UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

ESSAYS ON CORPORATE BOND MARKETS

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

FAN CHEN
Norman, Oklahoma
2014

ESSAYS ON CORPORATE BOND MARKETS

A DISSERTATION APPROVED FOR THE
MICHAEL F. PRICE COLLEGE OF BUSINESS

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Acknowledgements

I would like to thank my dissertation committee members: Louis Ederington (Co-Chair), Pradeep Yadav (Co-Chair), Scott Linn, William Megginson, and Wayne Thomas. I am especially grateful to Louis Ederington, for his guidance and mentoring. His guidance has made this journey thoughtful and rewarding. I am really grateful to Pradeep Yadav for his kindness and support. Finally, I would like to thank my family for their love and trust.

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Abstract

The aim of my dissertation is to provide new insights into corporate bond markets from empirical corporate finance and bond market microstructure vintage points. The first chapter introduces the topic. The second chapter (Bondholder Wealth Effects surrounding Bond Offering Announcements: Theory and Evidence) investigates how and why prices of existing bonds respond to announcements of new debt issues. The third chapter (The Wealth Effects of Dividend Announcements on Bondholders: New Evidence from the Over-the-Counter Market) examines the announcement effect of dividend changes on bondholders using the over-the-counter bond transaction data from TRACE. The fourth chapter (Pre-Trade Transparency in Over-the-Counter Markets) explores the impact of NYSE pre-trade transparency on U.S corporate bond markets where the majority of trading is happened in over-the-counter markets.

Chapter 1: Introduction

In Chapter 2, I explore how and why prices of existing bonds respond to announcements of new bond issues. This topic is important and interesting for several reasons. First, given the increasing size and significance of corporate debt in capital markets, the impact that new debt offerings have on existing bondholders is of particular importance. The scarce extant literature provides inconclusive evidence on how the announcement of a new bond issue impacts the prices of the firm's existing bonds, which is primarily attributed to poor quality and availability of bond price data in the past; Second, an investigation of the impact of issuing new debt on existing bondholders can also help answer whether and, if so, how existing creditors react to increases in leverage. This is particularly important since, based on Lemmon, Roberts and Zender (2008), we know that firms choose to actively manage leverage ratios through *debt* rather than equity policies. Finally, no prior studies have examined how bond price reactions depend on characteristics of the new and existing bonds and the planned use of the new funds, which can provide more insights into which theory (wealth transfer or signaling) best explains bond returns surrounding bond offering announcements.

I use the Merton model as a theoretical framework to assess 1) the expected impact of a new bond offering on existing bond and stock prices, and 2) how the bond and stock price reactions are conditioned on characteristics of the new and old bonds and the planned use of the new funds. Most of my results are more consistent with the wealth transfer hypothesis than the signaling hypotheses. Using a sample of 1,356 new bond offering announcements by U.S. corporate bonds from 2005 to 2011, I find negative and significant average abnormal returns of issuers' existing bonds over a three-day event window surrounding the first announcement of the planned bond issues. In contrast, average abnormal stock returns of the issuing firms are positive but insignificant. Consistent with the wealth transfer hypothesis, bond market announcement returns estimated using daily corporate bond data from TRACE are more negative for a) longer-term outstanding bonds, b) when the new bonds are senior to existing bonds, and c) when the newly issued bonds mature before existing bonds. My finding that the bond price reaction (stock price reaction) is more negative (less positive) when funds are to be used for expansion than when they are to be used to repurchase stock suggests that there is also a signaling effect.

The evidence on the issue of whether paying out dividend will harm bondholders' interest or to what extent dividend policy will hurt existing creditors is limited, which is attributed to historical deficiencies in the quality and availability of bond price data. In Chapter 3, I investigate the announcement effect of dividend changes on bondholders using bond transaction data from the over-the-counter market. Most of my results are consistent with the signaling hypothesis. Abnormal bond returns over a three-day event window surrounding an increased (omitted) dividend announcement are positive (negative) and statistically significant. The bond market reaction to the dividend increases announcement is more positive for larger percentage dividend increases, speculative grade bonds, and the period from 2008 to 2010. My findings of insignificant (significantly negative) bond (stock) market price reaction to dividend decreases announcements suggest that there is a combination of signaling and wealth transfer effect surrounding dividend decreases announcements.

The availability of quote information, which is defined as pre-trade transparency, is very limited to investors in OTC markets. Consequently, the search process can be potentially costly to investors in OTC markets because of the sequential search and bilateral bargaining that characterizes consummation of trades (see Duffie (2010, 2012)). While working on corporate bond markets, I realized that bond markets are less pre-trade transparent than equity markets, and justify more pre-trade transparency given the bilateral trading nature in the market. Chapter 4 investigates the impact of pre-trade transparency on over-the-counter markets, and finds that NYSE pre-trade transparency reduces US corporate bond transaction costs by 10 basis points. In addition, pre-trade transparency tends to favor traders rather than dealers by enhancing traders' bargaining capability. Pre-trade transparency also increases a bond's value since bonds exhibiting NYSE pre-trade transparency have significantly lower bond yields than bonds without pre-trade transparency (6.27% vs. 7.89%).

Chapter 2: Bondholder Wealth Effects surrounding Bond Offering Announcements: Theory and Evidence

During the period from 1997 to 2006, US companies raised funds totaling $4.6 trillion from the corporate debt market. During the same period, US firms only raised $1.5 trillion from common equity issuances, approximately less than one third of the new capital acquired through debt issuances.[1] Moreover, the Securities Industry and Financial Markets Association reported that from 1996 to 2012 corporate debt issuances increased from $344 billion to $1.36 trillion, annually.[2] This significant increase in volume of publicly issued debt has increased securities regulators' concern about investors' interest in the newly issued debt. For example, on February 28, 2014, the Securities and Exchange Commission probed Goldman Sachs, Citigroup and other banks on how the institutions divvied up new bond issues among investors.[3] Provided the increased preference of firms to acquire additional capital through debt issuances and regulators' increased interest in investors' wealth effects surrounding new bond issues, it is pertinent to investigate the impact of newly issued debt on existing bondholder wealth. Bond offerings may lead to a transfer of wealth from existing bondholders to stockholders. This wealth transfer might be experienced as new bond issues decrease the amount of collateral associated with the firm's outstanding bonds, therefore, increasing the default risk of the firm. Moreover, if the newly raised funds are employed to finance risky investment projects or make dividend payments, a firm's

[1] If the stock repurchase is considered as negative equity issuance, the net equity issuance is negative in most years during the same period.
[2] Includes all non-convertible debt, Medium-Term Notes (MTNs) and Yankee bonds, but excludes CDs and federal agency debt.
[3] http://online.wsj.com/news/articles/SB10001424052702304026804579410711208114586?mg=reno64-wsj

default risk increases more. As stockholders have a residual claim on a firm's assets/earnings after bondholders are repaid, additional debt further incentivizes firms (or management) to pursue risky projects since if the projects are successful, shareholders will be entitled to receive any profits in excess of those used for the repayment of debt.

I examine the impact of new debt offering announcements on bondholder wealth in a sample of 1,356 issue-level bond offerings during the period from 2005 to 2011. In sharp contrast to previous studies, I find evidence of a wealth transfer from existing bondholders to stockholders. Over a three-day event window, I find negative and statistically significant bond market reactions to new bond offerings. By contrast, stock markets react positively to the announcement of new bond issues. To the best of my knowledge, I also provide the first evidence on the determinants of the magnitude of the wealth transfer from existing bondholders to stockholders surrounding a new bond issue. Consistent with the wealth transfer hypothesis, existing bondholders' losses are greater when the new bond is senior to existing bonds and existing bondholders actually experience positive returns when the new bond is junior to the existing bonds. Moreover, consistent with the view that bonds with shorter maturities are defacto senior to longer-term bonds, given that they must be redeemed sooner, I document smaller losses for shorter-term bondholders and larger losses for longer-term bondholders. In addition, stockholder gains are positively related to the maturity of existing bonds. Consistent with the view that potential uses of newly raised funds can lead to an increased wealth transfer from existing bondholders to stockholders, I find negative bondholder returns and positive stockholder returns surrounding a new bond issuance when the firm plans to use the newly borrowed money to repurchase stocks. While the wealth transfer hypothesis predicts a greater negative bond price reaction when the funds are used to repurchase stock than to expand the size of the firm, I find the opposite. This suggests that the new bond issue and its intended use have a signaling impact. The larger positive stock price reaction when the funds are used to repurchase stock is also consistent with a combination of the wealth transfer and signaling hypotheses.

One essential feature of risky-debt valuation models is a direct relation between default risk and the probability that debt values will exceed asset values (e.g. Merton (1974) and Galai and Masulis (1976)). My work explores how bond and stock prices react to new bond issues employing the Merton model as a theoretical framework for assessing the expected impact of a new bond offering on existing debt and stock values. According to the Merton model, a firm's equity can be considered as a call option on the assets of the firm, and the payoff on the firm's debt as equivalent to a default-risk-free loan plus a short position in a put option on the assets of the firm.[4] Thus the predicted impact of the new debt on existing equity and debt price is conditional on the relative seniority and maturity of the new and existing debt and on the intended uses of the newly raised funds.

A handful of studies examine the impact of new bond offerings on existing bondholders, yet the evidence is conflicting and inconclusive. Using monthly corporate bond returns, Kolodny and Suhler (1988) find that a new debt offering announcement has a positive effect on existing bondholders' returns, while Akhigbe, Easterwood and

[4] This is a model that began with Merton (1974) and Galai and Masulis (1976) and is a general model used in the extant literature. I refer to the model as the Merton model in the present paper.

Pettit (1997) document insignificant bond market reactions in the week following the announcements of new debt offerings.[5] The conflicting evidence is possibly due to the past quality and availability of bond price data.[6] Kolodny and Suhler (1988) manually collect bond price data from Moody's Bond Record. Akhigbe, Easterwood and Pettit (1997) employ bond price data from NYSE bond market, which is a small, odd-lot market characterized by infrequent trading. The infrequent trading on the NYSE could lead to severe bid-ask bounce when estimating bond returns. Since these researchers were forced to use hand collected data, their sample sizes tended to be small and include only heavily traded bonds.[7] Additionally, the aforementioned and most prior bond market event studies on various corporate events tended to use large event windows on the order of a month or a week, which can be attributed to a lack of daily bond data.

A contribution of this paper over previous studies is employing comprehensive data on over-the-counter (OTC) corporate bond transactions from Trade Reporting and Compliance Engine (TRACE), which provides greater precision and accuracy in estimating bond market price reactions to new debt offering announcements. TRACE is the first to collect and disseminate comprehensive information on OTC corporate bond trades by making bond transaction prices publicly available 15 minutes following the

[5] Kolodny and Suhler (1988) find that the equity market returns surrounding new debt offering announcements are slightly positive and Akhigbe, Easterwood and Pettit (1997) document negative equity market reactions to new debt offering announcements. However, both equity market returns are not significantly different from zero.

[6] Akhigbe, Easterwood and Pettit (1997) obtain Friday bond transaction price information from the Commercial and Financial Chronicle, and from Dow-Jones News Retrieval. This bond price information is for bonds traded on the NYSE.

[7] Kolodny and Suhler (1988) estimate monthly bond returns for 66 debt offerings during 1973-1981 and Akhigbe, Easterwood and Pettit (1997) calculate weekly bond returns for 399 debt offerings during 1980-1992.

transaction.[8] By the end of January 2005, the transaction data available in TRACE is representative of approximately 99 percent of trades equaling 95 percent of the market value. Bessembinder, Kahle, Maxwell and Xu (2009) and Ederington, Guan and Yang (2012) document that studies using daily bond transaction data from TRACE offer more accurate inference due to the increased specification and power of test statistics. In this paper, I calculate daily abnormal standardized bond returns (ABSR) for the window spanning from one day before to one day after a new debt offering announcement. The power of typical event study statistics is diminished because of the substantial heteroskedasticity caused by term-to-maturity, rating and other bond characteristics. Standardizing bond returns by their time-series standard deviations leads to more powerful tests since it helps address the heteroskedasticity concerns in bond returns. In robustness checks, I find qualitatively similar results using the three-day cumulative abnormal bond return to measure bond market reactions.

An investigation of bondholder wealth effects in bond offerings provides a new perspective into the creditor wealth effects associated with changes in a firm's capital structure.[9] Lemmon, Roberts and Zender (2008) find that firms actively manage leverage ratios through debt policy rather than equity policy.[10] An offering of new

[8] See SEC Release No. 34-49920; File No. SR-NASD-2004-094. The trades of the Rule 144a market, which is still opaque, are not included in this figure.

[9] The wealth effects of new debt offering announcements on existing bondholders or stockholders could also be due to the deviation from the optimal capital structure (the best debt-to-equity ratio). Bondholders and stockholders may experience positive (negative) returns if a firm's capital structure is closer to (more deviated from) the optimal level after the new debt issuance. I also examine this alternative explanation in the paper.

[10] Leary and Roberts (2005) and Hovakimian (2006) also suggest that capital structure rebalancing plays a vital role in a firm's debt policy.

bonds increases a firm's leverage ratio.[11] Previous literature finds that stock market reactions are positively correlated with the change in a firm's leverage ratio. For instance, the empirical finance literature documents positive stock price responses to stock repurchase announcements and negative responses to seasoned equity offerings (SEOs).[12] Evidence on the bond market's response to the change in leverage is mixed. Dann (1981) finds no bond market reaction while Maxwell and Stephens (2003) find negative excess bond returns surrounding the announcement of stock repurchases. For SEOs announcements, Kalay and Shimrat (1987) document negative bond market reactions but Elliot, Prevost and Rao (2009) find positive returns to bondholders. However, evidence on the relationship between the bond market's responses and the change in a firm's leverage ratio caused by bond offerings is limited. My evidence shows that, existing bondholders react negatively while stockholders react positively to the increase in the leverage caused by new debt offerings.

The remainder of this paper is organized as follows. Section 1 reviews the literature and develops hypotheses. Section 2 describes the data and gives details about the empirical method utilized to estimate abnormal bond standardized returns. Section 3 presents my empirical results, and Section 4 concludes the paper.

[11] My untabulated descriptive statistics suggest that the average firm's financial leverage increases significantly at the fiscal year of the new bond offerings. The average (median) increase in leverage ratio after the issuance in my sample is 15.78% (6.94%) and statistically significant at the level of 0.01.

[12] For stock repurchases, see Dann (1981), Vermaelen (1981), Comment and Jarrell (1995), Ikenberry, Lakonishok, and Vermaelan (1995), and Stephens and Weisbach (1998). Eckbo and Masulis (1995) provide a survey on SEOs studies and document an average of -3% common stock returns are associated with SEOs.

1. Literature and Hypotheses Development

1.1. Effects of New Bond Offerings on Existing Bond and Stock Market Returns

The Merton model provides some insight into how new bond offerings should influence stocks and existing bond prices differently. Throughout the following equations (1) to (8), and (15) to (20), I make the following assumptions:[13] 1) each firm issues a single new bond, 2) each firm has only a single class of existing bonds (zero-coupon bonds) and non-dividend paying stocks, 3) the new and existing bonds have the same seniority and maturity, 4) no additional investments, no new debt offerings or bond redemptions occur between time t (t=0 when a firm issues a new debt) and T (existing debts' maturity), 5) a firm's asset risk, σ, is unchanged by the new bond issue and 6) newly raised funds are used for expansions. Represent the time T values of the assets of the firm, the debt, and the equity as A_T, V_T, and E_T. D is the face value of the firm's debt maturing at time T. The value of the debt and stock at time T will depend on the value of the firm's assets A_T. Stockholders are the legal owner of the firm and bondholders are the creditor of the firm. In order to possess the firm's assets, stockholders must pay bondholders D at time T. If A_T>D, stockholders will pay D to the bondholders and they own the remaining assets: A_T-D>0. However, if A_T<D, stockholders cannot fully pay off the debt. Stockholders would give up the ownership by declaring bankruptcy and permit the bondholders to own the assets. Therefore, a firm's equity can be considered as a call option on the assets of the firm. The value of the equity at time T, E_T, is

$$E_T=\max(0, A_T-D) \quad (1)$$

[13] Other needed assumptions can be found in Merton (1974).

max (0, A_T-D) is the time T payoff on a call with strike D and underlying A_T so time 0 value of equity can be modeled as call:

$$E_0=Call_0\ (Strike=D, Underlying= A_T) \tag{2}$$

Suppose the number of shares is a constant C between time 0 and T. The stock value per share is $P_{s0}=E_0/C=Call_0/C$. Since a firm's value is equal to the sum of equity and debt value, the value of the debt at time T, V_T, is

$$V_T=A_T-E_T= A_T-\max(0, A_T-D) \tag{3}$$

If the firm is solvent, i.e., if $A_T>=D$, the bondholders receive D. If the firm is bankrupt, i.e., if $A_T<D$, the bondholders receive A_T. The expression can also be written as:

$$V_T=D- \max(0, D- A_T) \tag{4}$$

max (0, D-A_T) is the time T payoff on a put with strike D and underlying A_T. So the payoff on the firm's bond is equivalent to a default-risk-free loan plus a short position in a put option on the assets of the firm.[14] Therefore, the debt value on the new debt issuance date, V_0, can be calculated as:[15]

$$V_0=A_0-E_0= De^{-rT}-Put_0\ (Strike=D, Underlying= A_T) \tag{5}$$

The bond value per bond with face value $1,000 at time 0 is:

$$P_{b0}= V_0/D = [(De^{-rT}-Put_0)/D] \times 1000 \tag{6}$$

[14] It can also be expressed as the payoff of a bond is equivalent to the payoff of the assets of the firm plus a short position in a call option on the assets of the firm.

[15] Put-call parity: $s(t)-c(t)= ke^{-rT}-p(t)$. s(t) is the spot price of the underlying asset at time t; c(t) is the value of the call at time t. p(t) is the value of the put at time t; and ke^{-rT} is the present value of a zero-coupon bond with a face value of k maturing at time T.

When a firm issues a new bond, the firm's asset and debt values both increase.[16] However, they pose different effects on bondholders' interests. The protection of existing debts may be enhanced since the newly raised funds, whether or not they are used for new investment, implicitly provide an additional asset guarantee for the existing debts. On the other hand, newly issued debt results in an increase of the firm's debt level, and thus leads to increased default risks to existing debts. Therefore, the impact of new bond offerings on stock (F_0) and bond prices (L_0) at time 0 will depend on changes in both asset (A_0) and total debt level (D). The reason that asset (A_0) impacts call option value is due to the increase in debt (D), so it is an indirect influence of debt on the call option value through A_0. Using the Merton model, I am able to document that a new debt offering impacts a firm's stock and bond prices differently:

$$\text{Stocks}: F_0 = \frac{\partial P_{s0}}{\partial D} + \frac{\partial P_{s0}}{\partial A_0}\frac{\partial A_0}{\partial D} = \frac{N(d_1) - e^{-rT}N(d_2)}{C} > 0, \text{since } d_1 > d_2 > 0 \quad (7)$$

$$\text{Bonds}: L_0 = \frac{\partial P_{b0}}{\partial D} + \frac{\partial P_{b0}}{\partial A_0}\frac{\partial A_0}{\partial D} = \frac{1000 \times (D - A_0)N(-d_1)}{D^2} < 0, \text{ since } D < A_0 \quad (8)$$

Proofs can be seen in Appendix A

Therefore, the wealth transfer hypothesis posits a positive stockholder reaction and a negative bondholder reaction to announcements of new bond offerings.[17] In

[16] This may not be the case when a firm intends to use the newly raised funds for stock repurchases where a firm's debts increase but assets do not, or refinancing current debt where neither assets nor debts rise.

[17] These predictions are based on the assumption that the intended use of newly borrowed funds is expansions. In my following analysis, I show that the wealth transfer hypothesis also predicts that an intended use of newly raised funds for stock repurchases is associated with negative bond returns and positive stock returns. In contrast, negligible bond and stock market reactions to new debt offering announcements are expected when the newly raised funds are used to refinance existing debt. On average,

addition, the wealth transfer hypothesis predicts that the sum of changes in equity and existing debt values is zero when a pure wealth transfer from existing bondholders to stockholders occurs.[18]

Miller and Rock (1985) assume that managers convey information to markets through their financing decisions. Specifically, in their model, a firm's decision to raise external capital conveys information to the market that current cash flows are lower than expected. As a result, with no distinction among different financing sources, a negative market reaction for both existing debt and equity would be expected. Consistent with the equity half of expectation, Spiess and Affleck-Graves (1999) document a significant negative long-term stock market response at the announcement of new straight debt offerings and find that the underperformance is more severe in periods with high debt issue volume. They conclude that debt offerings, like stock offerings, signal that the firm is overvalued. Consequently, this theory predicts that bond and stock market participants will react negatively to firms' new bond offerings, and that bond and stock market reactions should be positively correlated. While both the wealth transfer and negative signaling hypotheses predict a negative bond market response to a new bond offering, their predictions for the stock market differ as summarized in Panel A of Table 1.

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new debt offering announcements will be associated with negative abnormal bond returns and positive abnormal stock returns for different intended uses of newly raised funds. Accordingly, the prediction of the wealth transfer hypothesis in the first row, Panel A of Table 1 can be viewed as the universal sample.

[18] Taking derivatives of equation (2) with respect to D (A_0 is also a function of D), yields the impact of new debt offering on existing stocks' value (not per share): $N(d_1)- e^{-rT}N(d_2)>0$ since $N(d_2)< N(d_1)$.Taking derivatives of equation (5) with respect to D, I obtain the impact of new debt offering on a firm's debt value (including new and existing debts), not per bond value, is $1- N(d_1)+ e^{-rT}N(d_2)>0$ provided that $N(d_1)<1$. Since the new bonds will sell for their value, new bonds' value will equal the change in firm assets and the impact on a firm's new debt value should equal 1. Therefore, the impact of new debt offering on existing debt value is $1- N(d_1)+ e^{-rT}N(d_2)-1=e^{-rT}N(d_2)-N(d_1)<0$ since $0<N(d_2)< N(d_1)$. Consistent with the wealth transfer hypothesis, changes in equity and existing debt values are negatively correlated and the sum of the changes is 0. The proofs are upon request.

In the Ross (1977) model, managers of good firms distinguish their firms from bad firms by issuing debt since the issuance of debt signals that their firms' expected future cash flows can cover the debt repayment. On the other hand, an issue of new debt is costly for bad firms' managers to follow since the bankruptcy penalty will be imposed on managers when firms cannot repay the new debt when it expires. Additionally, Jensen (1986) suggests that firms with more free cash flow choose to maintain a high leverage ratio as a credible pre-commitment to pay out the excess cash, thereby reducing the possibility of wasting cash to meet their own interests. Debt commits a firm to pay out cash which also prevents managers from investing in negative net present value projects. Downes and Heinkel (1982) show that more valuable firms use greater amounts of debt financing. Leland and Pyle (1977) also conclude that a firm's value and debt level are positively correlated. Managers hold a large fraction of equity in an effort to signal the good quality of their firms, and thus prefer to issue more debt to retain their large ownership stake in the firm. Graham and Harvey's (2001) survey finds that "managers attempt to time interest rates by issuing debt when they feel that market interest rates are particularly low." Barry, Mann, Mihov, and Rodriguez (2008) show that firms issue more debt when interest rates are low relative to historical rates. Accordingly, a new debt issuance could also signal a lowering cost of capital which will benefit both existing bondholders and stockholders.

1.2. Effects of Bond Offerings on the Price of Multiple Debt Classes

Extant stock market studies on bond offerings lump all bonds together since equity is subordinated to all bonds. However, the wealth implications can differ for senior and subordinated debts in a bond market event study. If the new debt is subordinated and the existing is senior, then the wealth transfer hypothesis would imply a positive reaction since the new issue increases the quantity of assets available to service the existing senior debt. If the new debt is senior, then the reaction of the firm's subordinated debt should be stronger than the reaction of its existing senior debt according to the wealth transfer hypothesis. To verify this argument, I use the Merton model to examine the impact of new debt offerings on the value of multiple debt classes. Throughout the following equations (9) to (14), I make the following assumptions: 1) each firm issues a single new bond, 2) there are two debt tranches: senior and junior debts in a firm with the same maturity and their face values are D_s and D_j, respectively, 3) the new debt and two existing debts mature at the same time, 4) no additional investments, no new debt offerings or bond redemptions occur between time t (t=0 when a firm issues a new debt) and T (existing debts' maturity), 5) a firm's asset risk, σ, is unchanged by the new bond issue, and 6) newly raised funds are used for expansions. I refer to values of the two tranches as senior V_{bs} and junior V_{bj}, respectively. By definition, senior debt has priority in the event of bankruptcy (and hence, is less risky) since junior bondholders are paid only after the claims of senior bondholders are satisfied in full. Senior bondholders are the first to be paid at maturity T. Represent the time T value of the firm's assets as A_T If $A_T<D_s$, stockholders would declare bankruptcy, permitting the bondholders to own the firm's assets. Senior bondholders will receive A_T. If $A_T>D_s$, senior bondholders will receive D_s. Thus, the total senior debt value at maturity T, V_{bsT}, can be expressed as:

$$V_{bsT}= A_T\text{-max}\ (0, A_T-D_s)=D_s\text{-max}(0, D_s-A_T) \quad (9)$$

$\max(0, D_s - A_T)$ is the time T payoff on a put with strike D_s and underlying A_T so time 0 value of senior debt, V_{bs0}, can be modeled as:

$$V_{bs0} = D_s e^{-rT} - Put_0\,(Strike = D_s, Underlying = A_T) \qquad (10)$$

From the expression, a firm's senior debt value is equal to the value of a risk-free debt plus a short position in a put on the firm's asset A_T with strike D_s at time 0. The senior bond value per bond with face value of $1,000 is: $P_{bs0} = (V_{bs0} / D_s) \times 1000$.

Junior bondholders are the next to be paid. If $A_T < D_s$, senior bondholders receive A_T but junior bondholders receive 0 since $A_T - D_s < 0$. If $A_T > D_s$, and $A_T < D_s + D_j$, stockholders would still declare bankruptcy, allowing the senior and junior bondholders to possess the assets, and junior bondholders receive the amount of the assets less the payment to senior bondholders, or $A_T - D_s > 0$. If $A_T > D_s + D_j$, stockholders will pay off senior bondholders D_s and junior bondholders D_j in order to possess the firm's assets. Thus, the total junior debt value at maturity T, V_{bjT}, is given by:

$$V_{bjT} = \max(0, A_T - D_s) - \max(0, A_T - D_s - D_j) \qquad (11)$$

$\max(0, A_T - D_s)$ is the time T payoff on a call with strike A_T and underlying D_s so time 0 value of junior debt, V_{bj0}, can be modeled as:

$$V_{bj0} = Call_0\,(Strike = D_s, Underlying = A_T) - Call_0\,(Strike = D_s + D_j, Underlying = A_T) \qquad (12)$$

Junior bondholders own a call option permitting them to buy the firm at time 0 for D_s, and have written a call option permitting the stock holders to buy the firm for $D_s + D_j$. The junior bond value per bond with face value of $1,000 at time 0 is: $P_{bj0} = (V_{bj0} / D_j) \times 1000$

When the new bond is subordinated to existing bonds, the newly issued bonds will increase a firm's asset value but not affect senior debt's principal value. Therefore, the impact of new debt offerings on existing bond prices is:

$$\frac{\partial P_{bs0}}{\partial A_0}\frac{\partial A_0}{\partial D_s} = \frac{1000 \times N(-d_1)}{D_s} > 0 \tag{13}$$

Proofs can be seen in Appendix A.

When the new bond has the same seniority as existing bonds, the newly issued bonds will influence both asset value and debt principal value. Let us assume that all bonds are senior bonds, given that a majority of debt offerings in my sample are senior debt issuances. The proof is the same as the general case equation (8), and existing bond prices will go down.

When the new bond is senior to existing bonds, existing bonds become subordinated to the new bond. In addition to the change in asset value, the offering also causes the principal value of senior debt in equation (11) to change.[19] Therefore, the impact of new debt offerings on existing bond prices is:[20]

$$\frac{\partial P_{bj0}}{\partial D_s} + \frac{\partial P_{bj0}}{\partial A_0}\frac{\partial A_0}{\partial D_s} = \frac{\partial P_{bj0}}{\partial D_s} + \frac{\partial P_{bj0}}{\partial A_0}$$
$$= [\frac{N(d_1) - e^{-rT}N(d_1 - \sigma\sqrt{T})}{D_j} - \frac{N(d_1^{'}) - e^{-rT}N(d_1^{'} - \sigma\sqrt{T})}{D_j}] \times 1000 < 0 \tag{14}$$

Proofs can be seen in Appendix A.

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[19] When the intended use of newly borrowed funds is stock repurchases, a firm's asset value will not change. Accordingly, the value of equation (13) will be zero and equation (14) will become: $\frac{\partial P_{bj0}}{\partial D_s} = -[\frac{e^{-rT}N(d_1 - \sigma\sqrt{T}) + e^{-rT}N(d_1^{'} - \sigma\sqrt{T})}{D_j}] \times 1000 < 0$

[20] Smith and Warner (1979) predict that the issuance of debt with higher priority will expropriate wealth from current bondholders.

When a new bond has a shorter maturity than existing bonds, then the existing bonds effectively become subordinated to the new bond. This subordination effect, since the new bond will be redeemed before existing bonds, is expected to lead to a negative wealth effect at the offering announcement for existing bonds. This is hypothesized to be comparable to firms issuing a new bond senior to existing bonds. In equation (14), I find that the impact of the issuance of a more senior bond on existing bonds' values is negative. I hypothesize a comparable negative effect when a bond with shorter maturity is issued. When a new bond has the same maturity as existing bonds, the impact of new bond offerings on existing bonds is negative as modeled in equation (8). When a new bond has a longer maturity than the existing bonds, the existing bonds effectively become senior to the new bond. This valuable seniority effect should help to reduce existing bondholders' losses. Existing bond prices should still go down, given the average effect of bond offerings depicted in equation (8). However, the decreasing level of bond prices should be smaller in the situation when a new bond's maturity is longer than existing bonds' maturities.

Implications of the signaling hypotheses for the relation between issue maturity and bond price reactions are less clear. On one hand, choosing a shorter maturity may indicate that the issuer is able to repay the newly issued debt in a short period of time, which would be a more positive signal. On the other hand, if an announcement of newly issued bonds signals a pessimistic future for the firm, the negative implication might be stronger for longer maturity existing bonds. I summarize the predicted signs of the relationship between relative variables and bond market reactions surrounding the debt issue in Panel B of Table 1.

1.3. Debt Maturity, and Debt Credit Ratings Relationships

Previous studies find that the bond market response to corporate events may vary with the maturities of bonds and rating of bonds. Billett, King and Mauer (2004) show that in mergers and acquisitions, target firms' bonds experience larger positive returns when the target bonds have a shorter maturity than do acquirer bonds. They also find that target bonds earn greater positive returns when the target's bond rating is below the acquirer's, which is consistent with co-insurance benefits on target bonds. No evidence has been provided on how bond returns vary due to bond credit ratings and maturities surrounding debt offering announcements. This study will fill this gap. I intend to examine how stock and bond returns vary in relation to existing bonds' maturities and credit ratings, which can provide more insight into which theory best explains stock and bond returns surrounding bond offering announcements. For instance, as shown below, the wealth transfer hypothesis predicts that firms' existing debt maturity should be negatively related to bond market reactions but positively related to stock market reactions. In contrast, the negative signaling hypothesis predicts firms' existing debt maturity should be negatively related to both bond and stock market reactions. Based on the Merton model as expressed in equations (7) and (8), I derive the following predictions for the wealth transfer hypothesis:[21]

[21] Taking derivatives of equations (7) and (8) with respect to the asset risk, σ, yields the relationship between a firm's asset volatility and the impact of new bond offerings on stock (F_0) and bond (L_0) prices (Proofs can be seen in Appendix A.):

$$\text{Stocks}: \frac{\partial F_0}{\partial \sigma} = \left[\frac{\partial N(d_1)}{\partial \sigma} - e^{-rT}\frac{\partial N(d_2)}{\partial \sigma}\right] / C > 0 \tag{17}$$

$$\text{Bonds}: \frac{\partial L_0}{\partial \sigma} = [N^{'}(-d_1)\frac{(D-A_0)}{D^2}\frac{d_2}{\sigma}] \times 1000 < 0 \tag{18}$$

Taking derivatives of equations (7) and (8) with respect to time to maturity, T, yields the relationship between existing bonds maturities and the impact of new bond offerings on stock (F0) and bond (L0) prices:

$$\text{Stocks}: \frac{\partial F_0}{\partial T} = \{(N'(d_1) - e^{-rT}N'(d_2))\left(\frac{(r+\frac{1}{2}\sigma^2)T - \ln(A_0/D)}{2\sigma T\sqrt{T}}\right)$$

$$+\frac{1}{2}e^{-rT}N'(d_2)\sigma T^{-0.5} + re^{-rT}N(d_2)\}/C \qquad (15)$$

which is >0, if $\ln(A_0/D) > (r+\sigma^2/2)T$ [22]

$$\text{Bonds}: \frac{\partial L_0}{\partial T} = N'(-d_1)\frac{(D-A_0)}{D^2}\frac{[\ln(A_0/D)-(r+\sigma^2/2)T]}{2\sigma T^{1.5}}\times 1000 \qquad (16)$$

which is <0, if $\ln(A_0/D) > (r+\sigma^2/2)T$

Proofs can be seen in Appendix A.

The negative (positive) signaling hypothesis predicts a pessimistic (prosperous) future for the firm. Accordingly, this hypothesis would imply that longer maturity bonds could suffer (benefit) more than shorter maturity bonds if the increased (decreased) default risk is more detrimental (beneficial) for bonds maturing further out in time.[23] Lower rated bonds that may not be secured or have a lower priority claim over assets

[22] The assumption of $\ln(A_0/D) > (r+\sigma^2/2)T$ holds in my sample. I use my empirical data to check the validity. D (A_0) is measured as a firm's total long-term debt outstanding (asset) at the preceding fiscal year of the announcement. I use 3-month Treasury bill interest rate at the announcement month to proxy for the risk-free interest rate r. Asset risk, σ^2 , is the standard deviation of unlevered stock returns (std. dev.), which is estimated using daily stock returns over the window -240 to -40 prior to the event date. Unlevered returns are computed by multiplying the stock returns by (1 − Leverage), where Leverage is the ratio of the book value of total debt to the sum of the book value of total debt and market value of equity at the end of the corresponding fiscal year. A firm's debt maturity, T, is defined as the weighted average of the existing bonds' maturities, using the principal of each existing bond relative to the total debt outstanding as weights. Then I calculate the difference between the value of $\ln(A_0/D)$ and $(r+\sigma^2/2)T$. In my sample, only 8 out of 859 debt offerings have negative differences.

[23] Merton (1974) suggests that long-term bonds are riskier than short-term bonds.

and their returns surrounding the new debt issue should be impacted more strongly by lower (higher) future earnings prospects. Consistent with this, Hite and Warga (1997), Plummer and Tse (1999), Billet, King and Mauer (2004), Downing, Underwood and Xing (2009), Elliott, Prevost and Rao (2009), Easton, Monahan and Vasvari (2009), and May (2010) find that bond market reactions are stronger for lower rated bonds than for higher rated bonds surrounding various corporate events.[24] Consequently, the negative (positive) signaling hypothesis would predict that the negative (positive) reaction to bondholders should be stronger for longer maturity bonds, and lower rated bonds. The wealth transfer hypothesis draws the same implication. However, the difference between these two hypotheses lies in their predictions about stock market reactions. The negative signaling hypothesis also predicts a negative effect on stock prices while the wealth transfer hypothesis predicts a positive effect. According to the negative signaling hypothesis, any factor that negatively impacts bond prices will negatively influence stock prices. In direct contrast, the wealth transfer hypothesis predicts that any factor that is detrimental to bondholders will have a favorable effect on stockholders. The above model implications in equations (15) and (16) support this prediction. I summarize the predictions of the above competing hypotheses concerning the signs of relevant variables in Panels B of Table 1.

[24] Hite and Warga (1997) and May (2010) study the bond market reactions surrounding bond credit rating changes. Billet, King and Mauer (2004) study the bond market responses to the announcement of mergers and acquisitions. Elliott, Prevost and Rao (2009) investigate bond price changes to seasoned equity offerings. Plummer and Tse (1999), and Easton, Monahan and Vasvari (2009) examine how earnings announcements influence bond market prices. Downing, Underwood and Xing (2009) conduct an intraday analysis of bond returns to changes in treasury returns.

1.4. The Intended Uses of Newly Raised Funds and Security Market Reactions surrounding New Debt Offering Announcements

My paper also contributes to the literature by examining how security market price reactions to new debt offering announcements vary according to the intended use of these newly raised funds. Previous sections and equations assume that firms use newly raised funds for expansions. In this section, I extend the study by investigating how existing security prices change as a function of two other intended uses: stock repurchases and debt refinancing. A wealth transfer from bondholders to stockholders may arise when firms use newly raised funds to fund share repurchases. Existing studies regarding the wealth transfer hypothesis of repurchase announcements offer mixed evidence. Dann (1981) finds no evidence of wealth transfer surrounding stock repurchases. Using a large sample of firms, Maxwell and Stephens (2003) document negative abnormal bond returns and positive abnormal stock returns around the announcement of share repurchases. Stock repurchases distribute cash to stockholders, and thus reduce the cash available to service debt. If this reduction is significant, bonds' default risks should increase and a wealth transfer from bondholders to shareholders should ensue. In addition, if stock repurchases are financed through the issuance of new debt, wealth transfers become increasingly more likely. Firms may issue new debt merely to refinance existing debt. Since proceeds from this type of issue are substituting existing debt dollar-for-dollar, refinancing current debt does not create or destroy value to firms compared to the intended uses of expansions or stock repurchases. Accordingly, the refinancing uses should have a negligible wealth impact on a firm's existing securities.

Collecting debt offering announcement information from Factiva, I identify firms' intended uses of newly raised funds. In section 1.1, the stock value per share is expressed as $P_{s0}=E_0/C=Call_0$ (Strike=D, Underlying= A_T)/C, and the bond value per bond with face value \$1,000 at time 0 is P_{b0}= [(De^{-rT}-Put_0 (Strike=D, Underlying= A_T))/D] ×1000. The Merton model yields implications for how a firm's intention to use newly borrowed funds impacts outstanding bond and stock prices:

1). When a company plans to use the newly raised money to buy back stock, debt (D) increases but assets (A_0) do not. In addition, the firm's amount of outstanding stock (C) is expected to decrease after the repurchase. Taking derivatives of P_{s0} with respect to D, yields the relationship between the intended use of newly raised funds for stock repurchases and the change in stock prices. Holding a firm's total stock market value constant, the negative relationship between stock prices and shares outstanding implies a reduction in the quantity of stock outstanding and an accompanying positive effect on stock prices. Suppose, *p* represents the stock price at the time of stock repurchases. Therefore,

$$\begin{aligned}\text{Stocks}: \frac{\partial P_{s0}}{\partial D} - \frac{\partial P_{s0}}{\partial C}\frac{\partial C}{\partial D} &= \frac{\partial P_{s0}}{\partial D} - \frac{\partial P_{s0}}{\partial C}\frac{1}{p} \\ &= \frac{pA_0 N(d_1) - (pD + C)e^{-rT}N(d_2)}{pC^2} > 0 \end{aligned} \tag{19}$$

Proofs can be seen in Appendix A

Taking derivatives of P_{b0} with respect to D, yields the relationship between the intended use of newly raised funds for stock repurchases and the change in bond prices:

$$\text{Bonds}: \frac{\partial P_{b0}}{\partial D} = -\frac{A_0 N(-d_1)}{D^2} \times 1000 < 0 \tag{20}$$

Proofs can be seen in Appendix A

2). A firm's intention to use the borrowed funds for expansions leads to increases in both assets (A_0) and debt (D). Taking derivatives of P_{s0} (P_{b0}) with respect to D yields the relationship between the intended use of newly raised funds for expansions and the change in stock (bond) prices. The derivatives are the same as the predictions in equations (7) and (8).

$$\text{Stocks}: F_0 = \frac{\partial P_{s0}}{\partial D} + \frac{\partial P_{s0}}{\partial A_0}\frac{\partial A_0}{\partial D} = \frac{N(d_1) - e^{-rT}N(d_2)}{C} > 0, \text{since } d_1 > d_2 > 0 \tag{7}$$

$$\text{Bonds}: L_0 = \frac{\partial P_{b0}}{\partial D} + \frac{\partial P_{b0}}{\partial A_0}\frac{\partial A_0}{\partial D} = \frac{1000 \times (D - A_0)N(-d_1)}{D^2} < 0, \text{ since } D < A_0 \tag{8}$$

3). In the case of debt refinancing uses, neither assets (A_0) nor debt (D) rises. Accordingly, the derivative of P_{s0} (P_{b0}) with respect to D is 0.

By comparing the relative magnitude of the above equations, I can predict the relative size of bond and stock market reactions for firms' different intended uses of funds surrounding a debt offering announcement. Specifically, taking the difference between equations (19) and (7) yields the relative magnitude of stock market reactions for the use of stock repurchases versus expansions:

$$\text{Stocks}: (19) - (7) = \frac{(pA_0 - pC)N(d_1) - (pD + C - pC)e^{-rT}N(d_2)}{pC^2} > 0 \tag{21}$$

Proof can be seen in Appendix A.

Taking the difference between equations (20) and (8), yields the relative magnitude of bond market reactions for the use of stock repurchases versus expansions:

$$\text{Bonds}: (20) - (8) = [-\frac{A_0 N(-d_1)}{D^2} \times 1000] - \frac{1000 \times (D - A_0)N(-d_1)}{D^2}$$

$$= -\frac{1000 \times DN(-d_1)}{D^2} < 0 \tag{22}$$

Accordingly, the wealth transfer hypothesis predicts bond and stock market reactions to be strongest when the intended use is a stock repurchase and weakest when the intended use is to refinance existing debt.

The empirical finance literature finds that investors tend to view the announcement of stock repurchases favorably.[25] Accordingly, the positive signaling hypothesis predicts that both bond and stock prices should increase when a firm intends to use the newly borrowed money to buy back stocks. If a firm's security investors view the expansion uses of bond proceeds as unwise (negative signals), the investors will react negatively to the expansion use announcements. The intended use of debt refinancing may signal that a firm cannot refinance its expiring debt internally, and thus both bond and stock prices should experience negative returns around the announcement. However, signaling hypotheses do not predict the relative size of bond and stock market reactions for firms' different intended uses of funds surrounding a debt offering announcement. I summarize predictions regarding the sign of the relationship between firms' intended use of newly raised funds and security market reactions surrounding the new bond issue in Panel C of Table 1.

2. Data and Methodology

I collect straight debt offerings made by public firms between January 1, 2005 and December 31, 2011 from the Securities Data Corporation's (SDC) Global New Issues database. Bond price data are gathered from the Trade Reporting and

[25] Positive abnormal stock returns surrounding the announcement of stock repurchases are well documented in the literature. For example, Dann (1981), Vermaelen (1981), Comment and Jarrell (1995), Ikenberry, Lakonishok, and Vermaelan (1995), and Stephens and Weisbach (1998).

Compliance Engine (TRACE), which provides comprehensive coverage of bond trades beginning in February 2005.[26] I require that: 1) stock price data be available from the Center for Research in Security Prices (CRSP), 2) bond price data be available on TRACE, 3) firm accounting information be available from the Compustat Fundamentals Annual dataset, and 4) bond-specific information be obtainable from the Mergent Fixed Income Security Database (FISD). My final sample consists of 1,356 debt offerings, which (since 352 offerings involve multiple debt issuances on the same announcement day) yields 859 firm-level debt offerings.[27] For multiple debt offerings issued by the same firm on the same day, I calculate an average maturity, rating and seniority level as the weighted average of each component offering's maturity, rating and seniority level in these cases, where the component weights are the proceeds of each bond issuance relative to total offering proceeds.[28]

2.1. Identification of Announcement Dates of Straight Debt Offerings

Prior studies of straight debt offerings use various sources to identify debt offering announcement dates as there is no one universal dataset that provides reliable date information.[29] I use four datasets to verify the first announcement date of new debt

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[26] TRACE began providing bond transaction data for AAA, AA, A, BBB bonds with issue size greater than $1 billion in July 2002. Since that time, data pertaining to other grades of bonds have been disseminated. TRACE's dissemination of bond transactions in the OTC market was not comprehensive until 2005.

[27] In untabulated results, I exclude 26 firm-level debt offerings issued by utility firms (SIC codes 4900-4999) and 12 offerings issued by financial firms (SIC codes 6000-6999). The results are qualitatively similar to results reported in the paper.

[28] As a robustness test, I find consistent results when treating each firm's multiple debt offerings as independent debt offerings. However, this method likely results in high correlation between returns of bonds issued by the same firm, which would inflate t-statistics of estimated coefficients.

[29] Dann and Mikkelson (1984), Eckbo (1986) and Mikkelson and Partch (1986) use the earliest date of the issuances reported in the Wall Street Journal as the debt offering announcement date. Kolodny and Suhler (1988) define the announcement date as one day before the announcement appearing in the Wall Street

offerings: SDC, FISD, Bloomberg and Factiva. SDC and FISD report the new debt issue date, while Bloomberg reports what it calls the "announcement date". I match sample observations from SDC with Bloomberg, using each debt offering's 9-digit CUSIP, coupon payment, and the principal value.[30] After merging these datasets, I find that most SDC and FISD issue dates, also known as offering dates, are equivalent to the Bloomberg "announcement date". Apparently, Bloomberg uses the issuance date as its "announcement date". Since it is possible that the firm publicly announced the offering prior to the actual offering, I use Factiva to identify the first announcement date for new debt offerings. In the window from one month before to one month after the date of a new debt issue date (collected from SDC), I manually check the following dates using Factiva: 1) the first time the company or its underwriter announced the new bond issue; 2) the rating agencies' press release date; and 3) the first time the announcement is released on Reuters.

SDC issuance dates and Factiva announcement dates coincide for 686 firm-level debt offering observations. Factiva announcement dates fall earlier than the SDC issuance dates for 120 of the observations of which 63 of the observations are only one trading day before the announcement date. 52 firm-level debt offering announcement

Journal. Akhigbe, Easterwood and Pettit (1997) define the announcement date as the filing date in the Securities and Exchange Commission's Registered Offerings Statistics file and Moody's Bond Survey. Dutordoir and Hodrick (2012) identify the debt offering announcement date as the earliest of the filing date reported in SDC and the date at which the issuance is first mentioned in Factiva.

[30] One concern with using the FISD and Bloomberg databases is that these two datasets only report the number of current total outstanding, not the historical issuance volume. Therefore, I rely on SDC for identifying each new bond's principal values, and for new bond ratings.

dates cannot be identified using Factiva, and therefore the issue date in SDC is used as the debt offering announcement date.[31]

In most cases, bond issues are preceded by a registration and in many cases a firm files a registration for multiple debts and then issues at different times over following years.[32] For example, the debts AT&T issued on August 28, 2007, December 3, 2007 and January 29, 2008 were all covered by the registration filed on May 23, 2007. On average the difference between the SEC filing dates and Factiva announcement dates is 478 calendar days.

2.2. Descriptive Statistics

Since new debt offering announcements may be accompanied by other important company specific news and I wish to measure the impact of the debt offering announcement only, I use Factiva to search for other company specific news during the three-day event window, from one day before the announcement through one day following the announcement. If the news published in this period includes information that can be considered as contaminating the announcement, I record it as contaminated. Contaminating news pertains to informational items such as quarterly earnings, dividend declarations, mergers or acquisitions, equity offerings and stock repurchases. The Factiva search reveals that 193 firm-level debt offering announcements are

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[31] For the one case in which the Factiva announcement date appears later than the SDC issuance date, I employ the SDC issuance date.

[32] Before a firm issues debt, it needs to file a Form S-3ASR (Form S-3 registration under the Securities Act of 1933). Most S-3ASR files only indicate that the firm may issue debt or other securities but do not give details about the number and type of debt that a firm will sell. The date at which a firm files the form on SEC is the filing date reported in the SDC. When a firm decides to issue the number and type of debt, the firm will submit a prospectus supplement: FWP (Free Writing Prospectus). The date at which a firm submits the FWP to the SEC is the issue date in SDC. Form S-3ASR and FWP are downloadable from the EDGAR in SEC: http://www.sec.gov/edgar/searchedgar/companysearch.html.

"contaminated" by companies' other relevant news. Consistent with Dutordoir and Hodrick (2012) finding that a majority of contaminated straight debt and equity offering announcements are combined with earnings disclosures, 97 of my contaminated announcements are accompanied by quarterly earnings disclosures. After eliminating contaminated observations, the uncontaminated sample includes 1,044 debt offering announcements at the issue level that represent 666 debt offering announcements at the firm level. Below, I report results for both the total and uncontaminated samples.

Panel A of Table 2 reports the number of new bond offerings at the issue and firm levels per sample year. At the issue level, the number of new debt offerings increases from 92 in 2005 to 249 in 2011. In particular, the number of debt offerings has increased significantly since the global financial crisis in 2008. This is likely due to the low interest rates in effect since the financial crisis which likely enticed companies to borrow record amounts in the bond market.[33] Panel B presents descriptive statistics on the new debt offerings and issuing firms. The average issuance size at the firm-level is $ 1,112 million. The average ratio of issuance size to total assets is 0.06, while the average ratio of issuance size to total long-term debt outstanding is 0.28. On average, the new bond's maturity is three years longer than the existing debt's maturity. The median rating for the new bonds is BBB or Baa. There is no significant difference in credit ratings between the new and existing bonds.

Using hand-collected data regarding new bond offering announcements from Factiva, I identify firms' intended uses of newly raised funds. 8% of new debt offerings

[33] See, for example, http://online.wsj.com/article/SB10001424052748703377504575650514192556880.html.

are used to fund debt incurred by stock repurchases, 14% are used for expansions,[34] and 31% are used for debt refinancing. An intended use is identified as unclear if the news announcement lists multiple possible intended uses or otherwise does not clearly specify a single intended use. Debt offerings with unclear intended uses account for 47% of the total debt offerings. Firms in my sample tend to be large, consistent with the notion that publicly-traded debts are issued by large corporations. The 859 firm-level bond offerings affect 3,738 existing bonds. Firms are more likely to issue new debt with the same seniority as their existing debt, as evidenced by only 3.67% of existing debt having a different debt priority than new debt offerings. 2.84% of the existing bonds are subordinated to new bonds, and only 0.83% of the existing bonds are senior to new bonds. The ratio of outstanding bonds having a shorter maturity than newly issued bonds is 67.92%.

2.3. Abnormal Standardized Bond and Stock Returns

Measuring abnormal bond returns presents several challenges which are either not present, or less serious, in stock market event studies. Most notably, bonds trade much less frequently; indeed on the average day, the average bond does not trade. Second, firms generally have only one class of common equity but may have multiple bonds which must be combined into a single firm-bond return. Third, prices on long-term and low rated bonds are much more sensitive or volatile than prices on short-term and high rated bonds so there is considerable heteroskedasticity. The heteroskedasticity

[34] For example, on March 20, 2006, Home Depot Inc. issued $4 billion of debt to finance its acquisition of Hughes Supply Inc., a distributor of construction, repair and maintenance products. Another example is, on October 24, 2007, the wireless phone company America Movil sold $1 billion of long-term bonds to use the proceeds to upgrade their networks to third-generation technology, expanding its network in Brazil, and switching its Puerto Rico network to GSM from CDMA technology.

in bond returns is likely much more severe than for stocks since individual bonds' characteristics, such as term-to-maturity, credit ratings and liquidity, vary and prices are much more volatile on low rated, long maturity, and illiquid bonds than on high rated, short maturity, and liquid bonds. Ederington, Guan and Yang (2012) find dramatic improvement in the power of tests when this heteroskedasticity is corrected by standardizing bond returns by time-series standard deviations, based on returns 50 days before and after the event. Consequently, I measure firm-bond returns following the procedures outlined in Bessembinder et al. (2009) and Ederington et al. (2012).

Following Bessembinder et al. (2009), and Ederington et al. (2012), I restrict my sample to industrial, non-convertible, non-putable, and non-zero coupon bonds. In addition, I require that bonds: 1) be denominated in US dollars; 2) have a par value of $1,000, 3) make semi-annual coupon payments, 4) mature in 50 years or less and greater than one year, 5) be rated by Moody's and/or S&P, and 6) neither be in default nor have a tender offer outstanding. For bond transactions data in TRACE, I restrict my sample to bonds traded at least 100 times and that have two-day returns available at least 10 times over the 2005-2011 period.[35] Using the bond transactions data from TRACE, average daily bond prices are calculated with the "trade-weighted price", where the trades are weighted by the square root of trade size.[36] Raw returns on each individual bond (RR (-1, +1)) are equal to the change in the logarithmic price on day t+1 relative to the price on day t-1:

[35] More requirements on bond transactions data can be seen in Ederington, Guan and Yang (2012).

[36] I use the clean price, which is reported in TRACE, to compute bond returns in equation (23). A bond buyer pays the "dirty" price which is the clean price plus accrued interest since the last coupon date, so the dirty price reflects what the bond buyer pays and receives. However, the dirty price tends to decrease by the amount of the coupon payment on the coupon payment date, and thus bond raw returns calculated utilizing the dirty price tend to be large and negative on the date of the coupon payment.

$$RR(-1,+1) = \ln(P_{t+1}) - \ln(P_{t-1}) \quad (23)$$

where P_{t-1} indicates the daily "trade-weighted price" of the bond on day t-1. Standardizing each RR(-1,+1) by its estimated standard deviation over the (-25,+25) period σ_i yields the standardized raw return, SRR(-1, +1)= RR(-1,+1)/σ_i.[37] Normally, default risk (proxied by bond ratings) and time to maturity are two of the most salient risk factors considered in estimating abnormal bond returns. Thus, portfolios matched by bond rating and time to maturities are used to proxy for the expected return on the bond in the absence of the new offering. Following Ederington et al. (2012), I partition bonds into 24 benchmark portfolios by six Moody's rating classifications (Aaa and Aa, A, Baa, Ba, B, and below B) and four maturity classes (1 to 3 years, 3+ to 5 years, 5+ to 10 years, and over 10 years).[38] For each benchmark portfolio on the same day, a standardized benchmark return, SBM (-1, +1), is calculated by dividing a benchmark portfolio return, BM (-1, +1), by the standard deviation of the benchmark portfolio return over the (-25, +25) period. Consequently, abnormal standardized bond returns, ABSR (-1, +1) are defined by first calculating standardized raw returns, SRR (-1, +1), recalculating a standardized rating-maturity benchmark SBM (-1,+1) and finally computing the abnormal standardized return as

ABSR(-1,+1) = SRR(-1,+1) - SBM(-1,+1) (24)

For multiple bond issues by the same firm, firm bond returns are computed as equally weighted averages of the abnormal standardized bond returns. A firm's

[37] Specifically, the standard deviation of three-day returns for bond n around day t from t-25 to t+25 excluding returns across event day t is used. At least six return observations over the 50-day period should be available.
[38] To be able to calculate the benchmark return for each group, Ederington et al. (2012) require that at least five bonds be traded in each rating/maturity group on day t-1 and t+1.

unstandardized abnormal returns tend to be dominated by its most volatile bonds. Averaging standardized returns effectively puts more weight on the firm's less volatile bonds. Expanded event windows are also used in the paper. Ederington et al. (2012) find much more powerful tests and an improvement of the representativeness of the sample using an expanded window. For instance, within the (-3,+3) window, it is possible to compute abnormal returns over several windows, including t-3 to t+3, t-3 to t+2, t-3 to t+1, t-2 to t+3, t-2 to t+2, t-2 to t+1, t-1 to t+3, t-1 to t+2, and t-1 to t+1. Composite returns, ABSR{-3,+3} and ABSR {-5, +5}, are averages of all ABSR from day -3 to +3 and day -5 to +5 respectively, are also used to investigate the bond market reaction to the announcement of new debt offerings. Composite ABSRs afford more powerful tests both because there are more observations (since bonds may not trade on days -1 and/or +1) and because single days' prices contain considerable noise. Bessembinder et al. (2009) find that non-parametric test statistics (signed-rank test for median value) are better specified and more powerful than parametric test statistics (t-test for mean value) in detecting corporate events influencing bonds equally. Additionally, mean returns reflect the aggregate experience of investors. Therefore, it is important to investigate both parametric and non-parametric tests when examining bond market reactions to corporate events. Accordingly, I present both parametric and non-parametric tests of existing bond returns surrounding new debt offering announcements.

To detect the stock price response, standardized cumulative abnormal returns during the same event window stretching from day -1 to +1, SCAR (-1, +1), are computed as cumulative abnormal market adjusted returns, CAR(-1, +1), divided by the time series standard deviation of abnormal returns over the window (-300, -46) relative to the announcement date σ_i, SCAR(-1,+1)=CAR(-1,+1)/σ_i [39] I use value weighted market index to proxy for the market return. Event windows of stock price responses are also expanded to day -3 to +3 and day -5 to +5 to match corresponding bond return event windows.

3. Empirical Results

3.1. Abnormal Standardized Bond and Stock Returns

To test the three hypotheses outlined in Panel A of Table 1, Table 3 reports mean and median abnormal returns of existing bonds and stocks surrounding the announcement of new debt offerings.[40] This calculation is carried out for three separate event windows ranging from 3 to 11 days in length, with the 11-day window capturing a total of 859 announcements of new debt offerings. Over a three-day event window in the total sample of Panel A, I find an abnormal standardized bond return of -0.16 (median of -0.20) for existing bondholders where both the t-statistics and Wilcoxon sign-rank tests are statistically significant at the 0.01 level. I also find negative and statistically significant abnormal standardized bond returns when contaminated observations are excluded in the uncontaminated sample. Across the other event windows analyzed in Panel A, I consistently find that both the mean and median abnormal standardized bond returns are negative and statistically significant at the 0.01 level. In Table 10 results of the total (uncontaminated) sample, the mean and median values of abnormal bond returns over the three-day event window are -28 (-25) and -25

[39] In unreported results, I use the time series standard deviation of abnormal returns over the window (-25, 0) to standardize stock abnormal returns and find qualitatively similar results.

[40] I also calculate abnormal standardized bond and stock returns surrounding new debt filing dates. In contrast with the significantly negative bond returns noted surrounding bond offering announcements, I do not find significant evidence of a bond (stock) market reaction to the filing announcement.

(-23) basis points, respectively. Both the mean and median values are statistically significant with p-values less than 0.01.

Stock market standardized returns in Panel B of Table 3 are positive but not statistically significant over the three-day event window. When the event windows are broadened, the stock market returns are positive and become statistically significant. In the total and uncontaminated samples, the abnormal standardized stock return over the (-3, +3) window is positive and statistically significant at the 0.01 level for tests based on both mean (0.1027 and 0.0890) and median (0.0837 and 0.0707) values. The finding that existing bondholders experience negative abnormal returns surrounding new debt offering announcements while stockholders experience positive abnormal returns is consistent with the wealth transfer predictions by the Merton model. However, I do not find significant evidence of the negative correlation between stockholder gains and bondholder losses implied by the wealth transfer hypothesis in unreported results for both total and uncontaminated samples.[41]

Panels A and B in Table 4 present abnormal standardized bond returns surrounding the following two groups of offerings: 1) offerings in which the new bonds are subordinated to existing bonds, and 2) offerings in which the new bonds are senior to existing bonds.[42] Unfortunately, there are few observations where seniority differs

[41] Given that most firm news impacts stock and bond returns in the same direction, the correlation is likely positively biased. The correlation in the uncontaminated sample is more negative than the total sample but not statistically significant.

[42] For each new debt offering, I compare the seniority of the new bond to the seniorities of all existing bonds. As an example, suppose a firm issues a senior unsecured bond. Further suppose that this company had five bonds outstanding prior to the issuance, two are senior secured bonds and the remaining three are junior bonds. The abnormal bond standardized returns of the former two bonds would be reported in the “New < Existing” category and the latter three in the “New > Existing” category. Within each category, the firm’s abnormal returns to existing bonds are computed on an equal-weighted basis. I employ the same method when examining the abnormal bond returns based on the maturities of new and existing debt in Panels C and D.

which could limit the power of the tests. Consistent with the Merton model implication in equation (13), Panel A in Table 4 shows that the three-day event window is accompanied by positive and significant abnormal standardized bond returns when newly issued bonds are subordinated to existing bonds. Also, as predicted by the Merton model, when newly issued bonds are senior to outstanding bonds, abnormal standardized bond returns are negative though insignificant. This difference in bond reactions over the event window (-1, +1) is statistically significant at the 0.10 level based on both parametric and nonparametric tests. Over the other event windows and in the uncontaminated sample in Panel B, the difference in bond price reactions when the new bond is senior to the existing and when it is subordinated has the predicted sign but is insignificant. In summary, I find weak evidence that existing bonds react more positively when the new bond issue is subordinated to, and therefore increases the protection enjoyed by, existing bonds and more negatively when it is senior to, and thus decreases the protection enjoyed by, existing bonds.

As discussed in section 1.2, even if new and existing bonds have the same priority, if the new bonds' maturity is shorter than the existing, they may have de facto seniority since they will be redeemed first. In Panels C and D of Table 4, I report abnormal standardized bond returns surrounding the following two groups of offerings: [43] 1) offerings where the new bonds' maturity is shorter than existing bonds, and 2) offerings where the new bonds' maturity is longer than existing bonds. Across both groups of bonds, abnormal standardized bond returns over the three-day event window

[43] In unreported results, I partition the sample, where new bonds and existing bonds have the same seniority, into the same three groups and the results are qualitatively the same as reported in Panels C and D in Table 4.

are negative and statistically significant at the 0.01 level. However, I find existing bonds experiencing more negative abnormal standardized returns surrounding the new debt issue when a new bond has a shorter maturity than existing bonds. When a new bond's maturity is longer than existing bonds, the existing bond standardized returns are also significantly negative, but the returns are statistically less negative than offerings where a new bond's maturity is shorter than existing bonds. In both total and uncontaminated samples, the mean (-0.13 and -0.13) and median (-0.16 and -0.16) of ABSR (-1, +1) are negative and statistically significant at the 0.01 level for the group of new bonds having a longer maturity than existing bonds. For the group of new bonds with a shorter maturity than existing bonds, the mean (-0.37 and -0.36) and median (-0.33 and -0.32) are smaller and statistically significant at the 0.01 level. These findings are consistent with the theoretical implications of the Merton model in section 1.2, that bondholders suffer greater (smaller) losses in the situation when a new bond's maturity is shorter (longer) than existing bonds' maturities.

To test whether the reaction depends on the riskiness of the existing bonds, in Table 5, I stratify the sample by whether the existing bonds are rated investment or speculative grade. Inconsistent with both the prediction of wealth transfer hypothesis and the existing literature, I find weak evidence that bonds rated investment grade (bond's rating above Ba1 or BB+) suffer greater losses than speculative rated bonds surrounding a new debt issue. Over the three-day event window, investment-grade rated bonds experience significantly negative mean (median) abnormal standardized returns of -0.20 (-0.21). On the contrary, speculative rated bonds have small negative but insignificant mean (median) abnormal standardized returns of -0.06 (-0.13). The difference in means of -0.14 is not significant but the difference in medians of -0.08 is marginally significant. In the uncontaminated sample, the difference in mean (median) bond returns between investment and speculative rating bonds across different event windows is not statistically significant.

As discussed in section 1.4, security market price reactions to new bond offering announcements vary depending on the announced intended uses of newly raised funds. Using hand-collected media news reports regarding new bond offering announcements from Factiva, I identify firms' intended uses of newly raised funds. As depicted in Panel B of Table 4, 47% of new debt offerings do not clearly specify a single intended use or list several potential intended uses. Panels A and B of Table 6 present announcement period evidence with regard to how the abnormal standardized returns to existing bondholders differ depending on the firm's intended use of the newly borrowed funds. Consistent with the Merton model prediction and inconsistent with the signaling hypothesis, existing bonds experience an average (a median) standardized return of -0.22 (-0.15) over a three-day event window in the total sample when the intended use of newly borrowed money is a stock repurchase. Also consistent with the Merton model, the bond price reaction is negative when the firm intends to use the funds for an asset expansion. However, inconsistent with the Merton model, the bond price reaction appears more negative when the funds are to be used for an expansion than when they are used to repurchase stock and there is a negative (though small) bond price reaction when the funds are to be used to refinance existing debt. Panel A of Table 6 demonstrates that a firm's intention to use the funds for expansions is associated with a mean (median) standardized bond return of -0.32 (-0.44) on day -1 to +1 and the return is significantly more negative than the bond return accompanying the announcement that the debt proceeds will be used to repurchase stock (column: (1)-(2)) or refinance debt (column (2)-(3)).

While the relative sizes of the bond price reactions when the funds are to be used for expansions versus stock repurchases are inconsistent with the wealth transfer hypothesis and the negative reaction to bond issues for stock repurchase purposes is inconsistent with the signaling hypothesis, the results in Table 6 are what would be expected if both hypotheses hold. As summarized in Panel C of Table 1, while the wealth transfer and signaling effects on bond prices tend to cancel out for bond issues used to repurchase stock, they tend to reinforce each other for bond issues associated with expansions. Thus, the findings of a negative reaction for issues associated with both expansions and stock repurchases but larger negative reaction for bond issues associated with expansions is consistent with a wealth-transfer-signaling combination.[44]

Moreover the small negative reaction to bond issues used to refinance existing debt is what one would expect if the bond issue signals that the old bonds could not be retired from internal sources. Whereas the wealth transfer hypothesis predicts no bond market reaction to bond refinancings, the signaling hypothesis predicts negative bond market reactions when the newly borrowed money is to be used to refinance existing debt. Consistent with the signaling hypothesis, I observe in Panel A of Table 6 a mean (median) standardized return of -0.09 (-0.18) when a firm intends to use newly raised funds for debt refinancing. Additionally, both mean and median composite returns

[44] Maxwell and Stephens (2003) examine monthly bond and stock returns around the announcements of repurchase programs and find evidence consistent with both signaling and wealth transfer hypotheses.

across the 7- and 11-day event windows in Panel A are negative and statistically significant at the 0.01 level. [45]

Panels C and D of Table 6 document abnormal standardized stock returns surrounding new debt issues, segmented by a firm's different intended uses. As with the bond price reactions, the relative stock price reactions, depending on whether the new funds are to be used to expand the firm or repurchase stock, are consistent with a combination of the wealth transfer and signaling hypotheses. Both hypotheses predict a positive stock price reaction when the funds are to be used for stock repurchases and the stock price reaction in Column (1) of Panels C and D is indeed large, positive, and significant in these cases. Whereas the wealth transfer hypothesis also predicts a positive (though smaller) stock price reaction when the funds are to be used to expand the size of the firm, the signaling hypothesis predicts a negative reaction if it signals that the expansion could not be financed internally or if it signals management puts growth ahead of profits. While the insignificant stock price reactions reported in Column (2) in this case are inconsistent with either hypothesis individually, they are consistent with a wealth-transfer-signaling combination.[46]

Somewhat surprising are the positive stock price reactions observed when the funds are to be used to refinance existing debt. Since firm leverage and size are unchanged, the wealth transfer hypothesis implies no reaction. The signaling hypothesis and bond price reaction results imply a negative stock price reaction but a small positive stock price reaction is observed. Perhaps the fact that the firm issued

[45] Difference in seniority and maturity between newly issued bonds and existing bonds may also impact existing bond returns when the intended use of newly borrowed money is a debt refinancing, and thus I will control for the difference of seniority and maturity in the multiple regression analysis.

[46] Extant studies on stock returns surrounding merger and acquisitions announcements (see, for example, Billet, King and Mauer (2004)) find that stocks experience insignificantly positive returns.

bonds rather than stock for this refinancing signals that management feels the equity is undervalued.

3.2. Regression Analysis of the Determinants of Bond and Stock Price Responses to Debt Offering Announcements

Conclusions from univariate analysis may be tentative, as the results could be confounded by other factors such as a firm's profitability or size and one cannot test which factors have incremental explanatory power. Accordingly, multivariate analyses are now used to further examine the hypotheses. I use composite returns during a seven-day event window, ABSR {-3, +3}, as the dependent variable in the bond regressions. Extant studies of stock offerings use a two-day (or three-day) return surrounding the offering announcement date as dependent variable but to calculate a two-day event window return requires price observations on both days 0 and +1. For my sample period 2005-2011, Ederington et al. (2012) shows that a mere 31.3% of two-day bond returns from day 0 to day +1 are actually calculable due to infrequent trading. Ederington et al. (2012) suggest using an expanded event window, such as from three days before the event through three days after. This both increases the number of bond observations and the power of the tests, while not increasing the Type I error rate (i.e., the false rejection rate). In stock regression analyses, I use three-day standardized cumulative abnormal returns, SCAR (-1, +1) as the dependent variable.

Some firms have multiple existing bond issues outstanding, as evidenced by an average (median) number of bonds per firm of 4.35 (3.00) in the sample. There are two methods to deal with multiple bond outstanding issues.[47] First, a few bond market event studies have considered each existing bond as an independent observation.[48] Given the likely high correlation between returns of bonds issued by the same firm, this method likely inflates the t-statistics and more heavily weights firms with multiple outstanding issues in the sample. Second, each firm can be treated as a separate observation averaging together the returns on all the firm's bonds. I treat each existing bond as a separate observation when examining how bond returns differ due to bond characteristics, such as existing bonds' credit ratings and the difference of seniorities (maturities) between new bonds and existing bonds.[49] To avoid underestimating the standard deviation associated with the potential correlation in bond returns within the same firm,[50] I estimate the regressions using firm clustered residuals. When investigating how bond and stock returns surrounding new debt offering announcements vary due to debt offering and firm characteristics, I estimate regressions treating each firm as a separate observation.

I control for other factors that may influence the bond and stock market's reaction to the announcement of a new bond issuance. All control variables (except high volume issues) discussed are measured in the fiscal year immediately preceding the new

[47] More discussions on the issues associated with these two methods can be seen in Eberhart and Siddique (2002).
[48] These studies include Jayaraman and Shastri (1988), Marais, Schipper, and Smith (1989), Hand, Holthausen, and Leftwich (1992), Warga and Welch (1993), and Cook and Easterwood (1994).
[49] As discussed in section 1.2, a new debt offering could impact a firm's senior and junior debt prices differently. When the new bond is subordinated to existing senior bonds, the existing senior bonds should experience a positive wealth effect surrounding the new debt offering announcement. In contrast, the new debt offering would pose negative wealth effects on existing junior bonds since the new debt has the same or higher seniority than the junior bonds. Moreover, an equal-weighted average of a firm's senior and junior bond returns could indicate that the debt issuance causes no impact to a firm's bond returns. This "null result" may also arise when computing the average of a firm's abnormal event-window standardized returns based on existing bonds' ratings and the maturities of new and existing debt.
[50] As robustness tests, I re-estimate the regressions by treating each firm as a separate observation. The results are qualitatively similar to those reported in Table 7.

debt offering announcement year. Definitions of variables can be seen in Appendix B. The wealth effects of new debt offering announcements on existing bondholders and stockholders could be attributed to the deviation from the target capital structure (historical average book leverage in Lemmon, Roberts and Zender (2008)). Accordingly, both bondholders and stockholders would experience negative (positive) returns if a firm's leverage ratio is more deviated from (closer to) a firm's target leverage ratio after the new debt issuance. I use an indicator variable to denote whether a firm is overleveraged or not. I predict negative signs of coefficients for the overleveraged firms since both firms' bondholders and stockholders would suffer losses surrounding new debt offering announcements when firms' leverage ratios deviate from the target level.

Spiess and Affleck-Graves (1999) document more severe stock underperformance around the debt offering announcements in high-volume years. Following Spiess and Affleck-Graves (1999), I define high-volume issues as those occurring in a month in which the total number of issues is greater than or equal to the median number of issues each month in my sample period of January 2005 through December 2011.[51] A firm's decision to secure outstanding debt with tangible assets helps to reduce the potential that existing bondholders will suffer from an increase in default risk when additional debt is issued. This benefit to existing bondholders increases with the amount of tangible assets a firm holds. A higher effective tax rate reduces the amount of internal cash flow available to service the payment of interest and principal. Hence, I expect bondholders of a firm with a large effective tax rate to suffer

[51] Spiess and Affleck-Graves (1999) use the median number of issues per year as a benchmark since their interest is in long-term post announcement stock performances.

more due to increased default risk. Except for debt refinancings, a new debt issue increases the firm's leverage and therefore the risk faced by bondholders. This impact likely depends on the firm's growth opportunities. When additional debt is issued, bondholders' claims in a profitable firm are more valuable than those in a less profitable firm. The profitability of a firm can serve as a signal that the firm is able to make timely payments of interest and principal. Therefore, bondholders of a profitable firm should suffer less when faced with greater default risk.

In Table 4 and section 2.1, I found weak univariate evidence supporting the Merton model prediction that the reaction of existing debt prices is more positive when the new bonds are subordinated to the existing. The difference in the ABSR (-1, +1) was significant at the 0.10 level but the ABSR (-3, +3) difference was not. In Table 7, I find that after controlling for other factors, the ABSR (-3, +3) difference is also significant at the 0.10 level.[52] However, the difference becomes insignificant in Column (5) when contaminated offering announcements are eliminated. This could be due to the small number of cases in which the new bond is senior or subordinated to the existing bond as shown in Panel B of Table 4.

Coefficients for most control variables are not statistically significant, suggesting that any possible confounding relationships are not a concern. Coefficients for the indicator variable of the overleveraged firms are not significantly different from zero. Coefficients for a firm's tangibility ratio are negative and significant, but become insignificant when the dependent variable is ABSR (-1, +1) in unreported regression results. In contrast to the expectation that a large firm's bondholders should suffer

[52] In untabulated results, the difference of coefficients becomes larger when using ABSR (-1, +1) as the dependent variable.

smaller losses surrounding the new debt issuance, the large firm's existing bondholders actually seem to experience more negative returns. The coefficients for a firm's size are negative and statistically significant at the 0.05 level.

The finding of Table 4 that the bond price reaction is more negative when the new bonds mature before the existing bonds (thus giving the new bonds de facto seniority) is reconfirmed after controlling for other factors. Column (2) of Table 7 shows that the difference of ABSR {-3, +3} surrounding the new debt issue when the new bonds' maturity is shorter than existing bonds' maturity and when the new bonds' maturity is longer than existing bonds' maturity is statistically significant at the 0.01 level.[53] These findings suggest that a debt offering could negatively impact existing bondholders due to asset claim dilution, as their claims on the firm's assets become subordinated to those of the new bondholders and leads to greater losses to existing bondholders.

To examine the incremental effects of the difference of maturity and seniority on existing bond returns, Columns (3) and (7) present regression results when considering both the difference of maturity and seniority between new and existing bonds in the regressions. The sign and significance level of coefficients on the indicator variables for the difference of maturity and seniority are qualitatively similar to the regressions considering the impact of the difference of maturity or seniority alone. Therefore, both the differences of maturity and seniority have explanatory power on existing bond returns surrounding new bond offering announcements. However, the difference of

[53] In regressions of Columns (2), (3), (6), and (7), I eliminate the offerings where the new and existing bonds have the same maturity. Therefore, the significance of the coefficient for bonds' maturity: New<Existing indicates the significance of the difference of abnormal standardized bond returns between a group of bonds when the new bonds' maturity is shorter than existing bonds' maturity and when the new bonds' maturity is longer than existing bonds' maturity.

maturity between new and existing bonds seems more important than the difference of seniority in explaining existing bond returns, as evidenced by the more significant coefficients on the indicator variables for the difference of maturity than the difference of seniority. This could be due to the greater number of cases in which new and existing bonds have different maturities than new and existing bonds have different seniorities, as depicted in Table 4.

In Table 7, I incorporate a binary variable, "investment", which assumes a value of 1 if an existing bond's rating belongs to an investment grade rated category and is 0 otherwise. In contrast to the wealth transfer hypothesis prediction as summarized in Panel B of Table 1, coefficients on the investment grade rating indicator variables in Table 7 are negative and not significantly different from zero controlling for other factors. This result is consistent with the univariate results reported in Table 5, where the difference in abnormal standardized bond returns between investment and speculative rated bonds is insignificant. However, bond maturity, defined as the logarithm of a firm's existing bonds' maturity, is another important dimension of bond default risk. The coefficients for existing bonds' maturities in Columns (4) and (8) of Table 7 are negative and statistically significant at the 0.01 level. This evidence suggests that existing bondholders' losses surrounding the issuance of new debt are positively related to bond maturities. In particular, a longer maturity indicates greater risk relative to a shorter maturity, and thus existing holders of long-term debt suffer greater losses surrounding new debt offering announcements.

Table 8 presents firm-level regression results on how the bond and stock market reactions depend on the intended uses of newly raised funds controlling for other factors. Consistent with the univariate results in Panels A and B of Table 6, the bond price reaction appears strongest (but not significantly different in most cases) when the funds are used for expansion controlling for other factors. This is inconsistent with the wealth hypothesis alone but consistent with a combination of wealth transfer and signaling hypotheses. Results in bond specifications show that coefficients for expansion use are more negative than the coefficients for stock repurchases or debt refinancing use, but the differences of estimated coefficients for different intended uses are not significant according to the F-tests in the bottom rows.

In Panels C and D of Table 6, I found strongest stock market reactions for intended use of newly borrowed funds for stock repurchases, and negligible stock market reactions when a firm uses the funds to expand the firm. These findings are inconsistent with either hypothesis individually, but are consistent with a wealth-transfer-signaling combination. Consistent with the univariate finding, the stock price reaction is strongest when funds are used for stock repurchases, and not significantly different from zero when funds are used for expansions controlling for other factors in Columns (3) and (4).

For firms with long-term existing bonds, abnormal standardized bond returns are more negative and statistically significant, as depicted in Columns (2) and (6), while abnormal standardized stock returns are more positive and statistically significant, as shown in Columns (4) and (8). This is consistent with a greater expropriation of wealth from existing bondholders to existing stockholders for firms with longer-term existing bonds.

In Table 9, I re-estimate the models from Tables 7 and 8 using the three-day cumulative abnormal return (CAR (-1, +1)) as the dependent variable in Panels A and B. I calculate daily bond prices from the TRACE transaction data using the "trade-weighted price, all trades" method established in Bessembinder et al. (2009). Following Bessembinder et al. (2009), I use a matching portfolio approach to compute abnormal bond returns by subtracting the return of a value-weighted index of matched corporate bonds. The results reported in Table 9 pertain only to the sub-sample of uncontaminated observations. The results are consistent with the previous finding that bond market announcement returns are more positive when the newly issued bonds are subordinated to the outstanding bonds, as evident by the positive and significant (p-value of 0.03) difference in bond CAR (-1, +1) in Column (1) of Table 9. Column (2) of Panel A provides further support of the finding that the reaction of existing debt prices is more negative when the new bonds mature prior to existing bonds. As expected I find evidence that existing long-term bondholders experience more negative abnormal bond returns surrounding the new debt issue, as supported by the negative and statistically significant coefficients for existing bond's maturity in Column (4). Panel B supports the finding from Table 8 for the differences of bond and stock market reactions for various intended uses. However, the significance level of difference is marginally diminished, which could be attributable to the heteroskedasticity in bond abnormal returns within the same firm.

4. Conclusions

Given the increasing importance and significance of debt in capital markets, the impact of new debt offerings on existing bondholders is particularly intriguing. There is a large existing body of literature studying how stock prices react to new bond issues, but empirical research on the impact of new debt offering announcements on existing bondholders yields inconclusive results, which can be attributed to difficulties associated with obtaining bond price data. In addition, no prior studies have examined how the bond price reactions depend on characteristics of the old and new bond issues. An investigation of the impact of issuing new debt on existing bondholders can also help answer whether and, if so, how existing creditors react to this increase in the leverage. My paper helps to fill these gaps.

I employ comprehensive daily corporate bond data from TRACE to estimate daily abnormal standardized bond returns surrounding the new debt offering announcements. Using the Merton model, I am able to derive and test several hypotheses concerning the relationship between a firm's security price changes and new debt offerings. Using a sample of 1,356 new debt issuance announcements made by firms with both bond and stock transactions data, I examine the wealth transfer hypothesis along with both the negative and positive signaling hypotheses. Most of my results are more consistent with the wealth transfer hypothesis than the signaling hypotheses though some suggest a signaling effect as well.

I also investigate the various factors that might impact relative wealth changes for bondholders and stockholders. The evidence indicates that bondholder losses are a function of the dilution in asset claims, existing debts' default risk, and the potential uses of newly raised funds. Specifically, I find more negative abnormal standardized bond returns: 1) when the new bond is senior to the existing bonds, 2) when the newly issued bonds' maturity is shorter than the existing bonds' maturity (which confers defacto seniority on the new bonds), 3) for longer-term outstanding bonds, and 4) when managers intend to use the newly raised funds for expansions. Consistent with a combination of wealth transfer and signaling hypotheses, I find a greater negative bond market reaction and a negligible stock market reaction to new debt offering announcements when the intended use of newly borrowed money is expansions than when it will be used to repurchase stock or refinance old debt.

Chapter 3: The Wealth Effects of Dividend Announcements on Bondholders: New Evidence from the Over-the-Counter Markets

"Sixteen of the banks have now repaid TARP. Most are eager to resume paying dividends and have asked permission to do so from the Federal Reserve. … Preventing profitable banks from paying reasonable dividends impedes bank lending and economic growth. It tilts the balance away from the issuance of new capital towards a slow-growth approach." William Isaac, chairman of LECG Global Financial Services and a former chairman of the US Federal Deposit Insurance Corporation, Financial Times, February 9, 2011.[54]

"But this too seems to call for dividend preservation for those firms vulnerable to systemic stress (rather than based on their Basel risk-weighted assets)." Viral Acharya, NYU Stern on February 14, 2011.[55]

"A dollar paid out to shareholders through either dividends or share repurchases is a dollar that would not be accessible to creditors in a situation of financial distress. For this reason, and to prevent the shifting of value from debt holders to equity holders, debt covenants typically restrict dividend payments when leverage is high." Anat R. Admati, Eugene F. Fama and others. Financial Times, February 15, 2011.[56]

The statements above represent two opposite views about dividend policies of banks that received government bailout money in 2008. To raise new capital later, William Isaac argues that firms need to pay out dividends now. Put another way, firms need to issue dividends to signal firms' profitability or attract stockholders so that firms can have more fresh capital injection in the future. However, this could seriously harm creditors' interest in turbulent periods when firms do not have sound capital. As acknowledged in the third statement, the wealth transfer from bondholders to stockholders in the form of dividends is perceived unfavorably during times of financial crisis, especially when the firm is highly levered. There has been limited evidence on the issue of whether issuing dividends will harm bondholders' interest or to what extent

[54] http://www.ft.com/cms/s/0/130d27a0-348e-11e0-9ebc-00144feabdc0.html#axzz1EGkLeXU1
[55] http://w4.stern.nyu.edu/blogs/regulatingwallstreet/2011/02/should-banks-be-allowed-to-pay.html
[56] http://www.ft.com/cms/s/0/44540816-38f7-11e0-b0f6-00144feabdc0,s01=1.html#axzz1EGkLeXU1

dividend policy will hurt creditors. My study fills this gap and adds to the current literature on the wealth effect of corporate events on both bondholders and stockholders.

Dividend policy can lead to conflicts of interest between shareholders and bondholders. Increases in dividends indicate lower cash to service debt and cuts in dividends suggest that management is conserving cash, indicating potential *wealth transfer* between bondholders and stockholders. An investigation of the effect of dividend announcements on bondholders and shareholders can yield a more complete picture of the wealth effect of dividend announcements. Many prior studies show that unexpected dividend increases lead to *wealth transfer* from bondholders to stockholders if the incremental part is financed issuing new debt or sacrificing promising investment opportunities.[57] Therefore, unexpected dividend increases would increase the default risk on bonds and a loss to bondholders should occur. So an announcement of increased dividends will be associated with negative bond returns. On the other hand, stockholders will benefit from the increased dividend payments. Evidence in prior studies suggests that an announcement of increased dividends is associated with significant abnormal positive stock returns.

Dividends can serve as a signal for firms' future cash flow. Miller and Modigliani (1961) were the first to suggest that dividends contain information about the firm's cash flow in the future. Accordingly, researchers developed the hypothesis of *signaling* - that dividend increases signal that management is confident that future earnings will be strong enough to continue paying the higher dividends in the future

[57] See, Galai and Masulis (1976), Black (1976), Black and Scholes (1973), Jensen and Meckling (1976), Kalay (1979, 1983), Myers (1977), and Smith and Warner (1979).

while dividend cuts signal that management expects lower earnings in the future. Therefore, an announcement of increased (decreased) dividends serves as a positive (negative) signal for a firm's future earnings which should have a positive (negative) effect on both bondholders and stockholders. Thus the signaling hypothesis predicts a positive (negative) bond price response to the announcement of a dividend increase (decrease) while the *wealth transfer* hypothesis implies a negative (positive) response.

There has been a large body of literature examining the effect of dividend announcements on stocks. Evidence suggests that dividend increases (decreases) are associated with significant positive (negative) stock price responses. However, evidence on the impact of dividend change announcements on bondholders is mixed. Three papers have tried to examine the wealth transfer versus signaling hypotheses of dividend announcements but provide mixed evidence. Woolridge (1983) and Handjinicolaou and Kalay (1984) provide evidence supporting the signaling hypothesis. On the contrary, Dhillon and Johnson (1994) find evidence for the wealth transfer hypothesis. The mixed evidence in these papers can be attributed to historical deficiencies in the quality and availability of bond price data. Since these researchers collected data by hand, their sample sizes tended to be small and include only heavily traded bonds. Moreover, these studies employ data on bond trades from the NYSE, which is a small, odd-lot market marked by infrequent trading. On the other hand, the corporate bond market is institutional in nature by trading over-the-counter (OTC). In addition, the aforementioned studies tend to use large event windows in the order of a month or a week, which can be attributed to a lack of frequently traded daily bond data. Using monthly returns relative to daily returns, particularly in small samples, can lead to the weaker power of tests (Brown and Warner, 1985; Bessembinder, Kahle, Maxwell and Xu, 2009). In this paper, I employ comprehensive data on the over-the-counter bond transactions to calculate daily abnormal bond returns surrounding an announcement of dividend changes. In a large sample of dividend change announcements during July 2002 to December 2010, I find a positive and statistically significant bond market response to dividend increases and a negative and statistically significant bond market response to dividend omissions over a three-day event window. These findings support the signaling hypothesis that has been used to explain stock price responses to dividend changes. Additionally, I find insignificant bond market and significantly negative (positive) stock market reactions to announcements of dividend decreases (initiations) over the three-day event window. This is inconsistent with the signaling hypothesis alone but consistent with a combination of signaling and wealth transfer hypotheses. As hypothesized above, while the signaling and wealth transfer effects on bond prices tend to cancel out, they tend to reinforce each other on stock price reactions surrounding dividend decreases and initiations announcements.

I also provide evidence on the determinants of the effect of signaling on bond returns surrounding a dividend increases announcement. A larger percentage dividend increase signals a more prosperous future for bondholders, thus bondholder gains are positively correlated with the magnitude of dividend increases. The signaling hypothesis predicts that riskier bonds should benefit more from events that decrease a firm's default risk. Consistent with this prediction, I find that speculative rated bondholders experience more positive returns surrounding the dividend increases announcement than investment rated bondholders. Consistent with the view that dividend signaling can be more convincing in turbulent periods, like the 2008 financial crisis, bonds experience greater positive returns after 2008. Furthermore, I find more positive returns for financially non-distressed firm bondholders on the announcement of a dividend increase, which is consistent with the prediction that positive signaling should be more apparent for financially good firms.

Lastly, my study contributes to the literature on bond price reactions to dividend announcements employing the over-the-counter bond transaction data from the Trade Reporting and Compliance Engine (TRACE). By the end of January 2005, the transaction data in TRACE, which accounts for 99 percent of trades equaling 95 percent of market value, were published in 15 minutes.[58] According to Bessembinder, Kahle, Maxwell and Xu (2009), prior studies using monthly data from the Lehman Brothers Bond Database (LBBD) or collecting daily bond data from *The Wall Street Journal* could offer an opposite inference due to misspecification and the lower power of test statistics that have been used in bond event studies. I find that, for both dividend increases and decreases announcements, abnormal returns within a period of (+2, +30) are negative and statically significant. The response to decreases is about two times larger in magnitude than that to increases. This is opposite to the findings in the three-day even window surrounding the dividend change announcement. These results support Bessembinder, Kahle, Maxwell and Xu (2009)'s finding that monthly bond event studies can lead to an opposite implication. Researchers should be wary when using monthly bond returns in event studies, especially when concurrent corporate events can cause a bias in abnormal returns.

[58] See SEC Release No. 34-49920; File No. SR-NASD-2004-094. The trades of the Rule 144a market, which is still opaque, are not included in this figure.

The remainder of the paper proceeds as follows. Section 1 provides a brief review of the related literature and develops my hypotheses. Section 2 describes the data and method. Sections 3 and 4 report univariate and multiple analysis of the bond price responses to dividend change announcements. Section 5 presents robustness checks of my findings. Section 6 concludes the paper.

1. Literature and Hypotheses Development

Using non-TRACE data, researchers have investigated various corporate announcements, such as stock offerings (Eberhart and Siddique, 2002; Elliott, Prevost, and Rao, 2009), spin-offs (Maxwell and Rao, 2003), share repurchases (Maxwell and Stephens, 2003), and mergers and acquisitions announcements (Billet, King, and Mauer, 2004), where the implications are different for equity and bonds. Among bond datasets that have been used in these studies, Lehman Brothers Bond Database (LBBD) is the most widely used. It provides a complete set of month-end bond data. However, there are two problems about the dataset. First, the price is the monthly bid price which is not the true transaction price. Second, the interval of the data is monthly. Dividend increases (decreases) tend to be announced when the firm is operating well (poorly). Compared to daily returns, monthly returns could be a result of confounding firm-specific news other than dividend announcements. Given the impracticality of deleting dividend announcements that are contaminated with non-dividend news during a month long window, calculations of monthly returns can be overstated. Additionally, the standard deviation of bond returns becomes inaccurate due to the noise added by confounding events. Therefore, the inferences from analyses of monthly returns around dividend changes are unclear in terms of the magnitude and statistical interpretation of bond market responses. To have a clear inference, it is better to conduct daily event studies using bond transaction data from TRACE.

Recent evidence finds that some corporate events lead to significant wealth transfers between bondholders and stockholders, i.e. Maxwell and Rao (2003) for spin-offs; Adams and Mansi (2009) for CEO turnover; but systematic evidence on dividend announcements has not been provided. The *signaling* hypothesis argues that increases (cuts) in dividends will lead to an increase (decrease) in bond prices because paying dividends can signal firms' future profitability.[59] On the other hand, the *wealth transfer* hypothesis predicts that increases (cuts) in dividends will lead to a decrease (increase) in bond prices. In this paper, I examine these two hypotheses by detecting bond price reactions to dividend announcements.

According to the signaling hypothesis, an unexpected increase in dividend payments signals a more prosperous future, leading to an increase in bond and stock prices. Therefore, dividend announcements should pose a similar effect on bondholders and shareholders. Positive (Negative) abnormal bond returns should be observed surrounding the announcements of increased (decreased) dividends. It leads to the following hypothesis:

Hypothesis 1: An announcement of an increase (decrease) in dividends will lead to an increase (decrease) in bond prices.

In contrast to the signaling hypothesis, the wealth transfer hypothesis argues that an increase in stock dividend payments reduces the cash flow available to meet bond

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[59] Ambarish, John, and Williams (1987), Bhattacharya (1979), John and Williams (1985), and Miller and Rock (1985).

principal and interest payments. If the reduction is significant, it could increase the probability of default on bonds. Therefore, dividend payments cause conflicts of interest between bondholders and stockholders. This hypothesis predicts a negative relation between bondholders' and shareholders' reaction to dividend announcements. Specifically, an announcement of increased (decreased) dividends should be followed by a positive (negative) response in stock markets but a negative (positive) response in bond markets. It leads to the following hypothesis:

Hypothesis 2: An announcement of an increase (decrease) in dividends will lead to a decrease (increase) in bond prices.

My study also contributes to understanding the determinants of bond market response to dividend announcements. Previous studies have found that the bond market response to corporate events could vary with the level of leverage, rating of bonds, and maturities of bonds. Handjinicolaou and Kalay (1984) find that bondholders' losses are positively correlated with a firm's financial leverage. Maxwell and Rao (2003) study the bondholders' wealth effects surrounding spin-offs and find that a bondholder's loss is correlated with the size of the spin-offs and risk of the parent firm (investment grade versus noninvestment-grade rating). Maxwell and Stephens (2003) find that the loss of bondholders surrounding stock repurchases is a function of the size of the repurchase and the rating of the firm's debt. Billett, King and Mauer (2004) show that in mergers and acquisitions, target bonds experience higher positive returns when the target bonds have a shorter maturity than the acquirer bonds. The relation between bond prices changes and ratings of bonds can depend on whether dividends increase or decrease. For instance, when the signaling hypothesis holds and dividends increase (decrease), it predicts a prosperous (pessimistic) future of a firm. Accordingly, riskier bonds (junior bonds or speculative bonds or longer maturity bonds or firms with higher financial leverage ratio) should benefit (suffer) more than other bonds (senior bonds or investment bonds or shorter maturity bonds or firms with lower financial leverage ratio). The reason is that decreases (increases) in the default risks of riskier bonds are much larger than for other bonds. Therefore, riskier bonds will react positively (negatively) and larger (smaller) than other bonds surrounding an announcement of dividend increases (decreases). On the other hand, the sign of bond market reaction will change when the wealth transfer hypothesis holds and dividends increase (decrease). Riskier bonds will suffer (benefit) more than other bonds. Increases (decreases) in the default risks of riskier bonds are much larger than other bonds. Therefore, riskier bonds will react negatively (positively) and smaller (larger) than other bonds. Consequently, I develop the following two hypotheses:

Hypothesis 3: When the signaling hypothesis (hypothesis 1) holds and dividends increase (decrease), bond market returns surrounding dividend announcements will be negatively (positively) correlated with bond seniority, negatively (positively) correlated with bond ratings, positively (negatively) correlated with bonds maturities, and positively (negatively) correlated with firms' financial leverage.

Hypothesis 4: When the wealth transfer hypothesis (hypothesis 2) holds and dividends increase (decrease), bond market returns surrounding dividend announcements will be positively (negatively) correlated with bond seniority, positively (negatively) correlated with bond ratings, negatively (positively) correlated with bonds maturities, and negatively (positively) correlated with firms' financial leverage.

2. Data and Methodology

2.1. Data

Following studies on dividend announcements, dividend announcements data are collected from the CRSP monthly event file. The event date of a dividend announcement is the declaration date recorded in CRSP. Dividend changes are calculated as the percentage difference in dividend payments between the current and previous periods. To be included in the sample, a dividend announcement must satisfy the following criteria:[60]

a) The firm's bond data are available on the TRACE during the event windows.

b) The firm pays a taxable cash dividend in U.S dollars in the current and previous periods.

c) The shares on which the distributions are paid are ordinary common shares and are not shares of closed-end funds or REIT'S (Real Estate Investment Trusts).

d) Announcements with a declaration date within four days before the ending of the earnings record month are excluded.

The period of dividend announcements data in my sample ranges from July 2002 to December 2010. The Mergent Fixed Income Securities Database (FISD)

[60] In robustness checks, I exclude dividend announcements made by utility firms (SIC codes 4900-4999) and 12 offerings issued by financial firms (SIC codes 6000-6999). In addition, I also eliminate dividend announcements contaminated by other company specific news during the three-day event window, from one day before the announcement through one day following the announcement. Company specific news includes quarterly earnings, mergers or acquisitions, equity offerings and stock repurchases. My findings are robust to these two changes in sample criteria.

provides specific information about bond characteristics like seniority, rating, accrued interest, and maturities. Stock returns and firms' accounting information are drawn from CRSP and Compustat, respectively. The above sample selection criteria results in a sample of 1,508 observations: 272 dividend decreases and 1,236 dividend increases.

Tables 10 and 11 provide descriptive statistics on the firm-level and bond-level characteristics of the sample. TRACE only provides comprehensive coverage of bond markets beginning in 2005. Therefore, I observe that there are fewer dividend announcements in earlier years. A large number of dividend decreases occurred in 2008 and 2009. Regarding the dividend per share, dividend increase firms pay a higher dividend than dividend decrease firms. For 2007, I see a decline in the magnitude of dividend per share and this trend continues until 2010. These two findings reflect the recent economic recession and financial crisis. On the other hand, the largest number of dividend increases happened in 2010, which indicates an economic recovery during that year. In Panel A of Table 10, I find more announcements of dividend increases than dividend decreases. The ∆DIV column reports the percentage change in dividend per share compared to the previous period. In total, the dividend change has a mean of 32 percent for dividend increases and -47 percent for dividend decreases. I do not find a significant difference in the leverage ratio between dividend decrease and dividend increase firms. In my sample, there are fewer financially non-distressed firms in the dividend decreases group than that in the dividend increases group. Panel A reflects that the mean financially non-distressed dummy is 21 percent for dividend decreases and 30 percent for dividend increases, which reflects that firms suffering financial distress are more likely to cut back on their dividend payments. In the dividend decreases group, I see a much smaller number of financially non-distressed or unconstrained firms from 2007 to 2008. Meanwhile, I observe the opposite direction in the dividend increases group, where there is a higher percentage of financially non-distressed and unconstrained firms in the sample.

In addition to the firm-level statistics, I also report the bond-level summary characteristics in Table 11. Similar to Table 10, there are fewer bonds included in earlier years of my sample period. Firms that cut dividend payments pay a slightly higher coupon rate than firms that raise dividend payments, which reflects the difference in bond ratings between these two groups. Dividend decrease firms have a lower bond rating than dividend increase firms. Panel A indicates that the mean bond rating is A3 (A or A2) for bonds impacted by dividend decreases (increases) announcements. Bonds in the dividend decreases group have shorter remaining maturities than that in the dividend increases group. The mean maturities are 7.00 and 7.59 years, respectively. Most bonds in the sample are investment grade bonds or senior bonds. However, dividend increase bonds are more likely to receive an investment grade rating or be senior to dividend decrease bonds. Specifically, the percentage of investment grade (secured or senior) bonds is 92 (95) percent for dividend increases and 85 (87) percent for dividend decreases. The above findings lead me to conclude that dividend increase bonds are better than dividend decrease bonds, because they have better bond ratings, lower interest rates, and are more likely to be investment grade or senior bonds. I find a significant decline in bond ratings for the dividend decreases group from 2008 to 2010. However, I do not find a significant change in the bond ratings of the dividend increases group during the same period. This asymmetric pattern reflects the fact that bonds are more likely to be downgraded when negative events (e.g. dividend decreases) occur to a firm in turbulent periods (e.g. a financial crisis).

2.2. Abnormal Bond Return Measures

Following Bessembinder, Kahle, Maxwell and Xu (2009), I restrict my sample to non-convertible, non-putable, and non-zero coupon bonds. In addition, I require that bonds: 1) be denominated in US dollars; 2) have a par value of $1,000, 3) make semi-annual coupon payments, 4) mature in 50 years or less and greater than one year, 5) be rated by Moody's and/or S&P, and 6) neither be in default nor have a tender offer outstanding. Compared to the stock market, the bond market is less liquid, which makes estimating daily abnormal bond returns more challenging than stock returns. To deal with the illiquidity, I require a bond to trade on at least 10 days during Day -1 to -20, which is the same as the one employed by Bessembinder, Kahle, Maxwell and Xu (2009). As suggested by Bessembinder, Kahle, Maxwell and Xu (2009), I use a matching portfolio approach to compute abnormal bond returns by subtracting the return of a value-weighted index of matched corporate bonds. Using the bond transaction data from TRACE, daily bond prices are calculated with the "trade-weighted price, all trades" method. Daily raw returns on individual bond issues (RR_t) are equal to the change in price plus accrued interest over the previous day's price divided by the previous day's price:

$$RR_t = \frac{P_t + AI_t - P_{t-1}}{P_{t-1}} \tag{1}$$

Where AI_t is accrued interest on Day *t* and *P* indicates the daily price of the bond.[61] Normally, default risk (proxied by bond rating) and time to maturities are two of the most salient risk factors considered in estimating bond returns. Thus portfolios matched by bond rating and time to maturities are used to proxy for expected return for the bond. I use the entire TRACE (excluding bonds that issued dividends in the period Day t-30 to Day t+30) universe to construct the matched corporate bond indices. I partition bonds by seven letter classifications based on Moody's ratings. If bonds are unrated by Moody, I use S&P's ratings of the bonds. The seven letter classifications are: Aaa, Aa, A, Baa, Ba, B and C. To control for the risk associated with maturity, I group the Aaa, Aa, A, B, and Ba classes into long and short maturity categories. Following May (2010), I choose the following cutoffs to guarantee that there is approximately the same amount of bonds within each category. For the Aaa, Baa, and Ba classes, the two categories are maturities less than seven years and seven years and above. For the A and B classes, the two categories are less than six years and six years and above. For the Aa class, the two categories are less than five years and five years and above. Given the much smaller number of traded bonds in the C class, this class is not further partitioned. Therefore, bond returns on a value-weighted index of matched portfolios, which are constructed using the ratings and maturities, are denoted as MR_t. To be included in a given index on Day t, a bond should be traded on Day t and Day t-1. The abnormal bond return on Day t (ABR_t) is computed as the bond raw return (RR_t), less the contemporaneous return of matched portfolios (MR_t):

$$ABR_t = RR_t - MR_t \tag{2}$$

[61] AI is calculated as annual coupon payment multiplied by n, the number of calendar days during the event window, and divided by 365.

For multiple bond issues by the same firm, I calculate abnormal returns weighting the principal value of each bond. Therefore, the abnormal bond performance for firm *i* on Day t is calculated as:

$$ABR_{i,t} = \sum_{n=1}^{k} ABR_{n,t}\omega_n \qquad (3)$$

Where *k* is the number of bonds issued by the same firm and ω is the ratio of bond *n*'s par value of debt initially issued to the total par value of firm *i*'s bonds in the sample. Cumulative abnormal returns (CARs) for bonds are calculated as the sum of the firm's daily abnormal returns over different window periods. Expanded event windows are also used in the paper. To detect the stock price response, cumulative abnormal returns during the same event window stretching from day -1 to +1, CAR (-1, +1), are computed as cumulative Fama-French model adjusted returns. Event windows of stock price responses are also expanded to match corresponding bond return event windows.

3. Univariate Analysis of the Bond and Stock Price Responses to Dividend Announcements

To discriminate between the two hypotheses outlined above, I conduct event studies to investigate bond and stock price responses around the announcements of increased and decreased dividends. Cumulative abnormal returns (CARs), defined as the sum of daily abnormal returns across the three-day event window from Day -1 to Day +1, are then calculated and employed as a measure of the bond market reaction to dividend announcements.

If the *signaling* hypothesis holds, dividend announcements should have the same effect on stockholders and bondholders. For instance, an announcement of increased dividends signals an optimal cash flow in the future which can also guarantee the timely payment of principal and interest for bonds. Thus, both bond and stock markets will react positively (negatively) to dividend increases (decreases) and this will support the *signaling* hypothesis (hypothesis 1). Accordingly, event window CARs of bond and stock prices should be positive (negative) surrounding the announcement of dividend increases (decreases).

If the *wealth transfer* hypothesis holds, dividend announcements should impact stockholders and bondholders differently. An announcement of increased (decreased) dividends predicts more (less) dividend payments in the future. This announcement causes a positive (negative) reaction in the stock market. On the other hand, it indicates that fewer (more) financial resources are available for future principal and interest payments, which will increase (decrease) the default risk on bonds. An increased (decreased) default risk will harm (benefit) the interest of firms' bondholders and lead to a negative (positive) reaction in the bond market. Therefore, event window CARs in bond markets should be negative (positive) surrounding the announcement of dividend increases (decreases). In contrast, CARs over the window in stock markets should be positive (negative) surrounding the announcement of dividend increases (decreases).

Panel A of Table 12 reports average CARs for the full sample of announced dividend increases and decreases. For each time window, a t-statistic calculated using the cross-sectional standard error of CARs for whether the mean CARs is different from zero is reported. Consistent with the signaling hypothesis (hypothesis 1), we can see that dividend increases have a positive and significant effect on bond prices in Panel A. For the 1,236 dividend increases announcements, the average CARs over Day -1 and Day +1 of 0.06 percent is significant according to the t-test. However, dividend decreases have no effect on bond prices during the same event window, which is not consistent with the prediction of negative bond market reactions to dividend decreases announcements by signaling hypothesis. Panel A of Table 12 demonstrates that a firm's dividend decreases announcement is associated with a mean return of zero. The insignificant bond market return is inconsistent with the signaling hypothesis, but is what would be expected if both signaling and wealth transfer hypotheses hold. The wealth transfer hypothesis predicts a positive effect and the signaling hypothesis predicts a negative effect of dividend decreases announcements on bond prices. Consequently, the signaling and wealth transfer effects on bond prices tend to cancel out each other.

In addition to significant bond market reactions on announcement windows, in Table 12, I also find evidence of negative CARs before and after dividend announcements, especially for dividend decreases announcements. These findings complement the findings of Aharony and Swary (1980), who report significant abnormal stock returns before and after dividend change announcements. In Panel A, the mean (-30, -5) and (+2, +30) CARs among dividend decreases are -0.87 and -0.80 percent, respectively and both are statistically significant at the five percent level. Furthermore, senior bonds (Panel B), speculative grade bonds (Panel C), and financially constrained bonds (Panel E) earn significantly negative abnormal returns prior to dividend decreases. Dividend announcements after the 2008 financial crisis elicit larger impacts on bond markets than those before the 2008 financial crisis. I find the same pattern for dividend increases announcements.

To investigate the cross-sectional variation of the bond market response to dividend changes, I partition the bonds sample into different groupings based on the variables that have been studied before. In Panel B, I split the bonds into senior and junior bonds, respectively.[62] A bond is considered as a senior bond if a bond is secured, senior issue of the issuer, and a junior bond otherwise. For dividend decreases, the mean (-1, +1) CARs are -0.01 and -0.10 percent, respectively. The negative reaction to dividend cuts seems to be more evident in junior bonds, which is consistent with the signaling hypothesis prediction that lower level bonds are more exposed to potential credit default events. However, the positive reaction to dividend increases seems to be driven by senior bonds with a reaction of 0.06 percent and statistically significant at the ten percent level. This is not surprising since more than 95% of the bonds in Table 10 are senior bonds. The signaling hypothesis predicts that that lower rated bonds benefit more from events that decrease firms' default risk. When I divide the sample of dividend increases announcements into investment grade and speculative grade bonds in Panel C, the average (-1, +1) CARs are 0.02 and 0.22 percent, respectively but only the speculative grade bonds group is significant at the 10% level. The significantly positive

[62] If a firm has both senior and junior bonds, the firm's bonds are separated into two groups of bonds: senior and junior bonds. Bond returns for each group are presented in Table 12. This results in an increase in the total number of observations in Panel B compared to Panel A. This is also the case when a firm has bonds with both investment and speculative credit ratings. As a robustness check, for each firm, I calculate an average rating and seniority level as the weighted average of each individual bond rating and seniority level in these cases, where the component weights are the proceeds of each bond outstanding relative to a firm's total value of bond outstanding. The result is qualitatively similar to the results reported in Panels A and B of Table 12.

speculative grade bond returns are consistent with the implication of signaling hypothesis in hypothesis 3.

Signaling can become more convincing in turbulent periods like the 2008 financial crisis. Bondholders will benefit more if firms increase dividend payments, while they will hurt more if firms cut dividend payments. Panel D presents the results by dividing the total sample of dividend announcements into two periods: before-crisis (before 2008) and after-crisis (after 2008). When the sample of dividend increases announcements is divided into before and after-crisis period, the mean (-1, +1) CARs are 0 and 0.13 percent, respectively. The former CAR is insignificant while the later CAR is significant based on the t-statistics test. As to dividend decreases announcements, I find that the post-announcement mean (+2, +30) CARs also differ across the two periods with -0.12 percent versus -1.21 percent, and the later CAR is statistically significant. The above evidence is consistent with the implication of the signaling hypothesis.

Akhigbe, Easterwood and Pettit (1997) find negative bond market reactions in the week following the announcements of new debt offerings when issuers are faced with an unexpected decrease in cash flow. To see how firms' financial conditions impact bondholders' wealth losses or gains surrounding dividend announcements, I split the sample firms into financially unconstrained (non-distressed) firms and financially constrained (distressed) firms under each type of dividend announcement in Panel E (F). Following van Binsbergen, Graham and Yang (2010), I measure financial distress employing a modified version of Altman's (1968) Z-score. Firms are considered nondistressed when their Z-scores are in the top tercile. Financially constrained firms are defined as firms having restricted long-term leverage. A more detailed description of the measurement can be seen in the Appendix C. According to the signaling hypothesis, signaling effects should be more apparent for financially good firms when they increase dividend payments. Consistent with this prediction, financially non-distressed firm bondholders earn a three-day return of 0.08 percent, while financially distressed firm bondholders earn a three-day return of 0.03 percent. However, I find financially constrained firm bondholders earn more positive returns than financially unconstrained firm bondholders. The mean (-1, +1) CARs surrounding dividend increases announcements in Panel E (Financially constrained vs. unconstrained firms) are 0.15 and 0.02 percent, respectively.

On the other hand, bondholders will suffer more from financially bad firms when firms cut dividend payments. The three-day event window announcement bond returns surrounding dividend decreases announcements fail to support this prediction, but post-announcement period bond returns lend support to this prediction. In Panel E, the mean (+2, +30) CARs for financially constrained firm bondholders is smaller than unconstrained firm bondholders (-2.05 vs. -0.49 percent). Moreover, the former one is statistically significant according to the t-statistics test.

According to the signaling hypothesis, an announcement of initiating (omitting) dividend payment serves as a positive (negative) signal for a firm's future earnings which should have a positive (negative) effect on bondholders. In contrast, the wealth transfer hypothesis implies a negative (positive) effect of dividend initiations (omissions) on bondholders since dividend initiations (omissions) can indicate lower (more) cash to service debt. Table 13 presents mean bond CARs for the sample of dividend initiations and omissions. I define a dividend initiation if a firm initiates its first dividend or resumes dividends after a period of at least five years from July 2002 to December 2010 and a dividend omission if a firm omits its dividend after a period of at least three years from July 2002 to December 2010. In Table 13, I find that bond markets do not react to dividend initiations over the announcement window (-1, 1). This is inconsistent with either hypothesis individually, but is consistent with a wealth-transfer-signaling combination. As summarized above, the signaling and wealth transfer effects of dividend initiations announcements on bond prices tend to cancel out each other.

Bond markets react negatively to dividend omissions over the announcement window (-1, +1) with a mean return of -0.38 percent, which is consistent with the signaling hypothesis. The negative return is statistically significant based on t-statistics test. In addition, there is a large negative reaction prior to a dividend omissions announcement with a mean CAR of -2.53 percent over the window (-30, -5). This finding suggests that dividend omissions are partially anticipated by the corporate bond market, and they complement the findings of Michaely, Thaler and Womack (1995), who finds significantly negative abnormal stock returns prior to dividend omissions announcements.

To directly compare the reactions across bonds and stocks of the same firms, I report the stock market reaction to dividend increases and decreases in Table 14. I calculate daily abnormal stock returns using the Fama-French three factors model. Consistent with prior studies (e.g. Aharony and Swary, 1980), I find that the stock market reacts positively to dividend increases but negatively to dividend decreases on

Day -1 to +1. The evidence of positive bond and stock announcement period returns surrounding the announcement of increased dividend supports the signaling hypothesis, which implies that dividend increases announcements should result in a positive change in both bond and stock prices. The significantly negative stock announcement period returns surrounding dividend decreases announcements are also consistent with a wealth-transfer-signaling combination because both signaling and wealth transfer hypotheses predict negative stock market reactions to the announcements.

As would be expected, signaling is more apparent after the financial crisis period with mean announcement day return of 0.22 percent and 0.34 percent surrounding dividend increases announcements when the sample is split into before and after crisis periods in Panel B and C of Table 14, respectively. Lastly, the stock market reactions to dividend changes are greater in magnitude than bond market reactions in the three-day event window. Perhaps the fact that stocks trade much more frequently leads to more spontaneous and greater reactions in stock markets than bond markets.

Table 15 reports stock market returns surrounding dividend initiations and omissions announcements. Consistent with Asquith and Mullins (1986) and Healy and Palepu (1988), stock markets react positively to the announcement of a dividend initiation across different event windows. A firm's stock price experience a mean positive return of 2.21 percent on the dividend initiations announcement day. Since both signaling and wealth transfer hypotheses predict a positive effect of dividend initiations announcements on stock prices, the significantly positive stock return is consistent with a combination of signaling and wealth transfer hypotheses. In the pre- and post-announcement periods, a firm's stockholders still earn positive returns.

In contrast, stock prices do not experience significance changes surrounding dividend omissions announcements across different event windows in Table 15. On the announcement day, the stock return is 0.06% and not significantly different from zero. The insignificant stock market reactions could be due to a combined effect of negative and positive signaling. Dividend omissions signal that management expects lower earnings in the future and thus should result in a negative stock price response. Additionally, dividend omissions during the turbulent periods, e.g. the 2008 and 2009 financial crisis, are viewed possibly by stockholders as a wise strategy to conserve cash.

4. Multiple Analysis of the Determinants of Bond Price Responses to Dividend Announcements

Other factors besides dividend changes could influence bond price responses. Handjinicolaou and Kalay (1984) find that bondholders' losses surrounding dividend announcements are positively correlated with a firm's financial leverage. Maxwell and Rao (2003) study bondholders' wealth effects surrounding spin-offs and find that a bondholder's loss is positively correlated with the risk of the parent firm (investment grade versus noninvestment-grade rating). Maxwell and Stephens (2003) show that the loss of bondholders surrounding stock repurchases is a function of the firm's debt rating. When a firm faces more default risks, the price of bonds with a longer maturity could drop more than shorter maturity bonds. Therefore, the bond market reaction to dividend announcements can vary with bond seniority, bond rating, bond maturity, and the firm's financial leverage ratio. To control for these factors, I include them in the regression analysis. *Junior_bond*, is an indicator variable with a value of 1 if a bond's seniority belongs to the category of junior; otherwise, 0. The bond rating, denoted as *Investment_grade,* equals 1 if the rating belongs to the category of investment-grade rating; otherwise, 0. *Maturity* denotes the natural logarithm of years remaining for bonds. Financial leverage, *FL,* is defined as the ratio of book value of long-term debt over the book value of the total assets of the firm. The financially unconstrained (non-distressed) firm, denoted as *FUC* (*FND*), equals 1 if the firm belongs to the financially unconstrained (non-distressed) group; otherwise, 0. The definitions of financially unconstrained and non-distressed firms are described in the Appendix C, and are consistent with the work of van Binsbergen, Graham and Yang (2010).

The *Signaling* hypothesis (hypothesis 1) implies that bond markets will react positively (negatively) to the announcement of dividend increases (decreases), which should induce positive correlation between bond market responses, which are measured by the three-day event window *CAR*, and the size of dividend changes, ΔDIV. In contrast, the *wealth transfer* hypothesis (hypothesis 2) predicts that the event window *CAR* should be negatively correlated with ΔDIV. I am also interested in investigating how bond market reactions differ due to seniority, rating, maturity and financial leverage, conditional on the dividend changes. To test the hypotheses outlined in section 2, the following regression is estimated via Ordinary Least Squares for dividend increases and decreases, respectively:

$$\begin{aligned}CAR(-1,1) &= Intercept + \beta_1 \Delta DIV_i + \beta_2 Junior\_bond_i + \beta_3 \Delta DIV_i * Junior\_bond_i \\ &+ \beta_4 Investment\_grade_i + \beta_5 \Delta DIV_i * Investment\_grade_i + \beta_6 Maturity_i + \beta_7 \Delta DIV_i * Maturity_i \\ &+ \beta_8 FL_i + \beta_9 \Delta DIV_i * FL_i (+\beta_{10} FUC + \beta_{11} \Delta DIV_i * FUC_i \ or + \beta_{12} FND_i + \beta_{13} \Delta DIV_i * FND_i) + \varepsilon_i \quad (4)\end{aligned}$$

Where for firm i, *CAR* is the cumulative abnormal bond return over the defined event window (-1, 1), all independent variables are defined as above, and ε is the random error term. If $\beta_1<0$ and is statistically significant, indicating a negative relation between dividend changes and bond market responses, this will lend support to the *wealth transfer* hypothesis (hypothesis 2). If $\beta_1>0$ and is statistically significant, indicating a positive relation between dividend changes and bond market responses, this will lend support to the *signaling* hypothesis (hypothesis 1). If β_1 is insignificant from 0, none of the hypotheses holds.

The relation between *Junior_bond* (*Investment_grade*, *Maturity*, *FL*, *FUC* and *FND*) and *CAR* depends on whether dividends increase or decrease. Therefore, I include interaction variables- $\Delta DIV_i*Junior\_bond_i$ ($\Delta DIV_i*Investment\_grade_i$, $\Delta DIV_i*Maturity_i$, ΔDIV_i*FL_i, ΔDIV_i*FUC_i and ΔDIV_i*FND_i) in the regression. For example, consider dividend increases ($\Delta DIV>0$). When a firm increases dividend payments and wealth transfer occurs, speculative (or subordinated) bonds will suffer more than investment grade (senior) bonds, given that they face more default risk. This implies that the dummy variable for investment grade bonds, *Investment_grade*, should be positively related to event window *CAR* ($\beta_5>0$). When a firm decreases dividend payments and wealth transfer occurs, speculative bonds will benefit more than investment bonds given that they face less default risk than before. This implies a negative relation ($\beta_5<0$). On the other hand, if a firm increases dividend payments and the signaling hypothesis holds, speculative grade bonds will benefit more than investment grade bonds and thus a negative relation can be expected ($\beta_5<0$).

When a firm increases dividend payments and wealth transfer occurs, the prices of bonds with a longer maturity will drop more than shorter maturity bonds, which indicates a negative relation between event window *CAR* and ΔDIV_i *$Maturity_i$ ($\beta_7<0$). If wealth transfer occurs, bondholders will face more default risk to an announcement of increased dividends when a firm has a higher financial leverage ratio, *FL*. I thus predict that there is a negative relation between event window *CAR* and ΔDIV_i *FL_i ($\beta_9<0$). I summarize the expected signs for β_3, β_5, β_7, β_9, β_{11} and β_{13} in Appendix D.

Table 16 reports regression results of dividend decreases and dividend increases separately. From model 1 to model 3, it can be seen that, neither signaling hypothesis nor wealth transfer hypothesis holds in the group of dividend decreases announcements given the insignificant coefficients for ΔDIV, β_1. However, I find strong evidence supporting the signaling hypothesis when firms increase dividend payments, given the positive and statistically significant coefficients for ΔDIV, β_1, across from model 4 to model 6. This finding is consistent with my earlier finding of significant positive bond market reactions to dividend increases announcements during a three-day event window in Panel A of Table 12.

Evidence for dividend decreases announcements is not significant since estimated coefficients for interaction variables in models 1 through 3 are not statistically significant. The signs of coefficients for interaction variables of investment rating and announcement year after 2008 are consistent with the implications of signaling hypothesis as summarized in Appendix D, but coefficients are not significantly different from zero.

Models 4, 5, and 6 also report multiple analysis results of the determinants of bond market returns surrounding dividend increases announcements. Bond market returns surrounding the announcements do not differ due to the difference of seniority, as evidenced by the insignificant coefficients of the interaction variable for junior bond, β_3. This could be due to the small number of bonds belonging to junior bond category. The bond reaction to dividend increases announcements is weaker when the firm's bond rating belongs to investment grade, indicating that speculative grade bonds react more positively to an increased dividend announcement than investment grade bonds. This finding is consistent with the evidence in the previous univariate analysis that a mean (-1, +1) CAR for speculative grade bonds is much larger than that for investment grade bonds. Both these two findings are consistent with the prediction of the signaling hypothesis that, riskier bonds should benefit more from events that decrease a firm's default risk.

In contrast to the expectations of the signaling hypothesis, the bond market reaction to the announcement of a dividend increase is significantly negative for bonds with longer maturities. The estimated coefficients, β_7, are negative and statistically significant at the one percent level. The negative sign of the coefficient for the financial leverage interaction variable contradicts the prediction of the signaling hypothesis. Consistent with the view that dividend signaling could be more evident during turbulent periods like the 2008 financial crisis, the coefficient for the indicator variable of dividend announcement year after 2008 is positive. There is weak evidence that financially unconstrained and non-distressed firm bondholders react more positively to increased dividend announcements given the insignificant positive estimated coefficients (β_{11} and β_{13} in Models 5 and 6 of Table 16). The weak evidence could be due to the control of the size of increased dividends.

In Table 17, I report Pearson and Spearman rank correlation coefficients between bond and stock returns in Panels A and B, respectively. If signaling hypothesis holds, then I expect to observe a positive relation between bond and stock returns. For the mean (-1, +1) CAR of increased dividend announcements, the Spearman rank correlation coefficient between bond and stock abnormal returns is significantly positive at the ten percent level. Particularly, the correlation in speculative rating bonds (I-S column in Panel B of Table 17) is 0.14 which is greater than investment rating group of bonds. However, there is no significant correlation between bond and stock abnormal returns surrounding the decreased dividend announcements within the same event window. In sum, the correlation coefficient results provide evidence of signaling for firms' bondholders and stockholders surrounding the increased dividend announcements.

5. Robustness Checks

As robustness checks for the measure of daily bond market reactions to decreased or increased dividend announcements, I use abnormal standardized bond returns as suggested by Ederington, Guan and Yang (2012). Ederington, Guan and Yang (2012) find dramatic improvement in the power of tests when bond return heteroskedasticity is corrected by standardizing bond returns by time-series standard deviations, based on returns 25 days before and after the event. The advantage of the Ederington, Guan and Yang (2012) method over Bessembinder, Kahle, Maxwell and

Xu (2007) method of measuring daily bond returns is that they consider the need to correct for heteroskedasticity by standardizing bond returns. Prices on long-term and low rated bonds are much more variable than prices on short-term and high rated bonds so there is considerable heteroskedasticity. The heteroskedasticity in bond returns is likely much more severe than for stocks since individual bonds' characteristics, such as term-to-maturity, credit ratings and liquidity, vary and prices are much more volatile on lower rated, long maturity, and illiquid bonds than on high rated, short maturity, and liquid bonds.

From Panels A and B of Table 18, abnormal standardized bond returns surrounding decreased on increased dividend announcements, on average, are not significantly different from zero. I further split firms' bonds into speculative and investment rating bonds. Panel A shows that abnormal bond standardized returns of speculative rating bonds around dividend decreases announcements are negative, but investment rating bond returns are positive. Both bond returns are not significantly different from zero. In the event window (-1, +1), the difference of bond returns (Spec-Investment) between speculative and investment rating bonds is negative. This supports the signaling hypothesis, which asserts that speculative bondholders suffer more losses than investment bondholders surrounding dividend decreases announcements. However, the evidence for signaling hypothesis is weak, given that the difference of bond returns is not significantly different from zero.

In Panel B, over a three-day event window surrounding an announcement of increased dividend, I find an abnormal bond standardized return of 20.63 (median of 16.54) percent for speculative rating bonds where the t-statistics and Wilcoxon sign-rank tests are statistically significant at the five percent level. In contrast, the return from investment rating bonds is negative and insignificant. The difference of the three-day abnormal bond standardized return between speculative and investment rating bonds is positive and statistically significant at the one percent level. The positive and significant difference remains across other event windows. The evidence is consistent with the signaling hypothesis, which predicts that speculative rating bonds should experience greater positive returns than investment rating bonds surrounding an increased dividend announcement. Consistent with my previous finding, signaling hypothesis holds for increased dividend announcements, but does not hold for decreased dividend announcements. Panel C stratifies the increased dividend sample by whether a dividend announcement is occurred before 2008 or after 2008. Consistent with my early finding of the difference of bond returns before and after 2008, bondholders earn larger positive returns surrounding the announcement of increased dividend after the 2008 financial crisis. In unreported regression results, the relationship between bond returns surrounding the announcement of increased dividend and the magnitude of increased dividend remains significantly positive, which is consistent with the finding in Table 17 when using Bessembinder, Kahle, Maxwell and Xu (2007) method to estimated abnormal bond returns.

6. Conclusions

Due to the poor quality and availability of bond price data, existing evidence on the effect of dividend announcements on bondholders is limited and mixed. I use the OTC bond transaction data from TRACE to explore the wealth effects of dividend change announcements on bondholders across a period from July 2002 to December 2010. In a large sample of dividend increases announcements, I find that the corporate bond market reacts positively to dividend increases announcements. The mean three-day abnormal bond return for dividend increases is 0.06 percent and statistically significant. Furthermore, dividend omissions can lead to an average three-day abnormal bond return of -0.38 percent that is statistically significant, which is consistent with the prediction of the signaling hypothesis that omitted dividends signal a pessimistic future of a firm.

Inconsistent with the implication of the signaling hypothesis that decreased (initiated) dividends signal a pessimistic (optimistic) future of a firm, bond market reactions to dividend decreases (initiations) announcements are not significantly different from zero. However, this is consistent with a wealth-transfer-signaling combination since the signaling and wealth transfer effects on bond prices tend to offset each other.

Consistent with previous studies, I find that stock markets react positively (negatively) and significantly to dividend increases (decreases) announcements. The dividend increases results suggest that the same inference on the influence of dividend increases announcements in the bond and stock markets can be explained by the signaling hypothesis rather than the wealth transfer hypothesis. Since the signaling and wealth transfer effects on stock prices tend to reinforce each other, the significantly negative stock market reactions to dividend decreases announcements are also consistent with a combination of signaling and wealth transfer hypotheses.

Lastly, consistent with the implications of the signaling hypothesis, the abnormal bond return is more positive for larger percentage dividend increases and among speculative grade bonds, which exhibits a significant three-day abnormal return of 0.22 percent. Consistent with the predictions of signaling hypothesis that positive signaling should be more apparent in turbulent periods and for financially good firms, I find that the bond market reaction to the announcement of an increased dividend is stronger for the period after 2008, and financially non-distressed firms. According to the signaling hypothesis, longer maturity bonds should experience greater positive returns than shorter maturity bonds surrounding dividend increases announcements. In contrast to the prediction, long-maturity bonds experience less positive returns surrounding the announcement of increased dividend.

Chapter 4: Pre-trade Transparency in Over-the-Counter Markets[63]

Over-the-counter (hereafter OTC) dealer markets are responsible for the operation of more than $1,000 trillion in financial assets, accounting for more than 90% of all value across financial asset classes.[64] This market is economically important, as less than $75 trillion worth of assets are traded annually across all stock markets and the annual GDP of the wealthiest nation (the United States) is less than $16 trillion. Given the significance of OTC markets, it is not surprising that extensive empirical literature exists on the transaction costs in these markets.[65] In OTC markets, it is important to obtain the best trade quote after searching for and negotiating with potentially fragmented liquidity providers. On the other hand, the availability of these quote information, which is defined as pre-trade transparency, is very limited to investors in OTC markets. Consequently, the search process can be potentially costly to investors in OTC markets because of the sequential search and bilateral bargaining that characterizes consummation of trades (Duffie, 2010; 2012). However, little evidence exists as to whether, and, if so, how, pre-trade transparency/opacity influences information search costs, and thus the transaction costs in OTC markets. This research helps fill this void in the literature.

Transparency is always an important element pertaining to market operations. While many have explored the importance and the consequences of bringing post-trade transparency to OTC markets, little research has been conducted to understand the

[63] This chapter is based on collaborative work with Zhuo Zhong.

[64] OTC markets consist of, for example, foreign exchange markets, markets for interest rate swaps, markets for credit default swaps, corporate and municipal bond markets.

[65] Bessembinder, Maxwell, and Venkataraman (2006), Goldstein, Hotchkiss, and Sirri (2007), and Edwards, Harris, and Piwowar (2007) for the U.S. corporate bond market; and Harris and Piwowar (2006) for the U.S. municipal bond market.

implications of pre-trade transparency in OTC trading. Post-trade transparency is often defined as the availability of trade information following a transaction, such as prices and volumes, whereas, pre-trade transparency is defined as the availability of information prior to a transaction, such as trade interest and quotations. OTC markets have come under intense scrutiny due to the lack of transparency during the 2008 financial crisis. In the crisis, the opacity of OTC markets made price discovery and liquidity very challenging. If more pre-trade transparency had been enforced, the situation might have been different. Furthermore, both regulators and practitioners view pre-trade transparency as equally important to post-trade transparency in OTC trading. In her keynote address in October 2010 at the National Association of Bond Lawyers 35th Bond Attorneys' Workshop, Elisse Walter, Chairperson of the Securities and Exchange Commission, said, *"Again, that is why I believe that improved pre-trade transparency is an important goal. Investors need better information and better access both to tap and provide liquidity in the market."*

Despite unanimous agreement on the importance of pre-trade transparency, practitioners differ on the perceived impact on the market. In March 2010, a survey report from the Association for Financial Markets in Europe showed that a third of traders believed greater pre-trade transparency would negatively impact liquidity.[66] However, in June 2010, a survey from the International Capital Market Association found that the majority of corporate bond market participants believed that pre-trade

[66] The survey was conducted on buy-side traders (not dealers). Source: *Financial News*. http://www.efinancialnews.com/story/2011-08-08/bond-trading-electronic-revolution

transparency was the most important measure to improve market liquidity.[67] These conflicting views about the perceived implications of pre-trade transparency help provide evidence that the effects are not mutually agreeable. This stark contrast in perception provides the basis for our question of whether, and, if so, how, an increase in pre-trade transparency will affect trading in OTC markets.

To guide our empirical research and explain the pre-trade transparency mechanism influencing OTC trading, we construct a search model, which is a specialized example of Zhong (2012). In the model, we consider traders' lack of pre-trade information as Knightian uncertainty. Unlike risk, where the odds of future states are known, Knightian uncertainty refers to the situation in which the odds of future states are unknown. Citing the lack of pre-trade information and the awareness of this deficiency in OTC markets indicates the vagueness of information possessed by traders, which gives credence to Knightian uncertainty in this search process. Our model shows that pre-trade information enhances a traders' willingness to search, which implicitly improves their bargaining capabilities. As a result, dealers have to lower their ask prices and increase their bid prices in order to secure trades. In other words, dealers have to compete for traders more aggressively. This results in not only smaller bid-ask spreads, but also less dispersion among bid-ask spreads.

[67] In the International Capital Market Association's report, 83% of survey respondents ranked pre-trade transparency as the most important measure for improving liquidity, compared with 57% who believed improvements in liquidity are best accomplished through post-trade transparency. ICMA said 41% of respondents to its survey were investors; 36% were sell-side firms, such as banks; 13% were companies involved in securities repurchase or lending; and the remaining 10% were companies such as exchanges, issuers, and underwriters. Source: http://www.icmagroup.org/assets/documents/Maket-Practice/Regulatory-Policy/MiFID-BMT/ICMA%20corporate%20bonds%20response%20to%20CESR%20FINAL%204June2010.pdf

We test our model implications through an empirical study on U.S. corporate bonds using the over-the-counter bond transaction data from TRACE. In the U.S., the majority of corporate bonds are traded in OTC markets, but some are traded on both OTC and NYSE markets. The NYSE's Bonds (previously known as the Automated Bond System) operates the largest centralized corporate bond market in the U.S. and is organized as an electronic limit order book system providing comprehensive pre-trade transparency. Thus, bonds traded on both OTC and NYSE markets are more pre-trade transparent relative to bonds that are only traded in OTC markets. Since we focus only on bond transactions occurred on the OTC market, the availability of the pre-trade quote, which is provided by the limit order book, is the only one relevant difference between these two groups of bonds in regards of trading environments. Bond traders benefit from the pre-trade quote information in NYSE Bonds since their bargaining power increases when they trade with dealers. Accordingly, the increases in bargaining power benefits bond traders on the OTC market by reducing their transaction costs.[68]

Based on this feature we conduct an observational study. First, we construct a group of bonds traded on both OTC and NYSE, identified as the OTC-NYSE group, and then we employ propensity score matching to identify a matched group of bonds that trade only in OTC, namely OTC-only group. Finally, we analyze the transaction costs, variances of transaction costs, and yields between these two groups. Consistent

[68] This is one possible explanation for lower transaction cost if we compare transaction costs in NYSE Bonds and OTC market directly. The lower transaction cost in NYSE Bonds could be the compensation that traders get for liquidity provision by posting limit orders on NYSE Bonds. In contrast, OTC transactions are more similar to a market order. The other alternative explanation of lower transaction cost on NYSE Bonds is the demand-based selection of trades. Hendershott and Madhavan (2014) find that electronic auctions are preferred for easier trades and in more liquid bonds. However, these two possible explanations do not apply to our finding since we only compare trading cost incurred on the OTC market, rather than the trading cost between the NYSE and OTC markets.

with our search model implications, we find smaller bond bid-ask spreads and smaller standard deviation of bid-ask spreads in the OTC-NYSE group compared to OTC-only group. Our findings are robust to a multitude of tests. In the univariate analysis, where bonds are matched by issuers, the OTC-NYSE group has on average 24 basis points smaller effective bid-ask spreads than the OTC-only group. The standard deviation of bid-ask spreads are also significantly smaller for the OTC-NYSE group of bonds. These findings are consistent across different rating categories. After acquiring a sample of OTC-only bonds with firm and bond characteristics similar to OTC-NYSE bonds via propensity score matching, the mean and standard deviation of bid-ask spreads of the OTC-NYSE group remain statistically and economically lower than the matched OTC-only group. The average effective bid-ask spread is 10 basis points lower on OTC-NYSE group of bonds. In our sample period from 2008 to 2011, OTC-only bond transactions between dealers and traders are roughly $1,058 billion per year. Therefore, if NYSE pre-trade transparency had been offered as part of OTC trading, traders would have saved approximately $1,058 million per year on transaction costs. A potential endogeneity issue for our empirical design of matching groups is that firms may choose to list bonds with smaller transaction costs on both OTC and NYSE markets. We address this concern with two-stage least square regressions utilizing a bond's listing probability as the instrumental variable, as suggested by Wooldridge (2002). Our regression results provide evidence that bonds' transaction costs, as measured by bid-ask spreads, are negatively correlated with the presence of NYSE pre-trade transparency with a p-value less than 0.01.

The reduction in bond transaction costs is also significant for sophisticated institutional traders. In a truncated sample, we focus specifically on institutional sized trades (trade size>$100,000) and find that bonds' bid-ask spreads are negatively related to whether a bond is listed on both OTC and NYSE. As institutional traders are likely to be informed traders (Anand, Chakravarty, and Martell, 2005), this suggests that improving pre-trade information favors traders over dealers. Pre-trade information is more likely to help traders enhance their bargaining capabilities than to help dealers to discern informed trading. If it were the latter that dominated, then we should observe a positive relation between bonds' bid-ask spreads and whether a bond is listed on both OTC and NYSE, which we did not.

Furthermore, NYSE pre-trade transparent bonds tend to have lower yields, suggesting that an improvement in pre-trade transparency causes a significant reduction in bond yields and thus adds value to bonds. Pre-trade transparency reduces bonds' transaction costs, thereby increasing bonds' liquidity. The increase of bond value associated with improving pre-trade transparency is the premium of improved liquidity.

We are aware of other three recent papers that has examined the impact of trade transparency on transaction costs in the U.S. corporate bond markets (Bessembinder, Maxwell and Venkataraman, 2006; Edwards, Harris and Piwowar, 2007; and Goldstein, Hotchkiss and Sirri, 2007). Employing a sample of institutional trades in corporate bonds, Bessembinder, Maxwell and Venkataraman (2006) find a reduction of trade execution costs for both TRACE eligible and non-eligible bonds after the introduction of the TRACE reporting system on July 1, 2002. The reduction for TRACE eligible bonds is more than twice as big as the TRACE non-eligible bonds. Using a comprehensive record of OTC corporate bond transactions, Edwards, Harris and Piwowar (2007) document a significant decrease of bond transaction costs after the TRACE reporting system was initiated. Goldstein, Hotchkiss and Sirri (2007) find that, depending on the trade size, the impact of last-sale trade (belonged to the TRACE reporting system), has either a neutral or a positive effect on BBB corporate bonds' liquidity, as measured by estimated bid-ask spreads.

Our paper differs from these recent papers in the following aspects. First, these studies use the introduction of TRACE reporting system to test the relation between corporate bonds trading and market transparency. More specifically, they focus on the influence of improving post-trade transparency, which is the release of transaction information following a trade. However, the focus of both our theoretical model and empirical study is on the influence of improving pre-trade transparency, which is the release of quote information. Given the bilateral trading nature in over-the-counter market, it is more critical to examine whether and if so, how the pre-trade transparency impacts transaction costs in OTC market. Second, Edwards, Harris, and Piwowar (2007) show a regression result that listing on the NYSE can reduce bonds' transaction costs, but they do not discuss it in details nor adjust for the endogeneity problem as it is not the focus of their paper. Given the importance of pre-trade transparency their result should be further explored. We extend their paper by resolving the endogeneity issue with the propensity score matching method and an instrumental regression. Lastly, we show that the improved pre-trade transparency in corporate bond markets favors traders over dealers as both volatility of bid-ask spreads and institutional sized trades' bid-ask spreads decrease, indicating more competition among dealers and that potential informed traders face smaller bid-ask spreads.

The next section provides a review of related literature. Section 2 presents the model of the search equilibrium in an OTC market. In Section 3, we conduct an empirical study on the corporate bond market to test the implications of our model. Sections 4 and 5 provide further discussions of our paper's implications. Finally, Section 6 concludes the paper.

1. Related Literature

Our paper adds to the literature on the relationship between pre-trade transparency and market quality. This relationship is important to the design of markets since it provides implications on market liquidity, informational efficiency, intermarket competition, and ultimately the welfare of market participants. However, academia has yet to reach a consensus on major issues in these areas. Baruch (2005) develops a model in which liquidity demanders and suppliers have differing degrees of access to the limit order book. The model predicts that liquidity demanders benefit from access to the book while liquidity suppliers benefit when the book is closed. Boehmer, Saar, and Yu (2005) find that the introduction of the NYSE's OpenBook service, which provides limit order book information, decreases the price impact of orders and improves the informational efficiency of prices. Eom, Ok, and Park (2007) find that market stability and informational efficiency of the price are improved when the Korea Exchange increases the number of publicly disclosed quotes. On the other hand, Madhavan, Porter, and Weaver (2005) find that increased pre-trade transparency leads to higher trading costs and volatility after the Toronto Stock Exchange disseminated real-time information on its limit order book to the public.

In addition to empirical and theoretical studies, the influence of pre-trade transparency has been investigated via experimental studies. Bloomfield and O'Hara (1999) show that pre-trade transparency has no impact on informational efficiency, bid-ask spreads, and trader welfare. Whereas Flood, Huisman, Koedijk, and Mahieu (1999) conclude that pre-trade opacity leads to more dispersed opening spreads and lower trading volume due to higher search costs. However, higher search costs result in much faster price discovery due to induced aggressive pricing strategies. In an experimental multiple-dealer market, Flood, Koedijk, van Dijk, and van Leeuwen (2002) show that pre-trade transparency reduces price efficiency and improves market liquidity, measured by dealers' bid-ask spreads. Despite fruitful yet divergent views in previous studies, there is no actual empirical evidence regarding the impact of pre-trade opacity in OTC financial markets on liquidity. Our paper fills this gap by comparing the mean and standard deviation of bid-ask spread of bonds traded in OTC-only markets with the bid-ask spread of bonds traded in both OTC and NYSE markets.

In contrast to past studies on post-trade transparency in the corporate bonds market, our paper focuses on the pre-trade transparency. Previous research focuses on the release of the TRACE data as a natural experiment and finds that transparency improves the OTC market's liquidity (see Bessembinder, Maxwell, and Venkataraman, 2006; Edwards, Harris, and Piwowar, 2007; and Goldstein, Hotchkiss, and Sirri, 2007). TRACE contains only information related to traded prices but doesn't contain information regarding quotes (pre-trade information), therefore, studies using TRACE focus specifically on post-trade transparency. Our paper adds new evidence on the impact from improving pre-trade transparency on the corporate bonds market. Carrion (2009) shows that bond trading costs on NYSE are lower than OTC markets, which is a market with greater pre-trade transparency. However, the lower bond trading costs on NYSE could also be attributed to the improvement of post-trade transparency on NYSE markets. The difference in bond trading costs between NYSE bonds and OTC bonds may also depend on unobserved bond or firm characteristics related to whether or not firms choose or are chosen to list bonds on the NYSE. Using TRACE bond transaction data, we compare the difference of OTC transaction costs between bonds traded on both the OTC and NYSE markets, and only on the OTC markets. We address any endogeneity concerns by employing propensity score matching methodologies and two-stage least square regressions.

Theoretical models on OTC market microstructure are based on the search modeling. Seminal work includes Duffie, Garleanu, and Pedersen (2005, 2007), which shows that the search cost determines the bid-ask spread in an OTC market. Further work includes Weill (2007), Vayanos and Weill (2008), Lagos and Rocheteau (2009), Rocheteau and Weill (2011), Afonso (2011), and Lagos, Rocheteau, and Weill (2011). Zhu (2011) constructs a search model where traders face contact-order uncertainty to examine how transparency affects OTC trading. Consistent with the model implication, we find pre-trade transparency results in lower US corporate bond transaction costs, which is one measure of bond market liquidity.

2. The Search Equilibrium in the OTC Market

To illustrate how pre-trade transparency affects OTC market's liquidity, we provide a close form example of the general model in Zhong (2012). Zhong (2012) models opacity as Knightian uncertainty faced by traders to study the relation between transparency and OTC market's liquidity. Our model is a special example with investors and dealers having different discount rates for future.

In a simple exchange economy where the dealer is the only intermediary, there are three types of agents: buying traders, selling traders, and dealers. Traders are heterogeneous in their internal valuations ν: more specifically, ν^B for the buyer and ν^S for the seller, both of which follow the uniform distribution over $[0, 1]$. Dealers are heterogeneous in transaction costs k, which follow the uniform distribution over $[0, 1]$. We do not model the heterogeneity among traders explicitly. This assumption is a reduced description of various reasons that prompt traders to trade. Transaction costs are expenses incurred by dealers in maintaining preferred inventory levels, as noted in the inventory literature.[69] These costs are different from transaction costs faced by traders. Traders' transaction costs are mark-ups which are dealers' profit margin in OTC trading. Due to different risk capacities, dealers' preferred inventory positions also differ, which implies heterogeneity in transaction costs among dealers. In addition, transaction costs also include operational fees or the expense of innovating financial products.[70] Thus, the heterogeneity in dealers' transaction costs can be interpreted as the

[69] See Amihud and Mendelson (1980) for specifics concerning preferred inventory levels.
[70] Unlike equity trading, in which traded assets are standardized, most OTC markets are for trades of customized products. Making a market for those tailored products requires professional knowledge and special training, both of which could incur a substantial cost. In addition, dealers sometimes create an OTC market by inventing a new financial product. The considerable expenses associated with innovation

variation among dealers in professional knowledge and special training in facilitating trades. Assuming the dealer is the only intermediary captures the essence of the OTC market: there is no central exchange where assets are traded publicly. In the OTC market, the only way for traders to obtain quotes is to contact individual dealers—specifically, one randomly picked dealer for every round of contact. Thus, transactions in the OTC market are carried out over a range of individually negotiated prices resulting from a costly sequential search process.

The dealer is infinitely lived and sets bid and ask prices to maximize expected profit. Traders, who have max-min preferences, engage in the sequential search process with Knightian uncertainty. Knightian uncertainty arises from lack of transparency in the OTC market. Opacity of the OTC market makes traders search without knowing the distribution of dealers' quotes. This process resembles the Ellsberg (1961)'s experiment, in which decision makers make decisions without knowing the distribution of balls in the urn. We use the ϵ-*contamination* to model Knightian uncertainty. Specifically, the set of priors available to traders is an ϵ-*contamination* of the historical distributions over bid and ask prices.[71] In particular, for any given ϵ, the buyer is endowed with the following set of priors,

$$\boldsymbol{P^B}(\epsilon) \equiv \{(1-\epsilon)P_a + \epsilon\mu : \mu \in \boldsymbol{M}\}, \qquad (1)$$

where P_a is the historical distribution of ask prices and $\boldsymbol{M}$ is the set of all probability measures on the Borel set of real numbers. Sellers are endowed with the following set

are partially covered by bid-ask spreads that dealers charge when intermediating trades over the new product.

[71] The ϵ-*contamination* refers to the procedure of introducing a set of priors by contaminating a single hypothetical prior with an ϵ probability ball around it. To be more specific,

$$\boldsymbol{P}(\epsilon) \equiv \{(1-\epsilon)P_0 + \epsilon\mu : \mu \in \boldsymbol{M}\},$$

where P_0 is the hypothetical prior and μ is any probability distribution in the relevant space.

of priors,

$$\boldsymbol{P^S}(\epsilon) \equiv \{(1-\epsilon)P_b + \epsilon\mu : \mu \in \boldsymbol{M}\}, \tag{2}$$

where P_b is the historical distribution of bid prices and $\boldsymbol{M}$ is the set of all probability measures on the Borel set of real numbers. In either $\boldsymbol{P^B}(\epsilon)$ or $\boldsymbol{P^S}(\epsilon)$, when ϵ is zero, the set consists of a unique prior, which means no Knightian uncertainty; as ϵ becomes larger, the level of Knightian uncertainty increases. As Knightian uncertainty represents the lack of transparency, ϵ measures the degree of transparency in OTC trading. Specifically, when the OTC market is fully transparent, traders face no Knightian uncertainty in their searches, i.e., ϵ is zero; when the OTC market becomes less transparent, traders face larger Knightian uncertainty, i.e., ϵ increases; and when the OTC market becomes completely opaque, traders face enormous Knightian uncertainty, i.e., ϵ equals one. This ϵ-contamination specification not only measures the OTC market transparency with its radius ϵ, but also incorporates historical ask and bid price information with its core P_a and P_b elements, respectively. In other words, traders construct their priors by contaminating the distributions of historical prices and how severely they contaminate the distributions depends on the transparency of the OTC market. We restrict both buyers and sellers to face the same level of Knightian uncertainty because we use Knightian uncertainty as the description of the trading environment rather than the source of heterogeneity among OTC traders. Traders discount future payoffs with β, and dealers discount future payoffs with $\beta\rho$.

To obtain the close form solution of the model, we let $\rho = \frac{1-\epsilon}{1-\beta\epsilon}$. This assumption does not alter model implications under the general setting (see Zhong (2012) for the general model).

2.1. The Trader's Decision

For any given ϵ, a buyer is trying to maximize his or her minimal expected future payoff,

$$\min\{\int I(a)dP : P \in \boldsymbol{P^B}(\epsilon)\}, \tag{3}$$

where $I(a)$ is the discounted future payoff. More specifically, $I(a) = \beta^t(v^B - a)$ if he or she trades at time t, or zero otherwise. That is,

$$I(a) = \begin{cases} \beta^t(v^B - a), & \text{if he or she trades at time } t; \\ 0 & , \text{ otherwise.} \end{cases} \tag{4}$$

According to Zhong (2012), traders' optimal trading strategies have the optimal stopping rule property. Specifically, a buyer, who values the asset at v^B, buys when the ask price is below his reservation buying price $r^B(v^B)$. Otherwise, the buyer keeps searching. The reservation buying price is

$$v^B = r^B(v^B) + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{a}}^{r^B(v^B)} P_a[a \leq \hat{a}]d\hat{a}. \tag{5}$$

Similarly, a seller, who values the asset at v^S, sells when the bid price is above his reservation selling price $r^s(v^s)$. And the seller continues to search in other cases. The reservation selling price is

$$v^S = r^S(v^S) - \frac{\beta(1-\epsilon)}{1-\beta}\int_{r^S(v^S)}^{\overline{b}} P_b\big[b \geq \hat{b}\big]d\hat{b}. \tag{6}$$

In the above, $\underline{a}$ is the minimal ask and $\overline{b}$ is the maximal bid.

2.2. The Dealer's Decision

A dealer posts a pair of stationary bid and ask prices to maximize his expected discounted profits. The dealer is constrained by keeping expected supply equal to expected demand because the dealer wants to maintain his preferred inventory level. This assumption that dealers carry no inventory across successive periods is extensively used in past studies on OTC trading.[72]

As N is the total mass of dealers operating in the market, $\frac{1-\underline{\nu}^B}{N} f^B(r^B)$ represents the density of buyers for every dealer. The number of buyers visiting the dealer who have reservation price r^B is as follows: 1 at date 0, $P_a[a \geq r^B]$ at date 1, $P_a^2[a \geq r^B]$ at date 2, ..., $P_a^t[a \geq r^B]$ at date t. If the dealer sets the ask to a, then the market demand at time t is

$$D_t(a) = \frac{1-\underline{\nu}^B}{N} \int_a^{r^B(1)} P_a^t[a \geq r^B] f^B(r^B) dr^B = \tag{7}$$

$$\frac{1}{N} \int_a^{r^B(1)} \frac{\left(1-F_a(r^B)\right)^t (1-\beta+F_a(r^B)(1-\epsilon)\beta)}{1-\beta} dr^B,$$

where $f^B(r^B)$ is the density of reservation buying prices

$$f^B(r^B) = \frac{1-\beta+F_a(r^B)(1-\epsilon)\beta}{(1-\beta)(1-\underline{\nu}^B)}. \tag{8}$$

In the above, F_a is the cumulative density function of ask prices.

By an analogous derivation, the date t supply associated with the bid price b is

$$S_t(b) \tag{9}$$

$$= \frac{1}{N} \int_{r^s(0)}^{b} \frac{F_b^t(r^S)\left(1-\beta+\left(1-F_b(r^S)\right)(1-\epsilon)\beta\right)}{1-\beta} dr^S.$$

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[72] The same assumption is made in Spulber (1996), Rust and Hall (2003), Duffie, Garleanu, and Pedersen (2005; 2007), and Lagos and Rocheteau (2009).

And F_b is the cumulative density function of bid prices.

Given demand $D_t(a)$ and supply $S_t(b)$, the dealer's objective is

$$\max_{a,b} \sum_{t=0}^{\infty} (\beta\rho)^t \big(aD_t(a) - (b+k)S_t(b)\big), \tag{10}$$

subject to

$$D_t(a) = S_t(b). \tag{11}$$

2.3. The Stationary Search Equilibrium

Propostion 1 characterizes the stationary search equilibrium in the OTC market.

Proposition 1

When $\rho = \frac{1-\epsilon}{1-\beta\epsilon}$, for any given ϵ, there exists a continuously differentiable symmetric equilibrium pricing policy, $a(k), b(k)$, with $a(k)$ increasing and $b(k)$ decreasing in k for all $\underline{0} \leq k < k^*$, where k^* denotes the marginal dealer whose profit is zero. Pricing policy functions are

$$a(k) = \frac{k}{4} + \frac{k^*}{4} + \frac{1}{2}, \tag{12}$$

$$b(k) = 1 - a(k), \tag{13}$$

$$k^* = \frac{4-4\beta}{4-3\beta-\beta\epsilon} \tag{14}$$

The spread, $a(k) - b(k)$, increases with k.

In the equilibrium, traders adopt an optimal search strategy (equations (9) and (10)) based on dealers' pricing strategies, and dealers maximize their profits based on traders' search strategies. In the equilibrium, traders' predictions of prices—that is, traders' sets of priors—systematically deviate from equilibrium prices, and the deviation is characterized by the ϵ-*contamination* of the equilibrium price. The systematic deviation depends on the transparency of the OTC market. When the OTC market is fully transparent, our equilibrium becomes the equilibrium obtained in Spulber (1996) as traders' sets of priors implode to singletons, which are equilibrium prices.

In Proposition 1, the spread is wider for the dealer with higher transaction costs. This coincides with the empirical findings in Li and Schürhoff (2012) and Hollifield, Neklyudov, and Spatt (2012), in which they show that inefficient OTC dealers charge wider spreads.

2.4. Comparative Statics

In this section, we perform comparative statics with respect to the change of transparency level, ϵ, on the equilibrium..

<u>Proposition 2</u>

For any $\epsilon_0, \epsilon_1 \in [0,1]$, if $\epsilon_0 < \epsilon_1$, then for any $k \in \left[0, \frac{4-4\beta}{4-3\beta-\beta\epsilon_1}\right)$, $a(k)|^{\epsilon_0} < a(k)|^{\epsilon_1}$ and $b(k)|^{\epsilon_0} < b(k)|^{\epsilon_1}$. Let $F_a^{\epsilon_0}$ and $F_a^{\epsilon_1}$ be the cumulative distribution function of the ask when $\epsilon = \epsilon_0$ and $\epsilon = \epsilon_1$, respectively, and let $F_b^{\epsilon_0}$ and $F_b^{\epsilon_1}$ be the cumulative distribution function of the bid when $\epsilon = \epsilon_0$ and $\epsilon = \epsilon_1$, respectively. If $\epsilon_0 < \epsilon_1$, then $F_a^{\epsilon_1}$ first order stochastically dominates $F_a^{\epsilon_0}$, $F_b^{\epsilon_0}$ first order stochastically dominates $F_b^{\epsilon_1}$.

<u>Proposition 3</u>

The average spread increases in ϵ.

Proposition 4

The variance of the spread increases in ϵ.

Proposition 2 indicates that dealers in a more transparent market (smaller ϵ) charge lower ask prices and higher bid prices. As a result, the average spread in the OTC market decreases as the market becomes less opaque (see Proposition 3). In addition, the variance of the spread in the OTC market also decreases with more transparency (smaller ϵ, see Proposition 4). The shrinking bid-ask spread and variance of the spread are due to the change in traders' perceptions of their outside options. When the OTC market becomes more transparent, traders are more certain about their search processes, which enhances their confidence in finding better offers from dealers. Thus, traders are more willing to search. In other words, traders have increased their bargaining power as they now have better access to bid and ask quotes. As a result, dealers in the more transparent market have to compete more aggressively to secure trades, which leads to smaller and less disperse spreads. Proposition 5 reflects traders' willingness to search as traders reservation buying prices decrease and reservation selling price increase. Proposition 6 shows that competition among dealers escalates as fewer dealers are acting in the equilibrium.

Proposition 5

For any $\epsilon_0, \epsilon_1 \in [0,1]$, if $\epsilon_0 < \epsilon_1$, then for any $v^B \in \left(\frac{1-\beta}{4-3\beta-\beta\epsilon_1} + \frac{1}{2}, 1\right]$, $r^B(v^B)|^{\epsilon_0} < r^B(v^B)|^{\epsilon_1}$, and for any $v^S \in \left[0, \frac{1}{2} - \frac{1-\beta}{4-3\beta-\beta\epsilon_1}\right)$, $r^S(v^S)|^{\epsilon_0} > r^S(v^S)|^{\epsilon_1}$.

Proposition 6

k^*, which measures the equilibrium population of dealers, is strictly increases in ϵ.

Though the implication on transaction costs is the same, there is advantage on modeling opacity with Knightian uncertainty rather than directly assuming traders experience higher search cost in a less transparent market. Our approach, which is more complicated, is able to explain the channel of how opacity in a market factors into traders increasing search cost. Opacity increases traders' model uncertainty in search. Then, the larger model uncertainty implicitly factors into traders' search cost, which reduces traders' patience in search, thereby increasing transaction costs in equilibrium.

3. An Empirical Study on the Corporate Bond Market

In section 1, our search model illustrates that pre-trade transparency affects OTC trading through enhancing traders bargaining capability. We test the empirical implications resulting from the model. More specifically, we conduct an empirical analysis on the corporate bond market to test if the average and standard deviation of bid-ask spread decrease as pre-trade transparency increases (see Propositions 3 and 4).

3.1. Data and Sample

Our initial sample ranges from November 1, 2008, to March 31, 2011, and includes 40,977 bonds with 26,658,403 trades and $7.6 trillion of volume. Firm characteristics data is obtained from COMPUSTAT, bond transactions data from the Trade Reporting and Compliance Engine (TRACE), and bond characteristics data from the Mergent Fixed Income Securities Database (FISD). An important file for the analysis is the "ISSUE EXCHANGE" master file that is retrieved from FISD. This file documents the exchange(s) (if any) where the bonds are listed. For a debt security to be listed on the NYSE, the debt issue must have a minimum market value or principal amount of $5,000,000. Additionally, the debt security must have an investment grade rating to a senior issue or a rating that is no lower than an S&P rating of "B". The credit rating is not required if the issuer of the debt security has equity securities listed on the NYSE. Through June 30, 2011, all bonds listed on NYSE Bonds are subject to an initial listing fee of $15,000. Effective July 1, 2011, all bonds listed on NYSE Bonds are subject to an initial listing fee of $5,000 and an annual listing fee of $5,000. According to NYSE Bonds trading guideline, any debt securities listed on the NYSE are eligible to trade on NYSE Bonds trading platform.[73] Hence, we are able to identify OTC traded bonds also traded on the NYSE. Since TRACE reports trades with very few bond characteristics, Mergent's FISD database is employed to secure comprehensive bond attributes, such as coupon, maturity, and ratings. FISD reports an exhaustive list of 35,779 bond characteristics that are available. Table 19 describes the sample selection procedure.

We filter the data by eliminating 739 put-able bonds, 869 bonds with abnormal prices (prices greater than $200 or less than $10), bond trading with subsequent corrections, bonds' trading side are not indicated, and bond trading affected by price reversions.[74] To exclude rarely traded bonds, we require the bond trade at least 9 times during the sample period, which eliminates 8,287 bonds from our sample. These filtering conditions leave a sample of 25,884 bonds and 24,958,872 trades. To compute

[73] http://www.nyse.com/bonds/nysebonds/1095449059236.html

[74] Note the bond return from time t to time $t+1$ as R_t^{t+1}; a price reversal happens if $R_{-1}^{0} < -10\%$ and $R_0^1 > -0.5R_{-1}^{0}$ or if $R_{-1}^{0} > 10\%$ and $R_0^1 < -0.5R_{-1}^{0}$. We adjust our filter rule from Bessembinder, Kahle, Maxwell, and Xu (2009). Bessembinder et al. (2009) define large return reversals as 20% or more price change which is reversed over 20% in the next observation. Our results are qualitatively the same when applying their rules to our sample.

same-bond-same-day effective bid-ask spreads, we further require bonds to have at least one buy and one sell transaction within a day as in Hong and Warga (2000), Chakravarty and Sarkar (2003) and Goldstein, Hotchkiss and Sirri (2005). Bonds that cannot be identified in the "ISSUE EXCHANGE" master file are also excluded from the sample. Lastly, we drop all interdealer transactions and bonds listed on an exchange other than the NYSE.[75] The final sample used for the empirical analysis contains 20,857 bonds responsible for 13,475,170 trades and roughly $4.4 trillion of volume. Table 20 provides descriptive statistics for the 20,857 bonds in the sample.

The average (median) bid-ask spread is 97 (100) basis points. 66% (6%) of bond issuers are classified as finance (utilities), though bond issuers are from a wide array of industries. Thus, we partition the bonds into three industry categories: Finance, Utilities, and Other for the multiple regression analysis. Private companies are able to issue publicly traded debt if they satisfy disclosure requirements similar to public companies. We identify public companies by matching the issuer's CUSIP in TRACE to equity's first 6-digit NCUSIP in the Center for Research in Security Prices (CRSP) data set.[76] In aggregate, we classify only 14.3% of sample bonds are issued by private firms. The mean (median) maturity of the sample bonds is 11.8 (10.0) years.

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[75] The empirical results are not affected at all even if we include those bonds listed on exchanges other than the NYSE, e.g., the Frankfurt Stock Exchange and the Luxembourg Stock Exchange.

[76] Unlike CUSIPs for stocks, CUSIPs for bond is somehow permanent. Cusip for issuer could be changed through the time, for many reasons, such as a slight change in company name. However, when issuers changed their name, the cusips for their bonds will not change (cusips for their stocks will change though.) In Mergent, issuer_cusip reflects the historical value. In CRSP, NCUSIP is a security's historical cusip.

3.2. The Estimation of Effective Bid-ask Spreads

The relation between transparency and liquidity is a pertinent issue in bond markets. In this paper, we investigate whether greater transparency in the corporate bond market with respect to pre-trade quote information leads to better liquidity as measured by lower bid-ask spreads. Since the quotation data for corporate bond trading is generally unobtainable, we are forced to estimate effective bid-ask spreads using transaction records. Hong and Warga (2000), Chakravarty and Sarkar (2003), and Goldstein, Hotchkiss and Sirri (2005) all calculate the "traded bid-ask spreads" over a one-day window in the corporate bond market. Specifically, this approach takes the average of the differences between selling prices and buying prices on the same day as the effective bid-ask spread. We estimate the effective bid-ask spread for a particular bond as the time series average of its traded bid-ask spreads in a one-day window. The traded bid-ask spread is the difference between the average daily selling price and average daily buying price divided by their sum:

1. Denoting i to each individual bond and t to time periods, we have

$$Spread_{it} = \frac{\overline{Sell}_{it} - \overline{Buy}_{it}}{\overline{Sell}_{it} + \overline{Buy}_{it}}, \tag{15}$$

where $\overline{Sell}_{it}$ and $\overline{Buy}_{it}$ are the average daily selling price and buying price, respectively.

2. Taking the time series average of $Spread_{it}$, we have

$$Spread_i = \sum_{t=1}^{T_i} \frac{Spread_{it}}{T_i}, \tag{16}$$

where T_i is the time length of the bonds in our sample.

3.3. The Empirical Design to Test Pre-trade Transparency in Corporate Bond Markets

Though the OTC market of corporate bonds has achieved greater post-trade transparency since the unveiling of the TRACE reporting system on July 01, 2002, the market still lacks of pre-trade transparency. There is no centralized and extensive report of pre-trade information such as real-time quote data in this market before NYSE Bonds is introduced. There are some potential data sources providing quote data, like proprietary market information vendors (e.g., Bloomberg Trade Order Management Solutions (TOMS)) or private electronic trading networks (e.g., Tradeweb, MarketAxess, Goldman Sachs GSessions, and BlackRock Aladdin Trading Network). These data sources are fragmented and have other limitations. For example, GSessions only operates each Tuesday and Thursday, in two five-minute sessions each day. The quotes provided in these systems are representative rather than firm. The depth at each quote is not informative to investors and investors are not identical since it is costly to purchase access to these trading systems.

In contrast to the OTC market's bilateral trading feature, NYSE Bonds is the largest centralized corporate bond market in the U.S. functioning through an electronic limit order book system.[77] The NYSE Bonds trading platform, where corporate bonds are traded, provides real-time full market-by-order depth, best limit quotes, and trades to all its participants. Pre-trade pricing data on individual corporate bonds is updated every 10 seconds. Firm and executable bids and offers entered by members or

[77] The NYSE conducts two daily bond auctions – an Opening Bond Auction at 4:00 a.m. ET and a Core Bond Auction at 9:30 a.m. ET. Orders not executed in either auction become eligible for continuous trading immediately after the auction.

sponsored participants are displayed on a full order book (NYSE BondBook) with full depth of market. On NYSE BondBook, there are no subject quotes and all quotes are firm. Orders are matched on a strict price-time priority basis. NYSE Bonds also adopts a Bonds Liquidity Providers (BLPs) program to maintain liquidity. Liquidity providers are obligated to maintain: 1) a bid at least 70% of the trading day in each of its assigned BLP bonds; 2) an offer at least 70% of the trading day in each of its assigned BLP bonds; 3) a bid or offer at the Exchange's Best Bid or Exchange's Best Offer at least 5% of the trading day in each of its assigned BLP bonds in the aggregate. The program currently covers over 2,800 debt securities issued by approximately 560 corporate issuers. Furthermore, to increase investor participation, the trading platform provides a variety of order types, cost-effective order executions, and equal access for bond investors to trading information. Undisplayed reserve interest will always yield to displayed orders at a particular price. All orders will only be matched with orders resident in the order book. Bonds are traded in decimal increments to two decimal digits.

The NYSE Bonds system provides the opportunity to test if pre-trade transparency has any effect on OTC trading. We design an observational study by constructing two groups of bonds. The first group, which is the treatment group identified as the OTC-NYSE group, consists of bonds traded on both OTC and NYSE markets. The second group, which is the control group classified as the OTC-only group, consists of bonds traded only in the OTC market. The objective is to compare effective bid-ask spreads and variance of the effective bid-ask spread between these two groups. As with all observational studies, our main challenge in drawing conclusions from this comparison is the endogeneity problem, as the assignment of bonds into the treatment and the control groups is not random. That is, the difference in bid-ask spreads between the OTC-NYSE and OTC-only group may depend on unobserved bond or firm characteristics related to whether or not firms choose or are chosen to list bonds on the NYSE. Sample selection bias could lead to biased estimates of the pre-trade transparency effect, which can provide favorable conclusions. Therefore, we need to control for the endogeneity that bonds with smaller spreads are chosen by their issuers to trade on both OTC and NYSE markets. We address this concern in the next section. Based on our model implications in propositions 3 and 4, below is our null hypothesis.

Hypothesis 1 The average and standard deviation of effective bid-ask spreads in the OTC-NYSE group are smaller than the average and standard deviation of effective bid-ask spreads in the OTC-only group.

3.4. Empirical Results on the Difference in Bid-ask Spreads between Bonds with and without NYSE Pre-trade Information

In this section, we report univariate and regression results of comparing the mean and standard deviation of bid-ask spreads of the OTC-NYSE and the OTC-only group. We address sample selection bias in several different ways. First, we focus on bonds issued by the same firm to control for firm characteristics. Second, propensity score matching is used to reduce selection bias by equating the OTC-NYSE and OTC-only group of bonds based on individual firm and bond characteristics. The advantage of this method is the ability to compare the difference in the mean and standard deviation of bonds' bid-ask spreads between OTC-NYSE and OTC-only bonds when controlling for firm and bond characteristics. Finally, we conduct multiple regression analysis to examine the statistical significance of the relationship between the NYSE pre-trade transparency and the size of bond bid-ask spreads. Estimates are provided for two-stage least squares estimation with the probability of listing bonds on the NYSE as the instrumental variable. We find consistent results for all the procedures above. Our results suggest that pre-trade transparency reduces the mean and standard deviation of effective bid-ask spreads in corporate bond trading. This result is consistent with hypothesis 1 and theoretical model implications discussed in the previous section.

In Table 21, we compare the average effective bid-ask spreads of bonds issued by the same firm. The number of bonds varies due to the availability of variables. The number of non-investment-grade bonds is significantly smaller than the number of investment-grade bonds in both groups. This is consistent with the notion that rating agencies are more willing to assign investment ratings to corporate bonds.

Results provided in Table 21 support our theoretical prediction that the pre-trade transparency helps reducing the mean and standard deviation of bid-ask spreads. For the total sample in Table 21, the average bid-ask spread for OTC-NYSE group bonds is 24 basis points lower than those of OTC-only group bonds, and the difference is statistically significant (p-value=0.00). In addition, we obtain consistent results across different credit rating categories. We find that the difference in the bid-ask spreads of non-investment-grade bonds is 51 basis points, which is much greater than the difference in superior bonds (difference of 22 basis points) and other investment-grade bonds (difference of 20 basis points). Both differences are significant with p-values less than 0.01. This suggests that the reduction of bid-ask spreads is more evident for low-credit-rating bonds relative to high-credit-rating bonds. In addition, we also find the same pattern for the standard deviation of bid-ask spreads. On average, the standard deviation is significantly smaller for OTC-NYSE bonds than OTC-only bonds across different rating categories in Table 21.

The number of bonds within the OTC-only bonds in Table 21 is far greater than that of OTC-NYSE bonds, suggesting that fewer bonds are traded on the NYSE than in OTC markets. Also, the coupon rate between the OTC-only group and OTC-NYSE group differs dramatically. It could be that firms choose bonds that are more liquid to trade on the NYSE. These findings suggest that the lower level and standard deviation of bid-ask spreads for OTC-NYSE group of bonds may be due to the significant difference of bond characteristics between the two groups. To compare the difference of bid-ask spreads between these two groups of bonds when controlling for both bond and firm features, we use propensity-score matching.

We utilize propensity-score matching to acquire a sample of bonds with characteristics similar to the bonds traded both in OTC markets and on the NYSE for the sample. First, we run logistic regressions to determine which factors influence firms' listing decisions. Using the estimated coefficients, we can obtain the predicted probability (propensity score) for each bond. Then we match each OTC-NYSE bond to an OTC-only bond based on the closest propensity score. Table 22 presents results of the logistic regressions and propensity-score matching.

We attempt to model firms' bond listing decisions from two avenues: firm characteristics and bond features. There has been no research on how firms decide to list bonds on the NYSE versus in OTC markets. Thus, we construct our model based on basic intuition and on studies of foreign firms' preferences on the U.S. bond market. We control for the following firm characteristics: size, leverage ratio, equity listing status, and accounting standard. The equity listing status of a firm affects bond listing choice since private firms are less likely to list bonds on the NYSE as they fail to meet the strict disclosure requirements imposed by the exchange. In addition, cross listing studies show that foreign firms listing equities on U.S. stock exchanges are more likely to choose the U.S. bond market (see Miller and Puthenpurackal (2002)). For the accounting standard, Gao (2011) shows that firms adopting International Financial Reporting Standards prefer the U.S. public bond market. Bond features, which complicate the valuation of bonds, may also affect a firm's listing decisions. For example, retail investors, who dominate the NYSE, may prefer a fixed rate bond to a variable one. This clientele effect can impact firms' decisions as to whether or not to list their bonds on the NYSE. In Appendix F, we present our variables of choice and their definitions.

Panel A in Table 22 provides our logistic regression results of firms' decisions to list bonds on the NYSE. The dependent variable is binary in nature with a value of 1 if a bond is listed on the NYSE and 0 otherwise. We find that firms who choose to list bonds on the NYSE are small firms or highly leveraged firms. Small or highly leveraged firms should experience more difficulty selling bonds in the debt market than large or low leverage firms. For instance, small firms have poorer information disclosure and less coverage than large companies (see Lang and Lundholm (1993, 1996)). This could increase the costs for small firms raising funds solely from OTC markets. Higher leverage firms pose greater risks to bond investors than low leverage firms. Therefore, these firms may attempt to promote the sale of their bonds by listing bonds both on the NYSE and in OTC markets to reach a greater number of investors. Gao (2011) finds that firms adopting International Financial Reporting Standards prefer to list bonds on the U.S. public bond market but she does not specify whether it is in OTC markets or on the NYSE. To investigate whether firms' accounting standards impact firms' listing choice in bond markets, we assign a dummy variable to firms adopting International Financial Reporting Standards in the logistic regressions. In Panel A of Table 22, we find that accounting standards have a positive effect on the choice to list debt on the NYSE given that both two coefficients are positive and highly significant. This result signifies that firms adopting International Financial Reporting Standards are more likely to list their bonds on the exchange. Bond issuers' industry category may affect bond-listing choice. Bond issuers in the utilities industry tend to issue bonds in the exchange, while issuers in the finance industry tend to issue bonds in the OTC markets.

The effect of a firm's equity listing status on debt listing choice is mixed. Signs of the coefficients for the dummy variable of when a firm is a private firm are contrasting in the logistic regressions. We are also interested in whether listing equities on the NYSE encourages firms to list their bonds on the NYSE since having equities on the NYSE may reduce the information disclosure cost of listing bonds on the NYSE. In unreported results, we find positively significant coefficients for indicator variables of whether a firm's stock is listed on the NYSE. This evidence is consistent with the notions that (1) the NYSE does not place any additional disclosure requirements on firms who already trade equities on the exchange as they already satisfy NYSE disclosure requirements for listing stock, and (2) the additional reporting costs associated with stringent disclosure requirements on bonds imposed by the NYSE are marginal for firms with equities listed on the NYSE.

We use the abovementioned variables to control for a firm's characteristics in its bond-listing choice. We also control for a variety of a bond's characteristics in modeling the listing choice of a bond. We find bonds with larger issuance sizes, longer maturity, higher credit ratings, or without variable rates are more likely to be listed on the NYSE. Besides that, global bonds and Yankee bonds are also more likely to be listed on the NYSE. Senior bonds and Rule 144a bonds are less likely to be listed on the NYSE.

Large or long-maturity debt offerings can be more costly and difficult to issue as issuers try to efficiently raise capital by selling debt. Apparently, listing bonds in both markets can help issuers raise funds more efficiently given the increase in investor base issuers can reach.

We find that the probability of listing bonds on the NYSE is negatively correlated with Moody's bond rating. This correlation indicates that the probability increases as credit quality increases. This relation continues to hold when we use an indicator variable for investment-grade bonds as a proxy for bonds' credit quality. This reflects the clientele effect, as higher rated bonds are usually associated with lower risks, so they are more preferred by retail investors, who prefer to trade on the exchange.

Variable interest payment bonds, with coupon payments adjusting to a schedule or a reference index (for example, LIBOR or Treasury bond interest rates), are less likely to be listed on the NYSE. This finding indicates that typically bonds with complicated instruments that are more complex for retail investors to value are not traded on the NYSE. Since the majority of traders on the NYSE are retail investors, complex bonds might not be favored on the NYSE and hence will tend to suffer from a liquidity shortage.

A separating equilibrium can help to signal the quality of foreign firms who choose to access the U.S. capital markets (see Karolyi (2006)). We find evidence that global bonds are more likely to be listed on the NYSE than domestic bonds. Furthermore, we find Yankee bonds, U.S. dollar-denominated bonds issued by foreign firms in the U.S. market, are more likely to be listed on the NYSE. However, not all types of bonds from foreign issuers are likely to be listed on the NYSE. Rule 144a bonds issued by foreign firms, which are traded only by large institutions (Qualified Institutional Buyers (QIBS)), are less likely to be listed on the exchange. This finding is consistent with the clientele effect as most institutional investors trade in OTC markets.

Panel B of Table 22 reports the comparison results after matching bonds by their propensity scores. We find that the average effective bid-ask spread for bonds traded both on the OTC and NYSE markets is still (about 7 and 10 basis points in two different regressions, respectively) lower than bonds traded only in OTC markets. The difference is statistically significant. Our data shows that in the sample period, approximately $1,058 billion per year is traded on bonds for which pre-trade quote information is not available.[78] These results indicate that traders could save a minimum of $1,058 million per year on transaction costs if pre-trade transparency were to be enforced. In Panel B, we also find that the standard deviations of bid-ask spreads for bonds having NYSE pre-trade transparency are smaller than bonds without the pre-trade transparency. Both

[78] In the sample period from November 1, 2008 to March 31, 2011, the sum of buy- and sell-sized trading volume in the OTC markets is $2,558 billion. Thus, the annual trading volume is approximately $1,058 billion.

parametric and non-parametric tests indicate this difference is statistically significant at the 0.01 level.

In the previous analysis, we examine the economic significance of the bid-ask spread difference between bonds with and without NYSE pre-trade transparency. We run multiple regressions to examine the statistical significance of the relation between the NYSE pre-trade transparency and bonds' bid-ask spreads when controlling other factors that may influence bid-ask spreads. We start this analysis with a OLS regression in Table 23. In addition to the OLS specification, we provide regression results using two-stage least square estimation (2SLS-Logistic I and II). The dependent variables, except as noted, in the regressions are effective bid-ask spreads which is the time-series average of the difference between the average daily selling price and average daily buying price divided by their sum. P-values of estimated coefficients are reported in parentheses. Consistent with our theoretical model predictions, we find that in each of the models presented in Table 23, NYSE pre-trade transparency is negatively correlated with bonds' bid-ask spreads, all else being equal.[79]

The first two regressors in Table 23 characterize the level of NYSE pre-trade transparency in corporate bond markets, respectively. From the OLS model, the effect of a bond being listed on the NYSE on the bid-ask spread is significantly negative. In addition, bond issuances by private firms have higher transaction costs than debt issued by publicly traded companies, as measured by the greater bid-ask spread. A private firm

[79] To control the effect of trade size on bond spreads, we consider the impact of retail-sized investors' trading on bid-ask spreads in unreported results and find qualitatively similar results. We include the percentage of retail-sized trades and trading volume in our regressions, respectively. We find a positive relationship between bid-ask spreads and the proportion of retail-sized trades and trading volume, indicating that small trades occur at higher transaction costs than do trades of institutional investors.

does not have to agree to disclosure requirements and thus has greater information opacity than a publicly listed firm. This opacity interferes with investors' ability to evaluate the bond and causes them to incur larger transaction costs. The coefficient for the issuance size is negative and statistically significant at the 0.01 level, indicating that large issues are cheaper to trade than small issues, consistent with Edwards, Harris, and Piwowar (2007). Bonds with a greater maturity are considered to possess greater risk compared to short term bonds, thus it should cost more to trade longer term bonds. We find consistent evidence with this notion, as long term bonds have larger bid-ask spreads than short term bonds. Different types of bonds issued by the firm may also impact bond trading costs. The estimated coefficients for global bonds are significantly negative. The lower transaction costs for global bonds could be due to the competition of bond transactions across different countries. Senior bonds have a priority claim in firms' residual assets when the firm faces bankruptcy and is more desired by investors. Therefore, a senior bond tends to have a lower transaction cost. Foreign bonds and Yankee bonds, issued by foreign firms, are more favored by investors in the market, which brings more liquidity to the bonds. This, in turn, makes foreign bonds and Yankee bonds cheaper to trade.

As discussed in section 3.4, our findings of the difference of bid-ask spreads between the OTC-only and the OTC-NYSE group bonds could be due to the sample selection bias. This means that omitted factors could simultaneously determine both bid-ask spread and firms' listing choice. Thus, we employ two-stage least squares (2SLS) estimation to enable causal inference. As recommended by Wooldridge (2002), estimated probability from logistic regressions is a better instrument than using bond or firm characteristics when the endogenous variable is a binary variable. The advantage of this method is that the misspecification of logistic model in the first stage regression is irrelevant in the IV regressions provided that the dummy variable for NYSE listing is partially correlated with the fitted probabilities. Using bond or firm characteristics instead of the fitted probabilities as instrumental variables could result in seriously inconsistent estimates if the logistic model for the binary endogenous variable is not correct (Wooldridge, 2002).

2SLS-Logistic I and II models of Table 23 examine the relation between bonds' bid-ask spreads and the NYSE pre-trade transparency using 2SLS specifications. In the first column of each model, we report results for the first stage regressions predicting the fitted value of being listed on the NYSE using probability of bonds being listed on the NYSE from Logistic I and II as the instrument variable, respectively. Instruments in both two models are positively significant, indicating relevance. The joint F-tests of significance are 187 and 259 respectively with p-values less than 0.01, indicating weak instruments are not a concern. Hausman tests indicate that 2SLS regressions provide more consistent estimated coefficients than OLS regressions.

Table 23, Columns 5 and 6 report results from the second stage regression using probability estimated from Logistic I model as the instrument variable. In this specification, the coefficient on bonds listed on the NYSE is negative with a p-value less than 0.01, which confirms the causal interpretation of NYSE pre-trade transparency on a bond's bid-ask spread. The last two columns of Table 23 presents results for a specification using probability estimated from Logistic II model as instrument variable. In this specification, the coefficient on the indicator variable for bonds being listed on the NYSE remains negative and highly significant. In addition, we find that the magnitude of the coefficient estimates in 2SLS regressions ($-0.72*10^{-2}$ and $-0.83*10^{-2}$) increase compared to estimated coefficients in OLS model ($-0.10*10^{-2}$). All other control variables have the same signs as the OLS specification. Transaction costs are greater for low-rated bonds relative to high-rated bonds, as evidenced by the positive and highly significant coefficients of Moody's bond ratings. It is common knowledge that high-rated bonds tend to be favored more by investors than low-rated bonds. Therefore, high-rated bonds cost less to trade than low-rated bonds as there is an increase in investor base. This relation continues to hold when we use an indicator variable for investment-grade bonds as a proxy for bonds' credit quality in unreported regressions results.

Overall, each of the regressions presented in Table 23 indicate that the NYSE pre-trade transparent bonds have lower transaction costs (smaller bid-ask spreads) compared to more opaque bonds even after controlling for other factors that impact bond transaction costs.

4. The Empirical Implications for Informed Traders

In the market microstructure literature, a sophisticated trader who has more information faces larger bid-ask spreads since dealers protect themselves against information asymmetry (see Glosten and Milgrom, 1985; Easley and O'Hara, 1987). Following this intuition, Pagano and Roell (1996) show that pre-trade transparency decreases bid-ask spreads as information asymmetry is eased, though not necessarily for all trade sizes. While they emphasize that pre-trade transparency enhances dealers' ability to discern informed trading, we emphasize that pre-trade transparency refines traders' information sets, leading to more bargaining power. This difference leads to different empirical predictions. Given that institutional traders have superior information in trading, Pagano and Roell (1996) predict that institutional-sized trades of pre-trade transparent bonds should have larger bid-ask spreads because institutional traders' information rents are reduced when more pre-trade information is provided. In contrast, our model predicts the opposite as pre-trade information increases institutional traders' bargaining ability, which implies smaller bid-ask spreads for them.

To test this prediction, we restrict the sample of bond transactions to institutional-sized trades (trade size>$100,000) in Tables 24 and 25.[80] On average, the institutional-sized trades have smaller bid-ask spread than total sample trades reported in Panel B of Table 22. This finding may suggest that institutional traders negotiate better prices than do retail traders. In Table 24, we find that the average effective bid-ask spreads are smaller on OTC-NYSE bonds (NYSE pre-trade transparent bonds) than OTC-only bonds for institutional-sized trades. Though the difference is not significant for investment grade bonds, we do find that it is statistically significant for non-investment-grade bonds. Consistent with our model prediction of smaller bid-ask spreads for institutional traders provided with more pre-trade information, we find smaller spreads in institutional sized trades. OTC-NYSE bonds in Logistic I model are three (two for Logistic II) basis points smaller than OTC-Only bonds in Panel A of Table 25. For informed traders (institutional traders), the standard deviation of bid-ask spreads of OTC-NYSE bonds is also smaller than OTC-Only bonds. Depending on the

[80] We follow Edwards, Harris and Piwowar (2007) to define institutional-sized trades as trades with a size greater than $100,000.

logistic model specifications, the standard deviation of bid-ask spreads is as much as 0.0007 smaller for OTC-NYSE bonds. All of these differences are statistically significant. Panel B of Table 25 continues to provide support the finding that OTC-NYSE bonds are more liquid after controlling for the sample selection bias with the 2SLS regressions. This finding is evidenced by the negatively significant coefficient for the indicator variable of bonds being listed on the NYSE in the second stage regressions. Collectively, these results provide supporting evidence for our search model, while not finding any supporting evidence of the information asymmetry model. Thus, the primary mechanism of pre-trade transparency affecting bonds' liquidity is through increasing traders' bargaining ability rather than increasing dealers' ability to discern informed orders. This implies that improving pre-trade transparency favors traders over dealers.

The lower bid-ask spread for institutional-sized trades on OTC-NYSE bonds documented in our paper provides evidence that the pre-trade transparency is important for institutional traders. If opaqueness is primarily a problem for naive individual investors then we should observe little or no effect of NYSE reporting when the sample is limited to institutional trades (trade size>$100,000) in Table 25. In contrast, the statistically significant effects documented in our paper support the conclusion that pre-trade transparency is important to not only naïve individual traders, but also sophisticated institutional investors as well.[81]

[81] Bessembinder, Maxwell and Venkataraman (2006) find that trade execution costs of institutional trades reduce after the introduction of TRACE on July 1, 2002.

5. Transparency and Valuation in the Corporate Bond Market

In section 2, we find that corporate bonds with NYSE pre-trade transparency have higher liquidity than those without NYSE pre-trade transparency. The increase in liquidity should add value to NYSE pre-trade transparent bonds, since investors value liquidity.[82] In Panel A of Table 26, we find that OTC-NYSE bonds on average have lower yields (higher prices) than OTC-Only bonds in the propensity-score matching specifications. For instance, OTC-NYSE bonds have an average yield of 6.27%, which is significantly smaller than OTC-only bonds' mean yield of 7.89% in the Logistic II model. After controlling for the sample selection bias by using the probability of being listed on the NYSE as the instrumental variable in Panel B of Table 26, our findings remain intact as OTC-NYSE bonds have significantly smaller yield than OTC-Only bonds. This is evidenced by the negatively significant coefficient for the indicator variable of bonds being listed on the NYSE. These results indicate that OTC-NYSE bonds have higher valuations, which verifies the conjecture that pre-trade transparency increases bonds' values. This finding is economically important since it also suggests that issuers listed on the NYSE Bonds platform have significantly lower cost of debt capital than otherwise identical firms.

In our model, we explain the mechanism that pre-trade transparency affects liquidity through the reduction of traders' perceived Knightian uncertainty. Hence, the above result implies that reducing Knightian uncertainty can increase the value of a bond. This provides an empirical support of Easley and O'Hara (2010b), in which they

[82] Amihud and Mendelson (1986) find that illiquid securities should compensate security investors with a liquidity premium. Lo, Mamaysky, and Wang (2004) argue that illiquidity leads to lower security prices and larger yield spreads given the same future cash flows since investors demand an ex ante risk premium. Chen, Lesmond and Wei (2007) find that illiquid bondholders are compensated with higher yield spreads and bonds' yield spreads decrease when liquidity improves.

show that an asset's value increases when its associated Knightian uncertainty decreases.

6. Conclusions

Given the significant importance of OTC market in financial markets and the bilateral trading nature in OTC market, a motivating question arises, "Whether, and if so, how, pre-trade transparency affects OTC trading?" Our theoretical and empirical evidence shows that pre-trade transparency in the OTC market decreases the mean and standard deviation of bid-ask spreads for traders who trade in the market.

We construct a search model by incorporating Knightian uncertainty into traders' search processes. Our empirical findings are robust to endogeneity of firms' bond listing decisions on NYSE. After controlling for endogeneity with propensity-score matching, the average effective bid-ask spread of OTC-NYSE bonds is 10 basis points smaller than the average effective bid-ask spread of OTC-only bonds. The 10-basis-point difference suggests that approximately $1,058 million could be saved on transaction costs if pre-trade information were revealed in the corporate bond market. Using the probability of being listed on the NYSE as an instrumental variable, we still find bonds' bid-ask spreads are negatively correlated with the presence of NYSE pre-trade transparency.

In contrast to the prediction of Pagano and Roell (1996), our theoretical and empirical evidence shows that improved pre-trade transparency increases traders' bargaining ability rather than dealers' ability to discern informed orders. Bond bid-ask spreads for institutional-sized trades on OTC-NYSE bonds are significantly smaller than OTC-only bonds after controlling bond and firm characteristics. This finding is robust across various univariate and multivariate tests.

Consistent with the notion that improved liquidity should add value to securities, we find that OTC-NYSE bonds have significantly lower bond yields than OTC-only bonds. For instance, OTC-NYSE bonds have a mean yield of 6.27%, while OTC-only bonds have an average yield of 7.89% after controlling for endogeneity with propensity-score matching. Upon, controlling for the endogeneity of firms' bond listing decisions on NYSE, we document a negative relationship between bond yields and NYSE pre-trade transparency. Therefore, the improved pre-trade transparency adds value to OTC-NYSE bonds.

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Appendix A: Chapter 2

From Black and Scholes (1973) model, we obtain the following formulas:

$$Call = A_0 N(d_1) - De^{-r(T-t)} N(d_2)$$

$$Put = De^{-r(T-t)} N(-d_2) - A_0 N(-d_1)$$

$$d_1 = \frac{\ln(A_0 / D) + (r + \sigma^2 / 2)(T-t)}{\sigma\sqrt{T-t}}$$

$$d_2 = \frac{\ln(A_0 / D) + (r - \sigma^2 / 2)(T-t)}{\sigma\sqrt{T-t}} = d_1 - \sigma\sqrt{T-t}$$

$$N(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{z^2}{2}} dz; N^{'}(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

It is assumed that t=0 when a firm issues a new debt in the following proofs. max (0, A_T-D) and max (0, D-A_T) indicate the payoff of the call and put at time T, respectively. $Call_0$ and Put_0 indicate the price of the call and put at time 0, respectively.

Proof of equation (7):

$$F_0 = \frac{\partial P_{s0}}{\partial D} + \frac{\partial P_{s0}}{\partial A_0}\frac{\partial A_0}{\partial D} = (\frac{\partial Call_0}{\partial A_0} + \frac{\partial Call_0}{\partial D})/C, \text{since } \frac{\partial D}{\partial A_0} = 1$$

$$\frac{\partial Call_0}{\partial A_0} + \frac{\partial Call_0}{\partial D} = N(d_1) + A_0 N^{'}(d_1)\frac{\partial d_1}{\partial A_0} - De^{-rT} N^{'}(d_2)\frac{\partial d_2}{\partial A_0} + A_0 N^{'}(d_1)\frac{\partial d_1}{\partial D} - De^{-rT} N^{'}(d_2)\frac{\partial d_2}{\partial D} - e^{-rT} N(d_2)$$

$$\frac{\partial d_1}{\partial A_0} = \frac{\partial d_2}{\partial A_0}, \frac{\partial d_1}{\partial D} = \frac{\partial d_2}{\partial D}$$

$$= N(d_1) - e^{-rT} N(d_2) + \frac{\partial d_1}{\partial A_0}\left[A_0 N^{'}(d_1) - De^{-rT} N^{'}(d_2)\right] + \frac{\partial d_1}{\partial D}\left[A_0 N^{'}(d_1) - De^{-rT} N^{'}(d_2)\right]$$

See Hull's book (page 308 in Chapter 13 of 6th edition : Options, Futures, and Other Derivatives) :

Since $A_0 N^{'}(d_1) - De^{-rT} N^{'}(d_2) = 0$,

$$F_0 = (N(d_1) - e^{-rT} N(d_2))/C$$

$$d_1 > d_2 > 0, F_0 = (N(d_1) - e^{-rT} N(d_2))/C > 0.$$

Proof of equation (8):

$$P_{b0} = (V_0/D) \times 1000 = [(De^{-rT} - Put_0)/D] \times 1000$$

$$L_0 = \frac{\partial P_{s0}}{\partial D} + \frac{\partial P_{s0}}{\partial A_0}\frac{\partial A_0}{\partial D} = \frac{\partial P_{s0}}{\partial D} + \frac{\partial P_{s0}}{\partial A_0}$$

$$= [\frac{De^{-rT} N^{'}(-d_2)\frac{\partial d_2}{\partial A_0} - A_0 N^{'}(-d_1)\frac{\partial d_1}{\partial A_0} + N(-d_1)}{D} + \frac{\left(e^{-rT} - \frac{\partial Put_0}{\partial D}\right)D - (De^{-rT} - Put_0)}{D^2}] \times 1000$$

$$= [\frac{N(-d_1)}{D} + \frac{Put_0 - \frac{\partial Put_0}{\partial D}D}{D^2}] \times 1000$$

$$= \{\frac{N(-d_1)}{D} + \frac{Put_0 - D\left[e^{-rT} N(-d_2) + De^{-rT} N^{'}(-d_2)\frac{\partial d_2}{\partial D} - A_0 N^{'}(-d_1)\frac{\partial d_1}{\partial D}\right]}{D^2}\} \times 1000$$

$$= [\frac{N(-d_1)}{D} + \frac{Put_0 - De^{-rT} N(-d_2)}{D^2}] \times 1000 = \frac{1000 \times (D - A_0) N(-d_1)}{D^2} < 0, \text{ since } D < A_0$$

Proof of equation (13):

$$P_{bs0} = [\frac{D_s e^{-rT} - Put_0(Strike = D_s, Underlying = A_T)}{D_s}] \times 1000$$

$$\frac{\partial P_{bs0}}{\partial A_0} = -\frac{\frac{\partial Put_0}{\partial A_0}}{D_s} \times 1000 = \frac{1000 \times N(-d_1)}{D_s} > 0$$

Proof of equation (14):

$$P_{bj0} = \frac{Call_0(Strike = D_s, Underlying = A_T) - Call_0(Strike = D_s + D_j, Underlying = A_T)}{D_j} \times 1000$$

$$d_1 = \frac{\ln(A_0 / D_s) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}, d_1^{'} = \frac{\ln(A_0 /(D_s + D_j)) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}$$

$$d_2 = \frac{\ln(A_0 / D_s) + (r - \sigma^2/2)T}{\sigma\sqrt{T}}, d_2^{'} = \frac{\ln(A_0 /(D_s + D_j)) + (r - \sigma^2/2)T}{\sigma\sqrt{T}}$$

$$\frac{\partial P_{bj0}}{\partial D_s} + \frac{\partial P_{bj0}}{\partial A_0}\frac{\partial A_0}{\partial D_s} = \frac{\partial P_{bj0}}{\partial D_s} + \frac{\partial P_{bj0}}{\partial A_0} = [\frac{N(d_1) - N(d_1^{'})}{D_j} - e^{-rT}\frac{N(d_2) - N(d_2^{'})}{D_j}] \times 1000, \text{since } \frac{\partial A_0}{\partial D_s} = 1$$

$$= [\frac{N(d_1) - e^{-rT}N(d_2)}{D_j} - \frac{N(d_1^{'}) - e^{-rT}N(d_2^{'})}{D_j}] \times 1000$$

$$= [\frac{N(d_1) - e^{-rT}N(d_1 - \sigma\sqrt{T})}{D_j} - \frac{N(d_1^{'}) - e^{-rT}N(d_1^{'} - \sigma\sqrt{T})}{D_j}] \times 1000$$

$$Let\ f(d_1) = N(d_1) - e^{-rT}N(d_1 - \sigma\sqrt{T})$$

$$= \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{d_1} e^{-\frac{z^2}{2}}dz - e^{-rT}\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{d_1-\sigma\sqrt{T}} e^{-\frac{z^2}{2}}dz$$

$$f^{'}(x) = \frac{1}{\sqrt{2\pi}}\left(e^{-\frac{d_1^2}{2}} - e^{-\frac{(d_1-\sigma\sqrt{T})^2}{2} - rT}\right) = \frac{1}{\sqrt{2\pi}}\left(e^{-\frac{d_1^2}{2}} - e^{-\frac{d_1^2 - 2\ln(A_0/B)}{2}}\right) < 0$$

$$d_1 > d_1^{'}, f(d_1) < f(d_1^{'}) \Rightarrow f(d_1) - f(d_1^{'}) = \frac{N(d_1) - e^{-rT}N(d_1 - \sigma\sqrt{T})}{D_j} - \frac{N(d_1^{'}) - e^{-rT}N(d_1^{'} - \sigma\sqrt{T})}{D_j} < 0$$

$$\frac{\partial P_{bj0}}{\partial A_0} + \frac{\partial P_{bj0}}{\partial D_s} < 0$$

Proof of equation (15):

$$\frac{\partial F_0}{\partial T} = (N^{'}(d_1)\frac{\partial d_1}{\partial T} - e^{-rT}N^{'}(d_2)\frac{\partial d_2}{\partial T})/C$$

$$= \{N^{'}(d_1)\left(\frac{2rT - d_2\sigma\sqrt{T}}{2\sigma T\sqrt{T}}\right) - e^{-rT}N^{'}(d_2)\left(\frac{2rT - d_2\sigma\sqrt{T} - \sigma^2 T}{2\sigma T\sqrt{T}}\right) + re^{-rT}N(d_2)\}/C$$

$$= \{(N^{'}(d_1) - e^{-rT}N^{'}(d_2))\left(\frac{2rT - d_2\sigma\sqrt{T}}{2\sigma T\sqrt{T}}\right) + \frac{1}{2}e^{-rT}N^{'}(d_2)\sigma T^{-0.5} + re^{-rT}N(d_2)\}/C$$

$$= \{(N^{'}(d_1) - e^{-rT}N^{'}(d_2))\left(\frac{(r + \frac{1}{2}\sigma^2)T - \ln(A_0/D)}{2\sigma T\sqrt{T}}\right) + \frac{1}{2}e^{-rT}N^{'}(d_2)\sigma T^{-0.5} + re^{-rT}N(d_2)\}/C,$$

which is > 0,

if $\ln(A_0/D) > (r + \sigma^2/2)T$

Proof of equation (16):

$$\frac{\partial L_0}{\partial T} = \frac{(D-A_0)}{D^2}.\frac{\partial N(-d_1)}{\partial T}\times 1000 = -N^{'}(-d_1)\frac{(D-A_0)}{D^2}\frac{\partial d_1}{\partial T}\times 1000$$

$$= -N^{'}(-d_1)\frac{(D-A_0)}{D^2}\frac{\partial\left(\frac{\ln(A_0/D)}{\sigma\sqrt{T}} + \frac{r+\sigma^2/2}{\sigma}\sqrt{T}\right)}{\partial T}\times 1000$$

$$= -N^{'}(-d_1)\frac{(D-A_0)}{D^2}\left[-\frac{1}{2}\frac{\ln(A_0/D)}{\sigma}.T^{-1.5} + \frac{1}{2}\frac{(r+\sigma^2/2)}{\sigma}.T^{-0.5}\right]\times 1000$$

$$= N^{'}(-d_1)\frac{(D-A_0)}{D^2}\frac{\left[\ln(A_0/D)-(r+\sigma^2/2)T\right]}{2\sigma T^{1.5}}\times 1000,$$

which is < 0 if $\ln(A_0/D) > (r+\sigma^2/2)T$

Proof of equation (17):

$$\frac{\partial F_0}{\partial\sigma} = \{\frac{\partial N(d_1)}{\partial\sigma} - e^{-rT}\frac{\partial N(d_2)}{\partial\sigma}\}/\text{C}$$

$$= \frac{\left[\sigma^2 T - \left[\ln(A_0/D)+(r+\sigma^2/2)T\right]\right]}{C\sigma^2\sqrt{T}}N^{'}(d_1) - \frac{e^{-rT}\left[-\sigma^2 T - \left[\ln(A_0/D)+(r-\sigma^2/2)T\right]\right]}{C\sigma^2\sqrt{T}}N^{'}(d_2)$$

$$= \frac{\left(\sigma^2 T - d_1\sigma\sqrt{T}\right)}{C\sigma^2\sqrt{T}}N^{'}(d_1) - \frac{\left(-\sigma^2 T - d_2\sigma\sqrt{T}\right)}{C\sigma^2\sqrt{T}}e^{-rT}N^{'}(d_2) = \frac{\left(\sigma^2 T - d_1\sigma\sqrt{T}\right)}{C\sigma^2\sqrt{T}}N^{'}(d_1) - \frac{\left(-d_1\sigma\sqrt{T}\right)}{C\sigma^2\sqrt{T}}e^{-rT}N^{'}(d_2)$$

$$= \frac{\left(\sigma^2 T - d_1\sigma\sqrt{T}\right)}{C\sigma^2\sqrt{T}}N^{'}(d_1) + \frac{d_1\sigma\sqrt{T}}{C\sigma^2\sqrt{T}}e^{-rT}N^{'}(d_2) > \frac{\left(\sigma^2 T - d_1\sigma\sqrt{T}\right)}{C\sigma^2\sqrt{T}}N^{'}(d_1) + \frac{d_1\sigma\sqrt{T}}{C\sigma^2\sqrt{T}}N^{'}(d_1) > \frac{\sigma^2 T}{C\sigma^2\sqrt{T}}N^{'}(d_1) > 0$$

Proof of equation (18):

$$\frac{\partial L_0}{\partial\sigma} = \frac{(D-A_0)}{D^2}.\frac{\partial N(-d_1)}{\partial\sigma}\times 1000 = -N^{'}(-d_1)\frac{(D-A_0)}{D^2}.\frac{\partial d_1}{\partial\sigma}\times 1000$$

$$= -N^{'}(-d_1)\frac{(D-A_0)}{D^2}\frac{\sqrt{T}\left[\sigma^2 T - \ln(A_0/D)-(r+\sigma^2/2)T\right]}{\sigma^2 T}\times 1000$$

$$= N^{'}(-d_1)\frac{(D-A_0)}{D^2}\frac{d_2}{\sigma}\times 1000 < 0$$

Proof of equation (19):

$$\text{Stocks}: \frac{\partial P_{s0}}{\partial D} - \frac{\partial P_{s0}}{\partial C}\frac{\partial C}{\partial D} = \frac{Call_0}{C^2} - \frac{e^{-rT}N(d_2)}{pC} = \frac{pA_0N(d_1) - pDe^{-rT}N(d_2) - Ce^{-rT}N(d_2)}{pC^2}$$

$$= \frac{pA_0N(d_1) - (pD+C)e^{-rT}N(d_2)}{pC^2}, \text{suppose } p \text{ is the stock price at the time of stock repurchases}$$

In a stock repurchase program, a firm's asset at T remains unchanged. Therefore: $A_0=A_T=D+C*p$, since p>1$, we have $pA_0-pD=pC>C>0$, $pA_0>pD+C$. Also, $d_1> d_2$, $N(d_1)>e^{-rT} N(d_1)>0$, consequently:

$$\text{Stocks}: \frac{\partial P_{s0}}{\partial D} - \frac{\partial P_{s0}}{\partial C}\frac{\partial C}{\partial D} = \frac{pA_0N(d_1) - (pD+C)e^{-rT}N(d_2)}{pC^2} > 0$$

Proof of equation (20):

$$\text{Bonds}: P_{b0} = (V_0/D)\times 1000 = [(De^{-rT}\text{-}Put_0)/D]\times 1000$$

$$\frac{\partial P_{b0}}{\partial D} = \frac{\left(e^{-rT} - \frac{\partial Put_0}{\partial D}\right)D - (De^{-rT} - Put_0)}{D^2}\times 1000$$

$$= \frac{Put_0 - \frac{\partial Put_0}{\partial D}D}{D^2}\times 1000$$

$$= \frac{Put_0 - D\left[e^{-rT}N(-d_2) + De^{-rT}N'(-d_2)\frac{\partial d_2}{\partial D} - A_0 N'(-d_1)\frac{\partial d_1}{\partial D}\right]}{D^2}\times 1000$$

$$= \frac{Put_0 - De^{-rT}N(-d_2)}{D^2}\times 1000 = -\frac{A_0 N(-d_1)}{D^2}\times 1000 < 0$$

Proof of equation (21):

$$Stocks: (19)-(7) = \frac{pA_0 N(d_1) - (pD + C)e^{-rT}N(d_2)}{pC^2} - \frac{N(d_1) - e^{-rT}N(d_2)}{C}$$

$$= \frac{(pA_0 - pC)N(d_1) - (pD + C - pC)e^{-rT}N(d_2)}{pC^2}$$

$Since\ A_0 = D + pC,\ pA_0 - pD = p^2C > C > 0,$ since stock price : p > \$1;

$Thus,\ p\,A_0 > pD + C > 0,\ pA_0 - pC > pD + C - pC = pD + C - D > 0,\ N(d_1) > e^{-rT}N(d_2) > 0$

$$Therefore,\ (19)-(7) = \frac{(pA_0 - pC)N(d_1) - (pD + C - pC)e^{-rT}N(d_2)}{pC^2} > 0$$

Appendix B: Variable Descriptions, Chapter 2

Variable	Description
Issuance size/ Assets	Offering size scaled by total assets in the fiscal year prior to the bond issue
Issuance size/ Long-term debt	Offering size scaled by long-term debt in the fiscal year prior to the bond issue
New bond maturity (years)	Natural logarithm of the number of years before the bond is expired; For multiple debt offerings issued by the same firm on the same day, I calculate an average maturity, rating and seniority level as the weighted average of each component offering's maturity, rating and seniority level in these cases, where the component weights are the proceeds of each bond issuance relative to total offering proceeds.
New bond rating	A value of 1 (2,3,…) is assigned to Moody's rating of Aaa (Aa1, Aa2,…); for multiple debt offerings, the calculation of a firm's new bond rating is the same as new bond maturity.
New bond seniority	A security level scale integer assigned to a new bond seniority (Senior Secured=1, Senior=2, Senior Subordinate=3, Junior=4, Junior Subordinate=5, Subordinate=6, None=7); for multiple debt offerings, the calculation of a firm's new bond seniority is the same as new bond maturity.
Existing bond maturity (years remaining)	Natural logarithm of the number of years remaining before the bond is expired; In multiple regressions of Table 9, for multiple outstanding bonds by the same firm, I compute an aggregrated maturity as the weighted average of each outstanding bond's maturity, where the weight is defined as the proceeds of each debt issuance relative to total offering proceeds
Existing bond rating	A value of 1 (2,3,…) is assigned to Moody's rating of Aaa (Aa1, Aa2,…)
Existing bond seniority	A security level scale integer assigned to an existing bond seniority (Senior Secured=1, Senior=2, Senior Subordinate=3, Junior=4, Junior Subordinate=5, Subordinate=6, None=7)
Intended uses: stock repurchases	Indicator variable equal to 1 when the intended use of newly raised funds is a stock repurchase.
Intended uses: expansions	Indicator variable equal to 1 when the intended use of newly raised funds is an expansion. Expansions uses include all financings of new risky projects such as mergers, future acquisitions, and capital expenditures.
Intended uses: refinancings	Indicator variable equal to 1 when the intended use of newly raised funds is a refinancing.
Firms' size (millions)	Natural logarithm of total assets in the fiscal year prior to the bond issue
Firms' leverage ratio	Long-term debt divided by total assets in the fiscal year prior to the bond issue

Asset risk	Standard deviation of unlevered stock returns (std. dev.), which is estimated using daily stock returns over the window -240 to -40 prior to the event date. Unlevered returns are computed by multiplying stock returns by (1 − Leverage), where Leverage is the ratio of the book value of total debt to the sum of the book value of total debt and the market value of equity at the end of the corresponding fiscal year.
Tangibility	Book value of net property, plant, and equipment scaled by total assets in the fiscal year prior to the bond issue
Tax rate	Sum of income taxes divided by the pretax income less appropriations to untaxed reserves
Firms' growth opportunities	Market value of equity (common shares outstanding multiplied by common stock prices) scaled by the book value of equity (total value of common/ordinary equity)
Firms' profit	Earnings before interest and tax (EBIT) over total assets

Appendix C: Definitions of Z-score and Financially Unconstrained, Chapter 3

According to van Binsbergen, Graham and Yang (2010), I calculate a modified version of Z-score and define financially non-distressed and unconstrained firms as follows:

$$ZSCORE = \frac{3.3 * \text{Pre-tax Income}(170) + 1.0 * \text{Net Sales}(12) + 1.4 * \text{Retained Earnings}(36) + 1.2 * \text{Working Capital}(179)}{\text{Total Book Assets}(6)}$$

Financially unconstrained firms,

$$\text{FUC} = \begin{cases} 1 \text{ if } \dfrac{\text{Long-term Debt Issuance}(111)}{\text{Total Assets}(6)} \geq 66th \text{ percentile} \\ \text{or } \dfrac{\text{Long-term Debt Reductions}(114)}{\text{Total Assets}(6)} \geq 66th \text{ percentile} \\ \text{or } \dfrac{\text{Equity Issuances}(108)}{\text{Total Assets}(6)} \geq 66th \text{ percentile} \\ \text{or } \dfrac{\text{Equity Reduction}(115)}{\text{Total Assets}(6)} \geq 66th \text{ percentile} \\ 0 \text{ otherwise} \end{cases}$$

Appendix D: Predicted Signs of Variables of Dividend Payment Announcements by the Signaling and Wealth Transfer Hypotheses

Interaction variables:	ΔDIV*Junior_bond (β_3)	ΔDIV*Investment_grade (β_5)	ΔDIV*Maturity (β_7)	ΔDIV*FL (β_9)	ΔDIV*FUC (β_{11})	ΔDIV*FND(β_{13})
A. Signaling holds						
Dividend increases	+	-	+	+	+	+
Dividend decreases	-	+	-	-	-	-
B. Wealth Transfer holds						
Dividend increases	-	+	-	-	-	-
Dividend decreases	+	-	+	+	+	+

Appendix E: Chapter 4

Proof of Proposition 1

Proof:

We will prove Proposition 11, then show that Proposition 1 is a special case of it.

Let's denote $D(a) = \sum_t (\beta\rho)^t D_t(a)$ and $S(b) = \sum_t (\beta\rho)^t S_t(b)$. Given that $D_t(a)$ is continuous and decreasing function on $[\underline{a}, \overline{a}]$, it is easy to see that $D(a)$ is continuous and decreasing on $[\underline{a}, \overline{a}]$. We note that, from the value function of the buyers

$$V^B(a) = \max\left\{0, v^B - a, \beta \int V^B(\hat{a}) d\theta_a\right\}, \tag{A1}$$

$\underline{a} = \underline{v}^B$ and $\overline{a} = r^B(1)$. Similarly, we have $S(b)$ continuous and increasing on $\left[\underline{b}, \overline{b}\right]$, in which $\underline{b} = r^S(0)$ and $\overline{b} = \overline{v}^S$. As $D_t(a) = S_t(b)$, we have $D(a) = S(b)$. Then, we define the inverse functions $A(q)$ and $B(q)$ mapping from q to prices.

From the inverse function theorem, we have

$$A'(q) = \left(\frac{\partial D}{\partial a}\right)^{-1} = \left(-\frac{1-\beta+F_a(a)(1-\epsilon)\beta}{N(1-\beta)\left(1-\beta\rho\left(1-F_a(a)\right)\right)}\right)^{-1}, \tag{A2}$$

$$B'(q) = \left(\frac{\partial S}{\partial b}\right)^{-1} = \left(\frac{1-\beta+\left(1-F_b(b)\right)(1-\epsilon)\beta}{N(1-\beta)\left(1-\beta\rho F_b(b)\right)}\right)^{-1}. \tag{A3}$$

As $a(k)$ increases in k and $b(k)$ decreases in k, we have

$$F_a(a) = P_a[\hat{a} < a] = P_k\left[\hat{k} < k\right] = \frac{k}{k^*}, \tag{A4}$$

$$1 - F_b(b) = P_b\left[\hat{b} < b\right] = P_k\left[\hat{k} < k\right] = \frac{k}{k^*}, \tag{A5}$$

where k^* is the marginal dealer whose profit margin and trading volume are zeros. Thus, the total mass of dealer N equals to k^*.

Plugging $F_a(a)$ and $F_b(b)$ into $A'(q)$ and $B'(q)$ respectively, we obtain

$$A'(q) = -B'(q) = \left(-\frac{1-\beta+\frac{k}{k^*}(1-\epsilon)\beta}{N(1-\beta)\left(1-\frac{\beta\rho(k^*-k)}{k^*}\right)}\right)^{-1}. \tag{A6}$$

For the dealer with transaction cost k, he chooses q to maximize the expected profit $(A(q) - B(q) - k)q$. The optimality condition implies,

$$A(q) - B(q) - k = \left(B'(q) - A'(q)\right)q. \tag{A7}$$

Thus, we obtain

$$A\big(q(k)\big) - B\big(q(k)\big) - k = \frac{2k^*(1-\beta)\left(1-\frac{\beta(k^*-k)}{k^*}\right)q(k)}{1-\beta+\frac{k}{k^*}(1-\epsilon)\beta} - k. \quad \text{(A8)}$$

Substituting $q(k) = D\big(a(k)\big)$ into equation (A8), we get

$$a(k) - b(k) - k$$
$$= \frac{2\left(1-\frac{\beta(k^*-k)}{k^*}\right)}{1-\beta+\frac{k}{k^*}(1-\epsilon)\beta}\int_{a(k)}^{r^B(1)} \frac{1-\beta+F_a(r^B)(1-\epsilon)\beta}{1-\beta\rho\big(1-F_a(r^B)\big)}dr^B \quad \text{(A9)}$$

Since, for any k, $D\big(a(k)\big) = S\big(b(k)\big)$, it implies that $\frac{\partial D}{\partial k} = \frac{\partial S}{\partial k}$. And since $A'(q) = -B'(q)$, we have $\frac{\partial a}{\partial k} = -\frac{\partial b}{\partial k}$. Thus,

$$a(k) + b(k) = C, \quad \text{(A10)}$$

in which C represents a constant.

From the buyer's reservation value, we have

$$1 = r^B(1) + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{a}}^{r^B(1)} P_a[a < \hat{a}]d\hat{a} = r^B(1) + \frac{\beta(1-\epsilon)}{1-\beta}\int_0^{k^*}\frac{k}{k^*}a'(k)dk.$$

(A11)

where the second equality is obtained by performing a change of variables.

Likewise, we have

$$0 = r^S(0) - \frac{\beta(1-\epsilon)}{1-\beta}\int_{r^S(0)}^{\overline{b}} P_b\big[b > \hat{b}\big]d\hat{b}$$

$$= r^S(0)$$
$$+ \frac{\beta(1-\epsilon)}{1-\beta}\int_0^{k^*}\frac{k}{k^*}b^{'}(k)dk. \quad \text{(A12)}$$

From the above, it is obvious that $1 = r^B(1) + r^S(0)$. Since $a(k^*) = \overline{a} = r^B(1)$ and $b(k^*) = \underline{b} = r^S(0)$, we have $a(k^*) + b(k^*) = 1$. This implies $C = 1$, and hence,

$$b(k) = 1 - a(k). \tag{A13}$$

Plugging the equation (A13) into the optimality condition (equation (A8)) and differentiating with respect to k, we arrive at the following differential equation

$$a'(k) - \frac{a(k)\big(\beta X(k)\big)}{2k^*} = \frac{1}{4} - \frac{1+k}{4}\frac{\beta X(k)}{k^*}, \tag{A14}$$

where

$$X(k) = \frac{\rho}{1 - \frac{\beta\rho(k^* - k)}{k^*}} - \frac{1-\epsilon}{1 - \beta + \frac{k}{k^*}(1-\epsilon)\beta}. \tag{A15}$$

The solution for the above differential equation is

$$a(k) = e^{\int_k^{k^*} -Y(z)dz}\left(\frac{k^*+1}{2} + \int_k^{k^*}\left(-\frac{1}{4} + \frac{1+z}{2}Y(z)\right)e^{\int_z^{k^*} Y(u)du}dz\right), \tag{A16}$$

where

$$Y(z) = \frac{\beta X(z)}{2k^*}. \tag{A17}$$

Thus, equation (A16) determines the equilibrium asks. And the equilibrium bids equal to $1 - a$.

To determine the equilibrium k^*, we apply $k^* = a(k^*) - b(k^*)$ to the buyer's reservation value $r^B(1)$ and get

$$1 = \frac{k^*+1}{2} + \frac{\beta(1-\epsilon)}{1-\beta}\left(\frac{k^*+1}{2} - \frac{1}{k^*}\int_0^{k^*} a(k)dk\right). \tag{A18}$$

To prove Proposition 1, we let $\rho = \frac{1-\epsilon}{1-\beta\epsilon}$. As a result, we have $X(k) = 0$, and hence , $a'(k) = \frac{1}{4}$. From eq (A18), we can show that $k^* = \frac{4-4\beta}{4-3\beta-\beta\epsilon}$. Since $a(k^*) - b(k^*) = k^*$, we have

$$a(k) = \frac{k}{4} + \frac{k^*}{4} + \frac{1}{2}.$$

Q.E.D.

Proof of Proposition 2

Proof:

Proposition 1 implies that if $\epsilon_0 < \epsilon_1$, then $k^*(\epsilon_0) < k^*(\epsilon_1)$ (We will prove this in details in Proposition 6). Based on Proposition 1, for any $\in \left[0, k^*(\epsilon_0)\right)$, $a(k;\epsilon_0) < a(k;\epsilon_1)$. For any $k \in \left[k^*(\epsilon_0), k^*(\epsilon_1)\right)$, we have $a(k;\epsilon_0) = 0 < a(k;\epsilon_1)$.

Since k follows a uniform distribution in $[0,1]$, the pricing function of a indicates that a follows a uniform distribution in $\left[\frac{k^*}{4} + \frac{1}{2}, \frac{k^*}{2} + \frac{1}{2}\right]$. Thus, $F_a = \frac{4a-2}{k^*} - 1$. Since k^* increases in ϵ, F_a decreases in ϵ, i.e., $F_a^{\epsilon_1}(a) < F_a^{\epsilon_0}(a)$.

Q.E.D.

Proof of Proposition 3

Proof:

The spread, $a(k) - b(k)$, which equals $2a(k) - 1$. Since $a(k)$ is linear in k, and since k is uniformly distributed on $[0, 1]$. Thus, we have $a(k)$ uniformly distributed on $\left[a(0), a(k^*)\right)$. The mean of $a(k)$ is $\frac{1}{2} + \frac{3k^*}{4}$, which increases in k^*. As from Proposition 3, we have the mean of $a(k)$ increases in ϵ, and hence, the spread increases in ϵ.

Q.E.D.

Proof of Proposition 4

Proof:

As mentioned in the proof of Proposition 3, the spread equals $2a(k) - 1$, it is obvious that the variance of the spread equals the variance of $a(k)$. Since $a(k)$ is uniformly distributed on $\left[a(0), a(k^*)\right)$, the variance of $a(k)$ is $\frac{1}{12}\left(\frac{k^*}{4}\right)^2$. Since k^*

increases in ϵ, we know that the variance of $a(k)$ increases in ϵ, and so does the variance of the spread.

Q.E.D.

Proof of Proposition 5

Proof:

Since the equilibrium is symmetric, i.e., the seller's reservation value is symmetric of the buyer's reservation value, it is suffice to prove the claim with the buyer's reservation value, $r^B(v^B)$. From the buyer's optimal search strategy, we have

$$v^B = r^B(v^B) + \frac{\beta(1-\epsilon)}{1-\beta}\int_{\underline{a}}^{\overline{a}} F_a(\hat{a})d\hat{a} = r^B(v^B) + \frac{\beta(1-\epsilon)k^*}{8(1-\beta)}. \tag{A19}$$

Therefore

$$\frac{dr^B}{d\epsilon} = \frac{2(1-\beta)\beta}{(4-3\beta-\beta\epsilon)^2} > 0. \tag{A20}$$

Q.E.D.

Proof of Proposition 6

Proof:

$$\frac{dk^*}{d\epsilon} = \frac{\beta(4-4\beta)}{(4-3\beta-\beta\epsilon)^2} > 0 \tag{A21}$$

Q.E.D.

Appendix F: Variable Definitions, Chapter 4

Firm characteristics information is collected from Compustat. Bond variables are from Mergent FISD.

Variable	Description
Firm size (log millions)	Natural logarithm of total assets in the fiscal year prior to the bond issue
Leverage	Ratio of long-term debt over total asset in the fiscal year prior to the bond issue
Firms' accounting standard-IFRS	Binary variable equal to 1 when the accounting standard that a company uses in presenting its financial statements is International Financial Reporting Standards
Firms' accounting standard-Domestic	Binary variable equal to 1 when the accounting standard that a company uses in presenting its financial statements is Domestic
Issuer is in finance industry	Binary variable equal to 1 when the issuer belongs to the finance industry
Issuer is a utility	Binary variable equal to 1 when the issuer belongs to the utility industry
Issuers' equity is private	Binary variable equal to 1 when the issuer is a private firm
Issue size (sq. root of millions)	Square root of the par value of debt initially issued.
Moody's bond rating	A value of 1 (2,3,…) is assigned to Moody's rating of Aaa (Aa1, Aa2,…)
Years to maturity	The number of years before the bond is expired
Global Bond	Binary variable equal to 1 when the issue is offered globally
Variable rate bond	Binary variable equal to 1 when the coupon type for the issue is variable
Foreign bond	Binary variable equal to 1 when the issue is denominated in a foreign currency.
Senior bond	Binary variable equal to 1 when the security is a senior issue of the issuer.
Rule144a bond	Binary variable equal to 1 when the issue is a private placement exempt from registration under SEC Rule 144a.
Yankee Bond	Binary variable equal to 1 when the bond is issued by a foreign issuer, but is registered with the SEC and is payable in dollars.
Listed on the NYSE	Binary variable equal to 1 when the bond is listed on the NYSE

Table 1. Predicted Signs of Variables for New Debt Offerings by the Wealth Transfer and Signaling Hypotheses, Chapter 2

Panel A presents signs of expected returns by different hypotheses. Panels B and C provide signs of the determinants of bond and stock price responses to debt offering announcements, respectively. I use "+/-" to represent an uncertain relationship and "?" if no implication.

Panel A: Predicted returns of bonds and stocks, and the correlation of returns surrounding new debt offering announcements

Hypotheses	Predicted Abnormal Bond Returns	Predicted Abnormal Stock Returns	Correlation between Abnormal Bond Returns and Stock returns
Wealth Transfer	-	+	-
Negative Signaling	-	-	+
Positive Signaling	+	+	+

Panel B: Predicted signs of the relationship between bond market returns and relevant variables surrounding new debt offering announcements.

Hypotheses	Seniority: New<Existing	Maturity: New<Existing	Existing Bond's Rating: Investment	Existing Bond's Maturity
Wealth Transfer	+	-	+	-
Negative Signaling	+/-	+/-	+	-
Positive Signaling	+/-	+/-	-	+

Panel C: Predicted signs of the relationship between stock market returns surrounding the new debt issue and firms' intended use of newly raised funds.

Hypotheses	Security Markets	Stock repurchases	Expansions	Refinancing	Repurchases-Expansions
Wealth Transfer	Bond markets	-	-	0	-
	Stock markets	+	+	0	+
Signaling	Bond markets	+	-	-	+
	Stock markets	+	-	-	+

Table 2. Descriptive Statistics

Panel A presents the number of straight debt offerings per sample year at the debt (issue) - and firm-level from 2005 to 2011. The ‘‘uncontaminated” sample consists of debt offering announcements not accompanied by contaminating news during day -1 to +1. Panel B provides descriptive statistics about the characteristics of debt offering, bonds and companies included in the sample. Bond offering characteristics including new bond’s issuance size, maturity and new bond ratings are collected from SDC. Other bond-specific information is obtained from the Mergent Fixed Income Security Database (FISD). All accounting variables are measured in the fiscal year immediately preceding the debt offering announcement year and obtained from the COMPUSTAT. Definitions of variables can be seen in Appendix B.

Panel A. Distribution of straight debt offerings per sample year

	Debt level		Firm level	
Year	Total sample	Uncontaminated sample	Total sample	Uncontaminated sample
2005	92	75	70	58
2006	110	98	73	63
2007	181	131	107	80
2008	166	124	100	76
2009	299	223	210	161
2010	259	201	169	130
2011	249	192	130	98
Total	1,356	1,044	859	666

Panel B. Descriptive statistics of bond and firm variables

Variables	Sample Size	Mean	Median	Std. Dev.	25th percentile	75th percentile
Issuance size (millions)	859	1,112	731	1,175	400	1,500
Issuance size/ Assets	859	0.06	0.04	0.06	0.03	0.08
Issuance size/ Long-term debt	859	0.28	0.17	0.49	0.10	0.31
New bond maturity (years)	859	11.71	10.02	8.60	7.07	14.02
Existing bond maturity (years remaining)	859	8.73	7.54	4.8	5.34	11.19
New bond rating	859	8.97	9.00	3.41	6.00	11.00
Existing bond rating	859	9.07	9.00	3.58	6.00	11.00
Intended uses: stock repurchases	859	0.08	0.00	0.27	0.00	0.00
Intended uses: expansions	859	0.14	0.00	0.35	0.00	0.00
Intended uses: refinancing	859	0.31	0.00	0.46	0.00	1.00
Intended uses: unclear	859	0.47	0.00	0.50	0.00	1.00
Firms' size (millions)	859	35,995	17,604	54,495	7,735	36,677
Asset risk (std. dev. of unlevered stock returns)	859	0.017	0.014	0.011	0.010	0.020
Tangibility	857	0.38	0.32	0.27	0.14	0.58
Tax rate	859	0.28	0.32	0.92	0.24	0.37
Firms' growth opportunities	857	5.72	2.52	43.51	1.65	4.20
Firms' profit	859	0.11	0.11	0.08	0.07	0.15
Proportion of new bonds' maturity shorter than existing bonds %	3,738	32.08				
Proportion of new bonds subordinated to existing bonds %	3,738	0.83				
Proportion of new bonds senior than existing bonds %	3,738	2.84				

Table 3. Bond and Stock Market Reactions surrounding Debt Offering Announcement Dates

The sample period ranges from 2005 to 2011. The unit of observation is a debt offering at the firm level. The ‘‘uncontaminated” sample consists of debt offering announcements not accompanied by contaminating news during day -1 to +1. ABSR represents abnormal standardized bond returns. Dates in braces i.e. {-3.3}, denote a composite return from day -3 to +3 including all possible ABSRs as defined in Ederington, Guan and Yang (2012). When a firm has multiple bonds, bond returns are calculated as an equal average of bond returns. CAR is computed as the raw stock return minus value-weighted market returns. SCAR represents standardized cumulative abnormal returns, which are defined as cumulative abnormal market adjusted returns divided by the time series standard deviation of abnormal returns over the window (-300, -46) relative to the announcement date. The significance level of the mean and median is based on t-test and Wilcoxon signed-rank test, respectively. The symbols ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: Bonds	Total Sample			Uncontaminated Sample		
	N	Mean	Median	N	Mean	Median
ABSR(-1,+1)	695	-0.16***	-0.20***	531	-0.16***	-0.21***
ABSR{-3,+3}	839	-0.15***	-0.14***	651	-0.13***	-0.13***
ABSR{-5,+5}	859	-0.13***	-0.12***	666	-0.12***	-0.10***
Panel B: Stocks	**Total Sample**			**Uncontaminated Sample**		
	N	Mean	Median	N	Mean	Median
CAR (-1,+1)	859	0.0007	-0.0002	666	0.0011	0.0001
CAR (-3,+3)	859	0.0045***	0.0033***	666	0.0039**	0.0023**
CAR (-5,+5)	859	0.0061***	0.0044***	666	0.0059**	0.0035**
SCAR (-1,+1)	859	0.0077	-0.0049	666	0.0253	0.0023
SCAR (-3,+3)	859	0.1027***	0.0837***	666	0.0890***	0.0707***
SCAR (-5,+5)	859	0.1096***	0.0896***	666	0.0951***	0.0695***

Table 4. Existing Bond Market Response to New Debt Offerings by the Difference of Seniority (Maturity) between New and Existing Bonds

This table presents existing bond returns surrounding new debt offering announcements segmented by the difference of seniority (maturity) between new and existing bonds. The sample period ranges from 2005 to 2011. Each existing bond is treated as a separate bond when comparing the difference of seniority and maturity. More details can be seen in the footnote 42. The ‘‘uncontaminated” sample consists of debt offering announcements not accompanied by contaminating news during day -1 to +1. ABSR represents abnormal standardized bond returns. Dates in braces i.e. {-3, +3}, denote a composite return from day -3 to +3 including all possible ABSRs as defined in Ederington, Guan and Yang (2012). When a firm has multiple bonds, bond returns are calculated as an equal average of bond returns. In Panels A and B, the column "Difference" indicates the difference in abnormal standardized bond returns (ABSR) between a new bond subordinated to an existing bond: Seniority: New<Existing and a new bond senior to an existing bond: Seniority: New>Existing. In Panels C and D: the column "Difference" indicates the difference of abnormal standardized bond returns (ABSR) between groups of a new bond's maturity shorter than an existing bond: Maturity: New< Existing and a new bond's maturity longer than an existing bond: Maturity: New>existing. The difference in means test uses the unequal variance t-test. The significance level of the difference in medians is based on a Wilcoxon rank-sum two sample test. The symbols ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Seniority: New<Existing			Seniority: New>Existing			Difference	
Panel A: Total	N	Mean	Median	N	Mean	Median	Mean	Median
ABSR(-1,+1)	17	0.46*	0.21*	40	-0.16	0.13	0.62*	0.08*
ABSR{-3,+3}	21	0.19	0.29	54	-0.07	-0.10	0.26	0.39
ABSR{-5,+5}	22	0.09	-0.02	57	-0.05	0.00	0.14	-0.02
Panel B: Uncontaminated								
ABSR(-1,+1)	14	0.30	0.17	31	-0.12	0.21	0.42	-0.04
ABSR{-3,+3}	18	0.17	0.21	41	0.00	0.01	0.17	0.20
ABSR{-5,+5}	18	0.02	-0.02	44	-0.04	0.04	0.06	-0.06

Table 4. Existing Bond Market Response to New Debt Offerings by the Difference of Seniority (Maturity) between New and Existing Bonds, Continued

	Maturity: New<Existing			Maturity: New>Existing			Difference	
Panel C: Total	N	Mean	Median	N	Mean	Median	Mean	Median
ABSR(-1,+1)	362	-0.37***	-0.33***	604	-0.13***	-0.16***	-0.24***	-0.17***
ABSR{-3,+3}	457	-0.29***	-0.23***	761	-0.14***	-0.13***	-0.15***	-0.10***
ABSR{-5,+5}	479	-0.25***	-0.18***	779	-0.11***	-0.08***	-0.14***	-0.10***
Panel D: Uncontaminated								
ABSR(-1,+1)	273	-0.36***	-0.32***	458	-0.13***	-0.16***	-0.23***	-0.16***
ABSR{-3,+3}	349	-0.26***	-0.23***	589	-0.11***	-0.10***	-0.15***	-0.13***
ABSR{-5,+5}	367	-0.23***	-0.16***	603	-0.09***	-0.07***	-0.14***	-0.09***

Table 5. Existing Bond Market Response to New Debt Offerings by Bonds' Credit Rating

The sample period is from 2005 to 2011. The ''uncontaminated" sample consists of debt offering announcements not accompanied by contaminating news during day -1 to +1. ABSR represents abnormal standardized bond returns. Dates in braces i.e. {-3, +3}, denote a composite return from day -3 to +3 including all possible ABSRs as defined in Ederington, Guan and Yang (2012). A bond is considered an investment-grade rated bond if the bond's rating belongs to the category of investment-grade rating (rating above Ba1 or BB+). In contrast, a bond is considered to be a speculative rated bond if its rating belongs to the category of speculative-grade rating (rating below Ba1 or BB+). When a firm has multiple bonds, bond returns are calculated as an equal average of bond returns. The column "Difference" indicates the difference of abnormal standardized bond returns (ABSR) between investment and speculative rated bonds. The difference in means test uses the unequal variance t-test. The significance level of the difference in medians is based on a Wilcoxon rank-sum two sample test. The symbols ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Existing bonds' rating:	Investments			Speculative			Difference	
	N	Mean	Median	N	Mean	Median	Mean	Median
Panel A: Total								
ABSR(-1,+1)	528	-0.20***	-0.21***	168	-0.06	-0.13	-0.14	-0.08*
ABSR{-3,+3}	622	-0.17***	-0.16***	220	-0.12**	-0.08*	-0.05	-0.08
ABSR{-5,+5}	636	-0.14***	-0.14***	226	-0.09*	-0.03	-0.05	-0.11*
Panel B: Uncontaminated								
ABSR(-1,+1)	396	-0.18***	-0.21***	135	-0.11	-0.18*	-0.07	-0.03
ABSR{-3,+3}	475	-0.13***	-0.14****	177	-0.12*	-0.08*	-0.01	-0.06
ABSR{-5,+5}	486	-0.11***	-0.11***	181	-0.12**	-0.08*	0.01	-0.03

Table 6. Existing Bond and Stock Market Response to New Debt Offerings by Firms' Intended Uses of Newly Raised Funds from Debt Financing

The sample period is from 2005 to 2011. The ''uncontaminated" sample consists of debt offering announcements not accompanied by contaminating news during day -1 to +1. ABSR represents abnormal standardized bond returns. Dates in braces i.e. {-3, +3}, denote a composite return from day -3 to +3 including all possible ABSRs as defined in Ederington, Guan and Yang (2012). When a firm has multiple bonds, bond returns are calculated as an equal average of bond returns. Using hand-collected data from Factiva, I identify a firm's intended use of newly raised funds from new debt offerings. An intended use is defined as stock repurchase (refinancing) when the intended use of newly raised funds is a stock repurchase (refinancing). Expansions uses include all financings of new risky projects such as mergers, future acquisitions, and capital expenditures. I define an intended use as unclear if the intended use is unclear or has many possibilities listed in the debt offering announcement news. The column named (1) - (2) represents the difference in bond/stock returns between stock repurchase uses and expansions uses. Likewise, (1) - (3) indicates the bond/stock return difference between stock repurchase use and refinancing use, and (2) – (3) indicates the bond/stock return difference between expansions uses and refinancing uses. The difference in means test uses the unequal variance t-test. The significance level of the difference in medians is based on a Wilcoxon rank-sum two sample test. The symbols ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Bonds																	
Intended use:	(1) Stock Repurchases			(2) Expansions			(3) Refinancings			(4) Unclear			(1) - (2)		(1) - (3)		(2) - (3)	
Panel A: Total	N	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median
ABSR(-1,+1)	51	-0.22**	-0.15***	98	-0.32***	-0.44***	212	-0.09	-0.18	334	-0.16***	-0.16***	0.10	0.29**	-0.13	0.03	-0.23**	-0.26***
ABSR{-3,+3}	65	-0.15**	-0.13**	117	-0.26***	-0.26***	259	-0.15***	-0.10***	398	-0.13***	-0.13***	0.11	0.13	0.00	-0.03	-0.11*	-0.16*
ABSR{-5,+5}	66	-0.14**	-0.10**	122	-0.20***	-0.19***	268	-0.12***	-0.10***	403	-0.11***	-0.12***	0.06	0.09	-0.02	0.00	-0.08	-0.09*
Panel B: Uncontamianated																		
ABSR(-1,+1)	42	-0.15	-0.14*	79	-0.38***	-0.48***	159	-0.09	-0.14	251	-0.15***	-0.16***	0.23*	0.34***	-0.06	0.00	-0.29***	-0.34***
ABSR{-3,+3}	52	-0.08	-0.12	95	-0.26***	-0.28***	198	-0.12**	-0.08**	306	-0.10***	-0.11***	0.18	0.16**	0.04	-0.04	-0.14	-0.20**
ABSR{-5,+5}	53	-0.09	-0.09	98	-0.19***	-0.19***	205	-0.11**	-0.09*	310	-0.10***	-0.10***	0.10	0.10	0.02	0.00	-0.08	-0.10*
	Stocks																	
Intended use:	(1) Stock Repurchases			(2) Expansions			(3) Refinancings			(4) Unclear			(1) - (2)		(1) - (3)		(2) - (3)	
Panel C: Total	N	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median
SCAR (-1,+1)	66	0.20*	0.18**	122	-0.04	0.00	268	0.07	0.01	403	-0.05	-0.06	0.25	0.18*	0.14	0.17*	-0.11	-0.01
SCAR (-3,+3)	66	0.31***	0.28***	122	0.03	-0.03	268	0.18***	0.12***	403	0.04	0.08	0.28**	0.31**	0.13	0.16	-0.15	-0.15
SCAR (-5,+5)	66	0.44***	0.34***	122	-0.06	-0.11	268	0.20***	0.13***	403	0.05	0.08	0.51***	0.44***	0.25**	0.21**	-0.26**	-0.23**
Panel D: Uncontamianated																		
SCAR (-1,+1)	53	0.23*	0.18*	98	0.00	0.01	205	0.02	-0.06	310	0.00	0.02	0.23	0.17*	0.21	0.24*	-0.01	0.07
SCAR (-3,+3)	53	0.25**	0.24*	98	0.06	-0.03	205	0.12**	0.08**	310	0.05	0.07	0.19	0.27	0.12	0.16	-0.06	-0.11
SCAR (-5,+5)	53	0.41***	0.31***	98	-0.03	-0.07	205	0.14**	0.10**	310	0.05	0.07	0.44***	0.38***	0.27*	0.20*	-0.17	-0.17

Table 7. Bond-level Regressions Explaining Existing Bondholders' Losses surrounding New Debt Offering Announcements

This table displays the bond-level regression results where the dependent variables are ABSR {-3, +3}. Dates in braces i.e. {-3, +3}, denote a composite return from day -3 to +3 including all possible ABSRs as defined in Ederington, Guan and Yang (2012). The sample period ranges from 2005 to 2011. The ''uncontaminated" sample consists of debt offering announcements not accompanied by contaminating news during day -1 to +1. New bonds' seniority: New<Existing (New>Existing) is a dummy variable with a value of 1 if the new bonds are subordinated to (senior than) existing bonds and 0 otherwise. New bonds' maturity: New<Existing is an indicator variable which equals 1 when new bonds' maturity is shorter than existing bonds and 0 otherwise. P-values of F-test for the difference of coefficients between New bonds' seniority: New<Existing and New>Existing are reported in the last row of the table. Existing bonds' rating: "investment" assumes a value of 1 if an existing bond's rating belongs to an investment grade rated category and is 0 otherwise. The indicator variable for a large offering equals 1 if the debt issuance size is greater than or equal to 4.46% of total assets and 0 otherwise. 4.46% is the median percentage of debt issuance size over the firm's total asset across the total sample. All other control variables are defined as in Appendix B. To avoid underestimating the standard deviation associated with the potential correlation in bond returns within the same firm, I estimate the regressions using firm clustered residuals. *P-values* for the significance of the coefficients are shown in parentheses. The symbols ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Total Sample				Uncontaminated Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.53**	0.57**	0.55**	0.75***	0.35	0.42*	0.39*	0.62***
	(0.04)	(0.03)	(0.03)	(0.00)	(0.14)	(0.08)	(0.09)	(0.01)
Bonds' seniority: New<Existing	0.39**		0.35*	0.33*	0.39**		0.35**	0.34**
	(0.04)		(0.07)	(0.07)	(0.02)		(0.05)	(0.05)
Bonds' seniority: New>Existing	0.09		0.07	0.07	0.20		0.19	0.17
	(0.52)		(0.61)	(0.62)	(0.23)		(0.26)	(0.30)
Bonds' maturity: New<Existing		-0.10***	-0.09***			-0.12***	-0.12***	
		(0.01)	(0.01)			(0.00)	(0.00)	
Existing bonds' rating: investment	-0.02	-0.06	-0.04	0.00	-0.03	-0.09	-0.05	-0.01
	(0.82)	(0.37)	(0.59)	(0.98)	(0.74)	(0.29)	(0.57)	(0.88)
Existing bonds' maturity (bond-level)				-0.14***				-0.16***
				(0.00)				(0.00)
Firms' leverage>Target leverage	0.01	0.00	0.00	0.01	0.03	0.02	0.02	0.02
	(0.82)	(0.94)	(0.92)	(0.86)	(0.59)	(0.71)	(0.68)	(0.64)
Indicator variable for a large offering (>=4.46%)	-0.14***	-0.15***	-0.15***	-0.14***	-0.14***	-0.15***	-0.16***	-0.15***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Asset risk	3.77	3.86	3.90	3.67	4.91	5.05	4.89	4.71
	(0.16)	(0.16)	(0.15)	(0.17)	(0.12)	(0.11)	(0.12)	(0.13)
High volume issues	-0.01	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.72)	(0.69)	(0.65)	(0.73)	(0.90)	(0.79)	(0.78)	(0.89)
Tangibility	-0.21**	-0.19**	-0.20**	-0.18**	-0.20**	-0.19**	-0.20**	-0.18**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Tax rate	-0.01	-0.01	-0.01	-0.01	-0.04	-0.04	-0.04	-0.03
	(0.79)	(0.76)	(0.79)	(0.81)	(0.32)	(0.29)	(0.32)	(0.35)
Firms' growth opportunities	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.20)	(0.16)	(0.16)	(0.33)	(0.35)	(0.28)	(0.26)	(0.50)
Firms' profit	-0.26	-0.24	-0.24	-0.36	0.22	0.23	0.24	0.11
	(0.52)	(0.55)	(0.55)	(0.36)	(0.57)	(0.58)	(0.56)	(0.77)
Firms' size	-0.06***	-0.05**	-0.05**	-0.05***	-0.04**	-0.04**	-0.04**	-0.04**
	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)	(0.05)	(0.04)	(0.03)
R-square in %	1.78	1.97	2.13	3.87	1.96	2.21	2.49	4.47
# of observations	3,505	3,480	3,480	3,505	2,611	2,593	2,593	2,611
Difference of coefficients for seniority (P-value)	0.08	NA	0.10	0.11	0.30	NA	0.38	0.35

Table 8. Firm-level Regressions Explaining Bond and Stock Returns surrounding New Debt Offering Announcements

This table displays the firm-level regression results. The sample period ranges from 2005 to 2011. The ‘‘uncontaminated” sample consists of debt offering announcements not accompanied by contaminating news during day -1 to +1. The dependent variable in bond regressions is ABSR {-3, +3}. Dates in braces i.e. {-3, +3}, denote a composite return from day -3 to +3 including all possible ABSRs as defined in Ederington, Guan and Yang (2012). In stock regressions, the dependent variable is SCAR (-1, +1). Intended uses are indicator variables for whether the firm intends to use the proceeds for stock repurchases, expansions, or debt refinancing. The indicator variable for a large offering equals 1 if the debt issuance size is greater than or equal to 4.46% of total assets and 0 otherwise. 4.46% is the median percentage of debt issuance size over the firm’s total asset across the total sample. Seniority: New-Existing indicates the difference of the seniority level between new bonds and firms’ existing bonds at the firm level. Maturity: New-Existing is the maturity difference between new bonds and firms’ existing bonds at the firm level. A bond’s maturity is defined as the natural logarithm of the number of years remaining before the bond is expired. Definitions of all other variables can be seen in Appendix B. *P-values* of F-test for the difference of coefficients between different intended uses of newly raised funds are reported in the bottom rows. The *p-values* for the significance of the coefficients are shown in parentheses. The symbols ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Total Sample				Uncontaminated Sample			
	Bonds		Stocks		Bonds		Stocks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.38	0.59**	-0.15	-0.40	0.19	0.47	-0.17	-0.34
	(0.15)	(0.03)	(0.68)	(0.29)	(0.53)	(0.12)	(0.67)	(0.38)
Intended uses: Stock repurchases	-0.02	-0.02	0.27**	0.26*	0.00	0.01	0.24*	0.24*
	(0.82)	(0.84)	(0.05)	(0.06)	(0.98)	(0.92)	(0.09)	(0.09)
Intended uses: Expansions	-0.13*	-0.12*	0.00	-0.01	-0.15*	-0.13	0.00	-0.01
	(0.09)	(0.10)	(0.98)	(0.89)	(0.09)	(0.13)	(0.99)	(0.91)
Intended uses: Refinancing	-0.05	-0.05	0.08	0.08	-0.03	-0.03	-0.02	-0.02
	(0.41)	(0.41)	(0.33)	(0.35)	(0.65)	(0.66)	(0.86)	(0.85)
Seniority: New-Existing	-0.18*	-0.18*	-0.12	-0.10	-0.11	-0.13	-0.19	-0.17
	(0.09)	(0.07)	(0.43)	(0.51)	(0.31)	(0.23)	(0.19)	(0.22)
Maturity: New-Existing	0.04		-0.09*		0.07*		-0.05	
	(0.29)		(0.07)		(0.10)		(0.35)	
Firms' existing bond maturities		-0.17***		0.16**		-0.21***		0.13*
		(0.00)		(0.02)		(0.00)		(0.08)
Existing bonds' rating: investment	-0.03	0.00	-0.09	-0.12	-0.02	0.02	-0.23**	-0.25**
	(0.72)	(0.96)	(0.42)	(0.27)	(0.83)	(0.83)	(0.04)	(0.02)
Firms' leverage>Target leverage	0.07	0.08	0.07	0.07	0.08	0.08	0.07	0.07
	(0.15)	(0.13)	(0.32)	(0.30)	(0.17)	(0.17)	(0.37)	(0.36)
Indicator variable for a large offering (>=4.46%)	-0.09	-0.10*	0.02	0.02	-0.07	-0.08	-0.02	-0.02
	(0.13)	(0.10)	(0.80)	(0.82)	(0.28)	(0.22)	(0.78)	(0.80)
Asset risk	6.11***	5.69**	0.42	0.75	5.65**	5.29**	0.91	1.07
	(0.01)	(0.02)	(0.90)	(0.83)	(0.04)	(0.05)	(0.80)	(0.76)
High volume issues	-0.01	-0.01	0.06	0.05	-0.04	-0.03	0.06	0.06
	(0.85)	(0.84)	(0.45)	(0.52)	(0.56)	(0.61)	(0.42)	(0.46)
Tangibility	-0.24***	-0.17*	0.19	0.12	-0.23**	-0.16	0.13	0.08
	(0.01)	(0.08)	(0.17)	(0.37)	(0.04)	(0.16)	(0.37)	(0.57)
Tax rate	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.04	-0.04
	(0.82)	(0.82)	(0.53)	(0.51)	(0.43)	(0.44)	(0.31)	(0.31)
Firms' growth opportunities	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.94)	(0.90)	(0.44)	(0.42)	(0.99)	(0.97)	(0.34)	(0.35)
Firms' profit	0.02	-0.04	-0.43	-0.38	0.47	0.39	0.02	0.07
	(0.96)	(0.92)	(0.42)	(0.48)	(0.25)	(0.34)	(0.97)	(0.90)
Firms' size	-0.05**	-0.04	0.01	0.00	-0.03	-0.02	0.03	0.02
	(0.05)	(0.13)	(0.76)	(0.90)	(0.25)	(0.45)	(0.48)	(0.60)
R-square in %	3.10	4.47	1.76	2.02	3.12	4.72	2.09	2.41
# of observations	836	836	855	855	650	650	664	664
F-test for repurchases = expansions (P-value)	0.33	0.36	0.09	0.08	0.25	0.26	0.10	0.10
F-test for repurchases = refinancings (P-value)	0.79	0.77	0.10	0.21	0.80	0.72	0.08	0.09
F-test for refinancings = expansions (P-value)	0.31	0.38	0.42	0.42	0.20	0.27	0.91	0.97

Table 9. Bond and Firm-level Regressions Explaining Bond and Stock Cumulative Abnormal Returns surrounding New Debt Offering Announcements

Panel A displays the bond-level regression results where the dependent variables are each bond's CAR (-1, +1). Panel B reports the firm-level regression results using a firm's bond and stock CAR (-1, +1) as dependent variables, respectively. CAR represents cumulative abnormal returns. Bond abnormal returns is estimated using the "trade-weighted price, all trades" method of Bessembinder et al. (2009) and stock cumulative abnormal returns is computed as the raw stock return minus value-weighted market returns. The sample period ranges from 2005 to 2011. The ''uncontaminated" sample consists of debt offering announcements not accompanied by contaminating news during day -1 to +1. In Panel A, New bonds' seniority: New<Existing (New>Existing) is a dummy variable with a value of 1 if the new bonds are subordinated to (senior than) existing bonds and 0 otherwise. New bonds' maturity: New<Existing is an indicator variable which equals 1 when new bonds' maturity is shorter than existing bonds and 0 otherwise. P-values of F-test for the difference of coefficients between New bonds' seniority: New<Existing and New>Existing are reported in the last row of the table. To avoid underestimating the standard deviation associated with the potential correlation in bond returns within the same firm, I estimate the regressions using firm clustered residuals. In Panel B, Intended uses are indicator variables for whether the firm intends to use the proceeds for stock repurchases, expansions, or debt refinancing. P-values of F-test for the difference of coefficients between different intended uses of newly raised funds are reported in the bottom rows. All other control variables are defined as in Appendix B. P-values for the significance of the coefficients are shown in parentheses. The symbols ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A:	Uncontaminated Sample			
	(1)	(2)	(3)	(4)
Intercept	0.003	0.005	0.004	0.007*
	(0.49)	(0.32)	(0.40)	(0.10)
Bonds' seniority: New<Existing	0.006**		0.006*	0.006**
	(0.03)		(0.06)	(0.05)
Bonds' seniority: New>Existing	0.006		0.006	0.005
	(0.14)		(0.15)	(0.17)
Bonds' maturity: New<Existing		-0.002**	-0.002**	
		(0.03)	(0.03)	
Existing bonds' rating: investment	0.001	0.000	0.001	0.001
	(0.52)	(0.89)	(0.58)	(0.41)
Existing bonds' maturity (bond-level)				-0.003***
				(0.00)
Firms' leverage>Target leverage	0.000	0.000	0.000	0.000
	(0.80)	(0.73)	(0.77)	(0.72)
Indicator variable for a large offering (>=4.46%)	-0.002**	-0.002**	-0.002***	-0.002**
	(0.02)	(0.02)	(0.01)	(0.02)
Asset risk	0.052	0.064	0.056	0.050
	(0.46)	(0.38)	(0.42)	(0.47)
High volume issues	0.000	0.000	0.000	0.000
	(0.88)	(0.98)	(0.96)	(0.89)
Tangibility	-0.002	-0.002	-0.002	-0.002
	(0.15)	(0.19)	(0.15)	(0.19)
Tax rate	-0.001	-0.001	-0.001	-0.001
	(0.36)	(0.31)	(0.36)	(0.40)
Firms' growth opportunities	0.000	0.000	0.000	0.000
	(0.47)	(0.67)	(0.72)	(0.61)
Firms' profit	0.000	-0.001	0.000	-0.001
	(0.95)	(0.90)	(0.95)	(0.85)
Firms' size	-0.001	-0.001	-0.001	-0.001
	(0.17)	(0.22)	(0.20)	(0.19)
R-square in %	1.06	1.01	1.37	2.65
# of observations	2,771	2,751	2,751	2,771
Difference of coefficients for seniority (P-value)	0.90	NA	0.98	0.96

Panel B:	Uncontaminated Sample			
	Bonds		Stocks	
	(1)	(2)	(3)	(4)
Intercept	0.005	0.008	-0.007	-0.014
	(0.33)	(0.13)	(0.65)	(0.40)
Intended uses: Stock repurchases	-0.001	-0.001	0.007	0.006
	(0.68)	(0.72)	(0.24)	(0.27)
Intended uses: Expansions	-0.002	-0.002	-0.002	-0.002
	(0.16)	(0.20)	(0.70)	(0.64)
Intended uses: Refinancing	-0.002	-0.002	0.002	0.002
	(0.16)	(0.17)	(0.59)	(0.62)
Seniority: New-Existing	-0.003	-0.003	-0.014**	-0.014**
	(0.21)	(0.17)	(0.02)	(0.02)
Maturity: New-Existing	0.001		-0.003	
	(0.28)		(0.24)	
Firms' existing bond maturities		-0.002**		0.004
		(0.04)		(0.11)
Existing bonds' rating: investment	0.001	0.001	-0.009**	-0.010**
	(0.57)	(0.41)	(0.05)	(0.04)
Firms' leverage>Target leverage	0.001	0.001	0.002	0.002
	(0.24)	(0.24)	(0.50)	(0.48)
Indicator variable for a large offering (>=4.46%)	-0.001	-0.001	0.001	0.001
	(0.57)	(0.54)	(0.73)	(0.75)
Asset risk	0.091*	0.088*	0.427***	0.431***
	(0.07)	(0.08)	(0.00)	(0.00)
High volume issues	0.000	0.000	0.002	0.002
	(0.90)	(0.97)	(0.47)	(0.53)
Tangibility	-0.004*	-0.003	-0.003	-0.005
	(0.06)	(0.13)	(0.58)	(0.44)
Tax rate	0.000	0.000	-0.002	-0.002
	(0.48)	(0.49)	(0.12)	(0.11)
Firms' growth opportunities	0.000	0.000	0.000	0.000
	(0.75)	(0.76)	(0.37)	(0.36)
Firms' profit	-0.008	-0.009	-0.008	-0.006
	(0.29)	(0.24)	(0.73)	(0.78)
Firms' size	-0.001	-0.001	0.001	0.001
	(0.15)	(0.23)	(0.60)	(0.66)
R-square in %	2.47	2.96	3.87	3.92
# of observations	664	664	664	664
F-test for repurchases = expansions (P-value)	0.55	0.57	0.20	0.20
F-test for repurchases = refinancings (P-value)	0.66	0.63	0.44	0.47
F-test for refinancings = expansions (P-value)	0.79	0.87	0.44	0.41

Table 10. Firm Level Characteristics, Chapter 3

This table presents the sample distribution and firm characteristics from July 2002 to December 2010. Panel A presents firm level characteristics for dividend decreases and increases announcements. Panel B reports firm level characteristics for dividend omissions and initiations announcements. Dividend indicates the dividend payment as of the dividend announcement day. ΔDIV indicates the size of dividend changes, which is calculated as the percentage difference in dividend payments between current and previous period. All the remaining variables are measured in the last fiscal year ending before the dividend announcement year. Assets are extracted from Compustat annual file. Financial leverage is defined as the ratio of book value of long-term debt over the book value of the total assets of the firm. Financial Non-distressed (Unconstrained) Dummy is an indicator variable equals 1 if a firm is financially non-distressed (unconstrained), and 0 if a firm is financially distressed (constrained). Following van Binsbergen, Graham and Yang (2010), I measure financial distress employing a modified version of Altman's (1968) Z-score. Firms are considered nondistressed when their Z-scores are in the top tercile. Financially constrained firms are defined as firms having restricted long-term leverage. A more detailed description of these two measurements can be seen in the Appendix C.

Panel A	Dividend decreases							Dividend increases						
Year	N	Dividend ($/Share)	ΔDIV	Assets($ Mill)	Financial leverage	Financially non-distressed dummy	Financially unconstrained dummy	N	Dividend ($/Share)	ΔDIV	Assets($ Mill)	Financial leverage	Financially non-distressed dummy	Financially unconstrained dummy
2002	NA	NA	NA	NA	NA	NA	NA	12	0.29	44%	147.68	0.28	25%	75%
2003	5	0.27	-50%	26.70	0.25	40%	100%	70	0.30	27%	131.56	0.20	31%	68%
2004	9	0.21	-42%	186.26	0.27	33%	56%	118	0.30	32%	104.15	0.21	21%	72%
2005	34	0.18	-40%	40.10	0.27	10%	90%	174	0.32	25%	80.58	0.26	21%	91%
2006	35	0.27	-36%	89.57	0.19	29%	88%	163	0.32	19%	89.03	0.24	28%	91%
2007	20	0.33	-42%	63.40	0.23	20%	90%	191	0.37	54%	88.13	0.23	31%	86%
2008	53	0.24	-49%	203.72	0.19	11%	77%	147	0.40	35%	75.04	0.25	35%	89%
2009	81	0.17	-60%	268.44	0.23	19%	87%	151	0.33	29%	54.16	0.25	38%	87%
2010	35	0.20	-32%	69.66	0.22	39%	82%	210	0.38	31%	60.15	0.26	34%	80%
Total	272	0.22	-47%	152.54	0.22	21%	84%	1,236	0.35	32%	81.47	0.24	30%	84%
Panel B	Dividend omissions							Dividend initiations						
	64	NA	NA	44.24	0.32	22%	93%	41	0.19	NA	41.52	0.35	16%	81%

Table 11. Bond Level Characteristics

This table presents bond characteristics in the full sample across the sample period from July 2002 to December 2010. Panel A presents firm level characteristics for dividend decreases and increases announcements. Panel B reports firm level characteristics for dividend omissions and initiations announcements. Bond characteristics data are extracted from Mergent Fixed Income Securities Database (FISD). Coupon rate is the bond's annual interest rate. Years to Maturity denotes the number of remaining years to maturity for bonds. Issued proceeds are the par values of the bond when initially issued. Bond rating issued by Moody is denoted as numerical values (Aaa=1…D=25). If bonds are unrated by Moody, I use S&P's ratings of the bonds. Investment dummy is a binary variable with a value of 1 if a bond's rating belongs to the category of investment-grade rating (rating above Ba1 or BB+) and is 0 otherwise. Senior dummy equals 1 if a bond is secured, senior issue of the issuer and 0 otherwise.

Panel A	Dividend decreases							Dividend increases								
Year	N	Coupon rate (%)	Years to maturity	Issued proceeds ($Mill)	Bond rating	Investment dummy	Senior dummy	N	Coupon rate (%)	Years to maturity	Issued proceeds ($Mill)	Bond rating	Investment dummy	Senior dummy
2002	NA	NA	NA	NA	NA	NA	NA	41	6.47	7.51	1,456.64	6.32	98%	93%
2003	8	5.52	5.53	643.75	7.13	100%	100%	496	6.21	7.32	825.50	4.47	99%	90%
2004	66	5.88	6.53	730.08	4.48	100%	82%	555	5.68	6.96	727.07	5.23	96%	95%
2005	94	5.98	8.03	453.85	9.93	49%	100%	817	5.70	6.85	678.69	6.15	90%	94%
2006	153	6.39	8.38	737.69	8.50	61%	94%	748	5.67	6.25	728.48	6.27	90%	94%
2007	57	6.09	7.65	602.24	8.11	81%	100%	782	5.73	7.15	747.03	6.61	89%	91%
2008	326	5.80	6.93	977.84	5.80	95%	78%	610	5.88	7.92	829.96	7.08	90%	97%
2009	602	5.75	6.13	1,104.01	6.40	93%	86%	568	6.18	9.45	773.29	7.63	92%	100%
2010	120	6.48	9.05	676.78	10.97	73%	99%	993	5.80	8.79	787.81	7.05	93%	100%
Total	1,426	5.92	7.00	917.11	7.09	85%	87%	5,610	5.83	7.59	763.65	6.40	92%	95%
Panel B	Dividend omissions							Dividend initiations						
	211	6.66	8.99	750.37	8.85	72%	100%	116	7.04	8.71	792.33	10.73	71%	100%

Table 12. Bond Market Responses to Dividend Change Announcements

The full sample consists of 272 announcements of decreased dividends and 1,236 announcements of increased dividends from July 2002 to December 2010. The sample is limited to bonds that traded on at least 10 days during Day -21 to Day -1, where Day 0 is the day of dividend announcements. CAR is the sum of the firm's daily abnormal bond returns over the event window. Daily abnormal bond returns are calculated as the bond's raw return less the contemporaneous return on a value-weighted portfolio of bonds matched on rating and maturity. Daily bond prices are calculated with the "trade-weighted price, all trades" method of Bessembinder, Kahle, Maxwell and Xu (2009). When a sample bond is not traded on a given day, the most recent observed daily price is used for that day. For firms with multiple bond issues, the firm's daily abnormal return is computed as the value-weighted average of abnormal returns on each bond issues. Using the Mergent FISD, I further partition the full sample into different categories based on bond characteristics: seniority (Panel B), and investment rating (Panel C). I also partition the full sample based on firm characteristics: financially unconstrained (Panel E) and non-distressed (Panel F). To examine the influence of financial crisis on dividend announcement effects, I divide the full sample into two periods: before and after 2008 in Panel D. The symbols ***, ** and * indicate significance at the one, five, and ten percent levels, respectively.

Event window (days)	N	Mean CARs	T-stat	N	Mean CARs	T-stat
Panel A: Full sample		Decreases			Increases	
(-30,-5)	272	-0.87%**	-2.18	1,236	-0.33%***	-3.13
(-4,-2)	272	-0.19%	-1.47	1,236	-0.06%*	-1.76
(-1,+1)	272	0.00%	0.00	1,236	0.06%*	1.66
(+2,+30)	272	-0.80%**	-2.39	1,236	-0.42%***	-3.45
Panel B:						
Decreases		Senior bonds			Junior bonds	
(-30,-5)	267	-0.85%**	-1.96	36	-0.24%	-0.16
(-4,-2)	267	-0.15%	-1.15	36	-0.20%	-0.42
(-1,+1)	267	-0.01%	-0.10	36	-0.10%	-0.34
(+2,+30)	267	-0.71%**	-2.10	36	-1.95%*	-1.78
Increases						
(-30,-5)	1,226	-0.33%***	-3.12	61	-0.38%	-1.33
(-4,-2)	1,226	-0.06%*	-1.79	61	0.10%	0.79
(-1,+1)	1,226	0.06%*	1.71	61	-0.09%	-0.87
(+2,+30)	1,226	-0.42%***	-3.35	61	-0.65%***	-2.82

Table 12. Bond Market Responses to Dividend Change Announcements, Continued

Panel C:	Investment grade			Speculative grade		
Decreases						
	N	Mean CARs	T-stat	N	Mean CARs	T-stat
(-30,-5)	212	-0.69%*	-1.74	69	-1.54%	-1.51
(-4,-2)	209	-0.17%	-1.18	69	-0.27%	-0.91
(-1,+1)	209	-0.02%	-0.18	72	0.05%	0.19
(+2,+30)	209	-0.72%**	-2.55	77	-1.00%	-1.10
Increases						
(-30,-5)	1,063	-0.25%***	-3.88	214	-0.85%	-1.50
(-4,-2)	1,063	-0.03%	-0.82	210	-0.28%**	-1.95
(-1,+1)	1,062	0.02%	0.65	210	0.22%*	1.74
(+2,+30)	1,064	-0.36%***	-5.67	214	-0.77%	-1.16

Panel D:	Decreases			Increases		
Event window (days)	N	Mean CARs	T-stat	N	Mean CARs	T-stat
Before 2008						
(-30,-5)	103	-0.45%	-1.23	733	-0.15%**	-2.56
(-4,-2)	103	0.03%	0.24	733	-0.05%	-1.35
(-1,+1)	103	-0.04%	-0.29	733	0.00%	0.15
(+2,+30)	103	-0.12%	-0.52	733	-0.20%***	-2.59
After 2008						
(-30,-5)	169	-1.14%*	-1.88	508	-0.59%**	-2.42
(-4,-2)	169	-0.33%	-1.63	508	-0.08%	-1.19
(-1,+1)	169	0.02%	0.11	508	0.13%*	1.90
(+2,+30)	169	-1.21%**	-2.35	508	-0.75%***	-2.69

Table 12. Bond Market Responses to Dividend Change Announcements, Continued

Event window (days)	N	Mean CARs	T-stat	N	Mean CARs	T-stat
Panel E: Financially unconstrained		Decreases			Increases	
(-30,-5)	204	-0.48%	-1.13	993	-0.29%***	-3.80
(-4,-2)	204	-0.20%	-1.51	993	-0.10%***	-2.66
(-1,+1)	204	-0.05%	-0.41	993	0.02%	0.70
(+2,+30)	204	-0.48%	-1.24	993	-0.43%***	-4.23
Financially constrained						
(-30,-5)	38	-1.72%**	-2.26	183	-0.44%*	-1.66
(-4,-2)	38	-0.36%	-0.96	183	0.12%	1.33
(-1,+1)	38	0.24%	0.50	183	0.15%*	1.75
(+2,+30)	38	-2.05%**	-2.39	183	-0.49%	-1.29
Panel F: Financially non-distressed						
(-30,-5)	51	-0.83%*	-1.80	354	-0.41%***	-2.69
(-4,-2)	51	-0.04%	-0.25	354	-0.07%	-1.27
(-1,+1)	51	-0.18%	-1.22	354	0.08%	1.22
(+2,+30)	51	0.12%	0.33	354	-0.58%***	-2.81
Financially distressed						
(-30,-5)	191	-0.64%	-1.37	822	-0.27%***	-3.10
(-4,-2)	191	-0.27%*	-1.79	822	-0.06%	-1.38
(-1,+1)	191	0.04%	0.26	822	0.03%	0.78
(+2,+30)	191	-0.95%**	-2.18	822	-0.38%***	-3.17

Table 13. Bond Market Responses to Dividend Initiations and Omissions Announcements

I define a dividend initiation as being when a firm initiates its first dividend or resumes dividends after a period of at least five years from July 2002 to December 2010 and a dividend omission if a firm omits its dividend after a period of at least three years from July 2002 to December 2010. The symbols ***, ** and * indicate significance at the one, five, and ten percent levels, respectively.

	Dividend initiations			Dividend omissions		
Event window (days)	N	Mean CARs	T-stat	N	Mean CARs	T-stat
(-30,-5)	41	-0.89%**	-2.13	64	-2.53%***	-4.72
(-4,-2)	41	-0.23%	-1.04	64	-0.29%*	-1.76
(-1,+1)	41	-0.23%	-1.45	64	-0.38%*	-1.81
(+2,+30)	41	-1.23%**	-2.12	64	-2.94%***	-5.18

Table 14. Stock Market Abnormal Returns surrounding Dividend Change Announcements Calculated Using Fama-French Model

The full sample consists of 269 announcements of decreased dividends and 1,236 announcements of increased dividends from July 2002 to December 2010. The sample is limited to bonds that traded on at least 10 days during Day -21 to Day -1, where Day 0 is the day of dividend announcements. CAR is the sum of the firm's daily abnormal stock returns estimated from Fama-French 3-factor model over the event window. To examine the influence of financial crisis on dividend announcement effects, I divide the full sample into two periods: before and after 2008 in Panels B and C. The symbols ***, ** and * indicate significance at the one, five, and ten percent levels, respectively.

	Decreases			Increases		
Event window (days)	N	Mean CARs	T-stat	N	Mean CARs	T-stat
Panel A: Full sample						
(-30,-5)	269	-3.04%**	-2.55	1,236	-0.59%**	-2.72
(-4,-2)	269	0.09%	0.25	1,236	0.08%	1.06
(-1,+1)	269	-0.73%	-1.31	1,236	0.53%***	6.19
(0,0)	269	-0.33%**	-1.97	1,236	0.27%***	4.87
(0,+1)	269	-0.61%	-1.30	1,236	0.53%***	6.77
(+2,+30)	269	0.07%	0.06	1,236	-0.28%	-1.19
Panel B: Before 2008						
(-30,-5)	103	-0.16%	-0.14	732	-0.03%	-0.13
(-4,-2)	103	0.01%	0.03	732	0.10%	1.26
(-1,+1)	103	0.34%	0.68	732	0.59%***	5.64
(0,0)	103	-0.25%	-0.80	732	0.22%***	3.35
(0,+1)	103	-0.08%	-0.18	732	0.51%***	5.40
(+2,+30)	103	0.74%	0.66	732	0.13%	0.48
Panel C: After 2008						
(-30,-5)	166	-4.82%***	-2.71	504	-1.39%***	-3.53
(-4,-2)	166	0.14%	0.26	504	0.04%	0.28
(-1,+1)	166	-1.39%*	-1.66	504	0.45%***	3.09
(0,0)	166	-0.39%	-0.74	504	0.34%***	3.53
(0,+1)	166	-0.95%	-1.32	504	0.55%***	4.15
(+2,+30)	166	-0.35%	-0.22	504	-0.88%**	-1.98

Table 15. Stock Market Abnormal Returns surrounding Dividend Initiations and Omissions Announcements Calculated Using Fama-French Model

I define a dividend initiation as being when a firm initiates its first dividend or resumes dividends after a period of at least five years from July 2002 to December 2010 and a dividend omission if a firm omits its dividend after a period of at least three years from July 2002 to December 2010. The symbols ***, ** and * indicate significance at the one, five, and ten percent levels, respectively.

Event window (days)	N	Mean CARs	T-stat
Panel A: Dividend initiations			
(-30,-5)	33	3.60%**	2.30
(-4,-2)	33	0.43%	0.71
(-1,+1)	33	2.50%***	3.64
(0,0)	33	2.21%***	4.72
(0,+1)	33	2.59%***	4.38
(+2,+30)	33	1.45%	0.94
Panel B: Dividend omissions			
(-30,-5)	62	-2.78%**	-2.29
(-4,-2)	62	-0.24%	-0.55
(-1,+1)	62	0.44%	0.81
(0,0)	62	0.06%	0.17
(0,+1)	62	0.65%	1.24
(+2,+30)	62	-0.16%	-0.14

Table 16. Regression Analysis of the Determinants of Bond Price Responses to Dividend Change Announcements

Dependent variables are CAR (-1, 1). CAR is the sum of the firm's daily abnormal bond returns over the event window. Daily abnormal bond returns are calculated as the bond's raw return less the contemporaneous return on a value-weighted portfolio of bonds matched on rating and maturity. Daily bond prices are calculated with the "trade-weighted price, all trades" method of Bessembinder, Kahle, Maxwell and Xu (2009). All estimated coefficients are multiplied by 1,000. *P*-values for the significance of the coefficients are shown in parentheses. The symbols ***, ** and * indicate significance at the one, five, and ten percent levels, respectively.

	Dividend decreases			Dividend increases		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ΔDIV (β_1)	-20.21	-17.21	-15.88	10.50***	6.85*	7.63***
	(0.27)	(0.33)	(0.22)	(0.00)	(0.09)	(0.00)
Junior_bond	1.71	1.84	1.56	0.13	-0.55	0.00
	(0.90)	(0.89)	(0.91)	(0.96)	(0.81)	(1.00)
ΔDIV*Junior_bond (β_3)	11.04	9.20	10.44	-3.71	-2.90	-3.15
	(0.57)	(0.63)	(0.59)	(0.74)	(0.79)	(0.77)
Investment_grade	1.86	2.23	2.02	-0.10	-0.45	-0.73
	(0.78)	(0.72)	(0.75)	(0.92)	(0.64)	(0.48)
ΔDIV * Investment_grade (β_5)	13.31	11.88	11.30	-6.58***	-5.97***	-4.91***
	(0.29)	(0.30)	(0.32)	(0.00)	(0.00)	(0.01)
Maturity(log years)	1.36	1.68	1.09	0.59*	0.69**	0.69**
	(0.54)	(0.46)	(0.62)	(0.06)	(0.02)	(0.02)
ΔDIV * Maturity (β_7)	6.20	6.75	5.67	-2.98***	-3.38***	-3.33***
	(0.13)	(0.11)	(0.16)	(0.00)	(0.00)	(0.00)
FL	-1.98			2.33***		
	(0.13)			(0.00)		
ΔDIV * FL (β_9)	13.26			-6.18		
	(0.75)			(0.27)		
After 2008	-1.02	-2.04	-1.26	0.72	0.62	0.65
	(0.85)	(0.72)	(0.81)	(0.32)	(0.38)	(0.36)
ΔDIV * After 2008	-3.97	-5.83	-4.42	0.73	1.46	1.25
	(0.72)	(0.61)	(0.69)	(0.62)	(0.25)	(0.34)
FUC		-2.96*			-1.55***	
		(0.10)			(0.00)	
ΔDIV * FUC (β_{11})		1.20			1.84	
		(0.93)			(0.62)	
FND			0.13			0.25***
			(0.16)			(0.00)
ΔDIV * FND (β_{13})			5.07			1.18
			(0.72)			(0.47)
Intercept	-2.77	-1.24	-2.91	-1.02	1.15	-0.10
	(0.76)	(0.89)	(0.68)	(0.46)	(0.43)	(0.93)
R-Square (%)	4.11	4.18	4.03	3.99	4.04	3.94
# of Observations	242	242	242	1,170	1,170	1,170

Table 17. Correlation Coefficients between Stock and Bond Returns surrounding Dividend Change Announcements

This table reports the correlation coefficients between stock and bond returns segmented by dividend changes and bond credit ratings. D-S (I-I) represents the correlation coefficients between a firm's stock returns and speculative (investment) rating bond returns surrounding dividend decreases (increases) announcements. The symbols ***, ** and * indicate significance at the one, five, and ten percent levels, respectively.

Panel A: Pearson correlation coefficients

	Total	Decreases	Increases	Speculative	Investment	D-S	D-I	I-S	I-I
(-30, -5)	0.24***	0.33***	0.12***	0.23***	0.26***	0.30**	0.38***	0.19***	0.10***
(-4, -2)	0.16***	0.33***	0.00	0.09	0.18***	0.25**	0.37***	-0.03	0.01
(-1,+1)	0.05**	0.07	0.04	0.05	0.05*	0.15	0.05	-0.04	0.06*
(+2,+30)	0.13***	0.11*	0.15***	0.14**	0.15***	0.06	0.16**	0.19***	0.13***
N	1,505	269	1,236	254	1,251	66	203	188	1,048

Panel B: Spearman correlation coefficients

	Total	Decreases	Increases	Speculative	Investment	D-S	D-I	I-S	I-I
(-30, -5)	0.13***	0.30***	0.08***	0.12**	0.14***	0.21*	0.34***	0.07	0.08***
(-4, -2)	0.06**	0.16**	0.03	-0.02	0.07***	0.25**	0.12*	-0.12*	0.07**
(-1,+1)	0.10***	0.06	0.10***	0.11*	0.09***	0.03	0.08	0.14**	0.08***
(+2,+30)	0.10***	0.18***	0.07***	0.04	0.11***	0.15	0.19***	-0.01	0.09***
N	1,505	269	1,236	254	1,251	66	203	188	1,048

Table 18. Abnormal Standardized Bond Returns surrounding Dividend Change Announcements

This table presents abnormal standardized bond returns surrounding dividend change announcements. The sample period is from January 2005 to December 2010. ABSR represents abnormal standardized bond returns. Dates in braces i.e. {-3.3}, denote a composite return from Day -3 to Day +3 including all possible ABSRs as defined in Ederington, Guan and Yang (2012). When a firm has multiple bonds, bond returns are calculated as an equal average of bond returns. Financial and utility industries are eliminated from the sample. Dividend announcements contaminated by quarterly earnings, mergers and acquisitions, equity offering and stock repurchases announcements from Day -1 to Day +1 are also excluded from the sample. In Panels A and B, Spec-investment indicates the difference of abnormal standardized bond returns (ABSR) between groups of speculative rating bonds and investment rating bonds. Panel C stratifies the increased dividend sample by whether an announcement of increased dividend is occurred before 2008 or after 2008. The difference in means test uses the unequal variance t-test. The significance level of the difference in medians is based on a Wilcoxon rank-sum two sample test. The symbols ***, ** and * indicate significance at the one, five, and ten percent levels, respectively.

Event window (days)	N	Mean	Median	N	Mean	Median	N	Mean	Median	Mean	Median
Panel A: Decreases	Total sample			Speculative rating			Investment rating			Spec-investment	
ABSR (-1, +1)	85	2.26%	5.70%	27	-0.57%	1.01%	58	3.58%	6.55%	-4.15%	-5.54%
ABSR {-3, +3}	115	5.59%	11.86%	37	-0.08%	-4.06%	78	8.28%	13.49%	-8.36%	-17.55%
ABSR {-5, +5}	124	4.42%	11.72%	39	2.15%	19.49%	85	5.46%	11.19%	-3.31%	8.30%
Panel B: Increases											
ABSR (-1, +1)	430	-2.80%	0.55%	50	20.63%**	16.54%**	381	-5.99%*	-0.76%	26.62%***	17.30%***
ABSR {-3, +3}	538	-0.10%	0.45%	74	16.41%**	15.30%**	466	-2.60%	-0.17%	19.01%**	15.47%***
ABSR {-5, +5}	556	-0.60%	0.65%	78	11.82%*	3.64%*	481	-2.47%	0.31%	14.29%**	3.33%**

Event window (days)	N	Mean	Median	N	Mean	Median	Mean	Median
Panel C: Increases	After 2008			Before 2008			Difference	
ABSR (-1, +1)	258	-0.11%	2.72%	172	-7.04%	-0.27%	6.93%	2.99%*
ABSR {-3, +3}	314	2.99%	2.29%	224	-6.07%	-3.61%	9.06%**	5.90%**
ABSR {-5, +5}	322	1.24%	0.43%	234	-4.65%	1.00%	5.89%	-0.57%

Table 19. Sample Composition, Chapter 4

The sample period is from November 1, 2008 to March 31, 2011. This table describes the composition of the final sample. From TRACE we collect bond trade data. Bond characteristics, such as coupon, maturity and ratings, are obtained from Mergent's FISD database. The filtering conditions applied rule out bonds that are: (i) put-able; (ii) with abnormal prices (less than $10 or greater than $200); (iii) subsequently corrected; (iv) affected by price reversions and (v) traded less than 9 times over the sample period. To estimate a bond's daily bid-ask spread, we further require bonds to have at least one buy and one sell within a day. Lastly, all but NYSE listed bonds are discarded.

	# of Bonds	# of Trades	Size($s)	Yield (%)	Coupon (%)	Dollar Volume (Billions)
Data downloaded from TRACE(Starting from Nov 1, 2008 to March 31, 2011)	40,977	26,658,403	285,916.96	8.98	N.A.	7,621.94
After filtering conditions:	25,884	24,958,872	276,633.09	8.04	5.90	6,904.32
Sell	25,146	9,058,715	279,239.83	6.90	5.90	2,529.54
Inter-dealer	25,167	10,019,697	206,389.84	8.32	5.92	2,067.92
Buy	24,263	5,880,460	392,306.06	9.35	5.85	2,306.86
Sample(only buy and sell plus NYSE)						
OTC-only	16,670	8,776,241	291,459.79	8.83	5.03	2,557.92
OTC-NYSE	4,187	4,698,929	396,650.13	5.91	6.10	1,863.83
Sell	20,857	8,225,185	280,275.13	6.89	5.90	2,305.31
Buy	20,857	5,249,985	403,132.08	9.23	5.88	2,116.44

Table 20. Sample Summary Statistics

This table presents the number of observations, mean, median, and standard deviation of all variables in the main sample. Definitions of variables can be seen in the Appendix F.

Variable	N	Mean	Median	Std Dev
Bid-ask Spread	20,857	0.0097	0.01	0.01
Firm size (log millions)	17,889	11.4508	11.49	2.30
Leverage	17,886	0.2229	0.17	0.19
Firms' accounting standard-IFRS	20,857	0.0284	0.00	0.17
Firms' accounting standard-Domestic	20,857	0.8002	1.00	0.40
Issuer is in finance industry	20,857	0.6574	1.00	0.47
Issuer is a utility	20,857	0.0610	0.00	0.24
Issuers' equity is private	20,857	0.1425	0.00	0.35
Issue size (sq. root of millions)	20,857	11.0846	5.43	11.22
Moody's bond rating	20,857	9.8220	7.00	7.56
Years to maturity (years)	20,857	11.8303	10.00	9.51
Global bond	20,857	0.1166	0.00	0.32
Variable rate bond	20,857	0.1334	0.00	0.34
Foreign bond	20,857	0.0001	0.00	0.01
Senior bond	20,857	0.0770	0.00	0.27
Rule144a bond	20,857	0.0021	0.00	0.05
Yankee bond	20,857	0.0826	0.00	0.28

Table 21. Effective Bid-ask Spreads Matched by the Same Issuer

This table presents the differences of bid-ask spreads between OTC-only bonds with OTC-NYSE bonds, at the issuer level across ratings. Moody's bond ratings are used to measure a bond's credit rating. If bonds are unrated by Moody's, S&P ratings are used in their place. OTC-only (OTC-NYSE) bonds indicate bonds listed in the over-the-counter markets (both over-the-counter market and the NYSE market). The bid-ask spread is estimated as the time series average of its traded bid-ask spreads in a one-day window. For each bond, the effective (traded) bid-ask spread is the difference between the average daily selling price and average daily buying price divided by their sum. Superior bonds include bonds that have a moody rating of Aaa, Aa1, Aa and Aa2 during the sample period. Other investment grade bonds consist of bonds that have a rating between Baa3 and Aa3. Bonds rated as or below Baa3 belong to non-investment grade bonds category. The bid-ask spread is winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) bid-ask spreads between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of bid-ask spreads. The p-value of each test is reported.

	OTC-only						OTC-NYSE						Difference			
	# of bonds	Mean(Basis Points)	t Value	Std Dev $*10^{-2}$	Coupon(%)	Age(Years)	# of bonds	Mean(Basis Points)	t Value	Std Dev $*10^{-2}$	Coupon(%)	Age(Years)	tt-test	Wilcoxn	Anova	Kruskal Wallis
Total	9,487	105	139.01	0.74	4.95	4.74	3,061	81	80.27	0.56	5.90	4.82	0.00	0.00	0.00	0.00
Superior Bonds (Aa2 and up)	635	79	26.04	0.76	3.29	3.17	124	47	12.35	0.42	4.28	3.49	0.00	0.00	0.00	0.00
Other Investment Bonds (Aa3-Baa3)	6,064	100	123.67	0.63	5.03	4.84	2,092	80	69.20	0.53	5.70	4.57	0.00	0.00	0.00	0.00
Non-investment Bonds	1,826	131	54.80	1.02	5.37	5.00	533	80	26.03	0.71	7.40	5.56	0.00	0.00	0.00	0.00

Table 22. Effective Bid-ask Spreads Differences by Propensity Score Matching

Panel A presents results of logistic regressions for the determinants of a firm's listing decisions. The probability is modeled as 1 when a bond listed in both the OTC market and NYSE. Logistic I and II represent logistic models with two different sets of independent variables below. Definitions of independent variables can be found in the Appendix F. P-values are reported in parentheses. Using the estimated coefficients in Panel A, the predicted probability (propensity score) for each bond is estimated and used to acquire a sample of OTC-only bonds with characteristics similar to bonds (based on the closest propensity score) traded both in OTC markets and on the NYSE in Panel B. The mean and standard deviation of estimated bid-ask spreads are reported in Panel B. The bid-ask spread is winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) bid-ask spreads between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of bid-ask spreads. The p-value of each test is reported.

Panel A: Dependent Variable: Listed on NYSE YES/NO				
Model:	Logistic I		Logistic II	
	Coefficient	P-value	Coefficient	P-value
Intercept	-1.46	(0.00)	-0.80	(0.00)
Firm size (log millions)			-0.13	(0.00)
Leverage			0.35	(0.01)
Firms' accounting standard-IFRS			0.96	(0.00)
Firms' accounting standard-Domestic			0.67	(0.00)
Issuer is in finance industry	-0.59	(0.00)	-0.21	(0.00)
Issuer is a utility	0.28	(0.00)	0.25	(0.00)
Issuers' equity is private	-0.57	(0.00)	0.72	(0.12)
Issue size (sq. root of millions)	0.06	(0.00)	0.05	(0.00)
Moody's bond rating	-0.05	(0.00)	-0.06	(0.01)
Years to maturity	0.02	(0.00)	0.02	(0.01)
Global bond	0.35	(0.00)	0.35	(0.01)
Variable rate bond	-2.83	(0.00)	-2.81	(0.01)
Foreign bond	0.66	(0.65)	0.76	(0.61)
Senior bond	-0.59	(0.00)	-0.70	(0.00)
Rule144a bond	-2.24	(0.00)	-1.87	(0.01)
Yankee bond	0.24	(0.00)	0.46	(0.00)
Pseudo R-square	0.19		0.19	
# of Bonds	20,857		17,886	
Panel B: Propensity Scoring Matched Bid-ask Spread Difference				
	OTC-only	OTC-NYSE	OTC-only	OTC-NYSE
Spread-Mean (bps)	84	77	87	77
S.D. $*10^{-2}$	0.64	0.55	0.67	0.54
tt-test for differences	0.00		0.00	
Wilcoxon-test for differences	0.00		0.00	
ANOVA	0.00		0.00	
Kruskal-Wallis	0.00		0.00	
# of Bonds	4,187		3,843	

Table 23. Effective Bid-ask Spreads and NYSE Pre-trade Transparency

This table reports regression results for the relation between a bond's effective bid-ask spread and whether a bond is listed on the NYSE. The sample period is from November 1, 2008 to March 31, 2011. The dependent variable, except as noted, is the estimated effective bid-ask spread, which is the time series average of the difference between the average daily selling price and average daily buying price divided by their sum. Prob of Being Listed on the NYSE is the propensity score computed from the logistic models in Table 4. All other independent variables are defined as in Appendix F. In the OLS model, we use a dummy variable of 1 to represent whether a bond is listed on the NYSE in the OLS regression. In the remaining two models, we present regression estimates using a two-stage least squares (2SLS) method with the probability of being listed on the NYSE from Logistic I and II models as instruments (as suggested by Wooldridge, 2002) for the dummy variable of bonds listed on the NYSE. All estimated coefficients reported are multiplied by 100. The bid-ask spread is winsorized at the 1st and 99th percentiles. P-values are reported in parentheses.

Model:	OLS		2SLS-Logistics I				2SLS-Logistics II			
Dependent variable	Bid-ask Spread		Listed on the NYSE=1/0		Bid-ask Spread		Listed on the NYSE=1/0		Bid-ask Spread	
Listed on the NYSE	**-0.10**	**(0.00)**			**-0.72**	**(0.00)**			**-0.83**	**(0.00)**
Prob of Beling Listed on the NYSE			50.99	(0.00)			63.02	(0.00)		
Issuers' equity is private	0.15	(0.00)	-2.89	(0.00)	0.11	(0.00)	6.24	(0.42)	-0.19	(0.57)
Issue size (log millions)	-0.02	(0.00)	0.51	(0.00)	-0.02	(0.00)	0.40	(0.00)	-0.01	(0.00)
Moody's bond rating	0.00	(0.94)	-0.17	(0.00)	0.01	(0.01)	-0.13	(0.00)	0.01	(0.00)
Years to maturity	0.02	(0.00)	0.23	(0.00)	0.02	(0.00)	0.17	(0.00)	0.02	(0.00)
Global bond	-0.09	(0.00)	4.06	(0.00)	-0.03	(0.11)	2.70	(0.01)	-0.04	(0.60)
Variable rate bond	-0.05	(0.00)	-9.43	(0.00)	-0.17	(0.00)	-7.99	(0.00)	-0.18	(0.01)
Foreign bond	-0.71	(0.06)	1.81	(0.93)	-0.69	(0.09)	1.66	(0.94)	-0.69	(0.16)
Senior bond	-0.27	(0.00)	-3.64	(0.00)	-0.31	(0.00)	-2.90	(0.01)	-0.26	(0.00)
Rule144a bond	-0.35	(0.00)	-11.92	(0.03)	-0.50	(0.00)	-8.34	(0.29)	-0.57	(0.00)
Yankee bond	-0.49	(0.00)	2.07	(0.03)	-0.47	(0.00)	1.82	(0.09)	-0.45	(0.00)
Intercept	1.05	(0.00)	4.53	(0.00)	1.10	(0.00)	3.43	(0.00)	1.12	(0.00)
Adj. R-square	0.23		0.17		0.14		0.17		0.09	
# of Bonds	20,857		20,857				17,886			

Table 24. Institutional Traders' Effective Bid-ask Spreads

This table reports effective bid-ask spreads of institutional-sized trades (trade size>$100,000). Total sample includes all bonds and sub sample includes bonds matched by the same issuer. The effective bid-ask spread is the difference between the average daily selling price and average daily buying price divided by their sum. The sample period is from November 1, 2008 to March 31, 2011. OTC-only (OTC-NYSE) bonds indicate bonds listed in the over-the-counter markets (both over-the-counter market and the NYSE market). Investment bonds represent bonds rated by Moody as Baa3 or a higher rating. Non-investment bond represent bonds with a Moody's rating of Ba1 or a lower rating. The bid-ask spread is winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) bid-ask spreads between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of bid-ask spreads. The p-value of each test is reported.

		OTC-only				OTC-NYSE				Difference			
		# of bonds	Mean(Basis Points)	t Value	Std Dev $*10^{-2}$	# of bonds	Mean(Basis Points)	t Value	Std Dev $*10^{-2}$	tt-test	Wilcoxn	Anova	Kruskal Wallis
Total Sample	Total	9,653	46	82.95	0.54	3,614	37	58.68	0.38	0.00	0.02	0.00	0.02
	Investment Bonds	5,681	39	64.19	0.46	2,726	38	51.09	0.39	0.29	0.00	0.32	0.00
	Non-investment Bonds	3,972	54	55.04	0.62	888	33	29.25	0.34	0.00	0.00	0.00	0.00
Sub Sample	Total	4,342	46	59.78	0.50	2,487	39	47.46	0.41	0.00	0.00	0.00	0.00
	Investment Bonds	3,197	41	51.53	0.45	1,981	40	42.29	0.42	0.16	0.37	0.17	0.37
	Non-investment Bonds	1,145	58	32.23	0.61	506	35	21.85	0.36	0.00	0.00	0.00	0.00

Table 25. Institutional Traders' Effective Bid-ask Spreads and NYSE Pre-trade Transparency

This table reports results for the relation between a bond's bid-ask spread and whether a bond is listed on the NYSE for the sample limiting to institutional-sized trades (trade size>$100,000). Panels A and B report propensity score matching and regression results, respectively. The estimated effective bid-ask spread in Panel A is computed as the time series average of the difference between the average daily selling price and average daily buying price divided by their sum. The bond bid-ask spread is winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) bid-ask spreads between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of bid-ask spreads. Panel B reports regression estimates using a two-stage least squares (2SLS) method with the probability of being listed on the NYSE from Logistic I and II as instruments (as suggested by Wooldridge, 2002) for the dummy variable of bonds listed on the NYSE. Definitions of other independent variables can be seen in Appendix F. All estimated coefficients reported in Panel B are multiplied by 100. P-values are reported in parentheses.

Panel A: Propensity Scoring Matched Bid-ask Spread Difference				
Model:	Logistic I		Logistic II	
	OTC-only	OTC-NYSE	OTC-only	OTC-NYSE
Spread-Mean (bps)	40	37	39	37
S.D.*10^{-2}	0.50	0.43	0.40	0.38
tt-test for differences	0.01		0.01	
Wilcoxon-test for differences	0.00		0.00	
ANOVA	0.11		0.01	
Kruskal Wallis	0.00		0.00	
# of Bonds	3,574		3,265	

Panel B: Dependent Variable: Bid-ask Spread								
Model:	2SLS-Logistic I				2SLS-Logistic II			
Dependent variable	Listed on the NYSE=1/0		Bid-ask Spread		Listed on the NYSE=1/0		Bid-ask Spread	
Listed on the NYSE			**-0.22**	**(0.04)**			**-0.50**	**(0.00)**
Prob of Beling Listed on the NYSE	**64.11**	**(0.00)**			**76.86**	**(0.00)**		
Issuers' equity is private	-2.89	(0.01)	0.02	(0.17)	2.91	(0.76)	-0.11	(0.32)
Issue size (log millions)	0.19	(0.00)	-0.01	(0.00)	0.12	(0.02)	-0.01	(0.00)
Moody's bond rating	-0.26	(0.00)	0.00	(0.80)	-0.17	(0.02)	0.00	(0.00)
Years to maturity	0.12	(0.00)	0.01	(0.00)	0.07	(0.11)	0.01	(0.00)
Global bond	3.28	(0.01)	-0.01	(0.59)	1.95	(0.12)	0.02	(0.29)
Variable rate bond	-10.23	(0.00)	0.05	(0.12)	-7.23	(0.00)	-0.05	(0.16)
Foreign bond	0.19	(0.99)	-0.37	(0.17)	0.31	(0.99)	-0.38	(0.20)
Senior bond	-2.09	(0.14)	-0.16	(0.00)	-1.38	(0.41)	-0.17	(0.00)
Rule144a bond	-8.72	(0.18)	-0.13	(0.09)	-5.35	(0.55)	-0.20	(0.06)
Yankee bond	2.05	(0.14)	-0.23	(0.00)	1.49	(0.33)	-0.23	(0.00)
Intercept	9.87	(0.00)	0.62	(0.00)	6.57	(0.00)	0.71	(0.00)
Adj. R-square	0.14		0.12		0.14		0.09	
# of Bonds	12,681				10,748			

Table 26. Bond Yield Differences by Propensity Score Matching

This table reports results for the relation between a bond's yield and whether a bond is listed on the NYSE for the total sample. Panels A and B report propensity score matching and regression results, respectively. Using the Logistic I and II models as described in Panel A of Table 4, the predicted probability (propensity score) for each bond is estimated and used to acquire a sample of OTC-only bonds with characteristics similar to bonds (based on the closest propensity score) traded both in OTC markets and on the NYSE in Panel A. For the missing bond yields, we use the trade price reported on TRACE and coupon and maturity date from FISD to compute a bond's yield-to-maturity. For multiple bond trading occurring within the same day, we compute trade-size weighted average of bond yields. Bond yields are winsorized at the 1st and 99th percentiles. tt-test (Wilcoxon) is used to test the difference of mean (median) bid-ask spreads between the two groups of bonds. Anova and Kruskal Wallis tests are used to test the difference of standard deviation of bid-ask spreads. Panel B reports regression estimates using a two-stage least squares (2SLS) method with the probability of being listed on the NYSE from Logistic I and II models as instruments (as suggested by Wooldridge, 2002) for the dummy variable of bonds listed on the NYSE. Definitions of other independent variables can be seen in Appendix F. Estimated coefficients reported in the first stage regressions of Panel B are multiplied by 100. P-values are reported in parentheses.

Panel A: Propensity Scoring Matched Bond Yield Difference				
Model:	Logistic I		Logistic II	
	OTC-only	OTC-NYSE	OTC-only	OTC-NYSE
Yield-Mean (%)	8.47	6.72	7.89	6.27
S.D.*100	0.17	0.13	0.17	0.10
tt-test for differences	0.00		0.00	
Wilcoxon-test for differences	0.00		0.00	
ANOVA	0.00		0.00	
Kruskal Wallis	0.00		0.00	
# of Bonds	4,236		3,752	

Panel B: Dependent Variable: Bond Yields								
Model:	2SLS-Logistic I				2SLS-Logistic II			
Dependent variable	Listed on the NYSE=1/0		Bond Yield		Listed on the NYSE=1/0		Bond Yield	
Listed on the NYSE			**-46.67**	(0.00)			**-50.91**	(0.00)
Prob of Beling Listed on the NYSE	**53.44**	**(0.00)**			**63.56**	**(0.00)**		
Issuers' equity is private	-1.81	(0.01)	0.20	(0.77)	4.84	(0.51)	4.43	(0.50)
Issue size (log millions)	0.49	(0.00)	0.28	(0.00)	0.39	(0.00)	0.35	(0.00)
Moody's bond rating	-0.16	(0.00)	1.18	(0.00)	-0.12	(0.00)	1.07	(0.00)
Years to maturity	0.21	(0.00)	-0.15	(0.00)	0.17	(0.00)	-0.08	(0.03)
Global bond	3.63	(0.00)	3.81	(0.00)	2.68	(0.01)	3.72	(0.00)
Variable rate bond	-9.30	(0.00)	-11.83	(0.00)	-7.92	(0.00)	-13.45	(0.00)
Foreign bond	2.69	(0.87)	0.33	(0.98)	2.45	(0.88)	1.2	(0.93)
Senior bond	-3.61	(0.00)	-5.74	(0.00)	-2.90	(0.01)	-6.06	(0.00)
Rule144a bond	-11.89	(0.02)	-20.73	(0.00)	-8.45	(0.26)	-20.19	(0.00)
Yankee bond	1.17	(0.21)	3.75	(0.00)	1.02	(0.33)	5.52	(0.00)
Intercept	5.23	(0.00)	9.70	(0.00)	4.08	(0.00)	10.55	(0.00)
Adj. R-square	0.16		0.13		0.17		0.23	
# of Bonds	21,533				18,221			