construct daily time series of credit ratings which I then aggregate monthly or annually by firm based on the context of my analyses. Subsequently, I match firm specific credit ratings with firm annual characteristics that I obtain from WRDS, Bloomberg, and Capital IQ.

	Private	Public	Matched Public
Firms	257	33,177	257
Observations	2,305	252,627	1,875
Years Per Firm	≈ 9	≈ 8	≈ 7
Mean Rating	BB	BBB-	BBB-
Median Rating	BB-	BBB-	BBB-
Total Assets	$5.59B	$5.16B	$6.14B
Total Liabilities	$4.07B	$4.27B	$5.22B
Sales	$3.01B	$1.61B	$3.51B
Total Revenues	$2.89B	$1.61B	$3.51B
Total Debt	$2.83B	$2.01B	$2.12B
Operating Income	$383M	$228M	$412M
EBITDA	$321M	$313M	$353M
Cash Flow	$299M	$108M	$232M
Leverage	56%	25%	24%
Profitability	12%	16%	12%
Cash Over Assets	6%	6%	5%

Table 2
Disagreement Between Credit Rating Agencies about Ratings Assigned to Private and Public Firms

Table 2 includes data for private and public firms that are matched within the same industry, by assets, sales and profitability. The dependent variable in the ordered logit regression models (1) and (2) is the absolute value of the difference between S&P and Moody's credit ratings. The dependent variable in models (3) and (4) is the squared difference between S&P and Moody's ratings. $Private_i$ is a dummy variable for private firms. The positive and statistically significant coefficient on $Private_i$ implies that rating agencies disagree more frequently about ratings given to private firms relative to public firms. Additional controls include profitability, log sales, assets, as well as year and industry fixed effects. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1) $\lvert S\&P_{i,t} - Moody_{i,t}\rvert$	(2) $\lvert S\&P_{i,t} - Moody_{i,t}\rvert$	(3) $(S\&P_{i,t} - Moody_{i,t})^2$	(4) $(S\&P_{i,t} - Moody_{i,t})^2$
$Private_i$	0.123***	0.095**	0.359***	0.296**
	(0.045)	(0.045)	(0.123)	(0.120)
$Profitability_{i,t}$		0.103		0.478
		(0.202)		(0.579)
$Assets_{i,t}$		0.009		0.126
		(0.027)		(0.127)
$Log(Sales_{i,t})$		-0.073**		-0.255*
		(0.036)		(0.130)
N	1009	1009	1009	1009
R^2	0.008	0.017	0.009	0.039
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 3
Debt and Equity Issuance for Private Firms

Table 3 includes data for private firms that issue bonds to public investors. The table demonstrates that private firms constrain debt issuance more than 9% percentage points, when their ratings are on upgrade or downgrade thresholds. The dependent variable in models (1) and (2) is the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$. The dependent variable in models (3) and (4) is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in firm debt issuance [models (1),(2)] and debt net of equity issuance [models (3),(4)] on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), and dummy variables for negative and positive rating outlooks ($NegativeOutlook_{i,t-1}$, $PositiveOutlook_{i,t-1}$). The regression specification includes controls such as lagged rating level, profitability, log of sales, and year and industry fixed effects. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(2) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(3) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$	(4) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$
$Plus_{i,t-1}$	-0.107***	-0.112***	-0.116***	-0.128***
	(0.0373)	(0.0369)	(0.0448)	(0.0451)
$Minus_{i,t-1}$	-0.0924***	-0.0914***	-0.0954**	-0.0972**
	(0.0349)	(0.0343)	(0.0406)	(0.0407)
$Rating_{i,t-1}$	0.0105	0.0149	0.0110	0.0170
	(0.00924)	(0.00942)	(0.0106)	(0.0110)
$NegativeOutlook_{i,t-1}$	0.0204	0.0189	-0.00219	-0.00762
	(0.0297)	(0.0295)	(0.0347)	(0.0350)
$PositiveOutlook_{i,t-1}$	-0.0601	-0.0636	-0.106**	-0.109**
	(0.0445)	(0.0437)	(0.0503)	(0.0502)
$Profitability_{i,t-1}$		0.295*		-0.0115
		(0.168)		(0.195)
$Log(Sales_{i,t-1})$		-0.172***		-0.133**
		(0.0512)		(0.0610)
$\frac{CashFlow_{i,t-1}}{Assets_{i,t-1}}$		0.437**		0.160
		(0.222)		(0.258)
N	545	545	511	511
R^2	0.334	0.364	0.348	0.358
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 4
Debt and Equity Issuance for Private and Public Firms

Table 4 includes data for private and public firms that issue bonds to public investors. The table demonstrates that private firms constrain debt issuance more than public firms, when their ratings are on upgrade or downgrade thresholds. The dependent variable in models (1) and (2) is the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$. The dependent variable in models (3) and (4) is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in firm debt issuance [models (1),(2)] and debt net of equity issuance [models (3),(4)] on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), interaction terms of a dummy variable for private firms with plus and minus dummy variables ($Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$), and controls such as lagged rating level, leverage, profitability, log of sales, and year and industry fixed effects. The coefficients on interaction terms $Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$, and $(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$ outline the discrepancy in debt issuance between public and private firms when their ratings are on downgrade or upgrade thresholds. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(2) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(3) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$	(4) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$
$Minus_{i,t-1}$	-0.0071***		-0.0100***	
	(0.0019)		(0.0024)	
$Plus_{i,t-1}$	-0.0066***		-0.0078***	
	(0.0019)		(0.0024)	
$Minus_{i,t-1} * Private_i$	-0.0506***		-0.0480***	
	(0.0136)		(0.0174)	
$Plus_{i,t-1} * Private_i$	-0.0452***		-0.0559***	
	(0.0149)		(0.0190)	
$Private_i$	0.0411***	0.0411***	0.0536***	0.0536***
	(0.0071)	(0.0071)	(0.0089)	(0.0089)
$Rating_{i,t-1}$	0.0008**	0.0008**	-0.0020***	-0.0020***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
$Leverage_{i,t-2}$	-0.0451***	-0.0451***	-0.0611***	-0.0610***
	(0.0045)	(0.0045)	(0.0055)	(0.0055)
$Profitability_{i,t-1}$	0.1270***	0.1270***	-0.0920***	-0.0919***
	(0.0109)	(0.0109)	(0.0134)	(0.0134)
$Log(Sales_{i,t-1})$	-0.0085***	-0.0085***	-0.0019**	-0.0019**
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
$Minus_{i,t-1} \& Plus_{i,t-1}$		-0.0068***		-0.0089***
		(0.0016)		(0.0019)
$(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$		-0.0483***		-0.0516***
		(0.0112)		(0.0142)
N	20283	20283	20257	20257
R^2	0.050	0.050	0.054	0.054
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 5
Debt and Equity Issuance for Private and Public Firms
Matched Sample of Private and Public Firms

Table 5 includes data for private and public firms, matched within the same industry, by assets, sales, and profitability. The table demonstrates that private firms constrain debt issuance more than equivalent public firms within the same industry, when their ratings are on upgrade or downgrade thresholds. The dependent variable in models (1) and (2) is the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$. The dependent variable in models (3) and (4) is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in firm debt issuance [models (1),(2)] and debt net of equity issuance [models (3),(4)] on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), interaction terms of a dummy variable for private firms with plus and minus dummy variables ($Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$), and controls such as lagged rating level, leverage, profitability, log of sales, and year and industry fixed effects. The coefficients on interaction terms $Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$, and $(Minus_{i,t-1}\&Plus_{i,t-1}) * Private_i$ outline the discrepancy in debt issuance between public and private firms when their ratings are on downgrade or upgrade thresholds. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(2) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(3) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$	(4) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$
$Minus_{i,t-1}$	0.0007		0.0021	
	(0.0168)		(0.0205)	
$Plus_{i,t-1}$	-0.0023		0.0054	
	(0.0169)		(0.0207)	
$Minus_{i,t-1} * Private_i$	-0.0600**		-0.0649**	
	(0.0259)		(0.0323)	
$Plus_{i,t-1} * Private_i$	-0.0739***		-0.0940***	
	(0.0277)		(0.0347)	
$Private_i$	0.0548***	0.0546***	0.0683***	0.0679***
	(0.0149)	(0.0149)	(0.0186)	(0.0186)
$Rating_{i,t-1}$	0.0065**	0.0064**	0.0022	0.0020
	(0.0028)	(0.0028)	(0.0035)	(0.0035)
$Leverage_{i,t-2}$	-0.0821***	-0.0820***	-0.0708***	-0.0707***
	(0.0206)	(0.0206)	(0.0253)	(0.0253)
$Profitability_{i,t-1}$	0.2620***	0.2620***	-0.1210	-0.1220
	(0.0674)	(0.0673)	(0.0826)	(0.0825)
$Log(Sales_{i,t-1})$	-0.0288***	-0.0286***	-0.0195**	-0.0194*
	(0.0079)	(0.0079)	(0.0010)	(0.0099)
$Minus_{i,t-1}\&Plus_{i,t-1}$		-0.0008		0.0037
		(0.0134)		(0.0164)
$(Minus_{i,t-1}\&Plus_{i,t-1}) * Private_i$		-0.0658***		-0.0777***
		(0.0211)		(0.0263)
N	1091	1091	1065	1065
R^2	0.114	0.114	0.111	0.111
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 6
Debt and Equity Issuance for Public Firms and Private Firms that are Backed by Private Equity Funds

Table 6 includes data for public firms and private firms that are backed by private equity funds. Private firms that receive financing from private equity funds are less sensitive to rating changes and have more channels to raise capital than non-backed private firms. Thus, their capital structure adjustments to rating being on upgrade/downgrade boundaries are more consistent with those of public firms, that have multiple channels to raise capital cost effectively. The dependent variable in models (1) and (2) is the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$. The dependent variable in models (3) and (4) is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in firm debt issuance [models (1),(2)] and debt net of equity issuance [models (3),(4)] on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), interaction terms of a dummy variable for private firms with plus and minus dummy variables ($Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$), and controls such as lagged rating level, leverage, profitability, log of sales, and year and industry fixed effects. The coefficients on interaction terms $Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$, and $(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$ outline the discrepancy in debt issuance between public and private firms when their ratings are on downgrade or upgrade thresholds. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(2) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(3) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$	(4) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$
$Minus_{i,t-1}$	-0.0070***		-0.0099***	
	(0.0019)		(0.0023)	
$Plus_{i,t-1}$	-0.0064***		-0.0075***	
	(0.0019)		(0.0023)	
$Minus_{i,t-1} * Private_i$	0.0100		0.0468	
	(0.0266)		(0.0329)	
$Plus_{i,t-1} * Private_i$	-0.0168		-0.0124	
	(0.0274)		(0.0339)	
$Private_i$	0.0147	0.0147	0.0094	0.0095
	(0.0119)	(0.0119)	(0.0147)	(0.0147)
$Rating_{i,t-1}$	0.0007**	0.0007**	-0.0022***	-0.0022***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
$Leverage_{i,t-2}$	-0.0483***	-0.0483***	-0.0677***	-0.0678***
	(0.0045)	(0.0045)	(0.0056)	(0.0056)
$Profitability_{i,t-1}$	0.1160***	0.1160***	-0.1060***	-0.1060***
	(0.0108)	(0.0108)	(0.0133)	(0.0133)
$Log(Sales_{i,t-1})$	-0.0083***	-0.0083***	-0.0018**	-0.0019**
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
$Minus_{i,t-1} \& Plus_{i,t-1}$		-0.0067***		-0.0087***
		(0.0015)		(0.0019)
$(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$		-0.0029		0.0183
		(0.0208)		(0.0257)
N	19984	19984	19984	19984
R^2	0.050	0.050	0.057	0.056
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 7
Debt and Equity Issuance for Private and Public Firms
Firms with Median Ratings Above Investment Grade

Table 7 includes data for private and public firms with median S&P credit ratings above investment grade. The regression demonstrates that the discrepancy in debt issuance between private and public firms when ratings are on upgrade/downgrade thresholds is prevalent for firms with low probability of default in addition to risky firms. The dependent variable in models (1) and (2) is the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$. The dependent variable in models (3) and (4) is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in firm debt issuance [models (1),(2)] and debt net of equity issuance [models (3),(4)] on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), interaction terms of a dummy variable for private firms with plus and minus dummy variables ($Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$), and controls such as lagged rating level, leverage, profitability, log of sales, and year and industry fixed effects. The coefficients on interaction terms $Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$, and $(Minus_{i,t-1}\&Plus_{i,t-1}) * Private_i$ outline the discrepancy in debt issuance between public and private firms when their ratings are on downgrade or upgrade thresholds. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(2) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(3) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$	(4) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$
$Minus_{i,t-1}$	-0.0049**		-0.0088***	
	(0.0022)		(0.0027)	
$Plus_{i,t-1}$	-0.0064***		-0.0094***	
	(0.0023)		(0.0028)	
$Minus_{i,t-1} * Private_i$	-0.0855***		-0.0423**	
	(0.0152)		(0.0196)	
$Plus_{i,t-1} * Private_i$	-0.0770***		-0.0528***	
	(0.0153)		(0.0196)	
$Private_i$	0.0763***	0.0759***	0.0661***	0.0663***
	(0.0099)	(0.0099)	(0.0126)	(0.0126)
$Rating_{i,t-1}$	0.0014***	0.0014***	0.0013**	0.0013**
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
$Leverage_{i,t-2}$	-0.0628***	-0.0626***	-0.0728***	-0.0730***
	(0.0077)	(0.0077)	(0.0094)	(0.0094)
$Profitability_{i,t-1}$	0.1340***	0.1340***	-0.0374**	-0.0376**
	(0.0154)	(0.0154)	(0.0188)	(0.0187)
$Log(Sales_{i,t-1})$	-0.0062***	-0.0062***	-0.0005	-0.0005
	(0.0001)	(0.0001)	(0.0012)	(0.0012)
$Minus_{i,t-1}\&Plus_{i,t-1}$		-0.0056***		-0.0091***
		(0.0018)		(0.0022)
$(Minus_{i,t-1}\&Plus_{i,t-1}) * Private_i$		-0.0813***		-0.0476***
		(0.0125)		(0.0161)
N	10054	10054	10029	10029
R^2	0.073	0.073	0.091	0.091
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 8
Debt and Equity Issuance for Private Firms and Public Firms with Number of Bonds Issued Above Industry Standard

Table 8 includes data for private firms that issue public debt as well as for public firms that issued number of bonds for each month in the data, that exceed the median number of bonds issued by firms in the same industry. Public firms with abnormally large bond issuance are particularly sensitive to credit rating fluctuations and thus are more comparable to private firms that are sensitive to credit rating changes due to limited availability of information about their performance. The dependent variable in models (1) and (2) is the change in debt over assets defined as $\frac{Debt_{i,t}-Debt_{i,t1}}{Assets_{i,t-1}}$. The dependent variable in models (3) and (4) is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in firm debt issuance [models (1),(2)] and debt net of equity issuance [models (3),(4)] on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), interaction terms of a dummy variable for private firms with plus and minus dummy variables ($Minus_{i,t-1}*Private_i$, $Plus_{i,t-1}*Private_i$), and controls such as lagged rating level, leverage, profitability, log of sales, and year and industry fixed effects. The coefficients on interaction terms $Minus_{i,t-1}*Private_i$, $Plus_{i,t-1}*Private_i$, and $(Minus_{i,t-1}\&Plus_{i,t-1})*Private_i$ outline the discrepancy in debt issuance between public and private firms when their ratings are on downgrade or upgrade thresholds. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(2) $\frac{Debt_{i,t}-Debt_{i,t-1}}{Assets_{i,t-1}}$	(3) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$	(4) $\frac{\triangle Debt_{i,t}-\triangle Equity_{i,t}}{Assets_{i,t-1}}$
$Minus_{i,t-1}$	-0.0181***		-0.0127**	
	(0.0055)		(0.0057)	
$Plus_{i,t-1}$	-0.0148***		-0.0136**	
	(0.0054)		(0.0063)	
$Minus_{i,t-1}*Private_i$	0.0030		0.0033	
	(0.0127)		(0.0225)	
$Plus_{i,t-1}*Private_i$	-0.0111		-0.0100	
	(0.0129)		(0.0244)	
$Private_i$	-0.0075	-0.0066	0.0118	0.0126
	(0.0146)	(0.0147)	(0.0207)	(0.0207)
$Rating_{i,t-1}$	0.0021	0.0021	-0.0011	-0.0012
	(0.0019)	(0.0019)	(0.0024)	(0.0024)
$Leverage_{i,t-2}$	-0.0702***	-0.0700***	-0.0910***	-0.0906***
	(0.0154)	(0.0154)	(0.0266)	(0.0268)
$Profitability_{i,t-1}$	0.2500***	0.2500***	-0.0167	-0.0164
	(0.0493)	(0.0495)	(0.0716)	(0.0717)
$Log(Sales_{i,t-1})$	-0.0170***	-0.0168***	-0.0040	-0.0038
	(0.0030)	(0.0030)	(0.0037)	(0.0038)
$Minus_{i,t-1}\&Plus_{i,t-1}$		-0.0165***		-0.0131***
		(0.0045)		(0.0048)
$(Minus_{i,t-1}\&Plus_{i,t-1})*Private_i$		-0.0035		-0.0027
		(0.0106)		(0.0188)
N	2013	2013	1987	1987
R^2	0.165	0.165	0.193	0.193
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 9
Debt Issuance Prior and Following IPOs when Ratings are on Upgrade/Downgrade Thresholds

Table 9 includes data for firms that filed for IPOs on NYSE and NASDAQ. The table demonstrates that firms constrain debt issuance substantially, during years prior to becoming public, when their ratings are on upgrade or downgrade thresholds. Model (1) limits the regression data to only pre-IPO observations. Models (2) and (3) include data for both pre and post IPO years. The dependent variable in all models is the change in debt net of equity over assets defined as $\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$. I regress the change in debt net of equity issuance on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), and interaction terms of these dummy variables with a dummy variable for the pre-IPO years ($BeforeIPO_{i,t-1} * Minus_{i,t-1}$, $BeforeIPO_{i,t-1} * Plus_{i,t-1}$) for models (2) and (3). All specifications include controls for firm evolution following an IPO such as number of years relative to an IPO, firm revenue growth, firm age and others. In addition, all specifications include firm and industry fixed effects. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	$\frac{[Debt_{i,t}-Debt_{i,t-1}]-[Equity_{i,t}-Equity_{i,t-1}]}{Assets_{i,t-1}}$		
	(1) Prior to IPO	(2) Prior and Following IPO	(3) Prior and Following IPO
$Minus_{i,t-1}$	-0.215***	0.005	0.018
	(0.076)	(0.036)	(0.043)
$Plus_{i,t-1}$	-0.204**	0.019	0.016
	(0.080)	(0.040)	(0.024)
$BeforeIPO_{i,t-1} * Minus_{i,t-1}$		-0.142**	-0.146**
		(0.061)	(0.071)
$BeforeIPO_{i,t-1} * Plus_{i,t-1}$		-0.142**	-0.100**
		(0.056)	(0.042)
$BeforeIPO_{i,t-1}$		0.098**	0.072*
		(0.047)	(0.040)
$S\&P_{i,t-1}$	0.021	0.030***	0.022
	(0.018)	(0.009)	(0.013)
$Leverage_{i,t-2}$	0.003	-0.014	-0.015
	(0.018)	(0.009)	(0.012)
$Profitability_{i,t-1}$	-1.618***	-1.365***	-1.335***
	(0.423)	(0.180)	(0.497)
$RevenueGrowth_{i,t-1}$	-0.151**	-0.068***	-0.047
	(0.061)	(0.024)	(0.065)
$FirmAge_{i,t-1}$	0.037	0.038	0.0001
	(0.032)	(0.026)	(0.0004)
$\frac{Cash_{i,t-1}}{Assets_{i,t-1}}$	0.009	0.109	-0.078
	(0.657)	(0.256)	(0.369)
$YearsRelativeToIPO_{i,t}$	6.370	6.266	0.0002
	(4.829)	(3.891)	(0.005)
N	401	1004	1004
R^2	0.522	0.275	0.163
Industry and Year FE	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes

Table 10
Private Firms' Investment when Credit Ratings are on Upgrade/Downgrade Thresholds

Table 10 includes data for investment of private firms that issue bonds to public investors. The table demonstrates that private firms constrain investment when their ratings are on upgrade or downgrade thresholds. Similarly to Blanchard, Lopez-de-Silanes and Shleifer (1994), I define investment as Capital Expenditure over Total Assets. I regress the change in firm investment defined as $\frac{CapitalExpenditure_{i,t} - CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}}$ on a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), lagged credit rating level ($Rating_{i,t-1}$), and a dummy for ratings outlooks ($RatingOutlook_{i,t-1}$). Additional firm controls include lagged leverage, sales, and profitability, as well as year and industry fixed effects. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	$\frac{CapitalExpenditure_{i,t} - CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}}$		
	(1)	(2)	(3)
$Minus_{i,t-1}$	-0.0637**	-0.0738**	-0.0846**
	(0.0322)	(0.0356)	(0.0424)
$Plus_{i,t-1}$	-0.0815**	-0.0908**	-0.0981**
	(0.0415)	(0.0448)	(0.0476)
$Rating_{i,t-1}$		0.0093	0.0056
		(0.0078)	(0.0088)
$RatingOutlook_{i,t-1}$		0.0843	0.0748
		(0.0790)	(0.0776)
$Leverage_{i,t-1}$		0.1300	0.0941
		(0.0907)	(0.0900)
$Log(Sales_{i,t-1})$		-0.0191	-0.0129
		(0.0154)	(0.0161)
$Profitability_{i,t-1}$		-0.1850	-0.2990
		(0.4810)	(0.3450)
$Constant$	0.0279	0.0990	0.1840
	(0.0272)	(0.1570)	(0.2490)
N	561	500	500
R^2	0.007	0.037	0.098
Industry and Year FE	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes

Table 11
Public and Private Firms' Investments when Credit Ratings are on Upgrade/Downgrade Thresholds

Table 11 includes data for investment of public and private firms that issue bonds to public investors. The table demonstrates that private firms constrain investment more than public firms when their ratings are on upgrade/downgrade boundaries. Similarly to Blanchard, Lopez-de-Silanes and Shleifer (1994), I define investment as capital expenditure over total assets. In all specifications, I regress the change in firm investment, defined as $\frac{CapitalExpenditure_{i,t}-CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}}$ on a lagged dummy for ratings with minus signs ($Minus_{i,t-1}$), a lagged dummy for ratings with plus signs ($Plus_{i,t-1}$), interaction terms of a dummy variable for private firms with plus and minus dummy variables ($Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$), lagged credit rating levels ($Rating_{i,t-1}$), and dummy for private firms ($Private_i$), as well as year and industry fixed effects. In models (2) and (4), I also control for firm leverage, sales, and profitability. Columns (3) and (4) report results for matched private and public firms within the same industry with the closest assets, sales, and profitability. The coefficients on interaction terms $Minus_{i,t-1} * Private_i$, $Plus_{i,t-1} * Private_i$, and $(Minus_{i,t-1} \& Plus_{i,t-1}) * Private_i$ outline the discrepancy in investment between public and private firms when their ratings are on downgrade or upgrade thresholds. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	Dependent Variable: $\frac{CapitalExpenditure_{i,t}-CapitalExpenditure_{i,t-1}}{Assets_{i,t-1}}$			
	(1) Unmatched Firms	(2) Unmatched Firms	(3) Matched Firms	(4) Matched Firms
$Minus_{i,t-1}$	0.0013	0.0021	0.0127	0.0236
	(0.0010)	(0.0015)	(0.0240)	(0.0295)
$Plus_{i,t-1}$	0.0010	0.0028*	-0.0048	0.0030
	(0.0010)	(0.0015)	(0.0240)	(0.0304)
$Minus_{i,t-1} * Private_i$	-0.0652***	-0.0727***	-0.0862**	-0.0997**
	(0.0082)	(0.0096)	(0.0390)	(0.0448)
$Plus_{i,t-1} * Private_i$	-0.0822***	-0.0912***	-0.0863**	-0.0967**
	(0.0087)	(0.0105)	(0.0415)	(0.0479)
$Rating_{i,t-1}$	-0.0003***	-0.0004	-0.0018	0.0036
	(0.0001)	(0.0002)	(0.0031)	(0.0048)
$Private_i$	0.0236***	0.0283***	0.0365	0.0391
	(0.0043)	(0.0052)	(0.0230)	(0.0261)
$Leverage_{i,t-1}$		-0.0115***		0.0461
		(0.0023)		(0.0316)
$Log(Sales_{i,t-1})$		-0.0019***		-0.0134
		(0.0005)		(0.0108)
$Profitability_{i,t-1}$		0.0488***		-0.1190
		(0.0072)		(0.1170)
N	35631	20635	1330	1124
R^2	0.011	0.016	0.040	0.047
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 12
Leverage for Private and Public Firms
Prior and Following Access to Public Debt Market

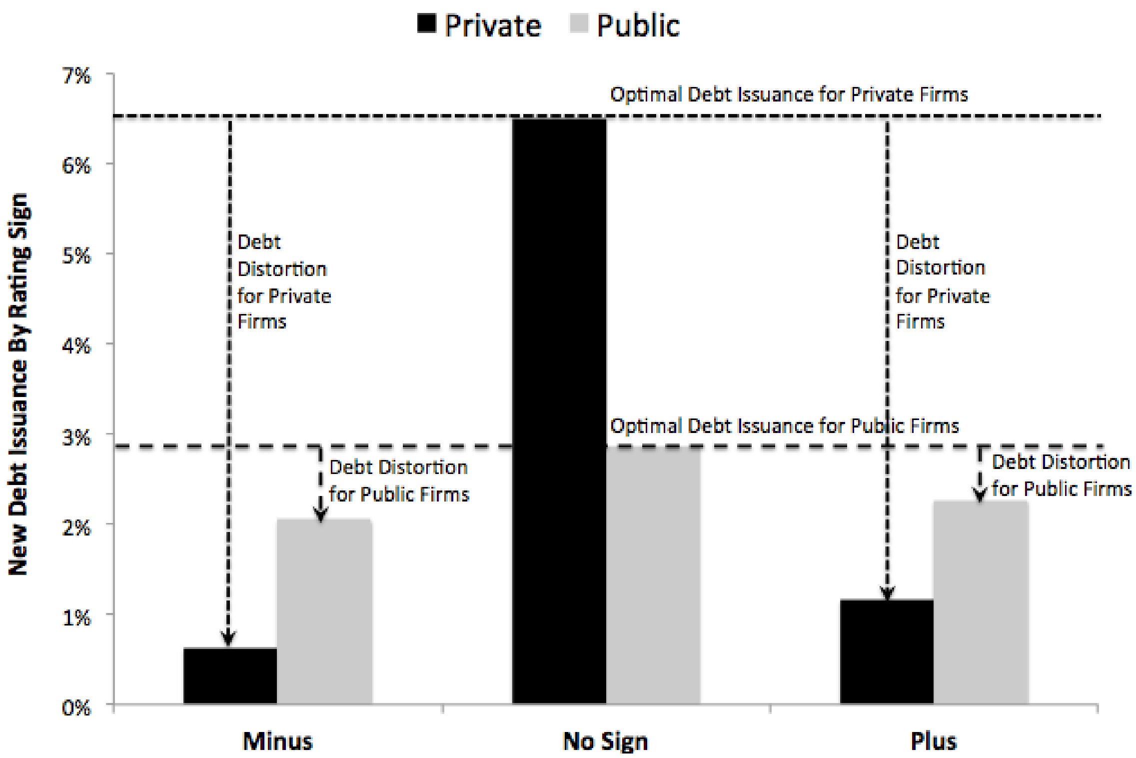
Table 12 includes data for matched private and public firms within the same industry, by assets, sales and profitability , during years prior and following to first debt issuance to public investors. The table demonstrates that prior to first access to the public debt market, private and public firms have similar leverage levels. However, following first credit rating, private firms issue substantially more debt as a share of assets in comparison with public firms. The dependent variable for all specifications is leverage, defined as $\frac{Debt_{i,t}}{Assets_{i,t}}$. I regress leverage on a dummy variable for years following first public debt issuance ($AccessToPublicDebt_{i,t}$), an interaction effect of this variable with a dummy for private firms [$(AccessToPublicDebt_{i,t}) * Private_i$], a dummy for private firms [$Private_i$], and lagged controls for profitability, log of sales, debt over earnings, and year and firm fixed effects. Standard errors in parentheses are clustered by firm. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
$(AccessToPublicDebt_{i,t}) * Private_i$	0.0973***	0.1000***	0.1130***	0.1060***
	(0.0375)	(0.0373)	(0.0235)	(0.0244)
$AccessToPublicDebt_{i,t}$	0.1130***	0.1420***	0.0957***	0.0963***
	(0.0266)	(0.0273)	(0.0163)	(0.0195)
$Private_t$	0.0451	0.0303	-0.1560***	-0.1710***
	(0.0278)	(0.0280)	(0.0521)	(0.0524)
$Profitability_{i,t}$		0.1772	-0.4390***	-0.4380***
		(0.1382)	(0.1211)	(0.1210)
$Log(Sales_{i,t})$		-0.0547***	-0.0097	-0.0071
		(0.0110)	(0.0108)	(0.0128)
$\frac{Debt_{i,t-1}}{EBITDA_{i,t-1}}$		-0.0574	0.0182	0.0134
		(0.1180)	(0.0657)	(0.0650)
N	676	672	672	672
R^2	0.089	0.146	0.784	0.801
Year FE	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

1.10 APPENDIX C: THEORETICAL MODEL

I develop a Bayesian updating model with normally distributed priors to demonstrate that private firms distort their debt issuance more than public firms when their ratings are on upgrade/downgrade thresholds in-order to send a favorable signal to the rating agencies by constraining debt issuance. Figure 8 depicts the average change in debt issuance for private and public firms by rating sign. When ratings do not have positive or negative signs, firms' decisions of debt issuance are not driven by concerns of signaling their credit worthiness to the rating agencies. Thus, public and private firms choose their debt issuance optimally when their ratings are not on upgrade or downgrade thresholds.

Figure 8
Debt Distortion for Private and Public Firms



Myers' and Majluf's (1984) pecking order theory suggests that the cost of financing increases with asymmetric information. Consequently, private firms will have larger discrepancy between the cost of debt and equity and therefore will issue more debt as a share of assets than public firms when signaling concerns are not prevalent. This explains why the change in debt issuance is larger for private firms than for public firms when credit ratings do not have a plus or minus sign (as described in figure 8). Figure 8 also demonstrates empirically that private firms distort their debt issuance substantially more than public firms when their ratings are on the boundaries. The model below provides theoretical foundation for that empirical result.

Private and public firms send a creditworthiness signal (S_{CR}) to the rating agencies by distorting debt issuance (x) when their ratings have a plus or minus signs. Kisgen (2006) demonstrates that firms constrain debt issuance when their ratings are on the boundaries since investors respond strongly to rating downgrades or upgrades that yield a new rating of a different letter group. Consistently, firms choose their debt issuance optimally without signaling concerns when their ratings do not have plus or minus signs, as they are not as concerned about upgrades or downgrades.

However, when ratings are on upgrade/downgrade thresholds, firms send signal $S_{CR} = C^* + \xi_{CR} + x$ to the rating agencies. The signal consists of steady-state firm riskiness of default (C^*), error term of firm riskiness of default (ξ_{CR}), and debt issuance distortion (x) that firms adjust to boost cash flow to equity holders and thus send a favorable signal to the CRAs when their ratings have plus or minus signs. Thus, the distortion of debt issuance (x) represents to what extent firms constrain their debt issuance to send signals to the rating agencies. The credit rating agencies in-turn, adjust the creditworthiness signal with their expected firm debt issuance distortion in equilibrium ($\widehat{x}$). Thus, the unbiased signal that the CRAs perceive is $\widehat{S}_{CR} = S_{CR} - \widehat{x}$.

Further, credit rating agencies that assign ratings to private firms, adjust their beliefs about firm riskiness using Bayesian updating given the unbiased signal from private firms ($\widehat{S}_{CR}$), and then issue their ratings $CR_{Private} = E[C^*|\widehat{S}_{CR}]$.

Similarly, rating agencies that assign ratings to public firms, adjust their beliefs given unbiased signals from public firms ($\widehat{S}_{CR}$), but they also observe equity information $S_1 = S^* + \xi_{S_1}$. This information consists of share steady-state value (S^*) and equity price error term (ξ_{S_1}). Then, rating agencies update their beliefs and issue their credit ratings to public firms given the aforementioned information $CR_{Public} = E[C^*|\widehat{S}_{CR}, S_1]$. Thus, the equations for share price and firms' signals to rating agencies can be summarized in equations 9-11.

$$S_1 = S^* + \xi_{S_1} \tag{9}$$

$$S_{CR} = C^* + \xi_{CR} + x \tag{10}$$

$$\widehat{S}_{CR} = C^* + \xi_{CR} + x - \widehat{x} = S_{CR} - \widehat{x} \tag{11}$$

I am assuming that $S^*, C^*, \xi_{CR}, \xi_{S_1}$ are normally distributed with mean $\mu = 0$ and positive variance. I am allowing for non zero covariance between S^* and C^* ($\sigma_{SC} \neq 0$). The assumptions are summarized in equations 12-14.

$$\begin{bmatrix} S^* \\ C^* \end{bmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_S^2 & \sigma_{SC} \\ \sigma_{SC} & \sigma_C^2 \end{pmatrix} \right] \tag{12}$$

$$\xi_{CR} \sim N \begin{bmatrix} 0 & \sigma^2_{\xi_{CR}} \end{bmatrix} \tag{13}$$

$$\xi_{S_1} \sim N \begin{bmatrix} 0 & \sigma^2_{\varepsilon_{S_1}} \end{bmatrix} \tag{14}$$

In equation 15, I outline a Bayesian updating model to show how credit rating agencies update their beliefs given signals from private firms, and subsequently assign credit ratings to private firms. Similarly, in equation 16, I describe a Bayesian updating model for how the rating agencies that assign ratings to public firms update their beliefs given creditworthiness signals that they receive from those firms as well as stock price information.

$$CR_{Private} = E[C^*|\widehat{S}_{CR}] = \frac{\sigma_C^2}{\sigma_C^2 + \sigma_{\xi_{CR}}^2}\widehat{S}_{CR} = \frac{\sigma_C^2}{\sigma_C^2 + \sigma_{\xi_{CR}}^2}(S_{CR} - \widehat{x}) \tag{15}$$

$$CR_{Public} = E[C^*|\widehat{S}_{CR}, S_1] = \beta_1\widehat{S}_{CR} + \beta_2 S_1 \tag{16}$$

Next, investors in private firms update their beliefs about the creditworthiness of private firms given credit ratings assigned by the rating agencies (equation 17). Consistently, investors in public firms update their beliefs about the riskiness of public firms given credit ratings and equity information (equation 18).

$$E[C^*|CR_{Private}] = E[C^*|\frac{\sigma_C^2}{\sigma_C^2 + \sigma_{\xi_{CR}}^2}\widehat{S}_{CR}] = E[C^*|\widehat{S}_{CR}] = \frac{\sigma_C^2}{\sigma_C^2 + \sigma_{\xi_{CR}}^2}\widehat{S}_{CR} = \alpha^{Private}\widehat{S}_{CR} \tag{17}$$

$$E[C^*|CR_{Public}, S_1] = E[C^*|\beta_1\widehat{S}_{CR}+\beta_2 S_1, S_1] = E[C^*|\widehat{S}_{CR}, S_1] = \alpha_1^{Public}\widehat{S}_{CR}+\alpha_2^{Public}S_1 \tag{18}$$

Subsequently, I demonstrate that investors respond more to signals from private firms than to signal from public firms by showing that the coefficient on $\widehat{S}_{CR}$ is larger for private firms (i.e $\alpha^{Private} > \alpha_1^{Public}$). I solve directly for the coefficient on $\widehat{S}_{CR}$ for private firms in equations 17 to get that $\alpha^{Private} = \frac{\sigma_C^2}{\sigma_C^2+\sigma_{\xi_{CR}}^2}$. However, to get α_1^{Public}, I solve the following multivariate normal model with conditional distribution;

$$[X_1|X_2 = a] \sim N\begin{bmatrix}\overline{\mu} & \overline{\Sigma}\end{bmatrix}$$

$$\overline{\mu} = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(a - \mu_2) = \Sigma_{12}\Sigma_{22}^{-1}a$$

$$\begin{bmatrix} C^* \\ S_{CR} \\ S_1 \end{bmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_C^2 & \sigma_C^2 & \sigma_{SC} \\ \sigma_C^2 & \sigma_C^2 + \sigma_{\xi_{CR}}^2 & \sigma_{SC} \\ \sigma_{SC} & \sigma_{SC} & \sigma_S^2 + \sigma_{\varepsilon_{S_1}}^2 \end{pmatrix} \right]$$

$$\begin{bmatrix} C^* \\ S_{CR} \\ S_1 \end{bmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} Z & Z & E \\ Z & A & E \\ E & E & B \end{pmatrix} \right]$$

$$\Sigma_{22} = \begin{bmatrix} A & E \\ E & B \end{bmatrix}$$

$$\Sigma_{12} = \begin{bmatrix} Z & E \end{bmatrix}$$

$$a = \begin{bmatrix} S_{CR} \\ S_1 \end{bmatrix}$$

$$\left| \Sigma_{22} \right| = AB - E^2$$

$$\Sigma_{22}^{-1} = \frac{1}{AB - E^2} \begin{bmatrix} B & -E \\ -E & A \end{bmatrix}$$

$$\Sigma_{12}\Sigma_{22}^{-1}a = \frac{1}{AB - E^2} \begin{bmatrix} Z & E \end{bmatrix} \begin{bmatrix} B & -E \\ -E & A \end{bmatrix} \begin{bmatrix} S_{CR} \\ S_1 \end{bmatrix}$$

$$\alpha_1^{Public} = \frac{ZB - E^2}{AB - E^2}$$

Since

$$\alpha^{Private} = \frac{\sigma_C^2}{\sigma_C^2 + \sigma_{\xi_{CR}}^2} = \frac{Z}{A} > \frac{ZB - E^2}{AB - E^2} = \alpha_1^{Public}$$

Thus

$$\alpha^{Private} > \alpha_1^{Public}$$

This implies that investors are more responsive to debt distortion signals from private firms than from public firms. Next, I define profit functions for public and private firms (respectively) as $\pi^{Public} = R(E[C^*|CR_{Public}, S_1]) - C(x)$ and $\pi^{Private} = R(E[C^*|CR_{Private}]) - C(x)$. Firm cost $(C(x))$ is a convex function with respect to debt distortion (x). Thus, the profit functions for public and private firms can be written as

$$\begin{aligned}\pi^{Public} &= R(E[C^*|CR_{Public}, S_1]) - C(x) = R(\alpha_1^{Public}\widehat{S}_{CR} + \alpha_2^{Public}S_1) - C(x)\\ &= R(\alpha_1^{Public}(C^* + \xi_{CR} + x - \widehat{x}) + \alpha_2^{Public}S_1) - C(x)\end{aligned}$$

$$\begin{aligned}\pi^{Private} &= R(E[C^*|CR_{Private}]) - C(x) = R(\alpha^{Private}\widehat{S}_{CR}) - C(x)\\ &= R(\alpha^{Private}(C^* + \xi_{CR} + x - \widehat{x})) - C(x)\end{aligned}$$

First order conditions with respect to debt issuance distortion (x):

$$\frac{d\pi^{Public}}{dx} = R'(E[C^*|CR_{Public}, S_1])\alpha_1^{Public} - C'(x^{Public}) = 0 \tag{19}$$

$$\alpha_1^{Public} = \frac{C'(x^{Public})}{R'(E[C^*|CR_{Public}, S_1]} \tag{20}$$

$$\frac{d\pi^{Private}}{dx} = R'(E[C^*|CR_{Private}])\alpha^{Private} - C'(x^{Private}) = 0 \tag{21}$$

$$\alpha^{Private} = \frac{C'(x^{Private})}{R'(E[C^*|CR_{Private}])} \tag{22}$$

Assuming that the increase in revenue is larger for private than public firms as a result of them adjusting their debt issuance to send a favorable signal to the rating agencies, it follows that

$$R'(E[C^*|CR_{Private}]) > R'(E[C^*|CR_{Public}, S_1]) \tag{23}$$

Since

$$\alpha^{Private} > \alpha_1^{Public}$$

Then

$$C'(x^{Private}) > C'(x^{Public})$$

Since $C(x)$ is a convex function

$$C'(x^{Private}) > C'(x^{Public}) \Rightarrow x^{Private} > x^{Public}$$

Therefore, private firms constrain debt issuance more than public firms when their ratings have plus or minus signs relative to their optimal debt issuance when their credit ratings are not on upgrade or downgrade thresholds.

2.0 CHAPTER 2

THE IMPACT OF ASYMMETRIC INFORMATION ON MORTGAGE SERVICER COMPENSATION

(with Michael Connolly)

2.1 INTRODUCTION

In this paper, we explore a new channel through which asymmetric information affects mortgage outcomes. We focus on the principal-agent problem arising between sellers and servicers of Fannie Mae mortgage-backed securities (MBS).[21] Under full information, mortgages for which the seller and servicer are the same institution should perform identically to those for which the seller and servicer are different institutions. However, in the presence of asymmetric information, sellers possess more information about the underlying quality of mortgages in the MBS pool than servicers do, resulting in better performance for same seller/servicer loans relative to different seller/servicer loans.[22] Exploiting unique institutional features of the Fannie Mae MBS market, we show that the decision of sellers to retain mortgage servicing rights (MSR) at the point of security issuance, our proxy for asymmetric information, corresponds with lower rates of default, foreclosure, and loss severity, but not with lower servicer compensation.

Among the many explanations put forth to explain the recent financial crisis, much attention in the academic literature has been devoted to the transition from an originate-to-hold to an originate-to-distribute model of mortgage lending in the U.S. The argument pervading much of this literature is that securitization

[21] Sellers are the institutions that "sell" pools of mortgages to Fannie Mae in exchange for mortgage-backed securities or cash. Servicers are the institutions that administer the loans, for example by collecting monthly mortgage payments, managing the relationship with mortgagors, and remitting payments to the trust (Fannie Mae) in exchange for servicing fees.

[22] The existing literature has documented that mortgages in which originators and servicers are affiliated are less likely to default, are priced at lower yields, and are more likely to be modified conditional on default (Demiroglu and James (2012); Conklin, Diop and D'Lima (2016); Le (2016)).

led to a misalignment of incentives between different parties in the securitization process.[23] New means of securitization created distance between many parties involved in originating, servicing, and holding mortgage loans. In contrast to much of the literature on loan sales, which test for asymmetric information in private-label MBS, we focus on the market for Fannie Mae-insured MBS. A distinguishing feature of these data is that the credit risk on the pool of loans is insured by Fannie Mae, precluding concerns that the servicing retention decision is in fact driven by the decision to retain the MBS itself.

The institutional setting that we consider affords a clean test of asymmetric information between sellers and servicers. On the one hand, there are a number of reasons why asymmetric information should not be a major factor among Fannie Mae-insured mortgages. Inclusion in Fannie Mae MBS pools is subject to strict underwriting standards and buyback provisions. The mortgages that we study in this paper are full-documentation and are originated based on "hard" information. Additionally, sellers and servicers are generally large, experienced financial institutions that are actively monitored by Fannie Mae. On the other hand, if sellers possess private information unobservable to servicers, then loans in which the seller and servicer are affiliated should out-perform loans in which they are not, conditional on risk characteristics. Furthermore, since non-performing loans are more costly to service than performing loans, we would expect that any differences in risk should be accounted for in servicing fees at the point of MBS issuance. Thus, we structure our empirical analysis around testing for the presence of asymmetric information in the Fannie Mae MBS market and whether this asymmetric information is factored into mortgage servicer compensation.

Using a dataset of conforming, 30-year, fixed-rate, fully-amortizing, single-family mortgages insured by Fannie Mae, we first find that same seller/servicer mortgages are significantly less likely to default and foreclose ex-post than dif-

[23] A non-exhaustive list of papers in this literature include: Mian and Sufi (2009); Berndt and Gupta (2009); Keys, Mukherjee, Seru, and Vig (2010); Purnanandam (2011).

ferent seller/servicer mortgages, conditional on observable risk characteristics. In particular, same seller/servicer loans are approximately 1.3 percentage points less likely to default than different seller/servicer loans. Evaluated at mean default rates in the sample, this corresponds with a 16 percentage point difference. We also find that seller/servicer loans are approximately 0.2 percentage points less likely to foreclose than different seller/servicer loans, which is an 8 percentage point difference when evaluated at the mean foreclosure rate. Conditional on foreclosure and risk characteristics, Fannie Mae loses approximately \$3000 more on different seller/servicer loans relative to same seller/servicer loans, or 4.5% of the mean loss on foreclosed loans. When evaluated at the total number of different seller/servicer loans in our sample, this corresponds with an approximate \$571 million loss to Fannie Mae, or 2% of the total loss on single-family loans in our sample. These differences in default and foreclosure rates are not driven by loans in which the seller is also the originator. This result suggests that the source of asymmetric information in same seller/servicer loans is not exclusively due to superior information from the originator.

Having established that same and different seller/servicer loans exhibit different risk profiles, we then ask whether this risk is priced in servicing contracts at the point of MBS issuance. Theory offers the implication that servicing fees should be an increasing function of default risk, as it is significantly more expensive to service non-performing loans than performing loans. This is due, among other factors, to a high labor cost of default management. Using a security-level dataset of 30-year, fixed-rate Fannie Mae MBS, we find no statistically significant difference in servicing fees for same seller/servicer pools relative to different seller/servicer pools. While asymmetric information between sellers and servicers of Fannie Mae MBS is not priced in servicing fees cross-sectionally, we exploit a quasi-experiment which altered the incentive to retain MSR. In December 2011, the FHFA implemented a policy whereby the guarantee fee charged between large and small sellers of Fannie Mae MBS shrank. This changed the incentive for small sellers to retain MSR relative to large sellers. In fact, we show that servicing fees for large sellers decline relatively more than for small sellers following the regulation. We conclude that the composition of same seller/servicer pools changed, which resulted in different pricing between large and small sellers following the policy change.

In Section 2 we describe the institutional background and the related literature. Section 3 describes the theory and testable hypotheses. Section 4 describes the two main datasets used in our analysis. Section 5 introduces the empirical models and presents results. Section 6 concludes.

2.2 BACKGROUND

2.2.1 Institutional Details

The securitization of Fannie Mae mortgage-backed securities (MBS) begins with the sale of pools of mortgages by financial institutions. These mortgages are originated by lenders, either underwriters themselves or third-party brokers, and are sold to Fannie Mae via a designated financial institution that meets certain requirements as a seller. Strict credit quality guidelines ensure that only conforming mortgages are eligible to be acquired by Fannie Mae. These loans are either purchased from the seller outright for cash, or they are securitized and exchanged for MBS. Fannie Mae assumes the credit risk (the timely payment of principal and interest to the investor) on the pool of mortgages in exchange for a guarantee fee. The seller has the option then to either hold the MBS or sell it into the secondary market. They also retain the right to service the asset or sell MSR to a third party. We study the choice by sellers to retain MSR on some Fannie Mae MBS as apposed to other MBS securities on which MSR are not retained.

Figure 9 displays the process of securitization of a mortgage into an MBS pool and the subsequent exchange of payments and fees by different parties.[24] The key assumption in this figure is that the seller, servicer, and investor are different institutions. First, a mortgage is originated (step 1), packaged and sold in a pool of loans by a seller to Fannie Mae (step 2), and exchanged for MBS (step 3). The seller then sells the MBS into the secondary market (step 4) and designates a *different* servicer on the pool (step 5) through the sale of MSR. At the beginning of each month, the mortgagor pays a fixed monthly payment of principal and interest to the servicer (step 6), which is then remitted to the trust at the end of the month in exchange for a servicing fee (step 7). Servicers must meet and abide by guidelines established by Fannie Mae, who serves also as master servicer

[24] Ashcraft and Schuermann (2008) provide an excellent overview of the major frictions in the sub-prime MBS market. We adapt their discussion to the particulars of the Fannie Mae MBS market.

of the MBS trust (step 8). Finally, Fannie Mae disburses payments to investors in exchange for a fee that assumes credit risk on the pool of mortgages (step 9).

In figure 10, we present a scenario in which the seller and servicer of the mortgage are the same institution, but the investor is a separate entity. In this case, much of the securitization process is consolidated. The trading desk of a financial institution exchanges the pool of mortgages for MBS (steps 2 and 3), then places the pool of MBS onto the secondary market for sale to investors (step 4). The servicing arm of that same institution handles the full servicing of the mortgages (steps 5 through 8). For our purposes, whether the seller retains the MBS is not a first-order concern, as Fannie Mae insures the credit risk on the underlying pool of mortgages in the MBS.

The primary difference between same and different seller/servicer mortgages is the consolidation of steps in the securitization process. Our focus in this paper is the adverse selection problem between sellers and servicers (step 5 in figure 9). Sellers possess private unobserved information about the quality of the pool of mortgages relative to servicers. Thus, we would expect sellers to either screen loans more aggressively for which they subsequently plan to hold the servicing rights, or to cherry-pick those of highest quality to service[25]. Note that in this figure we abstract from the channel of origination. In the case where the originator, seller, and servicer are the same institution, we would expect that asymmetric information is likely to be greatest.

A number of factors likely mitigate the magnitude of this adverse selection problem. First, Fannie Mae implements strict underwriting standards and credit quality guidelines in its issuance of MBS. Sellers are subject to buyback provisions in the event that the borrower defaults in the first few months of a mortgage. They also pay a fee for the right to sell mortgages to MBS, and thus are able to perform a critical function of liquidity transformation relatively cheaply. Being unable to do

[25]Demiroglu and James (2012) find that the former reason explains much of the difference in default rates of private-label MBS

so would risk reputational and monetary loss for the seller. Taken together, these facts suggest that the institutional structure is in place to minimize the likelihood that asymmetric information should be sufficiently large to generate differences in performance.[26]

2.2.2 Literature Review

Our paper relates to a broad literature on securitization and mortgage outcomes, including default rates and loan performance[27], modification and foreclosure[28], and pricing[29]. Our paper also contributes to the literature studying the effect of the government-sponsored enterprises (GSEs) on mortgage outcomes (Adelino, Frame, and Gerardi (2017)). Relative to these papers, we focus our analysis on mortgages that are securitized in Fannie Mae MBS pools. As such, we exploit variation within securitized pools of mortgages, which helps study information frictions not arising necessarily from observable risk characteristics.

Recent work has explored the relationship between originator-servicer affiliation and mortgage performance. Demiroglu and James (2012) show that originator-sponsor and originator-servicer affiliation in private-label MBS deals results in significantly lower deal default rates. They interpret their result as evidence that having "skin in the game" increases loan screening incentives of originators, how-

[26]Another major friction is the moral hazard problem between the servicer, who exhibits unobserved risky effort that can adversely affect the distribution of cash flows to the trust and to the investor. Fannie Mae can somewhat reduce this friction through monitoring (step 8 in figure 9) by implementing procedures for servicers to follow regarding default management. There is also moral hazard between the mortgagor and the servicer (step 6 in figure 9) regarding the right to strategically default on a mortgage. This friction would likely be mitigated by originators that have an incentive to maintain a relationship with the borrower. We do not observe if the mortgagor has a pre-existing relationship with the originator/seller, and thus cannot rule out the explanation for retention of MSR based on relationship lending.

[27]Keys, Mukherjee, Seru, and Vig (2009, 2010); Purnanandam (2011); Demiroglu and James (2012); Keys, Seru, and Vig (2012); Nadauld and Sherlund (2013); Jiang, Nelson, and Vytlacil (2014); Bubb and Kaufman (2014); Rajan, Seru, and Vig (2015); Begley and Purnanandam (2017)

[28]Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2011); Agarwal, Amromin, Ben-David, and Dinc (2012); Adelino, Gerardi, and Willen (2013, 2014); Kruger (2016); Ratnadiwakara (2016); Reid, Urban, and Collins (Forthcoming); Kuong and Zeng (2015)

[29]Ashcraft, Goldsmith-Pinkham, and Vickery (2010); He, Qian, and Strahan (2012)

ever this should matter only among deals where "soft" information would matter most. In fact, they find that both measures of affiliation are positively related to performance only among *low-documentation* deals. They also find that this result is not driven by cherry-picking. They compare unaffiliated loans originated and not retained by sponsors with those originated by mortgage brokers, and find no difference in default rates between the two sets of loans. Finally, they show that as the share of loans in a deal serviced by the originator increases, the average yield spread on the MBS falls, but only among low-documentation deals. Essentially, market prices somewhat reflect the difference in risk between affiliated and unaffiliated deals. He, Qian, and Strahan (2012) document that originator-servicer affiliation is correlated with higher yields on AAA tranches of MBS deals, but lower yields on non-AAA tranches. Conklin, Diop and D'Lima (2016) show that originator-servicer affiliation affects mortgage modifications, conditional on a loan being in serious default. This relationship holds even among loans originated based on "hard" information. They also find that re-default rates of originator-servicer loans are lower following modification. In a related paper, Le (2016) also finds lower likelihood of re-default.

Our study contributes to the existing literature on affiliation in a number of important dimensions. First, we add to the literature relating affiliation and ex-ante pricing by focusing on mortgage servicer compensation, instead of MBS yields. This is an important distinction since servicing fees directly affect the incentive to foreclose on defaulting loans. Second, we relate affiliation with likelihood of foreclosure. Third, in contrast to much of the prior literature, we focus on the Fannie Mae MBS market. Doing so allows us to study the asymmetric information problem among high-documentation loans. Furthermore, we can approximate excess servicing fees based on the institutional features of this market. Finally, we explore how guarantee fee bargaining power can affect the composition and servicing fees of same seller/servicer MBS deals.

2.3 THEORY AND HYPOTHESES

In this section, we briefly discuss the underlying theory and develop hypotheses for our empirical tests. Levitin and Twomey (2011) show that retention of mortgage servicing rights can be profitable for mortgage servicers as long as the likelihood of default on the serviced loans is low. For performing loans, servicers have developed highly efficient, low-cost payment processing systems, which facilitate processing mortgage payment transactions on a large scale. However, servicing can be costly for non-performing loans since servicers face high labor costs associated with default management, as well as escalating costs associated with mortgages in foreclose.

Sellers of mortgage-backed securities specializing in transactions processing retain servicing rights on loans where the probability of default is low since servicing non-performing mortgages can be four to five times more expensive than servicing performing loans (Levitin and Twomey (2011)). Two theories have been put forth in the literature to justify the reason that sellers retain low-risk mortgages at the point of MBS issuance. First, among originated loans, they choose to retain servicing rights on loans where they expect the lowest likelihood of default, a practice called "cherry picking." The assumption underlying this theory is that the seller possesses unobserved private information about asset quality which the servicer does not account for in pricing servicing rights. Alternatively, sellers that also originate mortgages underlying MBS pools can choose to actively screen loans more carefully and retain servicing rights on loans with lower likelihood of default.[30]

The decision to retain servicing rights on MBS proxies for asymmetric information between sellers and servicers. There are a number of reasons why sellers are at an informational advantage regarding borrower and loan quality relative to servicers. First, sellers often originate the mortgages which they include in MBS

[30]Demiroglu and James (2012), Keys, Mukherjee, Seru, and Vig (2010), and Purnanandam (2011) provide evidence that screening incentives affected loan performance during the financial crisis.

pools. As a result, they can extract "soft" information about borrower and loan riskiness. Second, even if sellers acquire mortgages from different originating institutions, they often have long-standing relationships with the originators which allow them to learn about borrower quality. Lastly, sellers are often large financial institutions that have sophisticated models which allow them to assess the risk profile of loans and borrowers. This is particularly true of many large sellers in the Fannie Mae MBS market, which serve as aggregators of loans originated by smaller institutions.

The institutional setting that we consider affords a clean test of asymmetric information between sellers and servicers. While the literature has found some evidence of information frictions in the agency MBS market (Downing, Jaffee, and Wallace (2009)), we exclusively utilize dataset of conforming, 30-year, fixed-rate, single-family mortgages insured by Fannie Mae. There are a number of reasons why we would expect that asymmetric information about borrower quality should not matter for these data. First, all of the mortgages that we study are full-documentation loans, which subsequently are securitized as Fannie Mae MBS, one of the most liquid mortgage products in the world. Demiroglu and James (2012) argue that "soft" information should be less important for full-documentation deals, and thus differences in borrower quality should not be large enough to generate differences in loan performance, which they show for private-label MBS. Second, it is not necessarily clear ex-ante that the acquiring servicer is at an informational disadvantage relative to the seller. In fact, in our dataset, the servicers that purchase MSR on the secondary market are large financial institutions, with years of experience servicing Fannie Mae mortgages. Third, Fannie Mae has strict underwriting standards governing the types of loans that can be sold and securitized in a pool. This includes buy-back provisions in the case of fraud or early delinquency. In fact the market for Fannie Mae MBS is liquid enough to be traded too-be-announced (TBA) as a way of providing liquidity to originators. Fourth, sellers of Fannie Mae MBS face both reputational risk, for originating loans of dubious quality, and warehousing risk, for being stuck with loans that do not meet underwriting standards. Finally, since Fannie Mae is the master servicer on all of its MBS products, they actively monitor servicer performance. This includes the possiblity of removing MSR from under-performing servicers. With this background, we would expect that differences in borrower quality should be relatively minor across same and different seller/servicer loans.

In our first set of tests we evaluate whether retention of servicing rights is related to subsequent mortgage performance using loan-level data. Under the null hypothesis of full information, we would expect that *mortgage default rates for same seller/servicer loans are the same as for different seller/servicer loans (H1).* Under asymmetric information, sellers have the incentive to retain servicing rights on higher-quality loans to avoid default management labor costs associated with poor performance. We also test if *same seller/servicer loans are equally likely to enter foreclosure as different seller/servicer loans (H2).* If the servicer is the same institution as the seller at the point of foreclosure, and the servicer possesses private information about borrower quality, then we would expect that the servicer would be less likely to foreclose. Lastly, we test whether *the loss incurred by Fannie Mae on foreclosed properties is equal for same seller/servicer and different seller/servicer loans (H3).*

In our second set of tests we evaluate if retention of servicing rights is priced in mortgage servicing fees. We test whether differences in risk profiles between same and different seller/servicer mortgages are factored in to servicer compensation due to higher expected default risk. Formally, we test the null hypothesis under full information that *same seller/servicer MBS pools have identical excess servicing fees as different seller/servicer MBS pools (H4).*

In our last set of tests, we exploit a quasi-experiment in order to identify whether servicing fees differ between same and different seller/servicer loans. Fannie Mae announced guidelines in December 2011 that set guarantee fees for the smallest volume sellers of MBS closer to those of the largest sellers in order to eliminate price advantages for the latter group.[31] Prior to this regulatory change, a common practice in the Fannie Mae MBS market, known as aggregation, resulted in small sellers frequently selling mortgages to large sellers without the option to retain servicing rights, in part due to the higher guarantee fees charged to small sellers. This change in regulation made it more cost effective for small sellers to retain servicing rights on more of their high-quality loans. Thus, we test the null hypothesis that *same seller/servicer MBS pools had identical excess servicing fees for pools sold by small and large sellers following the Fannie Mae 2012 change in guarantee fees (H5).* We hypothesize that one consequence of this change in regulation is that the riskiness of MBS pools sold by small and large sellers also changed. In particular, given the cost advantage of a narrowing gap in guarantee fees, small sellers had a greater incentive to retain servicing rights on riskier loans than before, while large sellers had a greater incentive to retain servicing rights on less risky loans.

2.4 DATA

For loan-level analysis we use the Fannie Mae Single-Family Loan Performance dataset. These data include both origination characteristics and performance of 30-year, single-family, conforming, fully-amortizing, full-documentation fixed-rate mortgages acquired by Fannie Mae between January 2002 and December 2015. Origination characteristics include the name of the seller of the mortgage to Fannie Mae and the channel by which the loan was originated (retail, broker, corre-

[31]As mentioned in the institutional background, guarantee fees are paid to Fannie Mae in exchange for insuring ultimate payment principal and interest of each mortgage. Starting from 2012, guarantee fees paid by the largest sellers increased 9 basis points to 34 basis points, while fees paid by the smallest sellers increased 7 basis points to 40 basis points (Federal Housing Finance Agency (2013)). The report suggests that the difference between the average guarantee fees paid by lenders in the extra-small-volume and the extra-large-volume groups declined by 2 basis points. In fact, over subsequent years, the gap between the largest and smallest sellers of Fannie Mae MBS narrowed due to the convergence of guarantee fees.

spondent). Borrower characteristics include the primary borrower's credit score, the number of borrowers, an indicator for first-time homebuyers, the purpose of the loan, the type of property, the number of units, occupancy status, the property state, the first three digits of the zip code of the property's location, and for certain mortgages, the percentage of insurance defined under the master primary insurance policy. Loan characteristics include the original interest rate, original unpaid principal balance, term of the loan, loan-to-value ratio, combined loan-to-value ratio (includes additional liens), debt-to-income ratio, origination date, and first payment date.

The performance file includes the reporting month from the time of acquisition by Fannie Mae to the termination of the loan and the name of the servicer in a given month. Current loan characteristics include the interest rate, unpaid principal balance, age, months to legal maturity, adjusted months to legal maturity (adjusted for delinquency), and the maturity date. The file also includes information on the number of months in delinquency, an indicator for whether or not the loan was modified, the reason and date for which the loan has zero balance, and detailed information on foreclosure costs.

From the data we identify loans for which the seller of the mortgage to Fannie Mae and the servicer of the loan in the first available month are the same institution. Fannie Mae restricts the release of information on seller and servicer identity to only those with greater than 1% unpaid principal balance in a given quarter. Loans not satisfying this criterion are denoted "OTHER" in the dataset. As a result, we can only identify loans with either both names available at the time of acquisition by Fannie Mae, or those loans with one name identified (for example if the seller is unidentified as "OTHER" but the servicer is "Bank of America")[32]. Table 13 lists the number of loans dropped by each criterion in the data screen-

[32] Our exclusion procedure is fairly conservative. We exclude loans that we suspect are same seller/servicer loans, but cannot definitively identify the identity of one party. Included in that case, we exclude loans from sellers that we know had the capability to service, but due to size restrictions do not appear in the data.

ing process. We first restrict the sample to all loans originated after 2002[33]. We drop missing data from our key variables of interest and loans in which we cannot definitively identify if the seller and servicer are the same institution.

In the loan-level analysis, we focus on two main outcomes of interest: default and foreclosure. Figures 11 and 12 show that default rates (90+ days delinquent) and foreclosure rates for same seller/servicer mortgages are lower than those on different seller/servicer mortgages.[34] Figure 13 shows that loan severity (the amount paid out to investors minus proceeds to Fannie Mae from foreclosure sale) is higher for different seller/servicer loans. All figures capture the general trend that default, foreclosure, and severity increased among loans originated during the housing boom. While these patterns are suggestive of potential differences between the two sets of mortgages, they could be driven by underlying risk characteristics. In particular, it could be that different seller/servicer loans are more likely to default and be foreclosed upon mainly because they are riskier.

Table 14 provides summary statistics for the sample of loans in our dataset. The two sets of loans differ in a statistically significant way on observable characteristics. Thus, any difference in performance might be driven by risk characteristics that are unobservable to the econometrician. Given the significant difference in borrower quality on observable characteristics, we control for a large range of borrower and loan characteristics in all regressions. In our regression specification, we make the identifying assumption that our set of borrower- and loan-specific control variables fully account for differences in risk characteristics, which we think is a reasonable assumption since we observe most of the characteristics that investors do. We then attribute any difference in performance due to differences in borrower quality observed by the seller, but not by the servicer, at the point of issuance of the MBS.

The other main dataset that we utilize in our analysis is monthly pool-level

[33]We have this restriction due to lack of servicer names before December 2001.

[34]Note that we calculate seller/servicer status as of the last observed date.

data on conventional long-term, single-family MBS generally maturing or due in 30 years or less, downloaded using the Fannie Mae PoolTalk®portal for securities issued between 2003 and 2015. We select these data in order to map most closely with the loan-level performance data.[35] For each security, we observe information on the pool (CUSIP number, pool/trust number, issue and maturity dates, the original security balance), as well as issuance statistics reflecting the risk of mortgages underlying the pool (the quartile distribution of loan size, coupon rates, LTV ratios, credit scores, loan terms, loan age, year of origination, state of origination, identities of sellers and servicers, loan purpose, property type, and occupancy type). Importantly, we observe the weighted average coupon rate and the weighted average pass-through rate on the security, the difference of which we use as a proxy for excess servicing fees.

Table 15 provides mean pool-level statistics. Overall, same seller/servicer securities have both lower weighted average interest rates and pass-through rates, smaller average loan size, but larger initial security balance. This is likely due to there being more loans in same seller/servicer pools overall. In terms of risk characteristics, same seller/servicer securities have higher average credit scores, but also higher LTV ratios. Thus, different seller/servicer pools look riskier on most observable dimensions. For all variables the difference is statistically different from zero, so we include them as controls in all pool-level regressions.

[35] We are unable to definitively match loan-level and pool-level data, although based on features of each dataset they are generated from similar underlying data.

2.5 EMPIRICAL METHODOLOGY

2.5.1 Model

We estimate the relationship between seller/servicer affiliation and performance of Fannie Mae mortgages. In our main loan-level regressions, we estimate the following linear model (i indexes loan)[36]:

$$\text{Outcome}_i = \alpha + \beta S_i + \gamma X_i + \epsilon_i \tag{24}$$

where Outcome_i is a dummy variable equal to 1 if the loan defaulted (foreclosed), 0 if not, S_i equals 1 if the loan is a same seller/servicer loan at the point of acquisition by Fannie Mae for the default regressions (at the last observed date for the foreclosure regressions), 0 if it is a different seller/servicer loan, and X_i are a set of loan and borrower characteristics. We also estimate a specification where loan severity, the net loss to Fannie Mae on foreclosed properties, is included as an outcome variable. We test the null hypotheses that default (H1) and foreclosure (H2) probabilities, and loan severity (H3) between same and different seller/servicer loans are identical ($\beta = 0$), conditional on risk characteristics.

Our main identifying assumption in estimating β is that we properly account for the information set of acquiring servicers at the time of transfer of MSR for the default regressions, and the last observed date for the foreclosure regressions. Fannie Mae provisions require that sellers provide servicers acquiring MSR with sufficient files and records regarding the mortgage loan[37]. In our regressions, we control for the full set of information provided by the Fannie Mae Single-Family Loan Performance database, including both origination and performance charac-

[36] Our results are robust to estimating the model via probit. We choose the linear probability model specification for computational ease.

[37] Section A2-5.1-02 of the Fannie Mae servicing guide states that: "If the seller/servicer does not service the mortgage loan, it must transfer the files and records to the servicer to ensure that the servicer will have complete information about the mortgage loan in its records." Included in the mortgage loan file are the mortgage or deed of trust, underwriting documents, and insurance policy information, among other documents.

teristics. We notably do not observe borrower income at origination, but we do utilize a number of variables that proxy, at least in part, for income. However, we recognize that, conditional on controlling for risk characteristics at origination, sellers might have based their decision to retain MSR on some borrower characteristic unobservable to the econometrician *and* acquiring servicer. We would expect that such an omitted factor would likely be positively correlated with the MSR retention decision, but negatively correlated with default probability, and thus bias downward our estimate of β. We acknowledge that this is certainly a concern for our estimation. However such a factor would have to matter systematically enough to bias our estimates conditional on controlling for the full set of observable characteristics and the Fannie Mae institutional setting.

In our second set of regressions, we determine whether mortgage servicer compensation reflects differences in risk between same/seller servicer and different seller/servicer loans. To answer this question, we first develop a proxy of excess servicing fees[38], which represent the compensation for risk that servicers expect for loans with higher default risk. Using an identity that is true of all Fannie Mae MBS, we calculate excess servicing fees as the difference between the weighted average coupon rate and the MBS pass-through rate, the guarantee fee, and the baseline servicing fee.[39]

$$\begin{aligned}&\text{Weighted Average Coupon Rate} - \text{Pool Level Pass-Through Rate} = \\ &\text{Guarantee Fee} + \text{Baseline Servicing Fee} + \text{Excess Servicing Fee}\end{aligned} \tag{25}$$

In the MBS data we observe the pass-through rate and weighted average interest rates. Guarantee fees are determined by negotiations between sellers and Fannie Mae each year and are adjusted for each loan pool as a function of observable risk characteristics. Baseline servicing fees are typically constant, except

[38] We do not explicitly observe excess servicing fees, although we utilize a feature of the Fannie Mae MBS market to argue that our estimates represent goods approximations of the true fees.

[39] While we do not observe the price at which MSR are transacted, we make the assumption that servicing fees reflect MSR valuations at loan issuance.

for adjustments due to observable risks. This implies that when we regress the difference between the weighted average coupon rate and the pass-through rate on a dummy variable for same/seller servicer loans and control for seller identity and risk characteristics, the coefficient on the same seller/servicer dummy variable represents, to an approximation, the difference between average excess servicing fees of same and different seller/servicer loans. In particular, our main MBS pool-level regressions are of the following form (here i indexes MBS security):

$$\begin{aligned} &\text{Weighted Average Coupon Rate}_i - \text{Pass-Through Rate}_i \\ &= \alpha + \beta_1 S_i + \gamma X_i + \epsilon_i \end{aligned} \tag{26}$$

where Weighted Average Coupn Rate$_i$ equals the at-issuance average of all interest rates in each MBS security (weighted by share of original unpaid balance), Pass-Through Rate$_i$ is the rate paid to holders of the MBS security, S_i is a dummy variable for same seller/servicer loans and X_i are a set of loan and borrower characteristics. We test the null hypothesis that our approximation of excess servicing is the same between same and different seller/servicer MBS pools (H4).

In our last set of tests, we exploit a quasi-experiment announced in December 2011 which increased guarantee fees on all Fannie Mae MBS, but did so more for large-volume sellers of MBS relative to small-volume sellers. The goal of those guidelines was to narrow the gap between the two types of sellers in order to give small sellers the incentive to retain servicing rights on loans which they previously sold off to aggregators.[40]

We exploit this quasi-experimental setting to estimate the differential effect of seller/servicer affiliation for small sellers relative to large on servicer compensation,

[40] According to an FHFA report in August 2016, the gap between the guarantee fees for large and small sellers decreased from 6 basis points in 2011 to 3 basis points in 2015. That fall in guarantee fees constitutes a reduction from 24% of the guarantee fees for the largest sellers by loan volume in 2011 (those sellers pay the lowest guarantee fees) to merely 5.17% of the guarantee fees paid by the largest sellers in 2015.

following the regulatory change.

$$
\begin{aligned}
&\text{Weighted Average Coupon Rate}_i - \text{Pass-Through Rate}_i \\
&= \alpha + \beta_1 S_i + \beta_2 Post_i + \beta_3 S_i \times Post_i + \gamma X_i + \epsilon_i
\end{aligned}
\tag{27}
$$

The major difference in equation (27) relative to equation (26) is the inclusion of $Post_i$, which is a dummy variable equal to 1 if the MBS pool was acquired following December 2011, and 0 otherwise.[41]. We test the null hypothesis ($\beta_3 = 0$) that same seller/servicer MBS had identical excess servicing fees for pools sold by small and large sellers following the change in guarantee fees (H5).

2.5.2 Results: Loan-Level Regressions

Loan-level regression results for mortgage performance variables are given in table 16. Same seller/servicer loans are approximately 1.3 percentage points less likely to default than different seller/servicer loans (16 percentage points less likely at mean default rates), conditional on risk characteristics. Loans in which the seller and servicer are affiliated at the point of foreclosure are also approximately 0.2 percentage points less likely to foreclose than different seller/servicer loans (8 percentage points less likely at mean foreclosure rates) and lose \$3000 less per foreclosed loan (4 percentage points lower loss at mean level of severity). Due to the fact that we omit all sellers and servicers with under 1% of total unpaid principal balance in a given quarter, we view these results as conservative estimates of the true effect. Variables that proxy for higher risk, such as the interest rate and LTV and DTI ratios, positively correlate with default, foreclosure, and severity. Variables that proxy for lower risk, such as credit score, first-time buyers, number of borrowers, and original unpaid principal balance, negatively correlate with default, foreclosure, and severity. Overall, we find evidence to reject null hypotheses (H1), (H2), and (H3). Taken together, the evidence suggests that there

[41]Note that we include controls for issuance year, and so are able to identify β_2

is asymmetric information between sellers and servicers in this market.

2.5.3 Results: MBS Pool-Level Regressions

In this section we evaluate whether the difference in the risk profile between same and different seller/servicer loans is priced in servicer compensation. Pool-level regression results are presented in table 17. Columns 1 and 2 provide evidence suggesting that our proxy for excess servicing fees does not differ between same seller/servicer and different seller/servicer pools. Thus, we are unable to reject null hypothesis (H4). The evidence suggests that sellers and servicers did not price in the additional risk associated with loans where servicing rights are not retained by sellers. This mispricing of servicing fees could be due to servicers not recognizing that the asymmetric information problem was significant enough to matter for perceptions of ex-ante default rates.[42]

2.5.4 Robustness: Originator/Servicer Affiliation

In table 18, we explore the source of asymmetric information by introducing a term for same originator/seller/servicer into the baseline regressions. If there is sufficient private information conveyed between origination and sale of the mortgage to Fannie Mae, we would expect this coefficient to be negative and significant. Overall, we do not find evidence to suggest that default and foreclosure rates, and severity between same originator/seller/servicer mortgages and same seller/servicer (different originator) mortgages differ.

[42] In unreported regressions, we also find limited evidence regarding the pricing or risk associated with loans where the sellers, servicers, and originators are not the same firm. While we find that same seller/originator/servicer loans have lower excess servicing fees, the marginal impact of an increase of an additional percent in the share of same seller-servicer loans being originated by the same firm, leads to merely 0.02 to 0.03 basis points decrease in excess servicing fees.

2.5.5 Robustness: Change in Guarantee Fees

We exploit a quasi-experiment to identify the effect of seller/servicer affiliation on excess servicing fees. In table 19, we present regression results that evaluate the impact of guidelines announced in December 2011 that increased Fannie Mae guarantee fees by 10 basis points and narrowed the gap between guarantee fees of large and small sellers. In all regression models in table 19, we find that the coefficients on the dummy variable for same seller/servicer loans are statistically insignificant. This suggests that at least prior to the implementation of FHFA guidelines, the difference in risk between same and different seller/servicer loans was not priced in excess servicing fees. In column 2, we find that the Fannie Mae regulation did in fact increase our proxy for excess servicing fees for all sellers. This is due to the fact that our proxy for excess servicing fees contains the guarantee fees as a component, and thus when guarantee fees rise following the regulation, mechanically the excess servicing fees should increase as well. Our proxy for excess servicing fees fell by approximately 5 bp for same seller/servicer pools following the implementation of these new guidelines.

There are two main explanations for why the riskiness of same and different seller/servicer loans changed following the guarantee fee regulation. First, large-volume sellers experienced larger increases in their guarantee fees following the regulation than small-volume sellers. This suggests that, in relative terms, it became less cost-effective for large sellers to retain servicing rights, implying that large sellers retained servicing rights on higher-quality loans following the regulation. For small sellers, it became more cost- effective to retain servicing rights, which gave them the incentive to retain servicing rights on riskier loans. As a result, following the Fannie Mae regulation, the pool of same seller/servicer loans became less risky for large sellers and riskier for small sellers. Second, as it became more cost-effective for small sellers to retain servicing rights, some of the risky loans on which servicing rights used to be sold to large sellers were then retained by small sellers. This suggests that the pool of different seller/servicer loans held by large sellers became less risky following the regulation. In columns 3 and 4 we demonstrate that the decrease in our proxy for excess servicing fees for same seller/servicer loans was driven by large sellers retaining less risky loans following the regulation.

2.6 CONCLUSIONS

This study is the first to evaluate the impact of asymmetric information between mortgage sellers and servicers on mortgage servicer compensation. We proxy for asymmetric information using the decision to retain mortgage servicing rights. Retention of servicing rights can be profitable for mortgage servicers as long as the likelihood of default on serviced loans is low. However, when the probability of default is high, servicing can be costly since servicers face high labor costs associated with default management of non-performing loans (Levitin and Twomey 2011).

Sellers of loans to Fannie Mae observe more information than independent servicers since in many cases they also serve as the originators, or have long-standing relationships with brokers that allow them to learn about borrower and loan quality. Finally, sellers often have more sophisticated models than servicers that allow them to utilize data from the secondary market to learn about loan performance. Since sellers have more information about borrower and loan quality than servicers, and servicing non-performing loans can be costly, sellers may choose to retain servicing rights on higher quality loans based on information unobserved to the servicers.

Using loan-level data on Fannie Mae-insured, full-documentation mortgages, we document that loans where sellers retain servicing rights are on average 1.3 percentage points less likely to default and 0.2 percentage points less likely to foreclose than loans where servicing rights were not retained by sellers, even after controlling for borrower and loan risk characteristics. Higher foreclosure rates among different seller/servicer loans correspond with larger costs to Fannie Mae. Conditional on risk characteristics, same seller/servicer loans lose approximately \$3000 less per loan in foreclosure than different seller/servicer loans. This represents an overall cost of \$571 million to Fannie Mae, or approximately 2% of the loss on all single-family loans in our sample.

If servicers internalize that loans for which servicing rights are not retained by sellers are riskier than loans for which servicing rights are retained, they should demand higher excess servicing fees to be compensated for this additional risk. We evaluate whether the retention of servicing rights is priced using a proxy for excess servicing fees. We find no evidence to reject the null hypothesis that excess servicing fees for same and different seller/servicer loans are identical.

Lastly, we exploit a quasi-experiment which changed the incentive to retain servicing rights for small sellers of MBS relative to large sellers. Starting from December 2011, the FHFA implemented guidelines to increase guarantee fees for all sellers, and narrow the gap in guarantee fees between large-volume and small-volume MBS sellers. We find that excess servicing fees for same/seller servicer pools decreased by approximately 5 bp following the regulatory change. This relative decrease was driven by the riskiness of the pool of retained loans for large-volume sellers declining relatively more.

2.7 REFERENCES

[1] Adelino, M., Frame, W. S., and Gerardi, K., 2017, The Effect of Large Investors on Asset Quality: Evidence from Subprime Mortgage Securities, *Journal of Monetary Economics*, Forthcoming.

[2] Adelino, M., Gerardi, K., and Willen, P., 2013, Why Don't Lenders Renegotiate More Mortgages? Redefaults, Self-Cures and Securitization, *Journal of Monetary Economics*, 60 (7): 835-853.

[3] Adelino, M., Gerardi, K., and Willen, P., 2014, Identifying the Effect of Securitization on Foreclosure and Modification Rates Using Early Payment Defaults, *The Journal of Real Estate Finance and Economics*, 49 (3): 352-378.

[4] Agarwal, S., Amromin, G., Ben-David, I., and Dinc, S., 2012, The Politics of Foreclosures, *working paper*.

[5] Agarwal, S., Amromin, G., Ben-David, I., Chomsisengphet, S., and Evanoff, D., 2011, The Role of Securitization in Mortgage Renegotiation, *Journal of Financial Economics* , 102(3), 559–578.

[6] Ashcraft, A., Goldsmith-Pinkham, P. and Vickery, J., 2010, MBS Ratings and the Mortgage Credit Boom, *Federal Reserve Bank of New York Staff Reports*, Staff Report no. 449.

[7] Ashcraft, A.B. and Schuermann, T., 2008, Understanding the Securitization of Subprime Mortgage Credit, *Federal Reserve Bank of New York Staff Reports*, Staff Report no. 318.

[8] Begley, T. A., and Purnanandam, A. K., 2017, Design of Financial Securities: Empirical Evidence from Private-Label RMBS Deals, *The Review of Financial Studies*, 30 (1): 120-161.

[9] Berndt, A. and Gupta, A., 2009, Moral hazard and adverse selection in the originate-to-distribute model of bank credit, *Journal of Monetary Economics*, 56 (5): 725-743.

[10] Bubb, R. and Kaufman, A., 2014, Securitization and moral hazard: Evidence from credit score cutoff rules, *Journal of Monetary Economics*, 63 (1): 1-18.

[11] Conklin, J.N., Diop, M., and D'Lima,W., 2016, Asymmetric Information in Loan Renegotiation: The Importance of Originator-Servicer Affiliation, *under review.*

[12] Demiroglu, C. and James, C.M., 2012, How Important is Having Skin in the Game? Originator-Sponsor Affiliation and Losses on Mortgage-backed Securities, *The Review of Financial Studies*, 25 (11): 3217-3258.

[13] Downing, C., Jaffee, D. and Wallace, N., 2009, Is the Market for Mortgage-Backed Securities a Market for Lemons?, *The Review of Financial Studies*, 22 (7): 2457-2494.

[14] He, J., Qian, J., and Strahan, P.E, 2012, Are All Ratings Created Equal? The Impact of Issuer Size on the Pricing of Mortgage-Backed Securities, *The Journal of Finance*, 67 (6): 2097–2137.

[15] Federal Housing Finance Agency, 2013, Fannie Mae and Freddie Mac Single-Family Guarantee Fees in 2012.

[16] Jiang, W., Nelson, A. A., and Vytlacil, E., 2014, Securitization and Loan Performance: Ex Ante and Ex Post Relations in the Mortgage Market, *The Review of Financial Studies*, 27 (2): 454-483.

[17] Keys, B.J., Mukherjee, T., Seru, A., and Vig, V., 2009, Financial Regulation and Securitization: Evidence from Subprime Loans, *Journal of Monetary Economics*, 56 (5): 700-720.

[18] Keys, B.J., Mukherjee, T., Seru, A., and Vig, V., 2010, Did Securitization Lead to Lax Screening? Evidence from Subprime Loans, *The Quarterly Journal of Economics*, 125 (1): 307-362.

[19] Keys, B.J., Seru, A., and Vig, V., 2012, Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets , *The Review of Financial Studies*, 25 (7): 2071-2108.

[20] Kruger, S., 2016, The Effect of Mortgage Securitization on Foreclosure and Modification, *working paper*.

[21] Kuong, J., and Zeng, J., 2015, Serve to Securitise: Mortgage Securitisation, Servicing, and Foreclosures, *working paper*.

[22] Le, T., 2016, Information Loss in Mortgage Securitization: Effect on Loan Modification, *working paper*.

[23] Levitin, A.J. and Twomey, T., 2011, Mortgage Servicing, *Yale Journal on Regulation*, Vol. 28, No. 1.

[24] Mian, A. and Sufi, A., 2009, The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis, *The Quarterly Journal of Economics*, 124 (4): 1449-1496.

[25] Nadauld, T. D., and Sherlund, S. M., 2013, The Impact of Securitization on the Expansion of Subprime Credit, *Journal of Financial Economics*, 107 (2): 454-476.

[26] Purnanandam, A., 2011, Originate to distribute Model and the Subprime Mortgage Crisis, *The Review of Financial Studies*, 24 (6): 1881-1915.

[27] Rajan, U., Seru, A., and Vig, V., 2015, The Failure of Models that Predict Failure: Distance, Incentives, and Default, *Journal of Financial Economics*, 115 (2): 237-260.

[28] Ratnadiwakara, D., 2016, Impact of Information Asymmetry and Servicer Incentives on Foreclosure of Securitized Mortgages, *working paper*.

[29] Reid, C. K., Urban, C., and Collins, J.M., 2015, Rolling the Dice on Foreclosure Prevention: Differences Across Mortgage Servicers in Loan Cure Rates, *Housing Policy Debate*, Forthcoming.

2.8 APPENDIX A: FIGURES

Figure 9
Different Seller/Servicer of MBS

Figure 9 displays the process of securitization of a mortgage into an MBS pool and the subsequent exchange of payments and fees by different parties. The key assumption in this figure is that the seller, servicer, and investor are different institutions. First, a mortgage is originated (step 1), packaged and sold in a pool of loans by a seller to Fannie Mae (step 2), and exchanged for MBS (step 3). The seller then sells the MBS into the secondary market (step 4) and designates a *different* servicer on the pool (step 5) through the sale of MSR. At the beginning of each month, the mortgagor pays a fixed monthly payment of principal and interest to the servicer (step 6), which is then remitted to the trust at the end of the month in exchange for a servicing fee (step 7). Servicers must meet and abide by guidelines established by Fannie Mae, who serves also as master servicer of the MBS trust (step 8). Finally, Fannie Mae disburses payments to investors in exchange for a fee that assumes credit risk on the pool of mortgages (step 9).

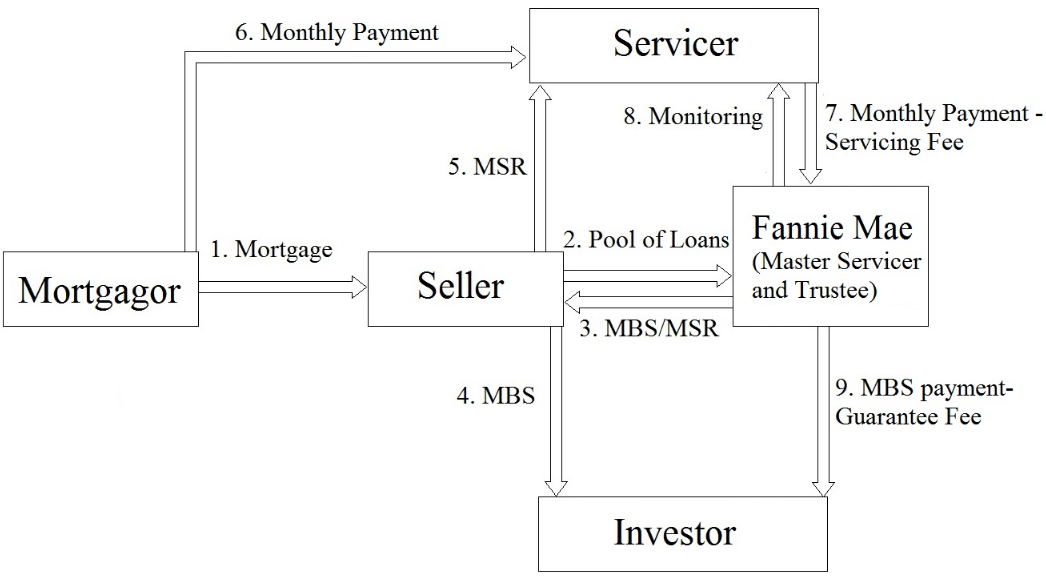


Figure 10
Same Seller/Servicer of MBS

Figure 10 presents a scenario in which the seller and servicer of the mortgage are the same institution, but the investor is a separate entity. In this case, much of the securitization process is consolidated. The trading desk of a financial institution exchanges the pool of mortgages for MBS (steps 2 and 3), then places the pool of MBS onto the secondary market for sale to investors (step 4). The servicing arm of that same institution handles the full servicing of the mortgages (steps 5 through 8).

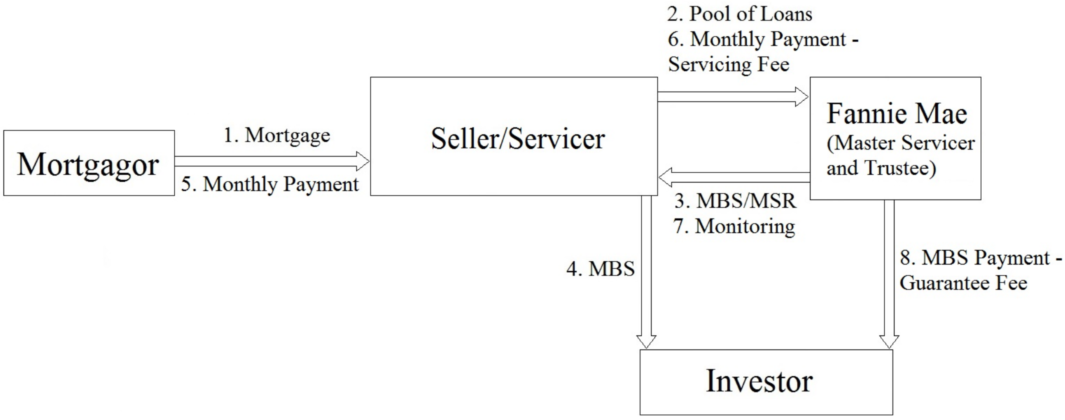


Figure 11
Default Rates by Seller/Servicer Type
and Acquisition Year Vintage

Figure 11 depicts the average annual default rates for same seller-servicer loans (gray bar) and different seller-servicer loans (black bar). It demonstrates that default rates (90+ days delinquent) for same seller/servicer mortgages are lower than those on different seller/servicer mortgages. The figure captures the general trend that default rates increased among loans originated during the housing boom.

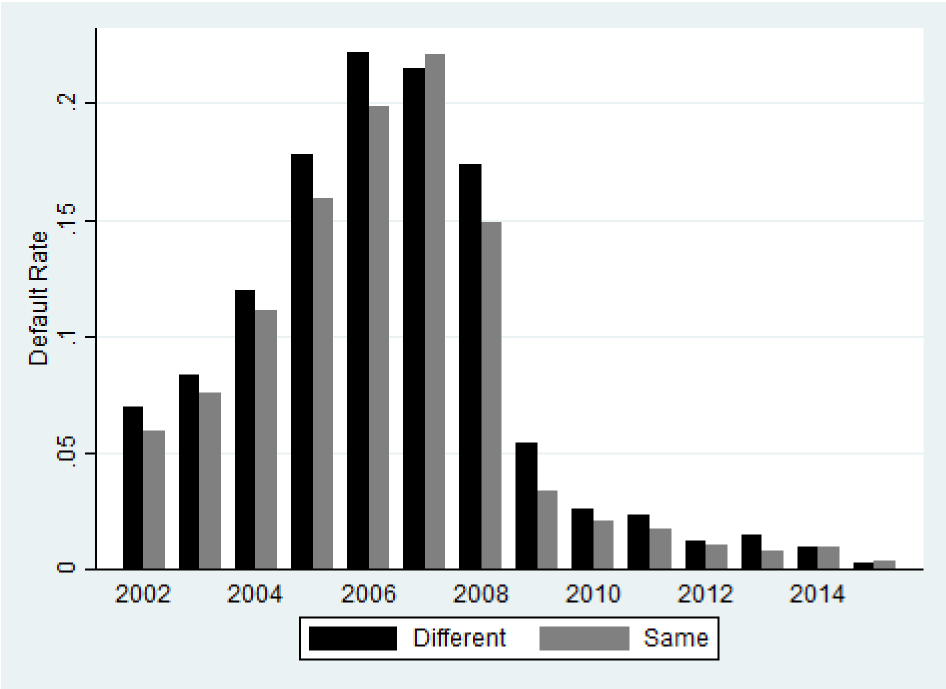


Figure 12
Foreclosure Rates by Seller/Servicer Type and Acquisition Year Vintage

Figure 12 depicts the average annual foreclosure rates for same seller-servicer loans (gray bar) and different seller-servicer loans (black bar). It demonstrates that foreclosure rates for same seller/servicer mortgages are lower than those on different seller/servicer mortgages. The figure captures the general trend that foreclosure rates increased among loans originated during the housing boom.

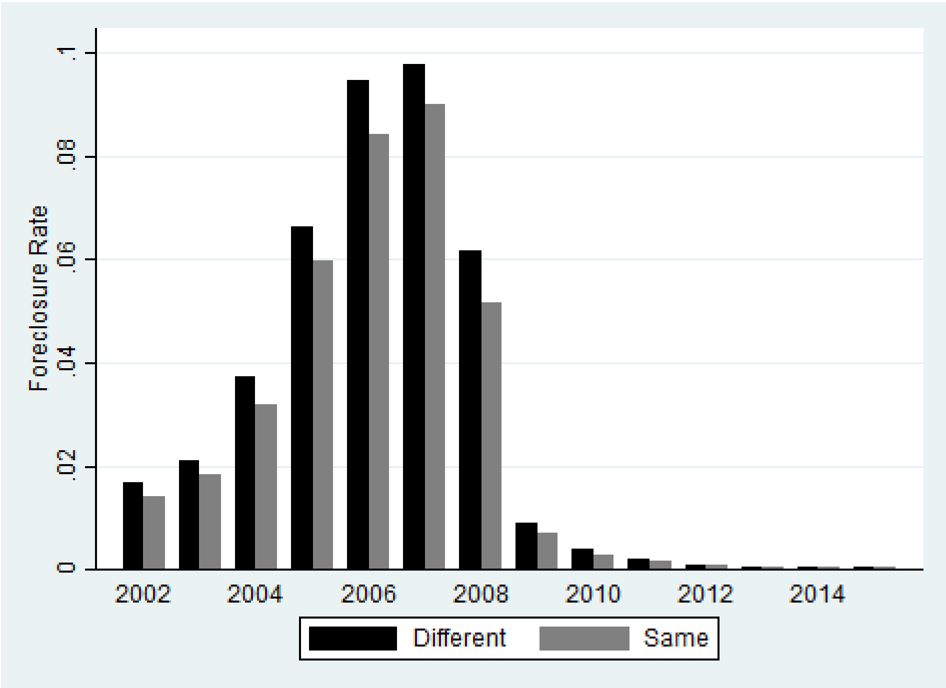
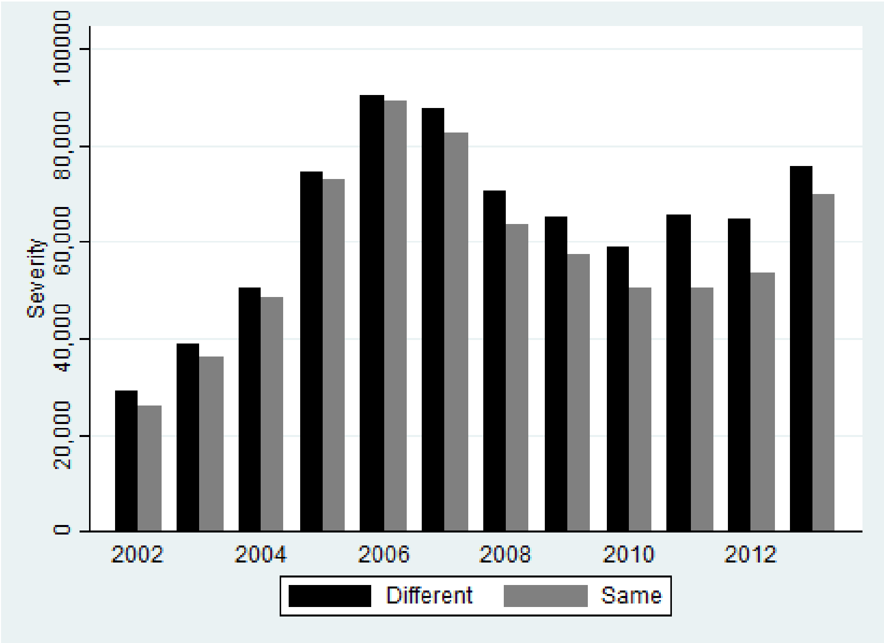


Figure 13
Severity by Seller/Servicer Type and Acquisition Year Vintage

Figure 13 depicts the annual severity rates for same seller-servicer loans (gray bar) and different seller-servicer loans (black bar). The figure shows that loan severity (the amount paid out to investors minus proceeds to Fannie Mae from foreclosure sale) is higher for different seller/servicer loans. The figure captures the general trend that severity rates increased among loans originated during the housing boom.



2.9 APPENDIX B: TABLES

Table 13
Data Screening of FNMA Mortgages (2002-2015)

Table 13 lists the number of loans dropped by each criterion in the data screening process. We first restrict the sample to all loans originated after 2002 (we have this restriction due to lack of servicer names before December 2001). We drop missing data from our key variables of interest and loans in which we cannot definitively identify if the seller and servicer are the same institution.

Total Number of Loans Acquired:	20,624,403
Drop Loans With:	
Seller and Servicer "OTHER"	6,158,511
Servicer "OTHER"	1,662,874
Seller "OTHER"	370,150
Missing Data	341,246
Total Number of Loans After Screening:	12,091,622

Table 14
Mean Loan-Level Statistics (2002-2015)

Table 14 provides summary statistics for the sample of same and different seller-servicer loans in our dataset, as well as a p-value for the difference in means for each of the categories. Different seller/servicer loans look riskier on most observable dimensions. For all variables the difference is statistically different from zero.

	Same mean	Different mean	p
Default Rate (90+ Days Delinquent)	7.98	9.81	0.00
Loan Characteristics:			
Original Interest Rate	5.50	5.84	0.00
Original Unpaid Balance ($000)	209.26	187.41	0.00
Original Loan-to-Value Ratio	71.64	73.07	0.00
Original Combined Loan-to-Value Ratio	72.69	74.07	0.00
Original Debt-to-Income Ratio	34.41	36.75	0.00
Borrower Characteristics:			
Credit Score	738.60	730.30	0.00
New Buyer	0.11	0.10	0.00
Number of Borrowers	1.57	1.55	0.00
Number of Units	1.04	1.05	0.00
Origination Channel:			
Retail	35.19	49.05	0.00
Broker	50.51	32.03	0.00
Correspondent	14.30	18.92	0.00
Mortgage Type:			
Purchase	37.97	42.59	0.00
Cash-Out Refinance	32.77	26.07	0.00
Not Cash-Out Refinance	29.22	31.27	0.00
Other Type of Refinance	0.05	0.07	0.00
Property Type:			
Single-Family	71.16	73.65	0.00
Condo	9.44	9.17	0.00
Co-op	18.18	16.03	0.00
Manufactured Home	0.46	0.59	0.00
Planned Unit Development	0.75	0.56	0.00
Occupancy Status:			
Principal	88.33	88.22	0.01
Second	4.55	4.25	0.00
Investor	7.11	7.53	0.00
Number of Observations	11,402,747	688,875	12,091,622
Seller/Servicer status at last observed date			
Foreclosure Rate	2.50	3.04	0.00
Number of Observations	5,790,731	6,085,582	11,876,313
Seller/Servicer status at foreclosure date			
Severity ($000)	66.73	69.12	0.00
Number of Observations	150,977	184,998	329,680

Table 15
Mean Pool-Level Statistics (2002-2015)

Table 15 provides summary statistics for the sample of same and different seller-servicer loans in our pool-level dataset. Overall, same seller/servicer securities have both lower weighted average interest rates and pass-through rates, smaller average loan size, but larger initial security balance. This is likely due to there being more loans in same seller/servicer pools overall. In terms of risk characteristics, same seller/servicer securities have higher average credit scores, but also higher LTV ratios. Thus, different seller/servicer pools look riskier on most observable dimensions. For all variables, the difference between same and different seller-servicer pools of loans is statistically different from zero.

	Same mean	Different mean	p-value
Weighted Average Coupon Rate	5.46	5.60	0.00
Pass-Through Rate	4.90	5.07	0.00
Excess Servicing Fee Proxy	0.56	0.53	0.00
Average Loan Size ($1000)	181.58	184.98	0.00
Original Balance ($1000)	18,362.46	8,370.21	0.00
Weighted Average Credit Score	718.93	677.65	0.00
Weighted Average LTV Ratio	76.47	73.53	0.00
Weighted Average Loan Age	1.06	7.03	0.00
Pool Loan Count	93.99	44.21	0.00
Number of Observations	181,175	7,965	189,140

Table 16
Seller/Servicer Affiliation and Mortgage Performance (2002-2015)

This table presents estimates from a linear probability model of the relation between seller/servicer affiliation and loan-level default, foreclosure, and severity rates for loans originated between 2002 and 2015. In column 1, the dependent variable is an indicator equal to 1 if the mortgage defaulted (90+ days delinquent) at least once before 2016Q1 and 0 otherwise. In column 2, the dependent variable is an indicator equal to 1 if the mortgage foreclosed before 2016Q1 and 0 otherwise. In column 3, the dependent variable equals loan severity (unpaid principal balance + delinquent interest + foreclosure costs + property preservation and repair costs + asset recovery costs + miscellaneous holding expense credits + associated taxes for holding property) - (net sales proceeds + credit enhancement proceeds + repurchase make-whole proceeds + other foreclosure proceeds). Coefficient estimates and corresponding standard errors are displayed in percentage points for columns 1 and 2, thousands of dollars in column 3. The last two rows give the mean default, foreclosure, and severity rates in each sample and the difference is calculated at the mean. Additional controls include: original combined loan-to-value ratio, number of units, the percentage of mortgage insurance on the property, property state, and indicators for seller identity, origination year, acquisition quarter X acquisition year, channel, loan purpose, property type, occupancy status, type of mortgage insurance. Standard errors are clustered by servicer at point of acquisition by Fannie Mae (column 1) or last loan date (columns 2 and 3). ***, **, and * indicate significance at the 1, 5, and 10 % levels, respectively.

Dependent Variables:	Default	Foreclosure	Severity
Explanatory Variables:	(1)	(2)	(3)
Same Seller/Servicer	-1.282***	-0.221*	-3.091*
	(0.382)	(0.118)	(1.661)
Loan Characteristics:			
Original Interest Rate	2.121***	1.294***	3.467***
	(0.290)	(0.108)	(0.612)
Original Unpaid Balance ($000)	-0.002***	-0.000	0.221***
	(0.000)	(0.000)	(0.009)
Original LTV Ratio	0.089***	0.024***	1.328***
	(0.007)	(0.003)	(0.053)
Original DTI Ratio	0.083***	0.026***	0.023**
	(0.010)	(0.002)	(0.010)
Borrower Characteristics:			
Original Credit Score	-0.109***	-0.024***	-0.037***
	(0.009)	(0.002)	(0.003)
First-Time Buyer	-0.707***	-0.264***	0.281
	(0.092)	(0.033)	(0.353)
Number of Borrowers	-2.586***	-1.177***	-1.071***
	(0.339)	(0.104)	(0.188)
Additional Controls	Y	Y	Y
Number of Observations	12,091,622	11,876,313	329,680
R-squared	0.137	0.065	0.315
Mean Rates	8.081	2.776	68.069
Difference in Rates	-15.864	-7.961	-4.541

Table 17
Excess Servicing Fees and Seller/Servicer Affiliation (2002-2015)

This table estimates the relation between seller/servicer affiliation and our proxy for excess servicing fees. Coefficient estimates and corresponding standard errors are displayed in basis points. Additional controls include indicators for seller identity, year of issuance, and distributional characteristics of the mortgages underlying each MBS pool. Standard errors are clustered by the month-year of security issuance. *** and * indicate significance at the 1 and 10 % levels, respectively.

Dependent Variables:	Excess Servicing Fee Proxy (bp)	
Explanatory Variables:	(1)	(2)
Same Seller-Servicer	0.0060	0.0023
	(0.0066)	(0.0049)
Loan Characteristics:		
Loan to Value		0.0019***
		(0.0004)
MBS Loan Count		0.0055
		(0.0072)
Loan Size		-0.0240
		(0.0641)
Loan Age		-0.0005
		(0.0007)
Borrower Characteristics:		
Credit Score		-0.0002
		(0.0001)
N	189,140	189,140
R^2	0.227	0.482
Seller Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
MBS and Borrower Controls	No	Yes
Clustered SE	Yes	Yes

Table 18
Originator/Servicer Affiliation and Mortgage Performance (2002-2015)

This table presents estimates from a linear probability model of the relation between seller/servicer affiliation, originator/seller/servicer affiliation, and loan-level default, foreclosure, and severity rates between for loans originated between 2002 and 2015. In column 1, the dependent variable is an indicator equal to 1 if the mortgage defaulted (90+ days delinquent) at least once before 2016Q1 and 0 otherwise. In column 2, the dependent variable is an indicator equal to 1 if the mortgage foreclosed before 2016Q1 and 0 otherwise. In column 3, the dependent variable equals loan severity (unpaid principal balance + delinquent interest + foreclosure costs + property preservation and repair costs + asset recovery costs + miscellaneous holding expense credits + associated taxes for holding property) - (net sales proceeds + credit enhancement proceeds + repurchase make-whole proceeds + other foreclosure proceeds). Coefficient estimates and corresponding standard errors are displayed in percentage points for columns 1 and 2, thousands of dollars in column 3. Additional controls include: original interest rate, original unpaid principal balance, original LTV ratio, original DTI ratio, original credit score, first-time buyer indicator, number of borrowers, original combined loan-to-value ratio, number of units, the percentage of mortgage insurance on the property, property state, and indicators for seller identity, origination year, acquisition quarter X acquisition year, channel, loan purpose, property type, occupancy status, type of mortgage insurance. Standard errors are clustered by servicer at point of acquisition by Fannie Mae (column 1) or last loan date (columns 2 and 3). *** and * indicate significance at the 1 and 10 % levels, respectively.

Dependent Variables:	Default	Foreclosure	Severity
Explanatory Variables:	(1)	(2)	(3)
Same Seller/Servicer	-1.167***	-0.182	-3.111*
	(0.361)	(0.115)	(0.395)
Same Originator/Servicer	-0.449	-0.110	0.069
	(0.295)	(0.001)	(0.395)
Additional Controls	Yes	Yes	Yes
Number of Observations	12,091,622	11,876,313	329,680
R-squared	0.137	0.065	0.315

Table 19
Excess Servicing Fees and Guarantee Fee Regulation (2002-2015)

This table estimates the relation between seller/servicer affiliation and our proxy for excess servicing fees. Coefficient estimates and corresponding standard errors are displayed in basis points. Large seller denotes a seller to Fannie Mae ranked in the top 50% based on amount of unpaid balance in a given year. Additional controls include indicators for seller identity, year of issuance, and distributional characteristics of the mortgages underlying each MBS pool. Standard errors are clustered by the month-year of security issuance. *** and * indicate significance at the 1 and 10 % levels, respectively.

Dependent Variables:	Excess Servicing Fee (bp)			
	All Data	All Data	Large Sellers Top 50%	Small Sellers Bottom 50%
Explanatory Variables:	(1)	(2)	(3)	(4)
Same Seller-Servicer	0.0023	0.0050	0.0067	-0.0081
	(0.0049)	(0.0052)	(0.0055)	(0.0161)
Post Dec-2011		0.1007***	0.1055***	0.0063
		(0.0138)	(0.0126)	(0.0392)
Same Seller-Servicer x Post Dec-2011		-0.0530***	-0.0587***	0.0483
		(0.0122)	(0.0118)	(0.0392)
Loan to Value	0.0019***	0.0019***	0.0017***	0.0019*
	(0.0004)	(0.0004)	(0.0004)	(0.0010)
Credit Score	-0.0002	-0.0002	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0004)
MBS Loan Count	0.0055	0.0057	0.0047	-0.1025
	(0.0072)	(0.0073)	(0.0072)	(0.1972)
Loan Size	-0.0240	-0.0223	-0.0367	0.0392
	(0.0641)	(0.0643)	(0.0682)	(0.1946)
Loan Age	-0.0005	-0.0006	-0.0004	0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0017)
Constant	-0.0077	-0.0189	0.0280	0.2899**
	(0.0607)	(0.0611)	(0.0588)	(0.1464)
N	189,140	189,140	179,349	9,791
R^2	0.482	0.482	0.478	0.633
Seller Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
MBS and Borrower Controls	No	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes

3.0 CHAPTER 3

ISSUER VERSUS INVESTOR-PAID RATING AGENCIES, EQUITY ANALYSTS, AND THE INFORMATION FLOW TO THE STOCK AND BOND MARKETS

(with Thomas Chemmanur and Francesca Toscano)

3.1 INTRODUCTION

Following the financial crisis, credit rating agencies' reputation was undermined as they were often criticized for issuing untimely and inaccurate ratings. Critics argue that the compensation structure of many rating agencies that are paid by bond issuers generates conflicts of interests that lead raters to inflate issuers' ratings scores. Equity analysts, on the other hand, seemed to adjust their forecasts more quickly with the onset of the financial crisis (Sidhu and Tan 2011). This could in part explain why they did not face similar scrutiny to the credit rating agencies following the financial crisis. Equity analysts and credit rating agencies (CRAs) have the same objective of providing valuations of firms' performance to investors. However, while bond raters provide assessment of the bonds' default risk, equity analysts are concerned with firms' equity performance, which includes assessments of firms' possibility of asset appreciation and dividend payouts.

The literature has investigated the information flows between equity analysts and credit rating agencies to better understand which one provides more precise and timely recommendations. Ederington and Goh (1998) suggest that credit rating agencies and equity analysts influence each others recommendations. Ederington and Yawitz (1987), on the other hand, show that credit ratings affect equity analysts' recommendations. They argue that given that credit rating agencies have access to information that is not available to equity analyst researchers, the analysts have an incentive to utilize the unique information available to rating agencies by following any of their changes. Finally, Fong et al. (2014) show that analyst coverage is likely to have a disciplining effect on credit rating agencies.[43] They argue that the larger is the number of equity analysts monitoring a firm, the lower is the asymmetric information between firm's managers and investors. This, in-turn, puts greater the pressure on credit rating agencies to provide reliable ratings.

While the literature has addressed the information flows between issuer-paid rating agencies and equity analysts, the impact of credit ratings issued by CRAs that are compensated by investors (investor-paid raters) on these information flows has not been studied. The investor-paid rating model gained popularity because it alleviates the conflicts of interests between issuers and the rating agencies. Since the raters are compensated by investors, they do not face pressure by bond issuers to inflate their ratings. Therefore, investor-paid credit ratings are believed to be timelier, more informative, and accurate in predicting default risk (Jiang et al., 2012, Cornaggia and Cornaggia, 2013).

In this paper, we evaluate the information content of signals by investor and issuer paid rating agencies, as well as equity analyst recommendations. Specifically, we investigate whether investor-paid rating agencies provide more informative and timely ratings than issuer-paid rating agencies and equity analysts. Further, we evaluate how the bond and stock markets respond to changes in valuations provided by issuer and investor paid rating agencies, as well as equity analysts. Next, we turn to studying the impact of bond ratings and analysts' recommendations on firms' investment decisions. Then, we evaluate how rating agencies and equity analysts respond to firms' leverage changes, and whether disagreement between equity analysts about firm performance translates into great disagreement in ratings issued by CRAs.

We conduct five tests to address the aforementioned empirical questions. First, we investigate who is the main information driver among the three financial gatekeepers (i.e., issuer-paid rating agencies, investor-paid rating agencies and equity

[43]Analyst coverage is defined as the number of equity analysts monitoring a firm

analysts). Specifically, we evaluate whether a change in any of these evaluations is able to trigger changes, of the same sign, in other evaluations. We find that investor-paid ratings impact signals by issuer-paid CRAs and equity analysts. This result is driven in-part by those investor-paid rating agencies being the first to make adjustments to their signals to reflect market conditions.

Second, we study the response of the bond and stock markets to issuer-paid and investor-paid rating changes, as well as to equity analyst recommendation adjustments. We find that bond investors are more responsive to ratings issued by the credit rating agencies, while equity investors are more susceptible to recommendations by equity analysis. These results are consistent with the hypothesis outlined in Merton (1987) that it is costlier for stock market investors to pay attention to bond analysts relative to paying attention to stock analyst forecasts. Conversely, it is costlier for bond market investors to pay attention to stock analysts rather than bond analysts. Investors in firms that have a high probability of default, however, respond more to investor-paid ratings than to signals by equity analysts or issuer-paid rating agencies.

Third, we investigate how rating agencies and equity analysts respond to changes in leverage. The intuition behind this test relies on the different objectives of rating agencies and equity analysts. Rating agencies focus on predicting bonds' default risk, while equity analysts focus on firms' equity performance. Consistently, we find that increases in leverage lead to lower ratings by CRAs, and more favorable recommendations by equity analysts due to firms' additional liquidity resulting from bond issuance. Specifically, investor-paid ratings perceive an increased leverage as an increase in the probability of default, which leads to lower ratings. On the other hand, equity analysts react positively to an increase in leverage being less concerned about default and more about liquidity and cash flow growth.

Fourth, we study how firms adjust their investment levels following issuer-paid and investor-paid rating changes as well as equity analyst recommendation adjustments. We find that firms' investment decisions are in-line with changes of ratings by investor-paid rating agencies. This result is consistent with investor-paid CRAs being perceived to produce timelier and more reliable signals. Lastly, we investigate whether disagreement between equity analysts about firm performance translates into disagreements in ratings assigned by issuer-paid and investor-paid CRAs. We find that heterogeneity in beliefs among equity analysts is correlated with heterogeneity in beliefs among bond rating agencies.

The aforementioned tests utilize data on S&P ratings from Compustat (as representatives of the issuer-paid rating agencies), Egan and Jones ratings obtained directly from the Egan-Jones Ratings Company (as representatives of the investor-paid CRAs), and equity analyst recommendations from the Institutional Brokers' Estimate System (I/B/E/S) database.

The paper is organized as follows. Section 2 presents an overview of the literature. Section 3 outlines the hypotheses tested throughout the paper. Section 4 describes the data. Section 5 describes the empirical results, and section 6 concludes.

3.2 RELATED LITERATURE

The literature has largely studied the capability of financial intermediaries to convey information to capital markets. Particular attention has been devoted to the role of equity analysts and credit rating agencies as well as to their interaction and impact on the capital markets.

Regarding the role of equity analysts, a big effort has been exerted to study the real effects of the information they provide. Verrecchia (1996) shows the informational role of security analysts in increasing firm value, Womack (1996) illustrates the capability of equity analysts to increase firm visibility, Brennan and Subrahmanyan (1995) and Roulstone (2004) provide evidence of the link between analyst following and increased liquidity of firms' securities. The informative power of equity analysts is often compared to the one of credit rating agencies. Although dealing with different assets and clients, several studies (Beyer et al., 2010; Fong et al., 2014) argue that sell-side equity analysts and credit rating agencies are competitors. They both provide information to the market and, although for different reasons, they both have an incentive to issue optimistic evaluations. Sell-side equity analysts have a tendency to assign optimistic stock recommendations to curry favour with the management (Lin and McNichols, 1998; Ertimur et al., 2011). On the other side, rating agencies have largely been accused of biasing their ratings optimistically on corporate debt (Becker and Milbourn, 2011; Kraft, 2011) and structured finance projects (Lynch, 2009; Riddiough and Zhu, 2010) to generate business. Which financial intermediary, between equity analysts and credit rating agencies, is able to deliver more timely and precise information is an open question that the literature has tried to address from different angles. Batta and Muslu (2011) compare the company adjusted reported earnings released by credit rating agencies with those of equity analysts to point out that, although both informative, adjusted earnings in equity analysts are better in predicting future earnings and cash-flows. Following Lui et al. (2007), Lui et al. (2012) shows that equity changes are timilier and have a larger overall stock price impact than credit rating changes.

A first attempt to establish a direction in the information flow between bond rating agencies and stock analysts is provided in Ederington and Goh (1998) which shows that the Granger causality flows both ways: bond downgrades are preceded by declines in actual and forecast earnings and actual earnings, as well as forecasts of future earnings, tend to fall following downgrades. Other subsequent papers try to answer the same question by focusing on the advantages that equity analysts have on rating agencies and vice-versa. Equity analyst recommendations are often thought to be more objective than the recommendations assigned by other intermediaries because of the large number of equity analysts that rate the same firm. Consequently, firms covered by many equity analysts are perceived as less opaque and thus riskier. Exploiting the idea that analyst coverage is a proxy for asymmetric information, part of the literature finds that the number of equity analysts monitoring a firm is negatively related to the firm's default risk (Cheng and Subramanyan, 2007) and is likely to reduce the optimistic bias in credit ratings[44](Fong et al., 2014). However, there is also evidence that rating agencies have access to information not available to equity analysts such as minutes of board meetings, profit breakdowns by profit and new product plans (Ederington and Yawitz, 1987). Following Jung et al. (2007), the informational advantage of credit ratings has increased starting from October 2000, when the Fair Disclosure Regulation became effective[45]. The larger information set available to credit rating agencies should lead to a greater reliance of equity analysts on rating evaluations.

As far as we are aware, current literature has focused on the interaction between equity analysts and credit rating agencies without investigating the role played by the compensation system adopted by those rating agencies. More in detail, previous works have focused on equity analysts and rating agencies paid by the rated firms (issuer-paid rating agencies). An alternative rating model is the one in which rating agencies get paid by investors (investor-paid rating agencies). The compensation structure adopted by the latter ensures a reduced exposure to conflicts of interest, a greater capability of providing timely ratings and hence, an enhanced informativeness (Jiang et al., 2012; Strobl and Xia, 2012; Cornaggia and Cornaggia, 2013; Xia, 2014). Althought studies on the performance of the two rating models have always been considerable, there is a gap in the literature that needs to be filled. To our knowledge, no previous paper has aimed to study

[44]The disciplining effects of competition on credit rating agencies, among credit ratng agencies, are studied theoretically in Bar-Isaac and Shapiro (2011), Bolton, Freixas, and Shapiro (2012), Camanho et al. (2010), Manso (2013), Mathis et al. (2009), and Skreta and Veldkamp (2011), among others. On the empirical front Becker and Milbourn (2011) find evidence that the entry of Fitch lead to better ratings. The opposite results are reported in Doherty et al. (2012) in their analysis of entry into insurance market by A.M. Best.

[45]The Fair Disclosure Regulation introduces restrictions on the information that companies can disclose to analysts. Credit rating agencies are not subject to these limitations.

the reciprocal influence of issuer-paid, investor-paid ratings and equity analyst. Similarly, literature has not compared the effects of all these recommendations on the bond and stock markets as well as their effects on corporate investment. We conduct a study on equity analysts and different rating models in the following sections.

3.3 THEORY AND HYPOTHESIS

In this section, we briefly discuss the underlying theory and develop hypotheses for our empirical tests. The study investigates the idea that while equity analysts and credit rating agencies have a similar objective of evaluating firms' quality, they employ different approaches to achieve this goal. Specifically, credit rating agencies provide opinions about the firm's probability of default. Equity analysts, on the other hand, issue recommendations that reflect firm's expected stock performance. Furthermore, while Standard & Poor's (S&P) and equity analysts are compensated by firms who they provide ratings for, Egan-Jones (EJR) is compensated by investors. This suggests that EJR has less incentive to inflate ratings or be reluctant to downgrade firms' ratings.

Since issuer paid rating agencies and equity analysts face pressure to provide favorable recommendations to firms that retain their services, we hypothesize that an investor paid rating agencies such as Egan and Jones (EJR) update their ratings faster to reflect the most up-to-date information available for investors. Issuer paid rating agencies such as S&P and equity analysis may be particularly slow to update their ratings when negative information about firm performance becomes available. Thus, we test whether EJR rating changes trigger shifts in S&P ratings and equity analyst recommendations of the same direction (**H1**).

As previously mentioned, equity analysts provide recommendations about the firm's expected stock performance while the investor and issuer paid rating agencies provide ratings that reflect the probability of default on firms' bonds. Therefore, equity investors may be more responsive to equity analysts' signals while bond investors and investors in risky firms will be inclined to pay particular attention to signals by rating agencies such as EJR and S&P. Thus, we test whether equity analyst recommendations have a stronger impact on firms' equity excess returns compared to ratings by EJR and S&P (**H2**). Similarly we test whether EJR and S&P ratings have a stronger impact firms' bond spreads compared to equity analyst recommendations (**H3**).

To further investigate the stock market response to signals by rating agencies and equity analysts about firm quality, we replicate our stock market analysis for a subset of firms that are classified to be speculative (i.e., firms whose ratings are below the S&P investment grade threshold). This analysis allows us to study which of the aforementioned signals has the largest impact on the equity performance of risky firms (with higher probability of default). Thus, we test whether EJR ratings have a stronger impact on equity excess returns for firms with higher probability of default, in comparison to S&P ratings and equity analyst recommendations (**H4**).

Moreover, to investigate the bond market response to the outlined signals about firms quality, we replicate our bond market analysis for firms that are classified as speculative and for firms that are crossing the investment threshold (i.e., firms that at time t-1 have a rating from Standard and Poor's equal to BBB- but are downgraded to a BB+ rating in the following period). We focus on these firms to better understand the reaction of the bond market to credit rating and equity analyst recommendation changes for poor performing firms. We expect a magnified effect of EJR rating changes on the bond spread if the analysis is restricted to firms with a high probability of default. Thus, we test whether EJR rating changes have a stronger impact on bond spreads for firms with higher probability of default, in comparison to S&P ratings and equity analyst recommendations (**H5**) and if EJR rating changes have a stronger impact on bond spreads for firms that were downgraded below investment grade, in comparison S&P ratings and equity analyst recommendations (**H6**).

Credit ratings and equity analyst recommendations affect firms' financing opportunities. Higher ratings or better equity analyst recommendations translate into an easier access to capital markets, which, in turn, implies greater investment opportunities. Consequently, we evaluate whether firms internalize issuer-paid, investor-paid and equity analyst recommendation changes and, consequently, utilize these ratings for their investment decisions. If investor-paid rating agencies have greater information content, we expect to see a greater increase (decrease) in firm's investment following investor-paid upgrades (downgrades) compared to rating changes by to issuer-paid agencies such as S&P or changes in equity analyst recommendations. Thus, we test whether EJR rating changes have a stronger impact on firm investment in comparison S&P ratings or equity analyst recommendations (**H7**).

Moreover, an increase in firm's leverage is likely to lead to lower ratings scores by the credit rating agencies since it will raise the firm's probability of default. At the same time, an increase in leverage implies that a firm was able to raise more capital cost effectively on the bond market, which suggests that it has greater investment opportunities. Thus, the effect of an increase in leverage on firm's expected stock performance is ambiguous and remains an empirical question. Hence, we test whether the impact of an increase in leverage has a differential effect on S&P and EJR ratings as apposed to equity analyst recommendations and evaluate the magnitudes of these effects (**H8**).

Finally, we evaluate whether greater disagreement between equity analysts about recommendations for firm's equity performance translates into a greater disagreement between EJR and S&P ratings. The intuition is that equity analysts disagree in their assessment of equity performance about some firms more than others. This heterogeneity in beliefs about firm quality can be driven by limited or noisy of information about firm performance. Consistently, for some firms, bond rating agencies are more likely to disagree in their assessment of default risk. Thus, we test whether higher disagreement in equity analyst recommendations is associated with a higher disagreement between EJR and S&P ratings (**H9**).

Thus, in summary, in this paper we test the hypotheses below:

H1 *EJR rating changes trigger shifts in S&P ratings and equity analyst recommendations of the same direction.*

H2 *Equity analyst recommendations have a stronger impact on firms' equity excess returns compared to ratings by EJR and S&P.*

H3 *EJR and S&P ratings have a stronger impact firms' bond spreads compared to equity analyst recommendations.*

H4 *EJR ratings have a stronger impact on equity excess returns for firms with higher probability of default, in comparison to S&P ratings and equity analyst recommendations.*

H5 *EJR rating changes have a stronger impact on bond spreads for firms with higher probability of default, in comparison to S&P ratings and equity analyst recommendations.*

H6 *EJR rating changes have a stronger impact on bond spreads for firms that were downgraded below investment grade, in comparison S&P ratings and equity analyst recommendations.*

H7 *EJR rating changes have a stronger impact on firm investment in comparison S&P ratings or equity analyst recommendations.*

H8 *Increase in leverage has a differential effect on S&P and EJR ratings as apposed to equity analyst recommendations*

H9 *Higher disagreement in equity analyst recommendations is associated with a higher disagreement between EJR and S&P ratings.*

3.4 DATA AND SAMPLE SELECTION

The sample requires the merge of different databases that provide information on ratings, equity analysts' recommendations, firm characteristics and stock returns details.

The first step we follow is to merge the *S&P database*, the *EJR database* and the *IBES database*.

The *S&P* long-term credit ratings are obtained from Compustat North America Ratings. All the observations for which there are no rating data are deleted from the sample. Following existing literature, we assign numerical values to each rating on notch basis: AAA=23, AA+=22, AA=21, AA-=20, A+=19, A=18, A-=17, BBB+=16, BBB=15, BBB-=14, BB+=13, BB=12, BB-=11, B+=10, B=9, B-=8, CCC+=7, CCC=6, CCC-=5, CC=4, C=3, D=2, SD=1. Since firm characteristics are available only quarterly, we construct a quarterly time series for the S&P rating database. To this aim, we average the rating actions happening in the same quarter meaning that if there are more than one rating action in the same quarter, we take the average of these ratings based on the above numerical conversion. The original S&P dataset includes 4,615 firms for a total number of observations of 143,950 from 1998 until 2014.

The *EJR* database is obtained directly from the Egan and Jones Rating company. The database contains issuers' names, tickers, rating actions, including new rating assignments and related rating dates. This database is constructed on a time series basis where each credit rating with a rating action is treated as an observation. We, thus, construct a quarterly time series for the EJR database where we assign a rating in the current quarter equal to the rating in the previous quarter if no rating action has occurred. Since EJR and S&P use the same rating scale, we use the same numerical conversion adopted for the S&P database. As before, we delete observations when rating data are not available. The original EJR database includes 2,402 firms for a total number of observations equal to

58,583 from 1999 until 2014.

We obtain all equity analyst recommendations issued between January 1993 and December 2014 from the *I/B/E/S* detail files. Equity analysts use a five-tier rating system. More specifically, the I/B/E/S recommendation file tracks each recommendation made by each analyst, where recommendations are standardized and converted to numerical scores where "1" denotes a *Strong Buy* recommendation, "2" denotes a *Buy* recommendation, "3" denotes a *Hold* recommendation, "4" denotes a *Underperform* recommendation and "5" denotes a *Sell* recommendation. The original I/B/E/S file provide recommendations that are analyst specific. We average all the recommendations in a given firm-year-month to get the average monthly recommendation for every firm in our sample. This delivers a sample of analysts recommendations that covers 1,799 firms for a total number of observations of 158,511 from 1994 until 2014. This database offers also the opportunity to construct a measure of heterogeneity in equity analysts beliefs. The measure, based on the standard deviation of analysts' recommendations, provides insights on how dispersed is the information they are able to provide.

The S&P, EJR and I/B/E/S databases are merged by firm ticker, year and month. The final database of equity analysts' recommendations and ratings contain 1,150 firms from 1999 until 2014.

The analysis requires additional data on Moodys' ratings. Moody's ratings are collected using the Moody's website. The rating scale adopted by Moodys is different from the S&P and EJR's one. In order to make the comparison across ratings more manageable, we convert Moodys' ratings using the following numerical conversion: Aaa=23, Aa1=22, Aa2=21, Aa3=20, A1=19, A2=18, A3=17, Baa1=16, Baa2=15, Baa3=14, Ba1=13, Ba2=12, Ba3=11, B1=10, B2=9, B3=8, Caa1=7, Caa2=6, Caa3=5, Ca=4, C=3. We collect ratings for a subset of large firms (firms whose assets are larger than 1 million). We are able to collect Moodys ratings for 286 firms. The total number of observations for the Moodys file is 3,652. The Moodys sample period goes from 2004 to 2014.

The file containing ratings and equity recommendations is augmented with financial statement and financial market data from Compustat and the Center for Research in Security Prices (CRSP).

Compustat provides firm specific variables. More precisely, by exploiting this dataset, we construct variables such as Investment, Size, Tangibility, Market-to-Book, Profitability, Long-Term Leverage, Debt Issuance and Cash-Asset ratio. Investment is defined as the ratio of Capital Expenditures over Assets. Size is constructed as the log of quarterly total assets. To construct this variable, we delete observations if total assets are equal or lower than zero. Tangibility is defined as the ratio of property plant and equipment over total assets. Market-to-Book is constructed as the ratio of the market value of assets over the book value of assets, where the market value of assets is defined as the market value of equity (close price multiplied by common shares outstanding) minus the book value of equity (total assets minus total liabilities plus deferred taxes and investment tax credit) plus the book value of total assets. We delete observations if market-to-book is equal or lower than zero. Profitability is proxied by the Return on Assets, computed as operating income before depreciation over total assets. The Long-Term Leverage is given by the long-term debt over total assets. Debt Issuance is constructed as the ratio between the first difference of the firm total debt and the lagged book value of total assets. Finally, the Cash ratio is computed as the ratio of cash over total quarterly assets. Missing values for all the variables cited above are deleted. To limit the effects of outliers, all the variables are winsorized at the 1% level.

We use CRSP data to get stock information data. The use of this dataset allows to construct two main variables. First, we can define the stock market excess return for every firm in our sample by looking at the difference between the stock market return and the return on a benchmark, the *S&P500* portfolio. Second, the use of the CRSP database provides the opportunity to construct an additional measure of heterogeneity in equity analysts beliefs, the *monthly turnover*.

A number of empirical papers in the finance literature (among others, Kandel and Pearson, 1995) as well as in the accounting literature (Bamber, 1987; Bamber, Barron and Stober, 1997) have used trading activity as a proxy for heterogeneous beliefs among investors. We construct the monthly turnover variable as the trading volume divided by the number of shares outstanding. This proxy is also used in Chemmanur, Loutskina and Tian (2008).

Finally, the analysis requires the use of bond data. Bond information is gathered from FINRA's Trade Reporting and Compliance Engine database (TRACE). This database contains information about bond prices, returns, yields and years to maturity. To get bond spreads, we collect the Treasury yields[46] from the US Treasury database, available online. We construct bond spreads for each firm as the difference between the bond yield of each security and the Treasury yield with comparable maturity and coupon. We drop observations if the spread is equal or lower than zero or if there are missing data.

3.5 EMPIRICAL MODELS AND REGRESSION RESULTS

3.5.1 Information Flow between CRAs and Equity Analysts

A preliminary work by Ederington and Goh (1998) has shown that equity analysts and credit rating agencies influence each other, meaning that actual earnings and forecasts of future earnings trend to fall following downgrades as well as downgrades tend to fall after declines in actual and forecast earnings. The analysis conducted by Ederington and Goh focuses on a time interval that goes from January 1984 until December 1990, it neglects any difference in the compensation system adopted by CRAs and, consequently, does not allow to study how the information released by different CRAs affect equity analysts and vice-versa.

[46] Treasury yields are interpolated by the Treasury from the daily yield curve, which relates the yield on a security to its maturity based on the closing-market bid yields on actively traded Treasury securities in the over-the-counter market. The yield values are read from the yield curve at fixed yearly maturities: 1, 2, 3, 5, 7, 10, 20, 30 years.

To study the information flow between issuer-paid credit rating agencies, investor paid credit rating agencies and equity analysts we will use a model in which S&P or EJR credit rating changes (or equity analyst recommendation changes) are regressed against past S&P and EJR rating changes as well as past equity analyst recommendations. The intuition behind this analysis relies on the need to check who is the main information provider among S&P, EJR and the equity analysts. If the idea that investor-paid credit rating agencies are more accurate and timely is true, then we should expect to see other information providers, as represented by the equity analysts and the issuer-paid credit rating agency S&P, to mimic the information sent by EJR ratings and to behave accordingly.

The specifications we use to test for the information flow among the three information providers are provided below:

$$\begin{aligned} \Delta IBES_{i,t} &= \alpha + \beta_1 \Delta EJR_{i,t-1} + \beta_2 \Delta S\&P_{i,t-1} + \beta_3 \Delta IBES_{i,t-1} + \gamma_1 \Delta EJR_{i,t+1} \\ &\quad + \gamma_2 \Delta S\&P_{i,t+1} + \eta X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{28}$$

$$\begin{aligned} \Delta EJR_{i,t} &= \alpha + \beta_1 \Delta IBES_{i,t-1} + \beta_2 \Delta S\&P_{i,t-1} + \beta_3 \Delta EJR_{i,t-1} + \gamma_1 \Delta IBES_{i,t+1} \\ &\quad + \gamma_2 \Delta S\&P_{i,t+1} + \eta X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{29}$$

$$\begin{aligned} \Delta S\&P_{i,t} &= \alpha + \beta_1 \Delta EJR_{i,t-1} + \beta_2 \Delta IBES_{i,t-1} + \beta_3 \Delta S\&P_{i,t-1} + \gamma_1 \Delta EJR_{i,t+1} \\ &\quad + \gamma_2 \Delta IBES_{i,t+1} + \eta X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{30}$$

The first Model studies the effect of past EJR ($\Delta EJR_{i,t-1}$) and S&P ($\Delta S\&P_{i,t-1}$) rating changes on future changes in equity analyst recommendations ($\Delta IBES_{i,t}$). The second model proposes a similar analysis where the effect of past changes in equity analyst recommendations ($\Delta IBES_{i,t-1}$) and S&P rating changes ($\Delta S\&P_{i,t-1}$) on future EJR rating changes ($\Delta EJR_{i,t}$) are taken into account. The third model focuses on S&P rating changes ($\Delta S\&P_{i,t}$) and how they are affected by past equity recommendation changes ($\Delta IBES_{i,t-1}$) and EJR rating changes ($\Delta EJR_{i,t-1}$).

Additionally, all the models include lead changes of the main variables in order to better investigate the direction of the information flow. Firm specific controls, year and industry fixed effects are included as well.

Results for the first model are presented in table (22). Column (1) shows the effects of past rating changes, from either S&P or EJR, on subsequent changes in equity analyst recommendations. Column (2) adds firm specific controls. Column (3) considers lead values for the main test variables as specified in Column (1). Column (4) focuses on the effect of the lead variables.

As shown in Columns (1), (2) and (3), past EJR rating changes have an effect on future equity recommendation changes. More in detail, EJR credit rating changes induce equity analyst recommendation changes of the same sign. S&P rating changes play no role on the equity analyst activity. Moreover, current changes in equity recommendations do not affect future changes in EJR or S&P. The main takeaway from table (22) is that equity analysts change their recommendations only following EJR rating changes. Similar analysis is shown in table (23) which provides results for our second model. Here, the dependent variable is represented by current changes in EJR ratings. Each column of the table has the same interpretation as before. The results outlines in table 23 suggest that EJR rating changes are independent of previous changes from either S&P or the equity analysts. The result persists when controlling for lead values and firm specific controls. Finally, results for third model are presented in table (24). Now, the dependent variable is represented by current changes in S&P ratings. The table illustrates that S&P follows all the signals available but it is not able to impact any of them.

Taken together, the results illustrate that EJR ratings are able to affect both S&P ratings and equity analyst recommendations. Equity analyst recommendations affect S&P ratings, but the credit rating changes of the latter have no power in generating subsequent changes in either EJR ratings or equity recommendations.

3.5.2 Impact of Leverage on equity analyst recommendations and Credit Rating Changes

Both equity analysts and credit rating agencies provide information about the state of firms or industries. They provide this information based on research that looks at the firms' bonds and stocks performance together with other relevant firm specific characteristics. Although the goal of credit rating agencies and equity analysts is similar (i.e. helping investors in the evaluation of firms' future prospects), the point of view assumed by equity analysts and credit rating agencies is different and translates into different job descriptions. Equity analysts provide recommendations about the firm's equity performance. On the other side, credit rating agencies are more interested in providing guidelines to investors about the firm's expected probability of default.

The different focus of equity analysts and credit rating agencies leads us to investigate what will be the effect, in terms of equity analyst recommendation changes and credit rating changes (from either S&P or EJR), of an increase/decrease in leverage. Intuitively, a change in leverage should affect differently the way equity analysts and credit rating agencies evaluate a firm. An increase in firm leverage might be interpreted as a way to boost the amount of cash available for firms' operations. Consequently, a higher level of leverage, could be interpreted *positively* from the point of view of equity analysts, who are more concerned with evaluating firms' equity performance. However, an increase in leverage can also be interpreted as a signal of an increased probability of default on firm's debt obligations. A higher leverage signals higher probability of default and, thus, might generate a *negative* assessment from credit rating agencies. In this paper we focus on two different credit rating agencies, S&P and EJR, that because of their adopted compensation systems, provide ratings that differ in accuracy and timeliness. EJR is an information provider for investors, and therefore is less likely to inflate ratings and more likely to invest in monitoring activity of the rated companies. Consequently, we should expect EJR to react more quickly to changes in leverage than S&P.

To capture the effects of a change in leverage on equity analyst recommendations and credit ratings, we consider the following regression models:

$$\Delta IBES_{i,t} = \alpha + \beta \Delta Leverage_{i,t-1} + \eta X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \tag{31}$$

$$\Delta EJR_{i,t} = \alpha + \beta \Delta Leverage_{i,t-1} + \eta X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \tag{32}$$

$$\Delta S\&P_{i,t} = \alpha + \beta \Delta Leverage_{i,t-1} + \eta X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \tag{33}$$

In the above models, we regress changes in equity analyst recommendations ($\Delta IBES_{i,t}$) or changes in credit ratings ($\Delta EJR_{i,t}$, $\Delta S\&P_{i,t}$) on past changes in firm leverage ($\Delta Leverage_{i,t-1}$) as well as on firm specific characteristics. Year fixed effects and industry fixed effects are included. Standard errors are clustered at the firm level. Results are presented in table (25). Column (1) shows the effect of changes in leverage on subsequent changes in equity analyst recommendations. Column (2) shows the effect of changes in leverage on future EJR rating changes. Column (3) presents the effect of past leverage changes on S&P credit rating changes.

The coefficient on $\Delta Leverage_{i,t-1}$ illustrates how equity analysts and credit rating agencies perceive changes in leverage. Consistently with the intuition described above, an increase in leverage generates a better equity analyst recommendation but a lower EJR credit rating. Put differently, an increase in the firm level of leverage generates an upgrade in equity analyst recommendations and a downgrade in EJR credit ratings. However, as pointed out in Column (3) of table (25), changes in leverage do not generate any subsequent change in S&P ratings. The insignificant coefficient on $\Delta Leverage_{i,t-1}$ when the dependent variable is represented by future S&P rating changes might be explained in light of the slower monitoring activity of S&P. The results confirm the intuition that a higher firm leverage is interpreted differently by credit rating agencies and equity analysts and that, among credit rating agencies, S&P is less responsive than EJR to leverage changes.

3.5.3 Impact of rating changes on investment

Next, we turn to evaluate the impact of EJR, S&P, and equity analysts upgrades and downgrades on firms' investments, defined as capital expenditure as a share of assets. We average the equity analysts recommendations as well as EJR and S&P ratings for every firm-year and merge those with annual firm characteristics publicly available from WRDS. The regression model below evaluates the impact of rating changes on investment. The dependent variable (investment) is defined as capital expenditure over assets. Columns (1)-(3) in table (26), outlines the impact of changes in ratings on investment, separately for EJR, S&P, and equity analysts recommendations (respectively), while model (4) incorporates all rating changes as independent variables. Firm controls include leverage, revenue, cash flow, as well as rating level controls for IBES, EJR, and S&P, and year and industry fixed effects. Standard errors are clustered by firm ticker.

The dummy variables $EJR_{i,t-1}^{upgrade}$ and $EJR_{i,t-1}^{downgrade}$ turn on when Egan and Jones average lagged annual ratings increase or decrease (respectively) by more than one rating notch. Similarly, $IBES_{i,t-1}^{upgrade}$ and $S\&P_{i,t-1}^{downgrade}$ turn on when S&P ratings rise or fall (respectively) by more than one notch for firm i during year $t-1$. Consistently, equity analysts recommendations are assigned values from 1 to 5, and $IBES_{i,t-1}^{upgrade}$, $IBES_{i,t-1}^{downgrade}$ dummy variables refer to lagged decreases or increases (respectively) of at least one level in the average levels of equity analysts recommendations[47].

$$\frac{CapitalExpenditure_{i,t}}{Assets_{i,t}} = \alpha + \beta_1 EJR_{i,t-1}^{upgrade} + \beta_2 EJR_{i,t-1}^{downgrade} + \beta_3 S\&P_{i,t-1}^{upgrade}$$
$$+\beta_4 S\&P_{i,t-1}^{downgrade} + \beta_5 IBES_{i,t-1}^{upgrade} + \beta_6 IBES_{i,t-1}^{downgrade} + \gamma X_{i,t-1} + \theta_t + \theta_{sic} + \epsilon_{i,t} \tag{34}$$

[47]The equity analysts recommendations are classified as follows: strong buy=1, buy=2, hold=3, sell=4, strong sell=5

The regression results in model (1) of table (26) suggest that EJR upgrades lead to an average statistically significant increase of 0.45 percentage points in investment[48]. Consistently, EJR downgrades lead to a decrease of 0.62 percentage point in capital expenditure over assets. This result is consistent with the intuition that investors respond strongly to EJR rating changes since those fluctuations have substantial impact on the cost of debt, which in-turn changes the availability of cash flow for investment.

Model (2), however, suggests that only a downgrade in S&P ratings has a statistically significant impact on investment at the %1 level, while the effect of upgrade in S&P on investment is significant only at the %10 level[49]. Similarly, model (3) suggests that only downgrades of equity analysts' recommendations lead to an average decrease of 0.53 percentage points in capital expenditure as a share of assets. Finally, in model (4), we include S&P and EJR rating changes as well as changes in equity analysts' recommendations as independent variables[50]. The results suggest that Egan and Jones upgrades and downgrades lead to statistically significant increases and decreases (respectively) in the investment levels. However, only downgrades in S&P ratings and equity analysts' recommendations have a negative impact on investment that is statistically significant at 1% level[51]. Those findings suggest that investors respond strongly to Egan and Jones rating changes, and only react to downgrades by equity analysts and S&P. Those findings reinforce the intuition that investors are highly responsive to EJR rating fluctuations since they internalize that it is an investor-paid rating agency that is accountable only to investors that retain it's services. This is in contrast to S&P, that is subjected to pressure from bond issuers to inflate their ratings, or

[48] Investment is defined as capital expenditure over assets

[49] S&P downgrade leads to a decrease of 0.74 percentage points in investment, defined as capital expenditure over assets.

[50] The regression also includes firm controls such as leverage, revenue, cash flow, as well as controls for S&P and EJR rating levels and equity analysts' recommendations.

[51] The effect of upgrade is only statistically significant at the 10% level in this case

sell-side equity analysts which are incentivized to recommend equity shares that their employer offers for sale.

3.5.4 Impact of upgrade/downgrade rating thresholds on Investment

In addition to evaluating the impact of rating changes on investment, we also study the effect of ratings being on upgrade or downgrade thresholds on firm investment, defined as capital expenditure over assets. Similarly to Kisgen (2006), we define rating downgrade and upgrade thresholds as ratings with minus and plus signs (respectively). Firms on upgrade or downgrade rating thresholds will incur a distinct changes in the cost of debt issuance if their ratings change. Thus to avoid a downgrade (when rating has a minus sign) or achieve an upgrade (when rating has a plus sign) firms will constrain debt issuance, to boost cash flow to equity holder, and thereby send a favorable signal to the rating agencies. Therefore, if firms constrain debt issuance when their ratings are on the boundaries, they have less free cash flow to invest in projects. Consequently, we hypothesize that when firms' ratings are on upgrade/downgrade thresholds, they may constrain investment.

We analyze the impact of rating boundaries on investment using the regression model specified below. The dependent variable (investment) is defined as capital expenditure over assets. $EJR^{Minus}_{i,t-1}$, $EJR^{Plus}_{i,t-1}$ are dummy variables that turn on when EJR ratings have negative or positive signs (respectively) next to the letter of the credit rating. Similarly, $S\&P^{Minus}_{i,t-1}$, $S\&P^{Plus}_{i,t-1}$ are dummy variables for downgrade and upgrade S&P rating boundaries. The regression model also includes controls for EJR and S&P rating levels as well as equity analysts' recommendations. Additionally, the model includes firm controls for revenue, leverage, cash flow, number of employees and debt over earnings as well as industry and year fixed effects. Finally, we cluster the standard errors by firm ticker.

$$\frac{CapitalExpenditure_{i,t}}{Assets_{i,t}} = \alpha + \beta_1 EJR^{minus}_{i,t-1} + \beta_2 EJR^{plus}_{i,t-1} + \beta_3 S\&P^{minus}_{i,t-1}$$

$$+\beta_4 S\&P^{plus}_{i,t-1} + \beta_5 EJR_{i,t-1} + \beta_6 S\&P_{i,t-1} + \beta_7 IBES_{i,t-1} + \gamma X_{i,t-1} + \theta_t + \theta_{sic} + \epsilon_{i,t} \tag{35}$$

The regression results are depicted in table (27). Models (1),(2) evaluate the impact of ratings being on upgrade/downgrade boundaries on investment, separately for EJR and S&P (respectively). Model (3) incorporates coefficients for upgrade/downgrade rating boundaries for both rating agencies. The results suggest that investors are highly sensitive to upgrade and downgrade thresholds of ratings issued by Egan and Jones but not to Standard and Poor's rating boundaries. Specifically, firms constrain investment approximately 0.18 percentage points when EJR ratings have plus or minus signs. However, we find no statistical evidence to suggest that firms reduce investment when their S&P ratings are on those upgrade/downgrade boundaries. These results are consistent with the intuition that investors respond more strongly to EJR than S&P rating thresholds, since unlike Standard and Poor's, Egan and Jones is compensated by investors rather issuers, and therefore is not incentivized to inflate credit ratings in order to appease bond issuers that retain their services.

3.5.5 Impact of rating changes on excess returns

In this section, we evaluate the impact of daily changes in Egan and Jones (EJR) and standard and Poor's (S&P) credit ratings, as well as changes in the equity analysts' recommendations on firms' excess stock returns, defined as daily share returns net of the S&P500 index.

Egan and Jones and standard and Poor's primary responsibility as credit rating agencies is to predict default probabilities of firms' bonds. This implies that credit rating agencies pay special attention to evaluating the riskiness of firms with high probability of default. Thus, investors may find credit ratings to be particularly informative when they consider firms with median ratings below investment grade, as those firms are more likely to default.

Moreover, unlike S&P, EJR is compensated by investors rather then issuers. Therefore, EJR is not subjected to pressure to inflate ratings to appease bond issuers, since it is primarily accountable to investors who pay for the firm's services. Consequently, investors may perceive EJR ratings as more accurate and thus respond more strongly when EJR rating change, which will result in larger impact of EJR than S&P changes on excess returns.

Further, equity analysts' job description differs substantially from both EJR and S&P. They provide recommendations about the firms' equity performance, rather then attempting to predict firms' default rates, which is the main responsibility of the credit rating agencies. This implies that investors in firms that are not likely to default, may find the equity analysts' recommendations about the firms' performance, to be more informative. Consequently, we hypothesize that investors in firms with low probability of default, may respond more strongly to changes in equity analysts recommendations rather then to fluctuations in EJR or S&P ratings.

To test our hypothesis, we evaluate the impact of changes in equity analysts' recommendation on excess equity returns using the regression models specified in the equations below. The dependent variable $Return_{i,t} - S\&P500_{i,t}$ is the difference between firms' daily returns and S&P500 index returns. $IBES_{i,t-1}^{Upgrade}$ and $IBES_{i,t-1}^{Downgrade}$ are dummy variables that turn on when the average lagged equity analysts recommendations for firm i increase or decrease (respectively) by at least one notch. Firm controls include leverage, market to book, return on assets, as well as controls for IBES, EJR, S&P rating levels, and industry and year fixed effects. Standard errors are clustered by firm ticker.

$$Return_{i,t} - S\&P500_{i,t} = \alpha + \beta_1 IBES^{Downgrade}_{i,t-1} + \beta_2 IBES^{Upgrade}_{i,t-1} + \gamma X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \tag{36}$$

$$Return_{i,t} - S\&P500_{i,t} = \alpha + \beta_1 EJR^{Downgrade}_{i,t-1} + \beta_2 EJR^{Upgrade}_{i,t-1} + \gamma X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \tag{37}$$

$$Return_{i,t} - S\&P500_{i,t} = \alpha + \beta_1 S\&P^{Downgrade}_{i,t-1} + \beta_2 S\&P^{Upgrade}_{i,t-1} + \gamma X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \tag{38}$$

In order to ensure that our assessment of the impact of changes in equity analysts' recommendations on excess returns are not driven by changes in S&P and EJR ratings, we construct a time window of 60 days prior and following changes in average analysts' recommendation where S&P and EJR levels remain constant. We identify time windows [-60,+60] such that for days [-60,-1] average analysts' recommendations remain constant, while during [0,+60], the equity analyst recommendations shift at least one notch upward or downward and remain constant afterwards.

Columns (1) and (2) in panel A of table (28), depict results for the impact of equity analysts' recommendation changes on excess stock returns while S&P and EJR ratings remain constant. Similarly columns (3),(4) and (5),(6) refer to the impact of EJR and S&P changes (respectively) on excess returns while we ensure that we construct time frames [-60,+60] around changes in EJR and S&P (respectively) such that the other ratings remain constant. The specifications of regression models 3-6 in tale (28) are similar to models 1-2, with the exception that we replace dummy variable for equity analysts' recommendation downgrades and upgrades with dummy variables for EJR and S&P downgrades and upgrades.

The negative and highly significant coefficient on $IBES^{Downgrade}_{i,t-1}$ in column (2) in table 28 (panel A) suggests that downgrades in equity analysts recommendations yield an average decrease of 16.4 percentage points in equity excess returns. Consistently, the positive and highly significant coefficient on $IBES^{Upgrade}_{i,t-1}$ implies that an upgrade of equity analysts' recommendations leads to an increase of 16.7

percentage points in excess returns within days [0,+60] following the change.

However, column (4) in table 28 (Panel A) suggests that only an EJR downgrade ($EJR_{i,t-1}^{Downgrade}$) impacts equity excess returns while EJR upgrade ($EJR_{i,t-1}^{Upgrade}$) does not have a significant effect. These results are hardly surprising since unlike equity analysts, credit rating agencies assess the riskiness of firms' default rates, and thus are likely to have a smaller impact on returns of well performing firms in comparison to equity analysts. Moreover, model (6) suggests that unlike equity analysts and Egan and Jones, S&P ratings do not have a significant impact on equity returns. These results are consistent with the idea that investors respond less to S&P ratings since they internalize that S&P is subjected to conflicts of interests with bond issuers that may impact the accuracy of their ratings.

Finally, in panel B, we preform similar regression analyses as in panel A, but we restrict our data sample only to firms with median S&P ratings below investment grade. In this instance, only downgrades and upgrades ($EJR_{i,t-1}^{Downgrade}, EJR_{i,t-1}^{Upgrade}$) of EJR have statistically significant impact on equity excess returns. This result is fully consistent with our intuition that investors respond strongly to EJR rating changes since EJR is an investor-paid rating agency whose main responsibility is the predict default risk, and unlike S&P, it is not subjected to pressure from bond issuers to inflate its ratings.

3.5.6 Impact of Equity Analyst Recommendations and Credit Rating Changes on Bond Market Spread

In this section, we analyze the effect of equity analyst recommendations and credit ratings from S&P and EJR on bond yields. Consistently with the previous section, we expect the impact of S&P rating changes on the bond market to be smaller than that of EJR since S&P faces pressure to inflate ratings of the issuers that pay them for their ratings. EJR on the other hand, is compensated by investors, and thus is likely to be more accurate and timely in their ratings. Consequently, we hypothesize that EJR rating changes would lead to larger bond spreads than changes in S&P ratings. It follows from Merton's (2007) "investor attention" theory that it is more costly for bond investors to pay attention to the signals from equity analysts than from bond analysts. Thus, we expect investors to respond more to changes in ratings by EJR and S&P in comparison to changes in recommendations by equity analysts.

The empirical model below outlines the regression that we run to evaluate the impact of changes in EJR, S&P, and equity analyst recommendations on the bond market

$$\begin{aligned} Log(Spread)_{i,t} \quad = \quad & \alpha + \beta_1 EJR^{downgrade}_{i,t-1} + \beta_2 EJR^{upgrade}_{i,t-1} + \gamma_1 IBES^{downgrade}_{i,t-1} + \\ & \gamma_2 IBES^{upgrade}_{i,t-1} + \lambda_1 S\&P^{downgrade}_{i,t-1} + \lambda_2 S\&P^{upgrade}_{i,t-1} + \\ & \eta X_{i,t-1} + \theta_{sic} + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{39}$$

The dependent variable in the regression model above is the logarithm of the bond spread. The bond spread is defined as the difference between the security yield and the treasury (T-Bill) yield. Security yields and treasury yields are matched by maturity and coupons. The logarithm of bond spread is regressed on EJR rating changes, equity analyst recommendation changes and S&P rating changes. Firm controls, year fixed effects and industry fixed effects are included as well.

Regression results are presented in table 29. The table is divided to three panels. Panel (A) includes the entire sample. Panel (B) focuses on a subset of speculative firms which are defined as firms whose average rating, from either S&P or EJR, is below the investment threshold. Panel (C) includes firms that at least once in their life were downgrades from investment-grade ratings to the speculative-grade range. In table 29, columns (1) and (2) describe the effects of EJR rating changes on the *log(spread),* without and with the inclusion of firm specific controls, respectively. Columns (3) and (4) provide a similar analysis when the EJR rating changes are replaced by the equity analyst recommendation changes. Columns (5) and (6) focus on the S&P changes. Finally, column (7) and (8) includes rating changes by EJR and S&P, as well as changes in equity analyst recommendations as independent variables.

As denoted in column (8), EJR rating upgrades reduce the bond spread by about 3.49 percentage points. EJR rating downgrades increase the bond spread by about 15.3 percentage points. Similarly to EJR downgrades, equity analyst recommendation downgrades have an impact on the bond market although the magnitude is reduced to 2.03 percentage points. Interestingly, upgrades from equity analysts do not seem to lead to statistically significant changes in the bond spread.

The magnitude of the impact of equity analysts on bonds spreads is relatively small since similarly to issuer-paid credit rating agencies, equity analysts are also exposed to conflicts of interests that may compromise the credibility and the informativeness of corporate equity recommendations. Equity analysts may decide to inflate equity recommendations to appease the management. The significant bond market response following EJR rating changes persists when we subset our sample to firms that are more likely to default. Those firms have S&P or EJR ratings below the investment grade threshold (*Panel (B)*).

In contrast to the regression results in panel A, S&P downgrades have a statistically significant effect on the bond market (increase of 8.1 percentage points in the bond spread). This result is consistent with the idea that firms that are more likely to default are more sensitive to rating fluctuations. Finally, in panel C, we subset our sample to firms that at least once in their life had a rating fall from the investment-range to the speculative grade. Our regression results suggest that only EJR rating changes are informative and impact bond spreads.

Overall, the results presented in this section illustrate that the EJR ratings impact bond spreads more than ratings provided by S&P and the equity analyst recommendations, independently of the sample considered.

3.5.7 Heterogeneity in equity analyst beliefs and rating disagreement

Finally, we evaluate whether credit rating agencies diverge in their risk assessment for firms where equity analysts disagree about their recommendations for firms' equity performances. We hypothesize that for firms where equity analysts disagree about future stock performance, rating agencies such as S&P that are compensated by bond issuers, and thus are likely to inflate ratings to cater to bond issuers, will be more concerned about reputational consequences. Therefore, they will issue conservative assessments of firms' probability of default. Consequently, as S&P will issue conservative ratings for firms where equity analysts diverge in their recommendations.

On the other hand, investor paid rating agencies, such as EJR, do not face pressure to inflate ratings as issuer paid ratings, such as S&P. Therefore, they do not feel the need to issue abnormally conservative ratings for firms where equity analysts diverge in their equity recommendations. This is because their assigned ratings reflect their most accurate belief about firms' riskiness of default and they are not influenced by conflicts of interests resulting from trying to appease bond issuers. Consequently, we hypothesize that rating agencies that have different models of compensations, for instance, EJR - an investors paid rater, and S&P - an issuer paid rater, will diverge in their risk assessment of default risk, particularly for firms where rating equity analysts disagree about firm quality. The empirical models below describe the regressions that we run to test if heterogeneity in beliefs among equity analysts translates into heterogeneity in beliefs among credit ratings agencies.

$$|S\&P_{i,t} - EJR_{i,t}| = \alpha + \beta_1 EquityAnalysts^{Std}_{i,t-1} + \gamma X_{i,t-1} + \theta_t + \theta_{sic} + \epsilon_{i,t} \quad (40)$$

$$|S\&P_{i,t} - EJR_{i,t}| = \alpha + \beta_1 TradingVolume_{i,t-1} + \gamma X_{i,t-1} + \theta_t + \theta_{sic} + \epsilon_{i,t} \quad (41)$$

Indeed, our results confirm this intuition. We test if S&P and EJR ratings diverge for firms where equity analysts diverge in their recommendations, by regressing the absolute value of monthly differences between S&P and EJR ratings ($|S\&P_{i,t} - EJR_{i,t}|$) on monthly standard deviations of equity analysts recommendation ($EquityAnalysts^{Std}_{i,t-1}$) as well as firm controls and year and industry fixed effects. Firm controls include lagged leverage, return on assets, market to book, cash over assets, sales, and rating level controls for equity analyst recommendations and S&P ratings. columns (1) and (2) in table 30 depict the results of the regression model described in the equation above. These results suggests that S&P and EJR levels diverge for firms with large standard deviation in equity analysts' recommendations[52]. Those results are consistent with our expectation that rating agencies with different compensations structures will respond differently to heterogeneity of beliefs among equity analysts.

Finally, as a robustness check, we substitute our measure of disagreement about firm equity value - standard deviation of equity analysts' recommendations, with another proxy for heterogeneity of beliefs about firms' values - trading volume of firms' equity shares. Thus, the new regression model has similar specifications to the one in columns (1) and (2), with the exception that we substitute $EquityAnalysts^{Std}_{i,t-1}$ with $TradingVolume_{i,t-1}$. We define $TradingVolume_{i,t-1}$ as trading volume for each firm and year, over total shares outstanding. We report regression results for the models in equation above in columns (3) and (4) of table 30. The results confirm our findings that rating agencies that differ in their compensation models (i.e. issuer versus investor paid) diverge in their as-

[52]Note that unlike in column (1) of table 30, the regression in column (2) includes firm controls.

signed ratings for firms where we observe large heterogeneity in equity analysts' recommendations.

3.6 CONCLUSIONS

This study evaluates the discrepancies in the information content of equity analyst recommendations, and ratings by issuer and investor paid credit rating agencies. We demonstrate that Egan and Jones, the largest investor-compensated rating agency in the U.S., issues timelier ratings that impact equity analysts' recommendations and S&P ratings. This result is consistent with the intuition that being an investor-paid rating agency, EJR does not face pressure to inflate ratings or delay downgrades.

Moreover, we show that changes in credit ratings by EJR and S&P have larger impact on bond yield spreads than equity analyst recommendations. Consistently, analysts' recommendations have a larger effect on firms' equity returns. This result is in-line with the intuition that bond investors rely on bond raters to better predict default risk, while equity investors rely more on equity analysts to predict overall firm performance. Interestingly, however, when firms have a high probability of default, even equity investors rely more heavily on the investor-paid rating agency (EJR) as a predictor of default risk.

Further, we demonstrate that changes in leverage are associated with lower EJR (Egan and Jones) ratings but higher equity analyst recommendations. This result suggests that rating agencies focus on default risk, and thus will evaluate higher leverage as a negative signal. Equity analysts, on the other hand, focus on overall firm performance, and therefore will balance the cost of higher default risk with the benefit of greater liquidity resulting from bond issuance.

Finally, we find that investor-paid rating agency (EJR) has a larger impact on firms' investment decisions than equity analyst recommendations and S&P ratings. This finding can be driven by the aforementioned result that EJR rating are timelier than equity analyst recommendation and S&P ratings, or by the fact that EJR does not face pressure to inflate ratings to please issuers, and thus can be more informative for firms' investment decisions. We conclude by demonstrating that disagreement among equity analyst on their recommendations about firms' performance is correlated with greater disagreement between S&P and EJR on firms' default risks.

3.7 REFERENCES

[1] Bamber L. S., 1987, Unexpected earnings, firm size and trading volume around quarterly earnings announcements. Accounting Review 62, 510-532.

[2] Bamber L. S., O. E. Barron and T. L. Stober, 1997, Trading volume and different aspects of disagreement coincident with earnings announcements. Accounting Review 72, 575-597.

[3] Bar-Isaac H. and J. Shapiro, 2011, Credit ratings accuracy and analyst incentives. American Economic Review (Papers and Proceedings) 101: 120-124.

[4] G. Batta and V. Muslu, 2011, Credit rating agency and equity analysts' adjustments to GAAP earnings.

[5] Becker B. and T. Milbourn, 2011, How did increased competition affect credit ratings. Journal of Financial Economics 101: 493-514.

[6] Bolton P., X. Freixas and J. Shapiro, 2012, The credit ratings game, Journal of Finance 67, 85-111.

[7] Brennan M. and A. Subrahmanyam, 1995, Investment analysis and price formation in securities markets. Journal of Financial Economics 38: 361-381.

[8] Beyer A., D. A. Cohen, T.Z. Lys and B. R. Walther, 2010, The financial reporting environment: Review of the recent literature. Journal of Accounting and Economics.

[9] Camanho N., P. Deb, and Z. Liu, 2010, Credit rating and competition, London School of Economics Working Paper.

[10] Chemmanur T. J., E. Loutskina and X. Tian, 2008, The role of venture capital backing in intial public offerings: Certification, screening or market power, Working Paper.

[11] Cheng M. and K. R. Subramanyan, 2007, Analyst following and credit ratings, Working Paper.

[12] Cornaggia J. and K. R. Cornaggia, 2013, Estimating the costs of issuer and credit ratings. Review of Financial Studies 26, 2229-2269.

[13] Doherty N. A., A. V. Kartasheva and R. D. Phillips, 2012, Information effect of entry into credit ratings market: The case of insurers' ratings, Journal of Financial Economics 106: 308-330.

[14] Ederington L. H. and J. C. Goh, 1998, Bond rating agencies and stock analysts: Who knows what when? Journal of Financial and Quantitative Analysis 33(4).

[15] Ederington L. H. and J. Yawitz, 1987, The bond rating process. Handbook of Financial Markets and Institutions, 6th ed, E. Altman, ed. NY: John Wiley and Sons.

[16] Ertimur Y., V. Muslu and F. Zhang, 2011, Why are recommendations optimistic? Evidence from analysts' coverage initiations. Review of Accounting Studies.16.

[17] K. Fong, H. Hong, M. Kacperczyk and J. D. Kubik, 2014, Do security analysts discipline credit rating agencies?, Working Paper.

[18] Jiang J. X., M. G. Stanford and Y. Xie, 2012, Does it matter who pays for bond ratings? Hostorical evidence. Journal of Financial Economics 105, 607-621.

[19] Kandel E. and N. D. Pearson, 1995, Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103, 831-872.

[20] Kraft P., 2011, Do rating agencies cater? Evidence from rating-based contracts. Working Paper, New York University.

[21] Lin H. and M. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations. Journal of Accounting and Economics 25: 101-128.

[22] Lui D., S. Markov and A. Tamayo, 2007, What makes a stock risky? Evidence from Sell-Side Analysts' Risk Ratings, Journal of Accounting Research 45 (3): 629-665.

[23] Lui D., S. Markov and A. Tamayo, 2012, Equity analysts and the market's assessment of risk, Working Paper.

[24] Lynch T., 2009, Deeply and persistently conflicted: Credit rating agencies in the current regulatory environment. Case Western Reserve Law Review 59: 227-304.

[25] Manso, Gustavo, 2013, Feedback effects of credit ratings, Journal of Financial Economics 109: 535-548.

[26] Mathis J., J. McAndrews and J. C. Rochet, 2009, Rating the raters: Are reputation concerns powerful enough to discipline rating agencies?, Journal of Monetary Economics 56: 657-674.

[27] Merton C., 1987, A simple model of capital market equilibrium with incomplete information, The Journal of Finance 42: 483–510.

[28] Riddiough T. J. and J. Zhu, 2010, Shopping, relationships and influence in the market for credit ratings. Working Paper, University of Wisconsin.

[29] Roulstone D. (2003), Analyst follwoing and market liquidity, Contemporary Accounting Research 20 (3): 551-578.

[30] Skreta V. and L. Veldkamp, 2011, Ratings shopping and asset complexity: A theory of ratings inflation, Journal of Monetary Economics 56: 678-695.

[31] Strobl G. and H. Xia, 2012, The issuer-pays rating model and ratings inflation: Evidence for corporate credit ratings, mimeo.

[32] Verrecchia R. E., 1996, Impact of analyst following on stock prices and the implications for firms' disclosure policies. Journal of Accounting, Auditing and Finance 11: 355-359.

[33] Womack K. L., 1996, Do brokerage analysts' recommendatons have investment value? Journal of Finance 51: 137-167.

[34] Xia H., 2014, Can investor-paid credit rating agencies improve the information quality of issuer paid-rating agencies? Journal of Financial Economics 111: 450-468.

3.8 APPENDIX A: TABLES

Table 20
Firm Characteristics for IBES, S&P, and EJR

The table provides summary statistics for each of the rating agencies IBES, EJR, and S&P. EJR and S&P ratings are assigned valuers from 1 to 23, where 23 refers to the rating with the lowest probability of default (AAA). IBES recommendations are assigned ratings from 1 to 5, where 1 refers to strong buy recommendation while 5 refers to strong sell recommendation.

	(1) IBES	(2) EJR	(3) S&P
Sample Period	1993-2014	1999-2014	1998-2014
Number of Firms	1,799	2,402	4,615
Number of Observations	158,511	58,583	143,950
Average Rating	2.357	13.977	13.623
Average Years Per Firm	9.18	6.25	12.36

Table 21
Annual Firm Characteristics

The table provides summary statistics for each of the rating agencies IBES, EJR, and S&P. EJR and S&P ratings are assigned values from 1 to 23, where 23 refers to the rating with the lowest probability of default (AAA). IBES recommendations are assigned ratings from 1 to 5, where 1 refers to strong buy recommendation while 5 refers to strong sell recommendation. Firm characteristics include: investment, cash ratio, leverage, total assets, liabilities, revenue, ebitda, operating income. The sample period goes from 1999 until 2014. The total number of firms is 1150. The total number of observations is 10,922.

Years	1999-2014
Firms	1150
Observations	10,922
Years Per Firm	≈ 9.5
S&P Average Rating	14.53 (≈BBB)
EJR Average Rating	14.49 (≈BBB-)
IBES Average Rating	2.43 (≈Hold)
Investment	5.8%
Cash	6.6%
Leverage	13.9%
Total Assets	$4.63B
Liabilities	$3.82B
Revenue	$1.46B
EBITDA	$260M
Operating Income	$109M

Table 22
Impact of EJR and S&P Rating Changes on Equity Analyst Recommendations

The table evaluates the impact of changes in EJR and S&P ratings on equity analysts' recommendations. The dependent variable is $\triangle IBES_{i,t}$ defined as $IBES_{i,t} - IBES_{i,t-1}$. In models (1), we regress changes in $\triangle IBES_{i,t}$ on $\triangle EJR_{i,t-1}$ and $\triangle S\&P_{i,t}$ as well as lagged rating levels, and year and industry fixed effects. Model (2) has similar specification to model (1), but we also incorporate firm controls such as lagged return on assets, log of sales, total debt, cash over assets, tangible assets, and lagged changes in equity analysts' recommendations. Model (3) also incorporates lead changes in EJR and S&P ratings ($\triangle EJR_{i,t+1}$, $\triangle S\&P_{i,t+1}$). ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Dependant Variable: $\triangle IBES_{i,t} = IBES_{i,t} - IBES_{i,t-1}$			
	(1)	(2)	(3)	(4)
$\triangle EJR_{i,t-1}$	-0.0494***	-0.0479***	-0.0479***	
	(0.0175)	(0.0175)	(0.0175)	
$\triangle S\&P_{i,t-1}$	-0.0256	-0.0221	-0.0215	
	(0.0204)	(0.0204)	(0.0204)	
$\triangle EJR_{i,t+1}$			-0.0260	-0.0267
			(0.0176)	(0.0176)
$\triangle S\&P_{i,t+1}$			0.0308	0.0295
			(0.0374)	(0.0374)
$\triangle IBES_{i,t-1}$		-0.0681***	-0.0681***	-0.0682***
		(0.00552)	(0.00552)	(0.00552)
$ROA_{i,t-1}$		-0.0967	-0.0929	-0.0979
		(0.0868)	(0.0868)	(0.0868)
$Size_{i,t-1}$		0.00675	0.00664	0.00691
		(0.00639)	(0.00639)	(0.00639)
$Debt_{i,t-1}$		-0.00100*	-0.00100*	-0.00101*
		(0.000568)	(0.000568)	(0.000568)
$\frac{Cash_{i,t-1}}{Assets_{i,t-1}}$		0.0480	0.0485	0.0445
		(0.149)	(0.149)	(0.149)
$Tangibles_{i,t-1}$		-0.0204	-0.0203	-0.0202
		(0.0426)	(0.0426)	(0.0426)
N	28946	28946	28946	28946
R^2	0.241	0.245	0.245	0.245
Firm Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 23
Impact of Equity Analysts' and S&P Ratings on Changes in EJR Ratings

The table evaluates the impact of changes in equity analysts and S&P ratings on EJR ratings. The dependent variable is $\triangle EJR_{i,t}$ defined as $EJR_{i,t} - EJR_{i,t-1}$. In models (1), we regress changes in $\triangle EJR_{i,t-1}$ on $\triangle S\&P_{i,t}$ and $\triangle IBES_{i,t-1}$ as well as lagged rating levels, and year and industry fixed effects. Model (2) has similar specification to model (1), but we also incorporate firm controls such as lagged return on assets, log of sales, total debt, cash over assets, tangible assets, and lagged changes in EJR ratings. Model (3) also incorporates lead changes in IBES and S&P ratings ($\triangle IBES_{i,t+1}$, $\triangle S\&P_{i,t+1}$). ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Dependant Variable: $\triangle EJR_{i,t} = EJR_{i,t} - EJR_{i,t-1}$			
	(1)	(2)	(3)	(4)
$\triangle IBES_{i,t-1}$	0.00137	0.000851	0.000756	
	(0.00306)	(0.00306)	(0.00306)	
$\triangle S\&P_{i,t-1}$	0.0128	0.00958	0.00976	
	(0.0113)	(0.0113)	(0.0113)	
$\triangle IBES_{i,t+1}$			-0.000839	-0.000863
			(0.00291)	(0.00291)
$\triangle S\&P_{i,t+1}$			0.0547***	0.0547***
			(0.0207)	(0.0207)
$\triangle EJR_{i,t-1}$		0.0216**	0.0212**	0.0217**
		(0.00969)	(0.00969)	(0.00967)
$ROA_{i,t-1}$		0.304***	0.302***	0.303***
		(0.0481)	(0.0481)	(0.0481)
$Size_{i,t-1}$		0.0100***	0.00987***	0.00980***
		(0.00354)	(0.00354)	(0.00354)
$Debt_{i,t-1}$		-0.000840***	-0.000833***	-0.000831***
		(0.000315)	(0.000315)	(0.000315)
$\frac{Cash_{i,t-1}}{Assets_{i,t-1}}$		0.206**	0.202**	0.203**
		(0.0827)	(0.0827)	(0.0827)
$Tangibles_{i,t-1}$		0.0107	0.0107	0.0104
		(0.0236)	(0.0236)	(0.0236)
N	28946	28946	28946	28946
R^2	0.041	0.043	0.043	0.043
Firm Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 24
Impact of Equity Analysts' and EJR Ratings on Changes in S&P Ratings

The table evaluates the impact of changes in equity analysts and EJR ratings on S&P ratings. The dependent variable is $\triangle S\&P_{i,t}$ defined as $S\&P_{i,t} - S\&P_{i,t-1}$. In models (1), we regress changes in $\triangle S\&P_{i,t}$ on $\triangle IBES_{i,t-1}$ and $\triangle EJR_{i,t-1}$ as well as lagged rating levels, and year and industry fixed effects. Model (2) has similar specification to model (1), but we also incorporate firm controls such as lagged return on assets, log of sales, total debt, cash over assets, tangible assets, and lagged changes in S&P ratings. Model (3) also incorporates lead changes in IBES and EJR ratings ($\triangle IBES_{i,t+1}$, $\triangle EJR_{i,t+1}$). ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Dependant Variable: $\triangle S\&P_{i,t} = S\&P_{i,t} - S\&P_{i,t-1}$			
	(1)	(2)	(3)	(4)
$\triangle IBES_{i,t-1}$	0.00230**	0.00222**	0.00219**	
	(0.000895)	(0.000895)	(0.000896)	
$\triangle EJR_{i,t-1}$	0.00624**	0.00633**	0.00631**	
	(0.00283)	(0.00283)	(0.00283)	
$\triangle IBES_{i,t+1}$			-0.000230	-0.000252
			(0.000853)	(0.000853)
$\triangle EJR_{i,t+1}$			0.00444	0.00459
			(0.00285)	(0.00285)
$\triangle S\&P_{i,t-1}$		-0.00429	-0.00437	-0.00385
		(0.00331)	(0.00331)	(0.00330)
$ROA_{i,t-1}$		0.0466***	0.0458***	0.0473***
		(0.0141)	(0.0141)	(0.0141)
$Size_{i,t-1}$		0.00244**	0.00244**	0.00240**
		(0.00104)	(0.00104)	(0.00104)
$Debt_{i,t-1}$		-0.0000307	-0.0000298	-0.0000243
		(0.0000921)	(0.0000921)	(0.0000921)
$\frac{Cash_{i,t-1}}{Assets_{i,t-1}}$		0.0737***	0.0733***	0.0732***
		(0.0242)	(0.0242)	(0.0242)
$Tangibles_{i,t-1}$		-0.000936	-0.000956	-0.000819
		(0.00691)	(0.00691)	(0.00691)
N	28946	28946	28946	28946
R^2	0.015	0.016	0.016	0.015
Firm Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 25
Impact of Leverage on Equity Analyst Recommendations and Credit Ratings

The table evaluates the impact of leverage on equity analysts' recommendations (model 1) and credit ratings (models 2 and 3) in the subsequent quarter. The dependent variable in model (1) is a change in equity analysts' recommendation $\triangle IBES_{i,t} = IBES_{i,t} - IBES_{i,t-1}$. The dependent variables in models (2) and (3) are $\triangle EJR_{i,t} = EJR_{i,t} - EJR_{i,t-1}$ and $\triangle S\&P_{i,t} = S\&P_{i,t} - S\&P_{i,t-1}$ (respectively). I regress the quarterly changes in the credit ratings and equity recommendations on lagged changes in leverage defined as $\triangle Leverage_{i,t-1} = Leverage_{i,t-1} - Leverage_{i,t-2}$. All regression specifications include controls for lagged leverage, return on assets, net income. cash over assets, tangible assets, debt, market to book, and sales. I also control for industry and year fixed effects. Standard error are cluster by firm ticker. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	(1) $\triangle IBES_{i,t}$	(2) $\triangle EJR_{i,t}$	(3) $\triangle S\&P_{i,t}$
$\triangle Leverage_{i,t-1}$	-0.886**	-0.521**	0.566
	(0.378)	(0.256)	(0.723)
$Leverage_{i,t-1}$	0.171**	-0.00799	0.0959
	(0.0817)	(0.0987)	(0.0796)
$ROA_{i,t-1}$	0.677***	0.418**	0.104
	(0.220)	(0.175)	(0.0965)
$NetIncome_{i,t-1}$	-0.00297	0.0228**	0.0152*
	(0.00970)	(0.0114)	(0.00773)
$CashOverAssets_{i,t-1}$	0.703*	1.628***	0.203
	(0.376)	(0.398)	(0.165)
$Tangibles_{i,t-1}$	0.00712	-0.0427	-0.0946**
	(0.0789)	(0.0828)	(0.0437)
$MarketToBook_{i,t-1}$	-0.0318*	0.0150	0.0283**
	(0.0166)	(0.0185)	(0.0131)
$Sales_{i,t-1}$	0.0169*	-0.00614	-0.0205**
	(0.00968)	(0.0122)	(0.00954)
N	5102	5102	5102
R^2	0.023	0.122	0.055
Industry and Year FE	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes

Table 26
Impact of Rating Changes on Investment

The table evaluates the impact of rating changes on investment. The dependent variable (investment) is defined as capital expenditure over assets. Models (1)-(3) evaluate the impact of changes in ratings on investment separately for EJR, S&P, and IBES (respectively), while model (4) incorporates all rating changes as independent variables. Firm controls include leverage, revenue, cash flow, as well as rating level coefficients for IBES, EJR, and S&P. The primary coefficients of interest are on the dummy variables for changes in the IBES, EJR, and S&P ratings.Standard errors are clustered by firm ticker. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Dependent Variable: $Investment_{i,t} = \frac{CapitalExpenditure_{i,t}}{Assets_{i,t}}$			
	(1)	(2)	(3)	(4)
$EJR^{upgrade}_{i,t-1}$	0.00454**			0.00359**
	(0.00185)			(0.00180)
$EJR^{downgrade}_{i,t-1}$	-0.00616***			-0.00454***
	(0.00146)			(0.00157)
$S\&P^{upgrade}_{i,t-1}$		0.00431*		0.00257
		(0.00229)		(0.00217)
$S\&P^{downgrade}_{i,t-1}$		-0.00743***		-0.00486***
		(0.00170)		(0.00188)
$IBES^{upgrade}_{i,t-1}$			0.00252*	0.00168
			(0.00132)	(0.00131)
$IBES^{downgrade}_{i,t-1}$			-0.00528***	-0.00434***
			(0.00160)	(0.00161)
$Leverage_{i,t-1}$	0.00411	0.00313	0.00221	0.00581
	(0.0216)	(0.0215)	(0.0217)	(0.0215)
$Revenue_{i,t-1}$	0.00127	0.00132	0.00165	0.00123
	(0.00200)	(0.00199)	(0.00199)	(0.00200)
$Cash_{i,t-1}$	-0.0140	-0.0124	-0.0105	-0.0142
	(0.0151)	(0.0150)	(0.0150)	(0.0150)
$IBES_{i,t-1}$	-0.00431***	-0.00443***	-0.00737***	-0.00597***
	(0.00115)	(0.00116)	(0.00156)	(0.00158)
$S\&P_{i,t-1}$	-0.00370***	-0.00311***	-0.00348***	-0.00340***
	(0.000788)	(0.000787)	(0.000771)	(0.000823)
$EJR_{i,t-1}$	0.00338***	0.00280***	0.00307***	0.00310***
	(0.000678)	(0.000665)	(0.000650)	(0.000707)
N	8875	8875	8875	8875
R^2	0.395	0.395	0.394	0.397
Industry and Year FE	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes

Table 27
Impact of Upgrade/Downgrade Rating Thresholds on Investment

The table evaluates the impact of rating being on upgrade or downgrade thresholds on investment. The dependent variable (investment) is defined as capital expenditure over assets. Models (1),(2) evaluate the impact of rating being on upgrade/downgrade boundaries on investment, separately for EJR and S&P (respectively). Model (3) incorporates coefficients for rating boundaries for both rating agencies. Firm controls include leverage, revenue, cash flow, number of employees, debt over earnings, as well as rating level coefficients for EJR, and S&P. The primary coefficients of interest are on dummy variables for rating thresholds of EJR and S&P. Additional controls include $Employees_i$, $\frac{Debt_{i,t-1}}{Earnings_{i,t-1}}$. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Dep. Var: $Investment_{i,t} = \frac{CapitalExpenditure_{i,t}}{Assets_{i,t}}$		
	(1)	(2)	(3)
$EJR^{Minus}_{i,t-1}$	-0.00183**		-0.00184**
	(0.000861)		(0.000861)
$EJR^{Plus}_{i,t-1}$	-0.00183**		-0.00181**
	(0.000857)		(0.000858)
$S\&P^{Minus}_{i,t-1}$		0.000870	0.000923
		(0.000885)	(0.000885)
$S\&P^{Plus}_{i,t-1}$		-0.000474	-0.000382
		(0.000890)	(0.000891)
$Leverage_{i,t-1}$	-0.0265***	-0.0258***	-0.0262***
	(0.00982)	(0.00982)	(0.00982)
$Revenue_{i,t-1}$	-0.00397***	-0.00391***	-0.00397***
	(0.00121)	(0.00122)	(0.00122)
$Liabilities_{i,t-1}$	0.00969	0.00945	0.00955
	(0.00649)	(0.00649)	(0.00649)
$Cash_{i,t-1}$	0.00670	0.00657	0.00677
	(0.00618)	(0.00618)	(0.00618)
$S\&P_{i,t-1}$	-0.00107***	-0.00103***	-0.00106***
	(0.000254)	(0.000254)	(0.000254)
$EJR_{i,t-1}$	0.00162***	0.00158***	0.00163***
	(0.000222)	(0.000221)	(0.000222)
N	7022	7022	7022
R^2	0.607	0.607	0.607
Industry and Year FE	Yes	Yes	Yes

Table 28
Impact of Rating Changes on Excess Return

The table evaluates the impact of rating changes on excess equity returns. The dependent variable (excess returns) is defined as $Return_{i,t} - S\&P500_{i,t}$. Models (1),(2) evaluate the impact of changes in IBES recommendations on equity excess returns. Similarly, models (3),(4) and (5),(6) evaluate the impact of changes in EJR and S&P ratings (respectively) on equity excess returns. Panel A includes data for all firms while Panel B includes data for firms with median S&P ratings below investment grade. Models (1),(3),(5) include controls for rating levels of IBES, EJR, and S&P. Models (2),(4),(6) also include firm controls such as leverage, return on assets, market to book, in addition to rating level coefficients for IBES, EJR, and S&P. For each regression, we create a time window of [-60,+60] days prior and following a rating changes. This time window ensures that during this time frame only one of the ratings changes while the others remained constant. Results in this table include data for all firms in the data. Standard errors are clustered by firm ticker. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Panel A: Impact of Rating Changes on Excess Return - All Firms Dependent Variable: $Return_{i,t} - S\&P500_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)
$IBES_{i,t}^{Downgrade}$	-0.0363***	-0.164**				
	(0.0106)	(0.0707)				
$IBES_{i,t}^{Upgrade}$	0.0398***	0.167**				
	(0.0114)	(0.0724)				
$EJR_{i,t}^{Downgrade}$			-0.00300***	-0.00411***		
			(0.000979)	(0.00138)		
$EJR_{i,t}^{Upgrade}$			-0.00139	-0.000639		
			(0.00161)	(0.00222)		
$S\&P_{i,t}^{Downgrade}$					0.00130	0.00174
					(0.00117)	(0.00133)
$S\&P_{i,t}^{Upgrade}$					-0.00171	-0.000858
					(0.00334)	(0.00300)
N	1386	1265	2921	2821	3310	3305
R^2	0.015	0.020	0.018	0.017	0.011	0.012
Firm Controls	No	Yes	No	Yes	No	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Impact of Rating Changes on Excess Return - Firms with Median S&P Rating below Investment Grade Dependent Variable: $Return_{i,t} - S\&P500_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)
$IBES_{i,t}^{Downgrade}$	-0.00328	0.00791				
	(0.00220)	(0.0296)				
$IBES_{i,t}^{Upgrade}$	0.00417	-0.00853				
	(0.00335)	(0.0284)				
$EJR_{i,t}^{Downgrade}$			-0.00457**	-0.0159***		
			(0.00206)	(0.00528)		
$EJR_{i,t}^{Upgrade}$			0.00330**	0.0138***		
			(0.00145)	(0.00476)		
$S\&P_{i,t}^{Downgrade}$					0.00328	0.00262
					(0.00240)	(0.00252)
$S\&P_{i,t}^{Upgrade}$					0.000244	-0.000353
					(0.00364)	(0.00361)
N	502	419	1356	1356	2112	2108
R^2	0.023	0.035	0.026	0.028	0.006	0.006
Firm Controls	No	Yes	No	Yes	No	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 29
Bond Market Response to Rating and Recommendation Changes

Panels A,B, and C show results for OLS regressions of *Log(Spread)* on rating changes, upgrades and downgrades, from *EJR* and *S&P*, equity analysts' recommendations from *IBES*, firm specific controls and bond specific controls. Panel A includes data for all firms. Panels B includes data for firms with S&P ratings below investment grade, while Panel C includes data for firms with S&P ratings that cross the investment grade. The bond spread is defined as the difference between the security yield and the treasury yield. Security yields and treasury yields are matched by maturity and coupons. Firm specific controls include: Size, Cash Ratio, Tangibility, Market-to-Book Ratio, Profitability, Debt Issuance, S&P and EJR rating levels, IBES recommendations. All the control variables are one period lagged and winsorized at the 1% level. Regressions (1) and (2) show the effect of EJR rating changes on the bond spread. Regressions (3) and (4) show the effect of IBES equity recommendations on the bond spread. Regressions (5) and (6) show the effect of S&P rating changes on the bond spread. Regressions (7) and (8) show the effect of all the rating changes and equity recommendations on the bond spread. Regressions (2), (4), (6) and (8) add firm and bond specific controls. Regressions (1)-(8) account for year and industry fixed effets. The results refer to the entire sample. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Panel A: All Firms
Dependent Variable: Log(Spread)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Up EJR	-0.0270***	-0.0287***					-0.0320***	-0.0349***
	(0.00960)	(0.0107)					(0.0113)	(0.0126)
Down EJR	0.150**	0.154**					0.152**	0.153**
	(0.0642)	(0.0631)					(0.0772)	(0.0747)
Up IBES			0.00488	0.00735			-0.00300	-0.000598
			(0.00724)	(0.00652)			(0.00727)	(0.00772)
Down IBES			0.0162	0.0219***			0.0142	0.0203**
			(0.0101)	(0.00843)			(0.00991)	(0.00864)
Up SP					0.0253	0.0130	0.0250	0.0118
					(0.0221)	(0.0237)	(0.0241)	(0.0257)
Down SP					0.0677***	0.0764***	-0.0129	-0.00518
					(0.0155)	(0.0169)	(0.0570)	(0.0512)
N	29977	29977	29977	29977	29977	29977	29977	29977
R^2	0.626	0.642	0.622	0.638	0.622	0.638	0.626	0.642
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Firms with S&P Ratings Below Investment Grade
Dependent Variable: Log(Spread)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Up EJR	-0.0293*	-0.0286*					-0.0281	-0.0284*
	(0.0168)	(0.0160)					(0.0172)	(0.0164)
Down EJR	0.0683***	0.0704***					0.0547***	0.0547***
	(0.0210)	(0.0211)					(0.0207)	(0.0206)
Up IBES			0.0148	0.0165			0.0121	0.0140
			(0.0131)	(0.0127)			(0.0130)	(0.0127)
Down IBES			0.00376	0.0121			0.00248	0.0111
			(0.0106)	(0.0101)			(0.0105)	(0.00991)
Up SP					-0.0270	-0.0318	-0.0262	-0.0327
					(0.0221)	(0.0213)	(0.0234)	(0.0228)
Down SP					0.100***	0.105***	0.0770***	0.0810***
					(0.0279)	(0.0273)	(0.0270)	(0.0258)
N	8398	8398	8398	8398	8398	8398	8398	8398
R^2	0.620	0.629	0.619	0.628	0.620	0.629	0.620	0.630
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel C: Firms with S&P Ratings that Cross the Investment Grade
Dependent Variable: Log(Spread)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Up EJR	-0.0369**	-0.0305**					-0.0357**	-0.0308**
	(0.0155)	(0.0153)					(0.0157)	(0.0155)
Down EJR	0.0709***	0.0789***					0.0646***	0.0722***
	(0.0186)	(0.0182)					(0.0183)	(0.0179)
Up IBES			0.00390	0.0116			0.00102	0.00869
			(0.0125)	(0.0120)			(0.0124)	(0.0119)
Down IBES			0.00148	0.0150			0.000560	0.0138
			(0.0102)	(0.00986)			(0.0104)	(0.00995)
Up SP					-0.0206	-0.0254	-0.0151	-0.0243
					(0.0201)	(0.0191)	(0.0211)	(0.0206)
Down SP					0.0644***	0.0597**	0.0376*	0.0285
					(0.0237)	(0.0233)	(0.0224)	(0.0223)
N	11530	11530	11530	11530	11530	11530	11530	11530
R^2	0.636	0.650	0.635	0.649	0.635	0.649	0.636	0.650
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year and Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 30
Impact of Heterogeneity in Equity Analyst Beliefs on Rating Disagreements

The table evaluates the impact of heterogeneity in beliefs about firms' equity value on disagreement between rating agencies, measured as $|S\&P_{i,t} - EJR_{i,t}|$. The heterogeneity in equity beliefs is measured by the standard deviation of analysts' recommendations ($EquityAnalysts^{Std}_{i,t-1}$) in models (1),(2), and trading volume over assets ($TradingVolume_{i,t-1}$) in models (3),(4). Models (2) and (4) also include firm controls such as lagged leverage, return on assets, market to book, cash over assets, sales, months from realization of equity analyst recommendations, and rating level controls for IBES and S&P. All regressions also include industry and year fixed effects. Standard errors are in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Dependent Variable:	$\lvert S\&P_{i,t} - EJR_{i,t}\rvert$			
	(1)	(2)	(3)	(4)
$EquityAnalysts^{Std}_{i,t-1}$	0.453***	0.412***		
	(0.0611)	(0.0611)		
$TradingVolume_{i,t-1}$			0.0510***	0.0330***
			(0.00629)	(0.00679)
$Leverage_{i,t-1}$		-0.443***		0.218**
		(0.121)		(0.0896)
$ROA_{i,t-1}$		-0.749		0.785*
		(0.630)		(0.463)
$\frac{Market_{i,t-1}}{Book_{i,t-1}}$		-0.0717**		-0.121***
		(0.0309)		(0.0227)
$\frac{Cash_{i,t-1}}{Assets_{i,t-1}}$		2.388***		0.889***
		(0.251)		(0.188)
$Sales_{i,t-1}$		-0.00100		0.0242**
		(0.0151)		(0.0111)
$IBES_{i,t-1}$		0.0448***		0.00768
		(0.0145)		(0.0107)
$S\&P_{i,t-1}$		-0.0355***		-0.00239
		(0.00750)		(0.00561)
N	9352	9314	9314	9314
R^2	0.185	0.202	0.195	0.200
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes