UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

THREE ESSAYS ON CREDIT MARKET

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

ZONGFEI YANG
Norman, Oklahoma
2015

THREE ESSAYS ON CREDIT MARKET

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

BY

Dr. Pradeep Yadav, Co-Chair

Dr. Louis Ederington, Co-Chair

Dr. William Megginson

Dr. Chitru Fernando

Dr. Scott Linn

Dr. Wayne Thomas

© Copyright by ZONGFEI YANG 2015
All Rights Reserved.

Acknowledgement

I would like to gratefully and sincerely thank my advisors, Dr. Louis Ederington and Dr. Yadav Pradeep, for their advising on this research, their support to my study and life, and their dedication to my work. Their guidance was paramount in providing a well-rounded experience consistent my long-term career goals.

I am sincerely grateful to my committee members: Dr. William Megginson, Dr. Chitru Fernando, Dr. Scott Linn, and Dr. Wayne Thomas for their insightful guidance and suggestions to my research.

Thanks also go to my senior students Drs. Veljko Fotak, Vikas Roman, and Kate Holland for their helpful suggestions especially during my early years in the Ph.D. program. My special thanks to Ashely Newton and Fang Lin and my fellow students for being excellent companies of studying and working in the past five years.

Finally, to my dearest parents, thank you for all of the love, support, encouragement and dedication.

Table of Contents

List of Tables

List of Figures

Abstract

My dissertation focuses primarily on credit markets from a corporate finance perspective, with a concentration on corporate bonds and security offerings. My dissertation consists of three essays. Essay One is titled “Underpricing of Corporate Bond Offerings: Evidence and Determinants”; Essay Two is titled “Calculating Abnormal Returns in Bond Market Event Studies”; and Essay Three is titled “Bond Market Reaction to Earnings Surprises and Post Earnings-Announcement Drift”. My research is partially motivated by the 2007/2008 financial crisis, which highlighted the importance of sound credit markets.

In recent years, the Federal Reserve policy has pushed base interest rates to record lows, which has helped fuel trillions of corporate-bond issuance activities. “Underpricing of Corporate Bond Offerings: Evidence and Determinants” examines whether and to what extent newly-issued corporate bonds are underpriced. The availability of the TRACE database, which contains comprehensive secondary market bond transaction prices, enables me to measure bond underpricing as the return from the offering price to the secondary market price immediately after the issue. This measure of underpricing is largely adopted by equity offerings literature. Whereas other recent studies find evidence of underpricing only for speculative grade bonds and/or initial public issues, I find significant underpricing for corporate bonds across all rating classes including investment grade bonds and seasoned offerings. My results raise questions concerning the efficiency of capital raising process in the bond market.

"Corporate Bond Market Event Study Methods" examines issues in the construction of corporate bond event studies using bond transaction data. Procedures used in studies to date have relatively low power to detect an event impacting bond prices. We show that this low power is largely due to the substantial heteroskedasticity in bond returns and infrequent trading. Focusing on handling these obstacles, we propose tests that yield considerably higher power.

The essay "Bond Market Post-Earnings-Announcement Drift" examines the bond market post-earnings announcement return patterns. While post-earnings announcement drifts (PEAD) is, as Fama put it, the granddaddy of all market anomalies in the equity market, whether PEAD exists in corporate bond market is understudied. We find evidence of bond market PEAD following especially positive earnings surprises, suggesting that negative information gets impounded into bond prices more efficiently than positive information. We further find that bond market PEAD appears to be driven by illiquidity, which we interpret as evidence that bond market efficiency is likely hampered by lack of liquidity.

Chapter 1: Essay One

Underpricing of Corporate Bond Offerings: Evidence and Determinants

Abstract

I document significant underpricing of new corporate bond issues in that offering prices are significantly below immediate post-offering secondary market prices – also, for additions to an existing indenture, below pre-offering secondary market prices. In contrast to previous studies, I find underpricing of both investment and speculative grade issues, for both firms with and without bonds outstanding, and for financial as well as non-financial firms. My evidence supports the valuation uncertainty, asymmetric information, and price pressure hypotheses. Further, underpricing appears due partially to agency conflicts between underwriters and issuers, as it is considerably lower when underwriters are marketing their own issues.

1. Introduction

The efficiency of the capital-raising process is of interest to both researchers and practitioners. While it is well-documented that both initial and seasoned public *equity* offerings are generally priced below their opening secondary market prices, it is less clear whether and to what extent newly-issued corporate *bonds* are underpriced.[1] The amount of academic research dedicated to corporate bond issuance is small in comparison to its economic importance. For example, from 2005 through 2013, firms issued a total of $9.4 trillion in corporate bonds targeted at US market, compared to $2.2 trillion in equity issuance. [2] Given the size of this market, any inefficiency in the capital raising process in the bond market will be costly to issuing firms.

This paper studies the efficiency of the bond market capital raising process by investigating whether corporate bond offerings are underpriced and if so, why. Recently, the SEC is reportedly probing the bond offering process.[3] Of particular interest to the SEC is whether underwriters give preferential treatment to big customers, thus allowing these investors to make a quick profit by re-selling the bonds at a higher price to investors that were shut out of the deal initially. For example, Bloomberg (4 March 2014) reported "a one-day profit of $2.54 billion reaped by buyers of Verizon Communications Inc.'s $49 billion offering in September (2013), a deal for which money managers put in orders of as much as $100 billion." Meanwhile, practitioners expressed concern:

---

[1] See Ljungqvist (2004), Ritter and Welch (2002), and Eckbo, Masulis, and Norli (2007) for related reviews on initial and seasoned equity offerings. Existing evidence on corporate bonds is discussed in section 2.1.

[2] Securities Industry and Financial Markets Association (SIFMA), http://www.sifma.org/research/statistics.aspx

[3] "Regulators Probing How Goldman, Citi and Others Divvied Up Bonds", Wall Street Journal, Feb. 28, 2014; "Bond Allocation Probe Seen Symptomatic of Race for Yield", Bloomberg, March 4, 2014; "Finra Scrutinizes Banks' Role in Bond Market", Wall Street Journal, April 10, 2014.

> *"Even worse than getting a smaller-than-wanted chunk of a new bond deal is then being offered the bonds from a trader right after the deal is priced at some unjustifiably higher price" − Christopher Sullivan, chief investment officer, United Nations Federal Credit Union. (Wall Street Journal, 10 April 2014)*

I investigate 2,380 bond offerings by 534 non-financial firms and, in a separate sample, 1186 offerings by 195 financial firms, from February 2005 through September 2012. I measure bond underpricing as the percentage difference between the offer price and the price at which the bond subsequently trades in the secondary market, an approach that is commonly used in the equity issuance literature but was not adopted by most previous bond studies due primarily to data limitations. The availability of the TRACE database, which contains comprehensive bond secondary market transaction prices, enables me to follow the above approach and therefore makes it easier to relate my bond market evidence to the existing stock market evidence. In contrast to existing bond studies that find underpricing for only speculative grade and/or initial bond offerings (IBOs), i.e., issues by firms with no outstanding public bond issues, I find investment grade and seasoned issues (issues by firms with outstanding public bond issues) are also underpriced. Additionally, I find underpricing for issues of financial as well as non-financial firms. For issues by non-financial firms, seasoned bond offerings (SBOs) underpricing averages 0.58% of the offer price among investment grade and 1.10% among high yield issues.[4] The magnitude of IBOs is slightly higher as investment grade (high yield) IBOs are underpriced by 0.59% (1.68%) on average. The extent of underpricing also varies over time and is substantially larger during the recent

[4] To gain perspective, U.S. Treasury bond underpricing is found to be tiny. For example, measuring underpricing as difference between the secondary market price and the auction stop-out price, Goldreich (2007) find the average U.S. Treasury bond underpricing to be 1.3 cents per $100 of face value.

financial crisis, peaking at 0.87% (1.37%) for investment grade (high yield) SBOs in 2009.

A potential concern is whether the estimated underpricing is sufficiently large to offer a trading opportunity for investors who acquire bonds in the primary market or if it merely reflects bid-ask spreads. To address this issue, I use aftermarket prices from only non-dealer customer sell trades and find underpricing still significant. Specifically, an investor who purchases a non-financial investment grade SBO at the offer price could immediately sell for a price 0.51% higher on average, and a high yield SBO for a price 1.05% higher.

While this level of underpricing is considerably smaller than that generally estimated for seasoned *equity* offerings (SEOs), it is non-trivial if we consider the size and frequency of bond offerings. For example, an average investment grade (high yield) seasoned bond offering raises $701 ($527) million based on my sample and thus the estimated underpricing translates to a loss in proceeds of over $4 million ($5.8 million) per deal. In contrast, the documented average SEO underpricing is around 2% and the average amount raised by an SEO is about $62 million (Altinkilic and Hansen (2003) and Corwin (2003)), translating to less than $2 million left on the table per deal.[5] Moreover, corporate bonds generally have a finite life of less than ten years. Thus if a firm does not substantially change its capital or debt structure, periodic refinancing of these bond issues will involve repeated issuance costs in the future.[6]

[5] I compare the magnitude of bond underpricing to seasoned instead of initial equity offerings as bond issuers are overwhelmingly seasoned issuers. Specifically, only 17 of the 2380 bond issues were issued by privately held firms.

[6] Bond underpricing also accounts for a large portion of the total direct and indirect floatation costs, as the underwriter gross spread is 0.57% (1.67%) on average for investment grade (high yield) issues.

Underpricing of this magnitude, especially for seasoned investment grade issues, is puzzling since bond issuers represent large and frequent seasoned issuers. Additionally, the pricing of bonds is less complicated than equities as it is relatively easy to find comparable traded bonds with the same rating and maturity. To explore the possible explanations for bond underpricing, I develop and test hypotheses based on existing underpricing theories of: (1) price uncertainty, (2) information asymmetry, (3) aftermarket illiquidity, (4) price pressure, and (5) agency conflicts between issuers and underwriters. I explore both cross-sectional and time-series determinants.

Consistent with the price uncertainty hypothesis (but possibly also with the information asymmetry and the aftermarket illiquidity hypotheses), I find that lower rated and longer maturity issues exhibit higher underpricing. Moreover, underpricing is higher for bonds with greater post-offering price volatility. Underpricing also increases as the time lag between offer pricing and distribution lengthens, consistent with Corwin's (2003) argument that the longer lag increases the likelihood of a change in market conditions prior to offer completion and thus increases underwriter uncertainty. Higher underpricing is also observed in periods when stock market and/or interest rate uncertainty is greater. These findings suggest that bond underpricing is related to both issue-specific and market-wide price uncertainty. In contrast, I find information asymmetry measures such as analyst coverage and whether the issuer is publicly traded or privately held do not significantly affect underpricing. It is possible that information asymmetry is less severe in bond offerings than in equity offerings since bond issuers are typically large seasoned issuers. I do not find a reliable relation between bond underpricing and common illiquidity measures such as the aftermarket bid-ask spread.

Moreover, I find evidence that bond underpricing reflects price pressure. First, even after accounting for changes in leverage, underpricing is positively related to the offer amounts, consistent with the notion that larger offer amounts exert greater downward price pressures. To further explore whether the price pressure is permanent due to a downward sloping demand curve for bonds or a temporary liquidity shock, I collect and exploit a unique sample of additional bond offerings to an existing indenture (which I term ABOs). ABOs differ from SBOs in that SBOs are new bond issues of a firm with other bonds outstanding while ABOs are additional bond issuance to an existing bond series (same CUSIP). I compare the ABO offer price with the pre-offer secondary market price and again find evidence of underpricing. Since an identical bond is already trading on the market, ABO underpricing is less likely to be driven by valuation uncertainty. Focusing on the secondary market, I find that the secondary market price drops significantly on the ABO issue date, and recovers partially, but not completely, after the offering. The partial recovery in the secondary market price indicates that temporary liquidity shocks play a part in ABO underpricing. Since the post-offer secondary market price does not fully recover to the pre-offering level, I cannot rule out the possibility that the bond demand curve is downward sloping as the market may not view different bonds with the same rating and maturity as close substitutes.

Further, I explore whether bond underpricing is partly due to agency conflicts between issuers and their underwriters. This hypothesis inherently assumes the existence of information asymmetry between the issuers and the underwriters, where the underwriters are better informed about the pricing of the security through their expertise in book-building (Baron (1982) and Biais, Bossaerts, and Rochet (2002)). Thus underwriters may underprice intentionally to minimize their marketing efforts, or to steer bonds to favored clients for quid pro quos (Loughran and Ritter (2004)).

To test the agency hypothesis, I begin by analyzing trading activities in the immediate aftermarket as the observed trading may shed some light on the unobservable offering allocation. I present evidence indicating possible "flipping" activities. Specifically, after excluding trades among market makers, secondary market trading activities are dominated by institutional sized sales (trades of $100,000 or more) and retail sized buys during the first few days after the offering. This finding suggests that some of the large investors who acquired bonds in the primary market were immediately reselling them to cash in and that smaller investors, whose desired allocations were unmet, were acquiring bonds in the secondary market at higher-than-offering prices. This finding is consistent with Aggarwal (2003), who observes that hot *equity* IPOs are commonly flipped, especially by institutions. Note that this finding does not necessarily indicate that underwriters underprice in order to steer bonds to favored clients. If underpricing occurs for any reason so that there is excess demand for the underpriced bonds, then those obtaining the bonds will be able to sell in the aftermarket at a profit.

To examine possible agency conflicts more directly, I turn to bond issues of financial firms. I study the financial sample separately from the main non-financial sample to make my findings comparable to existing studies which generally exclude financial firms from their analysis. However, the financial sample offers a unique opportunity to test the agency conflict hypothesis, since in some cases banks serve as lead managers when marketing their own bonds. Specifically, the underwriting bank's informational advantage is eliminated in a self-marketed issue (Muscarella and Vetsuypens (1989)) and any underpricing represents a direct cost to the underwriter. I find that the average underpricing is considerably lower for self-marketed offerings than non-self-marketed financial offerings, a finding consistent with the agency conflict hypothesis. The evidence of lower underpricing in self-marketed issues is robust after controlling for different characteristics between self-marketed and non-self-marketed offerings, market-wide conditions, and possible self-selection.

This study joins a large literature on security issuance costs and contributes to our understanding of the bond issuance process. To my knowledge, this is the first study dedicated to publicly-traded corporate bond issuance costs to document significant underpricing across all rating classes. More specifically, I find that bond underpricing is not restricted to high yield or initial bond issues, but is also significant for investment grade and seasoned offerings. This is to be contrasted with previous studies that either do not find evidence of bond underpricing or find underpricing only among high yield issues and/or initial offerings. The finding of underpricing of investment grade issues is of particular interest as the corporate bond market is dominated by investment grades issues. Specifically, of the total $9.4 trillion corporate bonds issuance from 2005 to 2013 on US market, $7.7 trillion were investment grade issues and only $ 1.7 trillion were high yield issues.

In addition, this study is one of the few studies to measure bond underpricing using the TRACE dataset, which contains comprehensive secondary market trades. Empirical evidence of corporate bond underpricing has been elusive, largely due to the absence of comprehensive second market data and therefore existing studies usually rely on a small subset of secondary market trades. For example, using transaction data from the NYSE, Datta, Iskandar-Datta, and Patel (1997) find underpricing only among high yield IBOs (1.86%) and even find overpricing for investment grade offerings. Likewise, based on secondary market trades by insurance companies only, Cai, Helwege, and Warga (2007) find IBO (SBO) underpricing averages 0.47% (0.18%) only among speculative-grade debts but no significant underpricing for investment grade bonds. [7]

Further, this study provides a more comprehensive analysis of the potential reasons for bond underpricing. Besides finding evidence consistent with prior studies that bond underpricing is attributable to issue-specific price uncertainty, I observe that it also varies with interest rate risk and market-wide uncertainty. My results on the importance of market-wide conditions for bond underpricing complement those of Lowry, Officer, and Schwert (2010) for equities, who analyze the importance of market-wide uncertainty for IPO underpricing. Additionally, I find evidence that bond underpricing reflects price pressure by collecting and analyzing the unique sample of ABOs.

Importantly, this study provides the first evidence among bond offering studies that agency conflicts potentially contribute to bond underpricing and thereby lends support to the agency conflict hypothesis modeled by Baron (1982) and Biais, Bossaerts, and Rochet (2002). In order to directly test the agency conflict hypothesis, this study examines and provides evidence for financial firms, which were largely

[7] Earlier studies measured underpricing indirectly by comparing yield spreads between the newly issued bond and a seasoned benchmark but also find mixed results (e.g., Ederington (1974), Sorensen (1982), and Lindvall (1977)). Section 2.1 reviews prior evidence of corporate bond underpricing in detail.

excluded from analysis in existing studies. My finding that underpricing is considerably lower when financial firms underwrite their own bonds joins the growing empirical evidence by Ljungqvist and Wilhelm (2003), Reuter (2006), and Liu and Ritter (2009), who find that agency conflicts attribute to *equity* IPO underpricing. My findings suggest the agency problem not only matters for equity IPO market, arguably dominated by small and young issuers facing powerful underwriters, it also matters for corporate bond issuers, who are typically large and frequent issuers.

The paper proceeds as follows. In Section 2, I discuss the existing literature and develop testable hypotheses related to bond underpricing. Section 3 provides a description of the data on non-financial bond issues. Section 4 presents evidence of bond underpricing and provide tests of alternative hypotheses. In Section 5, I introduce bond issues by financial firms and further investigate the agency conflict hypothesis. Section 6 concludes.

2. Related Literature and Hypotheses Development

2.1 Existing Evidence of Corporate Bond Underpricing

Although the underpricing evidence is well established for new equity issues, fewer empirical studies have investigated pricing efficiency for corporate bond offerings. In equity offering literature, over- or under-pricing is typically estimated as the "initial return" from the offer price to the post-offer secondary market price, in particular, a positive "initial return" indicates underpricing. For bond offerings, however, since this "initial return" measure requires secondary market transaction prices, research has been hampered historically by the lack of quality bond transaction price data. To circumvent this problem, early studies examined “yield spreads” between new bonds and a benchmark index of seasoned bonds with similar credit rating and maturity. For example, Ederington (1974) and Sorensen (1982) find new bonds on average have a higher offer yield than their matched seasoned bonds, and thus conclude that corporate bonds are generally underpriced. In contrast, Lindvall (1977) finds a negative yield spread, suggesting that new bonds are overpriced. However, the “yield spreads” approach may suffer from inaccurate estimation of the benchmark yield due to difficulties in properly matching the new bonds with seasoned bonds because they can differ in built-in options, covenants, and liquidity. In addition, as Weinstein (1978) points out, the aggregation procedure used in constructing an index of seasoned bonds averages yields rather than prices, which means that the bond yield indexes do not measure the yield on any real bond.

Later bond studies try to use “initial return” approach. For example, Weinstein (1978) finds a positive initial return over the issue month for a sample of 179 new bonds and concludes that bonds are underpriced. In contrast, focusing on newly issued investment-grade bonds, Fung and Rudd (1986) calculate “initial return” from the offer price to the bid price (using indicative dealer quotes) on the issue date and find little evidence underpricing. Focusing exclusively on initial bond offerings, Datta, Iskandar-Datta and Patel (1997) find underpricing for high yield issues but *overpricing* for investment grade issues based on NYSE transactions, which are dominated by small, retail trades.

More recently, Cai, Helwege, and Warga (2007) find that underpricing averages 47(17) Bps for high yield IBOs (SBOs) between 1995 and 1999 but *no* *significant* underpricing for investment grade bonds. It is important to note that their study is based on transactions from insurance companies only, which account for about 12.5% of dollar trading volume in TRACE-eligible securities (Bessembinder, Maxwell, and Venkataraman (2006)). Moreover, prices from only insurance company trades may not be representative of the entire bond market. First, insurance companies tend to be buy-and-hold investors who might not be engaged in frequent secondary market trading. Indeed, of the 439 bond IBOs in their sample, Cai et al. observe only 167 bonds traded by insurance companies on the issue day and only 82 bonds traded the next day. Second, even when insurance companies do trade in the aftermarket, their trading motives may not be representative of those of bond traders at large. For example, if insurance companies are in a better position than the average investor to obtain the desired bonds at the offer price, then their post-offer trades may be predominately sales (i.e., at dealer's bid prices) and thereby tend to underestimate the underpricing. Alternatively, if their appetite for corporate bonds has not yet been met during the offering, then they are likely to accumulate positions in the aftermarket, which makes their post-offer trades largely at the ask prices and thus tend to overestimate the underpricing. Cai et al. observe that for 590 bonds with insurance company trades during the first week of offer, only 196 bonds have sell trades, suggesting that insurance companies are net buyers on the secondary market and that their post-offer trades are primarily at the ask prices.

Two studies shed some light on bond pricing using TRACE data. Based on a sample of non-publicly disseminated TRACE data, Goldstein and Hotchkiss (2007) find evidence of underpricing for investment grade as well as high yield debt offerings.

Their focus, however, was on dealer behavior around offerings so that they lumped together initial and seasoned bond offerings issued by both financial and industrial issues. In addition, 54.1% of their sample consisted of Rule 144A offerings. Given that Rule 144A offerings are private placements, it is not clear whether publicly traded corporate bonds are underpriced. Another study by Kozhanov and Ogden (2012) uses both TRACE and FISD data. They study a sample of 923 investment grade bond issues from 2005 through 2009 and conclude that corporate bonds are generally *overpriced* at issuance since new bond issues have lower yields than seasoned benchmarks.

2.2 Hypotheses and Empirical Predictions on Corporate Bond Underpricing Determinants

2.2.1 Valuation Uncertainty Hypothesis

U.S. corporate bonds are typically issued via firm-commitment offerings, where an underwriter syndicate guarantees the proceeds of the issue (net of fees) to the issuer and organizes the sale of the bonds.[8] The underwriter accepts issue price risk when it signs the “Underwriting Agreement” to purchase the entire issue at an agreed upon fixed price. As Smith (1977) notes, this is similar to the underwriter selling a put option on the issue to the issuer for a fee. As such, the underwriter bears all the risk associated with price volatility between offer pricing and distribution. Thus, underpricing benefits the underwriter by lowering the risk of an unsuccessful sale and reducing their marketing efforts (Ederington (1974) and Edelen and Kadlec (2005)).

The valuation uncertainty theory implies that the degree of underpricing should be greater for issues with characteristics associated with higher valuation uncertainty.

[8] Only 11 out of the 2380 offerings in my sample bonds are non-firm commitment offerings.

Also underpricing should be greater during periods when interest rates are more volatile and market uncertainty is higher. Finally, As Corwin (2003) pointed out, a longer lag between offer pricing and distribution means more time for the market condition to change. Therefore the valuation uncertainty hypothesis predicts that underpricing should increase as the time lag lengthens.

2.2.2 Information Asymmetry Hypothesis

Traditional theories based on information asymmetry can be classified into theories in which investors are more informed than the underwriters and the issuers, theories in which some investors are more informed than others, and theories in which issuers are more informed than investors. All underpricing theories based on asymmetric information share the prediction that underpricing is positively related to the degree of information asymmetry.

In a setting where investors are more informed than the underwriters and the issuers, Benveniste and Spindt (1989), and Chemmanur (1993) suggest underpricing facilitates book-building by inducing the information production and revelation. Underpricing is used to compensate informed investors for revealing positive information to the underwriters. Empirically, the more positive the information (and so the greater the incentive to withhold it), the more underpricing is required.

In a setting where some investors are more informed than others, Rock (1986) develops a model in which underpricing is necessary to compensate uninformed investors and thereby ensure their participation in the new issue market. Rock’s theory is based on the assumption that informed investors will buy only the good offerings, leaving the bad for uninformed investors. Knowing this, uninformed investors will be reluctant to buy unless underwriters underprice in general. Therefore, underpricing is required to compensate uninformed investors for the winner's curse. However, since the corporate bond market is dominated by institutional investors, Rock's theory seems less applicable to bond offerings than to equity offerings.

Underpricing is also proposed as a mechanism to signal firm quality in equity initial public offerings (IPOs) when issuers have better information than investors (Allen and Faulhaber (1989), Grinblatt and Hwang (1989), and Welch (1989)). This strand of literature argues that though underpricing is costly, it allows the (high quality) issuers to recoup their upfront sacrifice post-IPO by returning to the market to sell future securities on better terms. Since bond issuers are overwhelmingly large seasoned issuers, signaling theory seems less applicable here.

Although hypotheses based on valuation uncertainty and on information asymmetry are conceptually different, empirically, they imply relation of the underpricing with many of the same variables. For instance, one natural proxy for uncertainty at the bond level is the credit rating as bond issuers with higher ratings are typically large and mature firms and have less uncertainty. Meantime, these firms are subjected to closer scrutiny by the market so that they are subject to less information asymmetry. Therefore, underpricing theories based on either uncertainty or information asymmetry would predict bonds with higher rating exhibit lower underpricing.

Moreover, uncertainty and information asymmetry may reinforce each other in affecting underpricing. The intuition is that an investor who decides to engage in information production implicitly invests in a call option on the security offering, which will be exercised if the 'true' price exceeds the strike price, that is, the offer price. The value of this option increases in the extent of valuation uncertainty. Thus, greater valuation uncertainty results in greater extent of information asymmetry (Beatty and Ritter (1986)). These theories therefore predict a positive relation between underpricing, ex ante uncertainty and information asymmetry.

2.2.3 Aftermarket Illiquidity Hypothesis

Ellul and Pagano (2006) propose a theory to explain IPO underpricing where investors worry about the after-market illiquidity that stems from the unresolved information asymmetry at the offering stage. Equilibrium stock returns must compensate investors for the losses expected from trading with better informed investors. In their model, some residual private information not resolved during offering stage creates an adverse selection problem in the aftermarket and is reflected in the bid-ask spread. They further argue that the amount of private information that remains undisclosed after the IPO depends partly on how much information is released at the IPO stage. Hence, their model predicts that bookbuilding process mitigates the residual information asymmetry and thereby reduces aftermarket illiquidity-related underpricing.

If there is unresolved information asymmetry at the bond offering stage, then it is possible that bond underpricing may be used to compensate investors for the relative illiquidity. Empirically, the aftermarket illiquidity hypothesis predicts that bond underpricing increases with aftermarket illiquidity measures, such as the bid-ask spread. However, since bond issuers are mainly large seasoned issuers and corporate bonds are typically issued via bookbuilding, aftermarket illiquidity is less likely to affect bond underpricing.

2.2.4 Price Pressure Hypothesis

Exploring the reasons for seasoned equity underpricing, Corwin (2003) argues that the SEO underpricing may be related to either permanent or temporary price pressure. The permanent price pressure hypothesis states that the firm is faced with a downward sloping demand curve for its security and a seasoned offer can be viewed as a permanent shift in the supply of the existing issues, which will therefore decrease the price of the outstanding security. Alternatively, one can view a seasoned offer as a temporary liquidity shock that must be absorbed by the market such that a discounted offer price may be necessary to compensate investors for absorbing the liquidity shock. If the shock is temporary, post-offer secondary market prices should return to pre-offer prices, resulting in a positive return "sweetener" to investors who purchase shares in the offering (Scholes (1972)).

Both temporary and permanent price pressure hypotheses predict that issues of larger size (relative to outstanding security) call for greater underpricing, ceteris paribus. However, the two hypotheses predict different price patterns of the existing security before and after the offerings. Specifically, the temporary price pressure hypothesis predicts that the post-offering secondary market prices should gradually rise and return to the pre-offer prices, i.e., prices will exhibit a V-shaped trend with the offering date price being the lowest. Whereas the permanent price pressure suggests that the post-offering prices will not (completely) return to pre-offering prices.

A sample of additional bond issues to an existing indenture (ABOs) allows me to further test the price pressure hypothesis. ABOs are similar to seasoned equity offerings in the sense that an existing bond is already trading on the market such that open market prices are easily observable. Therefore, these ABOs should bear less uncertainty and information asymmetry. However, adding more issues to the existing bonds would result in a sudden increase in the supply of the identical bonds, leading a price drop according to the price pressure hypothesis. Bond prices will return to the pre-offer prices if the drop was due to temporary liquidity shock, whereas they remain at a lower price if the drop was due to permanent price pressure.

2.2.5 Agency Conflicts of Interest Hypothesis

An alternative explanation to why firms leave money on the table can be attributed to an agency problem between the issuer and the underwriter. Early models such as Baron (1982) focused on how an underwriter's informational advantage over issuing companies might allow the underwriter to exert sub-optimal effort in marketing and distributing the security. If effort is not perfectly observable and verifiable, banks find themselves in a moral hazard situation when acting as the issuers' agents. Biais, Bossaerts, and Rochet (2002) combine the agency cost setting of Baron (1982) with Benveniste and Spindt's (1989) assumption that some investors hold pricing-relevant information, and highlight the possibility that bankers and institutional investors collude to extract informational rents from issuers.

Recent research also explores potential agency conflicts due to joint production of underwriting and other financial services such as brokerage, security analysis, lending, and asset management (Loughran and Ritter (2004)). Some evidence suggests that underwriters allocate underpriced issues to enrich buy-side clients in return for quid pro quos or for other prospective underwriting business in a practice known as "spinning" (Liu and Ritter (2009)).

Therefore, the agency conflict hypothesis assumes underwriters have an informational advantage and argues that underpricing saves underwriters' selling efforts and has the added benefit of enlarging investors' potential profit. If underwriters intentionally underprice bond issues to minimize their underwriting effort or steer bonds to favored clients for quid pro quos, the costs to them are much higher when they are underwriting their own bonds. As such, Muscarella and Vetsuypens (1989) studied a set of 38 self-marketed investment bank IPOs in the 1970s and 1980s, in which agency conflicts should be eliminated. However, they find the 38 IPOs appear to have been underpriced by roughly as much as other IPOs, which they interpret as contradicting the agency hypothesis. There were very few cases for a bank to underwrite its own IPO, so it is hard to draw large sample inference from their study. But it is not unusual for a bank to self-market its own bonds. I therefore study banks' self-marketed issues compared to non-self-marketed issues by financial firms. The agency hypothesis predicts lower underpricing when banks underwrite their own bonds.

3. Data Description and Variable Construction

3.1 Sample description

Data are collected from five main resources: 1) Securities Data Company's (SDC) Global New Issues Database for corporate bond offerings; 2) Mergent's FISD for supplementary bond characteristics; 3) Enhanced Trade Reporting and Compliance Engine (Enhanced TRACE) for bond secondary market transaction data; 4) BofA Merrill Lynch Index for market benchmark returns; and 5) Prospectuses on the SEC Electronic Data Gathering, Analysis, and Retrieval (EDGAR) service.

I begin with the sample of all corporate nonconvertible bonds issued by non-financial firms from February 1, 2005 through September 30, 2012 from the SDC database (I examine the sample of financial issues in Section 5 separately from the main sample). The sample period ends in September 2012 since the enhanced TRACE data are only available with an 18 month lag. I exclude Rule 144A issues, as their trades are exempt from reporting to TRACE. I also exclude private placements, pay-in-kind bonds, corporate pass-thru trusts, agency issues, and bonds not denominated in USD. This results in a sample of 2960 bond issues. I further delete 9 putable bonds, 49 emerging market issues, and 265 issues that are not fixed rate or bonds with coupon paying with irregular frequency. 2637 issues remain.

Since SDC contains little information on bond characteristics such as face value, coupon and rating, additional data are obtained from Mergent's FISD. 2581 of the 2637 issues are matched with a FISD record. [9] Moody's rating is used if available; otherwise Standard & Poor's or Fitch's rating is adopted.[10] I then delete 9 bonds with a face value not equal to $1000 and 6 not-rated issues.

Both SDC and FISD provide detailed offering information, including issue date, offer price, offering yield, maturity, and gross spread. Given potential errors in SDC's variables reported by prior studies, I cross-check these variables between SDC and FISD and find 858 observations with disagreement for one or more of the four variables. I verify them against prospectuses on SEC Edger and news sources from

[9] FISD and SDC are matched on bond CUSIP. Bond issues that have not been assigned CUSIPs in SDC are match by issuer CUSIP, issue date, offer price, and offer yield.

[10] There are 75 observations with rating disagreement between Moody's and S&P. I.e., one agency rated as investment grade and the other rated as high yield. In these cases, I adopt the higher rating for two reasons. First, the related SEC rule suggests "at least one NRSRO" for determining whether an issue is rated as investment grade. Second, SDC classifies all of these observations as investment grade issues.

Factiva. The prospectus on Edgar provides detailed information about offer price, gross spread, underwriters and brief on firm risk. I found much of the inconsistency between SDC and FISD was due to rounding errors but 253 issues were not identified in either Edgar or Factiva and therefore are deleted. I further deleted 39 bonds issued by university endowment funds or asset-backed pass-throughs which were misclassified as straight debts by SDC.

Secondary market bond trade prices and trading volume are obtained from the enhanced TRACE database, which also reports whether a trade represents a sale to a regular customer (S), a buy from a regular customer (B), or an inter-dealer trade (D). This information allows me to estimate underpricing accounting for bid-ask bounces and analyze aftermarket trading activities. Following Dick-Nielsen (2009), I eliminate duplicate, canceled, withdrawn and reversed transactions. Following Bessembinder, Kahle, Maxwell, and Xu (2009), I compare the yield-to-maturity (YTM) reported on TRACE to the YTM estimated from coupon, maturity date, and the trade price reported on TRACE and FISD and eliminate those trades with disparity more than ten basis points. The final sample for the main analysis consists of 2380 bond offerings by 584 non-financial firms.

To analyze agency hypothesis in section 5, I also collected data on financial issues, i.e. bonds issued by banks, credit institutions and insurance companies. These data allow me to test whether and to what extent underwriters underprice their own bonds. After applying the same data clean procedures as for the non-financial sample, I have 1186 bond offerings by 115 financial firms.

3.2 Calculation of Underpricing (Initial Returns)

For my baseline analysis, underpricing on bond issue *i* is measured as the initial return from the offer price, $P_{i,o}$, to the secondary market price on day t, $P_{i,t}$. Specifically,

$$Discount_{i,t} = \frac{P_{i,t} - P_{i,o}}{P_{i,o}}, \tag{1}$$

where $P_{i,t}$ is the average trade price on day *t*, where individual trade prices are weighted by trade size.[11] I use an average trade price (instead of the closing price as most equity studies did) because corporate bonds are thinly traded and have large bid-ask bounce. For instance, analysis from TRACE data suggests that an average corporate bond only trades 52 days a year (Bessembinder, et al. (2009)) and if traded on a day, the average daily number of trades is only 6 (Ederington, Guan, and Yang (2014)).

Most equity offering studies estimate underpricing as the percentage difference between the offer price and the first-day price. Using later prices, say at the end of the first week of trading, typically makes little difference because the full extent of any underpricing is evident fairly quickly (Ljungqvist (2004)). However, since bonds are thinly traded, it is unclear whether the full extent of any bond underpricing is captured by measuring the price change from offer price to the first-day secondary market prices. Also, as will be seen later, first-day trades are largely seller initiated trades (i.e., at the bid prices). I therefore not only estimate underpricing using trades on the first trading day, but alternatively measure underpricing using trades on later days.

To control for price changes due to any market movement between the offer pricing day and the day when the secondary market trades are observed, I calculate the

[11] I repeat all the analyses using equal weighted prices and the magnitude of underpricing is even larger than using trade size weighted average prices.

excess return of an individual bond over the return on a bond index of the same rating class during the same period. BofA Merrill Lynch Corporate Indices are used as benchmarks, which are broken down by ratings (AAA, AA, A, BB, B, and C). Benchmark returns are calculated as changes in index level from the offer pricing day $Index_{i,0}$ to the day when the secondary market trades are observed $Index_{i,t}$:

$$BRET_{i,t} = \frac{Index_{i,t} - Index_{i,0}}{Index_{i,0}} \tag{2}$$

Then an adjusted discount that accounts for bond market movements is calculated by subtracting from the raw discount the same period index return of the same rating class.

$$Adjusted\ Discount_{i,t} = Discount_{i,t} - BRET_{i,t} \tag{3}$$

3.3 Offer Announcement Date (Pricing Date) and Issue Date

Since I calculate the adjusted discount by subtracting from the raw discount the same period benchmark return, it is important to identify the exact day when the offer is priced to get $Index_{i,0}$. When a bond issue is set, issuers usually file a form with SEC under rule 424(b) with specifics such as offer price, coupon rate, gross spread, and syndicate members. This day is usually termed the "pricing date" or "issue date" in SDC. I verify the SDC issue date against the form 424(b) filing date on Edgar and various newswire services on Factiva and make sure the issue date is the earliest date when the specifics, especially the pricing, of the offer is announced. I correct 98 SDC issue dates.[12] The actual offering date is identified as the first day when a bond issue is

[12] SDC sometimes identifies the registration data as the issue day. However, 2217 out of the 2380 bond offerings are shelf-registered. Shelf offerings are often deferred by months or years after registration or even lead to no actual offerings. Moreover, a large proportion of them are universal shelf offerings, which

traded and reported to TRACE. Given that all secondary trades, including trades for newly issued bonds, are required to report to TRACE after February 2005, it is not unreasonable to assume that the first day with trading is the actual offering date.

I observe that in most cases, the offer price is set just few days (or even just a few hours) before the first TRACE trade. In my sample, 1766 issues are offered on the same day as the announcement dates and 2361 issued within one week from the pricing announcement. This means that market movements between pricing and offer are generally negligible.

3.4 Initial Bond Offerings (IBOs), Seasoned Bond Offerings (SBOs), and Additional Offerings to an Existing Indenture (ABOs)

I compare differences in underpricing among initial bond offerings (IBOs), seasoned bond offerings (SBOs), and additions to an existing indenture (ABOs). IBOs are offered by firms with no publicly traded debt and SBOs are offered by firms with publicly traded debt. 197 issues are "initial" bond issues (IBOs) and 2183 are issues with bonds outstanding. Note that for SBOs, the existing bonds of the same issuer may vary in maturity and covenants.

I also examine additional bond offerings (ABOs) which prior studies have lumped together with SBOs. ABOs are additions to an existing bond indenture. Appendix 1 illustrates an example of an ABO via excerpt from the prospectus filed with SEC. Since the secondary market prices before and after the offering are observable, the

---

can lead to either an equity or a bond offering. Therefore, the registration usually just indicates a "possible" bond offering at a later time and issuers usually don't provide pricing information on the registration dates.

sample of ABOs provide a unique setting for testing the price pressure hypotheses. I identify 84 ABOs in the sample.

[Insert Table 1]

Table 1 provides summary statistics for the non-financial issues sample. Panel A partitions the issues by rating categories and years to maturity for IBOs, SBOs, and ABOs, respectively. Panels B and C report issue characteristics for investment grade and high yield offerings, respectively. Bond offerings are dominated by investment grade issues, especially by A- and BBB- rated issues. Investment grade issues tend to be somewhat larger in offer size and with longer maturity than high yield issues. An average investment grade (high yield) SBO raises $701 ($527) million of proceeds and investment grade (high yield) IBO raises $707 ($383) million per deal. Issue characteristics of IBOs and SBOs do not differ appreciably. Relative offer size is defined as the amount of proceeds raised in the issue divided by pre-offer total bonds outstanding of the issuer. ABOs raise a substantially smaller relative offer size than SBOs. For investment grade issues, the mean relative offer size of an SBO is 33.57% while the mean relative offer size of an ABO is 10.59%. The underwriter gross spread is about 0.57% for investment grade SBOs and 1.67% for high yield SBOs. Underwriter gross spread is similar among SBOs, ABOs and IBOs. Unlike equity offerings which are typically underwritten by a solo lead manager, a bond offering is usually underwritten by more than three lead managers on average.

4. Empirical Findings

4.1 Overall Evidence of Underpricing and Time Trend

Evidence of corporate bond underpricing is reported in Table 2. I find significant evidence of underpricing for both investment grade and high yield bond offerings for IBOs, SBOs, and ABOs. Underpricing tends to be higher on speculative grade than on investment grade issues and slightly higher on IBOs than SBOs or ABOs. Calculated from offer prices to first-day average trade prices, for investment grade issues, the discount averages 0.46% for SBOs, 0.55% for IBOs and 0.48% for ABOs. For high yield issues, the discount averages 0.95% for SBOs, 1.50% for IBOs, and 0.96% for ABOs.

In sum, all types of offerings are significantly discounted including SBOs and IBOs for both investment grade and high yield offerings. This is to be contrasted with previous studies that only find underpricing for initial bond offerings among high yield bonds but find no underpricing for seasoned and/or investment grade issues (Cai et al. (2007) and Datta et al. (1997)). Moreover, this study is the first to look at ABOs separately and find that they are also significantly underpriced.

[Insert Table 2]

Note that underpricing estimated based on second day trades are significantly higher than that estimated from the first day trades, especially for SBOs. The mean discount for investment grade SBOs is 0.58% and 1.10% for high yield SBOs.[13] I explore the possible reasons in section 4.2.

[13] Underpricing estimated based on the third day trades is even slightly higher than that estimated from second day trades, but the differences are not statistically significant for all issue types. Results are available upon request.

The magnitude of underpricing varies substantially over time. This time-series pattern is illustrated in Figure 1. Before the 2008/2009 financial crisis, underpricing averaged less than 0.30% for investment grade SBOs and around 0.60% for high yield SBOs but it rises sharply during financial crisis and peaks in 2009. Specifically, underpricing rises to 0.87% for investment grade SBOs and 1.37% for high yield SBOs in 2009. Underpricing for IBOs follows the same pattern. Notably, underpricing slightly increased from pre-crisis to post-crisis. The time-series variation may suggest that underpricing is associated with market-level uncertainty.

[Insert Figure 1]

4.2 Underpricing and transaction Costs

A potential concern with underpricing estimates using average prices is that the average includes prices from both buy and sell transactions i.e., at both the bid and ask prices. As such, an investor may not be able to profit by buying at the offer price and re-selling in the immediate aftermarket. To address this concern, in Table 3, I estimate underpricing based on prices from customer buys (trades at the ask prices) and customer sells (trades at the bid prices) separately.[14]

[Insert Table 3]

Consistent with the existence of bid-ask bounce, the underpricing estimated using customer sell prices (Panel A) is lower than that using customer buy prices (Panel B). Using *second-day* trades, estimated underpricing for investment grade SBOs is 0.51% based on customer sell prices and 0.69% based on customer buy prices. Panels C

[14] I also calculated underpricing based on interdealer trades only and the estimation is close to that based on all trades. Results are available upon request.

and D report results for high yield issues; the estimated underpricing is 1.05% based on sell prices and 1.20% based on buy prices for SBOs. These results indicate that after accounting for bid-ask spreads, traders who obtain new bond issues in the primary can sell in immediate aftermarket at a profit.

Noteworthy, the implied bid-ask spreads, approximately 18 bps for investment grade and 15 bps for high yield bonds, are lower than Edwards, Harris, and Piwowar's (2007) estimate of the spreads at 24 bps for trades of 200 bonds. In untabulated results, I find that the bid-ask spread rises as trading subsides in the days and weeks following the offering.[15] The finding that the bid-ask spreads immediately after the offerings are much smaller than later when trading falls off is somewhat consistent with the evidence found for treasury bonds that "on-the-run' bonds are more liquid than "off-the-run" bonds (e.g., Goldreich, Hanke, and Nath (2005)).

Table 3 reveals three more interesting results. First, there are many more sells than buys on the first trading day, while the number of sell and buy trades are comparable on the second day. For instance, on the first day, there are 22851 sales of investment grade SBOs and only 11747 buys. But on the second day, there are 26385 sells and 28792 buys. This suggests that average prices based on trades on the first day tend to include more trades at the dealer bid prices than ask prices, resulting in lower underpricing estimates, as Table 2 reports. However, this is not the whole reason that average prices are higher on the second day since the estimated underpricing is also higher on the second day than on the first day when estimated from bid and ask prices

[15] I calculated bid-ask spread post-offer and the spread gets larger over time. The average investment grade SBO bid-ask spread is 0.05% on the first day, 0.12% for the first week, and 0.23% for the fourth week. Please note that the implied bid-ask by underpricing is the average buy price across all bonds minus the average sell buy across all bonds, while the average bid-ask spread is estimated by first calculating individual bid-ask spread and then averaging across all bonds.

separately. If we look at underpricing estimated using customer sell trades only, investment grade SBOs underpricing averages 0.51% using second day prices, as compared to 0.42% using first day prices. A third point worth mentioning is that the number of trades on the second day is larger, which should provide better price estimates. Given these potential issues in first-day prices, hereafter, I use average prices from second day trades as the primary underpricing estimates.

A potential concern with the estimates of underpricing using secondary market prices is that these could represent only a limited amount of trades, i.e., it is possible that market prices are bid up by a small number of investors whose demand was unmet during the primary market. To address this concern, I calculate the turnover rate in the immediate aftermarket as the total trading volume divided by the amount of bonds issued. On the first trading day, the average turnover rate (from both buy and sell trades) is 10.62% for investment grade SBOs and 20.37% for high yield SBOs.[16] During the first week of issuance, the average turnover rate for investment grade SBOs is 32.70% and 63.22% for high yield SBOs. These results are reported in Table 5. This evidence suggests that bond underpricing is not driven by just a few trades but indicates fairly active trading and possible immediate post-offering flipping activities.

4.3 Determinants of Bond Underpricing

Having shown significant underpricing of corporate bond issuance across all types of issues for both investment grade and high yield bonds, I next examine the relative importance of the economic and institutional factors suggested by the various

[16] By comparison, Professor Jay Ritter reports an average turnover rate of 39% on the first day of IPO. Available at http://bear.warrington.ufl.edu/Ritter/IPOs2011Turnover_04162012.pdf

underpricing theories discussed in Section 2. In Table 4, I report multiple regressions where the dependent variable is underpricing estimated from the offer price to the second-day average price, adjusted by bond market movement. Statistical significance is based on White's heteroskedasticity-consistent standard errors.[17]

To compare with previous studies, I first present a baseline analysis with explanatory variables from previous studies, such as rating and maturity. Cai et al. (2007) find that only speculative grade bonds are significantly underpriced and Datta et al. (1997) and Kozhanov and Ogden (2012) even find overpricing for investment grade bonds. Cai et al., also include maturity but they do not find maturity to be significantly related to underpricing. I also include an indicator for built-in call option as bonds with call options may be priced differently (Weinstein (1978) and Fang (2005)). The omitted category is bond issues rated AA or above with a maturity of five years or less. As shown in Table 4 Column (1), credit rating is a significant determinant of underpricing. The estimated coefficients on “A”, “BBB”, “BB” and “B and below” are monotonically increasing, which suggests that the underpricing is increasing as credit rating gets lower. In addition, underpricing increases as maturity lengthens. Finally, the estimated coefficient on “Call” option is negative, suggesting that bond issues with a call exhibit lower underpricing. I next conduct different regression tests by adding in explanatory variables specific to the hypotheses developed in Section 2.

4.3.1 Testing the Uncertainty and Asymmetric Information Hypotheses

I first test how underpricing relates to factors suggested by the price uncertainty and asymmetric information hypotheses. I investigate issue-specific and

---

[17] I have tested several alternative specifications: OLS standard errors, issuer cluster standard errors, issuer fixed effect, and year fixed effect and get qualitatively same results. Also, results using underpricing measures based on first day trades are qualitatively unchanged and available on request.

issuer-specific characteristics, and market-wide conditions. A bond's *credit rating* is a natural proxy for both valuation uncertainty and information asymmetry. As discussed in section 2.1, highly rated bonds likely have less valuation uncertainty. Also, highly rated issuers are typically large and mature firms, subjected to closer scrutiny by the market and therefore, the information asymmetry problems are likely less severe. Therefore, both the valuation uncertainty and information asymmetry hypotheses predict that bonds with higher ratings should exhibit lower underpricing. Indeed, we have already observed greater underpricing on speculative grade than on investment grade bonds in the univariate analysis in Tables 2 and 3 and multivariate regression in Table 4 Column (1). Bond *maturity* is another possible proxy for valuation uncertainty because for the same amount of change in market interest rates, the price change is greater on bonds with longer duration. As Table 4 model (1) shows, underpricing increases as maturity lengthens, consistent with the uncertainty hypothesis since longer maturity bonds are subject to higher price volatility and risk.

However, higher rated/shorter maturity bonds differ from lower rated/longer maturity bonds in other respects than just perceived risk. In fact, empirical evidence suggests credit rating may simultaneously affect bond liquidity and relative bargaining power between the issuer and the underwriter as well (Edwards et al. (2007) and Datta et al. (1997)). Maturity also tends to be correlated with liquidity (Edwards et al. (2007)). Therefore, finding a higher underpricing for lower rated/longer maturity issues may not disentangle which underlying factor(s) is dominant in driving bond underpricing. Therefore, I adopt other variables related to valuation uncertainty. First, I use *return volatility*, which also represents the underwriting syndicate's level of uncertainty concerning the securities' actual value (Yeoman (2001)). Since it is hard to measure ex-ante uncertainty, I use ex post bond price volatility as a proxy, measured as the standard deviation of daily bond price changes over the one month period after the offer. Another proxy for uncertainty is a *rating disagreement* dummy. A bond typically get ratings from more than one rating agencies, when the rating agencies do not agree on a bond's rating, it likely indicates either uncertainty about the bond's default risk or information asymmetry in that one of the rating agencies has information that the others do not. *"Rating Disagreement"* equals one if the specific issue is rated as investment grade by one rating agency but as speculative by another. My last proxy for uncertainty at the bond level is the time between pricing date and the actual offer day (the first day with trading). As Corwin (2003) points out, the longer the time span, the more likely that market conditions will change between the pricing and completion and thus more underwriter uncertainty.

I expect uncertainty and asymmetric information to be related to three issuer-specific characteristics. First, SBOs (and especially ABOs) are expected to exhibit less uncertainty than IBOs since the firms' bonds are already trading on the second market. Second, information asymmetry may depend on whether an issuer is a privately-held or publicly-traded firm as firms with publicly traded stocks are subject to periodic disclosure and market monitoring, and therefore are less likely to suffer from information asymmetry. To identify whether a bond issuer is a privately-helf firm, I use the issuer's company identifier (PERMCO) from CRSP's historical name file, supplemented by a manual search on Capital IQ.[18] I use analyst coverage as the last

[18] Bonds issued by the same firm but at different times may have different firm identifiers (CUSIPs) if a firm changes its name, experiences M&A or reorganizes. Moreover, bonds issued by a subsidiary may be

proxy for issuer-level information asymmetry. Many studies argue that security analysts amalgamate and distill private information in a manner that reduces information asymmetry (e.g., Frankel, Kothari, and Weber (2006)), and therefore more analyst coverage should result in less information asymmetry.

Finally, to examine the relation between market-wide uncertainty and underpricing, I use the VIX index to measure expected stock market volatility and the MOVE index to capture expected interest rate risk. VIX index is the Chicago Board Options Exchange (CBOE) measure of the implied volatility of S&P 500 index options. MOVE Index is developed by Merrill Lynch to measure implied volatility of US Treasury bonds and is essentially the interest rate equivalent of the VIX. Examining the association between bond underpricing and these two market level risk measures sheds light on possible time-varying pattern of bond underpricing.

[Insert Table 4]

Table 4, Models (2) and (3) provide evidence of uncertainty and information asymmetry hypotheses and lend support to the two hypotheses at the issue and market level. At the issue level, underpricing increases with bond price volatility and days from pricing to issue, consistent with price uncertainty hypothesis. But the coefficient on '"rating disagreement" is not significant, implying that the underpricing is not higher for the issues that have different ratings among rating agencies, after controlling for other uncertainty and information asymmetry factors. Bond underpricing also strongly

guaranteed by the parent but trade under the name and identifier of the subsidiary. As such, failure to track a firm's history may misclassify a publicly traded firm as private. After performing a manual search from Capital IQ, only 17 of the bond issues in my sample were issued by privately held firms as of the offering date.

increases with market uncertainty, as the estimated coefficients of the VIX and MOVE indices are significantly positive.

At the firm level, however, multivariate results are not as the price uncertainly and asymmetric hypotheses predict. Specifically, while IBO (ABOs) underpricing is slightly higher (lower) in univariate tests than SBOs, the underpricing is not significantly larger (less) for IBOs (ABOs) than for SBOs after controlling for other variables. The coefficient of the “private” firms dummy in Model (2) is also not significant, suggesting that underpricing is not higher for private firms. The latter results may be due to the fact that bond issues are overwhelmingly public firms as only 17 bonds are issued by private firms and all these private firms have existing public bonds outstanding. Model (3) includes the number of analysts covering the stock as a proxy for information asymmetry. Since a firm needs to be public to be covered by analysts, I dropped the observations of private firms in Model (3). There is no evidence that underpricing varies with analyst coverage.

Overall, the results for Models (2) and (3) suggest that variables related to both price uncertainty and information asymmetry are generally significant determinants of underpricing at the issue level and market-wide level but not at the firm level. Specifically, proxies for price uncertainty such as price volatility, days between pricing and issue completion and market uncertainty are significant, while proxies for information asymmetry such as the private firm dummy and number of analyst coverage are insignificant.

4.3.2 Testing the Aftermarket Illiquidity Hypothesis

To test the *aftermarket illiquidity hypothesis* proposed by Ellul and Pagano (2006), I use the daily post-offer bid-ask effective half-spread as explanatory variable, calculated as:

$$Bidask_{i,t} = \frac{p_{ask,i,t} - p_{bid,i,t}}{p_{ask,i,t} + p_{bid,i,t}} \quad , \tag{4}$$

where $p_{ask,i,t}$ is the weighted average of price on all customer buy trades (at dealer's ask prices) for bond i on day t, and $p_{bid,i,t}$ is the weighted average of price on all customer sell trades (at dealer's bid prices) for bond i on day t. This daily measure is then averaged over the first month of after the offering.[19] A higher bid-ask spread implies higher aftermarket illiquidity. As suggested by Ellul and Pagano (2006), liquidity risk may also affect the underpricing and therefore I include the volatility of bid-ask spread to measure liquidity risk.

The results are presented in Table Column (4). I find some evidence that higher bid-ask spreads are associated with higher underpricing but bid-ask spread volatility doesn't seem to be associated with bond underpricing. I use two alternative liquidity measures in untabulated tests: 1) Turnover, measured as total dollar trading volume for bond i during period t divided by the total offer amount and, 2) Amihud's (2002) illiquidity measure, modified for bonds, following Dick-Nielsen, Feldhutter, and Lando (2012). Neither of the two alternative liquidity measures is found significant.

4.2.3 Testing the Price Pressure Hypotheses

I next test the price pressure hypothesis, which suggests underpricing should increase with offer size, as larger offerings require the market to absorb more bond issues. Relative offer size is defined as follows:

[19] Using the average bid-ask spread over the first week after the offering yields similar results.

$$\text{Relative Offer Size}_i = \frac{Offer\ Amount\ of\ the\ Current\ Issue_i}{Total\ Bond\ Outstanding\ of\ the\ Issuer_i} \tag{5}$$

Table 4 Model (5) presents results for testing price pressure. The coefficient on relative offer size is significantly positive, suggesting that price pressure plays a role in bond underpricing. One might argue that a larger offer amount likely increases the leverage ratio of the firm and thus increasing the risk of default and lowering the bond's price but note that this leverage change should affect both the offer and the post-offer prices so should not impact the underpricing measure.[20]

To further investigate whether the price pressure is due to a downward sloping demand curve for bonds (permanent price pressure) or due to temporary liquidity shock, I examine the sample of additions to an existing bond indenture (ABOs). Since both pre- and post- offering market prices of the bond are observable, I can track the price pattern around the offering.

For each day t in the window from 25 days before and after the offering date, I measure a relative price as the average secondary market price on day t divided by the offer price, adjusted for market movements between the offer date and day t. A relative price above 100% means that the market price is higher than the offer price and therefore represents underpricing. Results are shown in Figure 2 where I include the offering price for illustrative purposes. As shown there, both pre- and post-offering secondary market prices exceed the offer price, indicating underpricing. For an average investment grade issue, the offer price is set about 1.17% below the average secondary market price on day t-1. After the offering, the secondary price is also higher than the

[20] Nonetheless, to mitigate this concern, I include in the regression the change in the book leverage, where book leverage calculated as total debt divided by total assets. In untabulated results, the coefficient on leverage change is significantly positive (t= 3.11), suggesting that underpricing is greater the larger leverage changes. However, after controlling for leverage change, the coefficient on relative offer size remains significantly positive (t=4.86) and the similar economic magnitude.

offer price (estimated underpricing is 0.46%). Moreover, the average price on day +1 is about 0.75% below the average secondary market price on day -1, which indicates a permanent price drop.[21] Similarly, for an average high yield issues, the offer price is set about 1.97% below the average secondary market price on day t-1, and is 1.20% below the post-offer secondary market price on day t-1. This is to be contrasted with the equity study by Corwin (2003), who finds that secondary market prices recover completely after seasoned equity offerings.

There are caveats associated with finding of the permanent price drop after the offer. Though we cannot rule out a permanent price pressure, it is somewhat surprising since there are many bonds with the same rating and maturity, which one would expect to be close substitutes. It is possible that the permanent price decline is due to the information brought by the new bond issue - especially the change in leverage. However, in a regression of the change from the pre-offer price to the post-offer price on the leverage change the adjusted r-square is only 4%.

[Insert Figure 2]

4.2.3 Full Set Regression

Results from model (1) to (5) of Table 4 suggest that bond underpricing is positively related to proxies for price uncertainty, aftermarket liquidity, and price pressure and to a lesser degree to proxies for information asymmetry. Next, I present a regression with the full set of explanatory variables in Model (6). This specification has fairly good explanatory power. The adjusted R-square increases from 5.5% in the

[21] In efficient markets, traders should anticipate any price pressure effect so secondary market prices should start declining prior to the offer date if the issue is announced earlier. There is no evidence of this in Figure 2 likely because there is little pre-offering news since ABOs are additions to a pre-existing indenture and registration.

baseline regression to 18.6%. The Model (6) result still strongly supports price uncertainty hypothesis in that related explanatory variables remain significantly positive. Relative offer size still significantly increases underpricing, suggesting price pressure matters for bond underpricing. Note that the coefficient on the bid-ask spread becomes insignificant in the full set regression, suggesting that aftermarket illiquidity measures lose explanatory power after accounting for other factors. Overall, the results show strong support for uncertainty and price pressure and to a less extent, for information asymmetry. The regression results fail to find a reliable relation between underpricing and aftermarket illiquidity.

5. Agency Conflict Hypothesis

The hypotheses tested above view underpricing as a mechanism to solve or mitigate problems associated with underwriter uncertainty, asymmetric information, aftermarket illiquidity, and/or price pressure. The underlying assumption of these theories is that underwriters behave in the best interests of their clients−the issuing firms. However, if underwriters have informational advantage over issuers such that underwriters are in a moral hazard situation, then their interests may not always be aligned with the issuers. The agency conflict hypothesis posits that underpricing saves underwriters' selling efforts and also possibly allows them to allocate hot offerings to favored customers in return for quid pro quos. Whether agency problem is relevant to bond underpricing is of special interest due to (as discussed above) the tremendous demand for corporate bond issues especially since the financial crisis has raised SEC concern. Of particular interest to the SEC is whether underwriters give preferential treatment to certain customers in bond offerings at the expense of the issuers or smaller investors.

5. 1 Post-Offering Trading Activities

An ideal test of whether underwriters underprice to tip favored investors would rely on detailed bond allocation information, which, however, is not publicly available. Since observed aftermarket trading activities may reveal the (unobserved) allocation and price setting conditions during the offerings (Krigman, Shaw, and Womack (1999)), I conduct a trading volume analysis, and in particular, look for possible flipping activities by certain investors.

[Insert Table 5]

Table 5 reports average secondary market trading activities for the first day, the second day, and the first week of trading, with results for investment grade in Panel A and high yield bonds in Panel B. On the first day of trading, the number of trades and trading volumes are aggregated for each bond issue for institutional-sized versus retail-sized trades and by non-dealer customer sells (designated "S" on TRACE) and buys ("B" on TRACE), separately. I then calculate the turnover rate for a bond on day t as:

$$\text{Turnover}_{i,t} = \frac{Total\ dollar\ trading\ volume_{i,t}}{Dollar\ Amount\ offerings\ of\ the\ Issue_{i}} \tag{6}$$

We can see that on the first day, there is a disproportionally higher incidence of institutional size (trades of 100 or more bonds) sell trades than buys. For investment grade SBOs, there are on average 13.7 institutional sells, amounting to $34.24 million dollar volume versus 7.21 institutional buys, amounting to $30.52 million. The sale turnover rate averages 5.88%, which is higher than the average buy turnover rate of

4.70%. In contrast, retail size (trades of 100 or less bonds) buys outweigh sells. Specifically, for investment grade SBOs, there are on average 4.8 retail size buys but only 1.5 sells on the first day. On the second day, the disparity in trade numbers between institutional sells and buys is reduced but retail size buys still exceed sells. For an average investment grade SBO, there are 16.1 (12.4) institutional sized sells (buys) versus 1.4 (10.3) retail sized sells (buys). Over the week, institutional size buys and sells become roughly even but retail sized buys continue to be active.

These findings suggest possible "flipping" activities by institutional investors. It also indicates that smaller investors whose demand may be unmet during the offering are purchasing in the aftermarket at higher prices. However, it should be noted that this does not necessarily indicate that underwriters intentionally underprice to steer bonds to favored clients. If underpricing occurs for any reason so that there is excess demand for the underpriced bonds, then those obtaining the bonds will be able to resell the bonds in the aftermarket at a profit. My bond market evidence is consistent with Aggarwal's (2003) study for equities. Aggarwal uses a unique IPO data from May 1997 to June 1998, the only period when SEC data on allocation from the lead underwriter are available. She finds evidence that hot IPOs are commonly flipped, especially by institutions. Specifically, shares are sold in the immediate aftermarket by investors who receive an initial allocation at the offer price.

5. 2 Self-marketed Vs Non-self-marketed: Financial Sample

In the underwriting process, underwriters negotiate both the underwriting spread and the offer price with the issuer. Issuers can readily compare the underwriting spread to that of other recent issues but likely find it difficult to judge if the offer price is appropriate as they have less information than the underwriters on investors' demand for the issues. Thus this informational advantage may lead underwriters to minimize their selling costs and risks by underpricing the issue while charging a "standard" spread.

To test the agency hypothesis of underpricing more directly, I study cases in which a bank serves as one of the lead managers while marketing its own bond issues. In these situations, the agency problem is largely mitigated. Moreover, if banks intentionally underprice in order to minimize their underwriting efforts or steer bonds to favored clients for quid pro quos, the costs to them for leaving money on the table are much higher when they are underwriting their own bonds.

Specifically, I examine bond offerings by financial firms during February 2005 to August 2012, because the self-marketed offerings are all issued by banks. I study the financial sample separately from the non-financial sample to facilitate comparison of my main results with previous bond studies which usually exclude financial firms from analysis. Mine is the first to explore bond offerings by financial firms in a context of examining offering expenses. There are 1186 straight bond issues of financial firms, of which 1155 are investment grade issues. 536 are self-marketed issues all of which are investment grade. Hence the analysis is restricted to investment grade issues.

Table 6 reports summary statistics for financial issues, with statistics for all financial offerings in Panel A and Panels B and C restricted to investment grade offerings. Financial firms have considerably larger mean outstanding debt than industrial firms though the median is similar. The non-self-marketed financial offer amount is comparable to non-financial offerings reported in Table 1 but the self-marketed offer amount is slightly larger. Moreover, self-marketed offers take fewer days from pricing to distribution and have fewer lead managers. Given the small number of self-marketed IBOs and ABOs, subsequent analysis is restricted to SBOs.

[Insert Table 6]

Table 7 reports general underpricing evidence for the 1155 investment grade issues by financial firms for self- and non-self-marketed issues respectively. The mean discount (comparing offer price to the first day average trade prices) is only 0.08% for self-marketed SBOs versus 0.35% for non-self-marketed SBOs and the difference is significant at the 1% level. Based on second day secondary market prices, the mean discount is 0.23% for self-marketed SBOs and 0.43% for non-self-marketed SBOs and the difference is still statistically significant. The univariate analyses suggest that SBO underpricing is consistently lower when banks underwrite their own bond issues.

[Insert Table 7]

To examine whether the underpricing disparity between self- and non- self-marketed SBOs exists after controlling for issue characteristics and other underpricing determinants explored above, I repeat the Model (6) regression from Table 4 for the sample of investment grade SBOs by financial firms in Table 8 and include a dummy variable equal to one for self-marketed and zero for non-self-marketed issues. In addition, the regression includes a year 2009 dummy designating offerings with issue dates between October 2008 and October 2009, when bank debts were possibly covered by FDIC’s debt guarantee program. Results from Table 8 show that most of the findings for non-financial issues apply to financial issues as well. Specifically, underpricing is higher for issues with lower ratings and/longer maturities and for issues with greater post-offer bond price volatility. Likewise, underpricing increases with interest rate risk and/or stock market uncertainty. Hence the evidence for the underwriter uncertainty and/or asymmetric information hypotheses also holds for the financial sample. However, the relative offer amount is no longer significant, suggesting that the price pressure hypothesis does not hold for financial offerings.

Notably, the coefficient for the "self-marketed" dummy variable is -0.137 and is statistically significant at the 5% level. The estimated difference between non-self-marketed and self-marketed offers is therefore 0.137%, which is lower than the 0.26% difference between the mean adjusted discounts in the univariate result from Table 7. This suggests that differences in other (observable) characteristics explain part, but not all of the underpricing difference between self-marketed and non- self-marketed SBO issues.

[Insert Table 8]

It is possible that (unobservable) factors that influence the decision to self-market are also correlated with those impact bond underpricing. It is also possible that the above explored factors impact underpricing differently for self- and non- self-marketed issues. To control for possible self-selection in the self-marketing decision and allow other (observable) underpricing determinants to have differential effects on self-marketed and non-self-marketed offerings, I therefore adopt a switching regression following similar procedures to Fernando, Gatchev, and Spindt (2005) and Fang (2005). Like Heckman's (1979) two-stage procedure models, a switching regression first performs a decision regression, where the inverse Mills ratio (endogeneity control) is generated. It then incorporates this decision into the second stage regression. The complete model is as follows:

First Stage: $$C = E \equiv Z_i\gamma + \eta_i > 0\ , \tag{7}$$

$$C = NE \equiv Z_i\gamma + \eta_i \leq 0, \tag{8}$$

Second Stage: $$Y_{E,i} = X_{E,i}\beta_E + \epsilon_{E,i}, \tag{9}$$

$$Y_{NE,i} = X_{NE,i}\beta_{NE} + \epsilon_{NE,i} \tag{10}$$

where the dependent variable C ϵ {E, NE} in the first stage Probit model is the decision to self-market (E) or non-self-market (NE). Z_i denotes factors influencing a financial firm's decision to self-market. The Probit models (7) and (8) generate estimates of γ and the inverse Mills ratio $\lambda_C(.)$, the conditional expectation of η_i given C. Y_i is observed only when a firm picks either E or NE (but not both). So equations (9) and (10) require the appropriate conditioning and can be compactly rewritten in regression form as:

$$Y_{C,i} = X_{C,i}\beta_C + \pi_C\lambda_C(Z_i\gamma), \tag{11}$$

where the estimates of γ and the inverse Mills ratio $\lambda_C(.)$ from stage one regression are fed into to derive parameters $\{\beta_E, \beta_{NE}, \pi_E, \pi_{NE}\}$. As Li and Prabhala (2007) point out, a key advantage of the switching regression is that we obtain more useful estimates of (unobserved) counterfactual outcomes.[22] Specifically, if a financial firm *i* chooses to self-market, we observe underpricing $Y_{E,i}$. However, we can ask what the outcome might have been had firm *i* chosen not to self-market, the unobserved counterfactual, and what the gain is from firm *i*'s having chosen to self-market its own issue. The net

[22] It is even superior than a propensity score match (PSM) since the PSM can only control for explicit factors but the switching model can control for unobservable private information (captured by the inverse Mills ratio).

benefit from choosing self-market is the actual underpricing of self-marketed issues less the counterfactual had it chosen not to self-market, estimated as follows:

$$Y_{E,i} - Y_{NE,i} = Y_{E,i} - (X_i\beta_{NE} + \pi_{NE}\lambda_{NE}(Z_i\gamma)) \quad , \tag{12}$$

where $Y_{NE,i}$ is the "counterfactual" underpricing estimated, had the firm chosen not to self-market and is obtained by using the coefficients from the non-self-marketed equation (10). Likewise, the expected difference for non-self-marketed issues is the actual underpricing of non-self-marketed issues less the counterfactual had it chosen to self-market, i.e., $Y_{NE,i} - Y_{E,i}$.

Table 9 Panel A reports the Probit regression for decision to self-market, where I include an explanatory variable indicating "possibility to self-underwrite" its own bonds, in addition to variables from Tables 4 and 8. A bond offering is possible to be self-marketed if the issuer is an investment bank or a commercial bank that has investment banking as one of its major businesses. Based on my sample, banks that provide bond underwriting services do not always choose to underwrite their own bond offerings. Further, a bank may choose to underwrite its own issues some of the time but not all of the time. The first stage results show that banks are more likely to underwrite their own bond issues if their bonds are rated A or above, and when they issue long term bonds. As expected, the possibility of self-underwriting is a significant determinant.

[Insert Table 9]

Table 9 Panel B reports the second stage regression for underpricing of self- and non-self-marketed offerings respectively. Most of the major underpricing determinants have roughly similar effects on underpricing for both self- and non- self-marketed issues. More importantly, the inverse Mills ratio derived from the first stage is included along with the other explanatory variables. The coefficients of the inverse Mills ratio are insignificant at conventional significance levels indicating that a selection bias does not seem to be relevant in this context.

Table 9 Panel C compares the actual and counterfactual underpricing for self- and non-self-marketed SBOs where the sample is restricted to issues possible to be self-marketed. The figure labeled "Counterfactual" for self-marketed issues is the estimated underpricing had the firm chosen not to self-market, and the counterfactual underpricing of 0.774% is calculated by applying equation (12) and using the coefficients estimated from the non-self-marketed regression in Panel B, the inverse mills ratio estimated in Panel A, and the issue characteristics of the self-marketed sample. The estimated mean underpricing had the self-marketed issues been not been self-marketed is 0.774% which is 0.533% greater than the mean actual underpricing for self-marketed offerings of 0.241%. Likewise, the "Counterfactual" of -0.322% for non-self-marketed issues represents the estimated underpricing had the firm chosen to self-market.[23] The estimated mean underpricing had they been self-marketed is negative (-0.322%), which is 0.800% lower than the mean actual underpricing for non-self-marketed offerings of 0.478%. In addition, the difference between the two counterfactual means is 1.096%, which is significant at the 1% level. These results reveal that after accounting for (unobservable) self-selection, the estimated difference in underpricing between self- and non-self-marketed issues is even greater than those estimated in Tables 7 and 8.

In summary, there is considerably less underpricing when underwriters are underwriting their own bonds among financial seasoned bond offerings. In other words,

---

[23] The number of observations is slightly lower than Table 8 because I restricted sample to publicly traded firms issues to facilitate the analyst coverage variable in the two-stage regression.

they are clearly "leave less money on the table" when marketing their own bond offerings, after accounting for observable bond characteristics, market conditions and possible self-selection.

6. Conclusion

This paper documents significant underpricing of corporate bond offerings measured as the initial return from the offer price to the post-offer secondary market price. In contrast to prior studies that find no bond underpricing or underpricing only among high yield issues and/or initial offerings, I find significant underpricing among both investment grade and seasoned bond issues and for both initial and seasoned offerings. Specifically, investment grade seasoned (initial) bond underpricing averages 58 (59) basis points, which transfers to over $4 million left on the table per deal, given that an average seasoned bond issue raises $701 million of proceeds based on my sample. Underpricing is even higher on speculative grade issues. Given that an average corporate bond matures in ten years and assuming that firms do not change leverage or debt structure substantially over time, periodic refinancing represents substantial cumulative issuing costs to bond issuers.

I further show that the significant underpricing does not merely reflect the bid-ask spread in that investors who obtain the bonds at the offer price are able to immediately resell in the secondary market at a profit after accounting for bid-ask spreads. Further, I find evidence suggesting possible "flipping" activities in that secondary market trading during the first week tends to be dominated by institutional size sales and retail size purchases. These findings have policy implications since it has been reported that the SEC is currently probing whether underwriters unfairly allocate new corporate debt issues to reward certain clients at the costs of the issuers or smaller investors.

In exploring the potential reasons for bond underpricing, I find support for the valuation uncertainty, asymmetric information, and price pressure hypotheses. Further, I find evidence that underpricing is significantly lower when underwriters underwrite their own bonds, suggesting agency conflicts between issuers and underwriters at least play a part. U.S. corporate bonds are predominantly issued via firm-commitment offerings in which the underwriters play an important role in setting the offer price. Since underwriters have more information about investor demand for the issue than issuers and do not bear the cost of underpricing except when underwriting their own bonds, it is possible they deliberately underprice in order to lower their risks and selling costs – or possibly to reward favored investors.

There is growing literature investigating the costs and benefits of the alternative security offerings mechanisms such as auctions. Existing evidence suggests auctions incorporate the information of all market participants into the setting of the offer price. Lowry, Officer, and Schwert (2010) suggest that for large seasoned *equity* issuers, the complexity of the pricing problem is not as severe and the value of auxiliary services provided by underwriters such as aftermarket price support and analyst coverage should be less important. To the extent that most bond issuers are large, well-known seasoned issuers (WKSIs), one wonders if they might find an auction to be the better alternative. Why corporate bond offerings stick to the traditional firm commitment offerings is of research interest.

Chapter 2: Essay Two

Corporate Bond Event Study Methods

Abstract

The procedures used in corporate bond event studies to date fail to control for heteroskedasticity due to differences in return volatility by term-to-maturity, rating, and other factors resulting in low test power. Bond return standardization yields considerably more powerful tests. Also, due to infrequent trading, use of bond transaction price observations over several days before and after an event, while giving more weight to returns calculated from transactions closer to the event, yields considerably more powerful tests than returns based solely on transactions the day before and the day after the event. Exploring the test bias caused by overlapping event dates, we find that, adjusted for rating and maturity, the correlation among standardized abnormal bond returns is small but that even fairly small correlations can result in biased test statistics. A bond market modification of the Kolari and Pynnönen (2010) procedure corrects this bias.

1. Introduction

This paper explores issues in the construction of corporate bond event studies. How bond prices react to events or new information is relevant to numerous issues in finance. For instance, is a dividend increase good news for bondholders because it signals that management expects high earnings in the future or bad news because it lowers the cash available to service the debt? There are multiple instances in which competing theories explaining the stock price reaction to an event have different implications for bond prices. For instance, do existing equity prices react negatively to a new seasoned stock offering announcement because investors reason that it signals that management thinks the firm's assets are overvalued (which would likely be bad news for bond holders as well) or because leverage is reduced thus benefitting bondholders at the expense of stockholders?

While equity market event studies are legion, the bond market event study set is much smaller. As discussed in Bessembinder, Kahle, Maxwell, and Xu (2009), historically this was probably partially due to the lack of quality data. Until the recent decade, bond market researchers were limited to either monthly quotes from Moody's, Standard and Poor's, or Lehman Brothers or daily closing prices from the NYSE Bond Exchange, which is a small, odd-lot market, accounting for only a sliver of bond trading volume. However, in July 2002 the National Association of Securities Dealers (NASD) began reporting over-the-counter trades of some bonds through its Trade Reporting And Compliance Engine (TRACE). In February 2005, coverage was extended to virtually all corporate bond trades. In addition, Mergent FISD and other sources now provide insurance company trades from the National Association of Insurance Commissioners

(NAIC), Datastream and Reuters provide daily dealer price estimates, and several providers sell credit default swap data. The availability of these new corporate fixed income databases raises the prospect of conducting the same sort of event studies for corporate debt that have become ubiquitous in equity markets.[24]

In the seminal paper on bond event study methods, Bessembinder, Kahle, Maxwell, and Xu (2009) (hereafter BKMX) show that: (1) among the bond databases they examine, the TRACE data yield the most powerful event test statistics, (2) t-test statistics are mis-specified for monthly data, (3) non-parametric tests are better specified and more powerful than the t-test – though likely to be less powerful when bond returns are skewed. For TRACE based event studies, they recommend: (1) calculating bond returns from average daily trade prices where each transaction price is weighted by trade size, (2) excluding trades of less than \$100,000 par value when calculating average daily prices, (3) calculating abnormal bond returns using value-weighted rating/maturity benchmarks, and (4) combining returns on a firm's bonds into a single firm return. We build on their study showing that whereas the test procedures used in bond event studies to date (including the BKMX procedure) have relatively low statistical power to detect bond price reactions to events or new information, it is possible to construct much more powerful tests. We also explore the test bias caused by overlapping event dates and adapt the Kolari and Pynnönen (2010) t-test correction to the bond market.

[24] Bessembinder et al. (2009) discuss major bond event studies to that date. More recent bond event studies, with databases in parentheses, include Chava et al. (2012) (TRACE and credit default swaps (CDS)), Clayton (2011) (TRACE, Lehman Brothers, and NAIC), Gao et al. (2011) (TRACE), Klein and Zur (2011) (FISD and TRACE), Wei and Zhou (2012) (TRACE), DeFond and Zhang (2008, 2014) (TRACE), Michayluk and Zhao (2010) (Datastream), Plunus et al. (2012) (Datastream), May (2010) (TRACE), Easton, Monahan, and Vasvari (2009) (FISD), Wei and Yermack (2011)(Reuters and CDS), Billingsley and Kovacs (2011) (TRACE), Ellul et al. (2011) (NAIC), and Deng et al. (2013) (TRACE).

In designing a bond market event study, a researcher faces hurdles which are either not present in the equity market or are less serious there. To begin, bond returns are characterized by considerable cross-sectional heteroskedasticity. Specifically, prices of long-term bonds are much more volatile than prices of short-term notes and prices of low-rated bonds are more volatile than prices of high-rated bonds. Also, volatility varies over time. Since the t-test assumes bond returns are identically distributed, failure to control for this heteroskedasticity (as is the case in all extant studies to our knowledge) results in mis-specified t-tests. We find that the low t-test power documented by BKMX(2009) is primarily due to this violation of the homoskedasticity assumption. More importantly, we find that reducing the heteroskedasticity by standardizing each bond's event window return by its return volatility leads to a substantial increase in t-test power. While the improvement in the power of the t-test is most dramatic, standardization also leads to a substantial increase in the power of the signed-rank test. As an example of how much standardization matters, we find that for an event which shifts bond returns by 15 basis points, the likelihood of Type II error for a t-test based on a sample of 300 possible firm-event dates falls from 78.4% for tests based on unstandardized abnormal returns over the (t-1, t+1) window to 31.5% for tests based on standardized returns.[25] Aside from running separate tests for investment grade and speculative grade bonds, to our knowledge, no bond event studies to date have corrected for the heteroskedasticity in bond returns. Another serious problem is that bonds trade much less frequently than equities. On an average day in our January 2005-December 2011 TRACE sample, 54.6% of industrial bonds do not trade at all. Since a return

[25] These are averages for events that shift returns up by 15 basis points and down by 15 basis points as reported in Table 2 and Panel B of Table 4.

calculation requires price observations on two days, the problem is magnified. Supposing an event occurs on random day t, 2-day returns from day t-1 to day t+1 can only be calculated for 31.3% of bond-days even after eliminating rarely traded bonds. Since some firms have several bonds outstanding, the percentage of firm-days for which firm-bond returns for the (t-1, t+1) event window are calculable is somewhat higher but still only 38.6%. Since most days have no return observations, this makes the panel regression procedures sometimes used in equity event studies very difficult for bonds. Moreover, when bonds do trade, the number of trades is small; the median number of trades in a bond given at least one trade is only three per day. Since bid-ask bounce is fairly large for bonds, this results in considerable return noise raising the question of whether it is advantageous to enlarge the event window to obtain more trade observations -- for instance, to utilize transaction prices on days t-2, t-3, etc., in addition to t-1, and on days t+2, t+3, etc., as well as day t+1, in calculating event window returns. Broadening the event window increases the number of trade observations but also increases the likelihood that forces other than the event of interest will cause bond prices to change so the net impact on test power is not clear a priori. We find that, despite the greater non-event noise over longer windows, using transaction prices on several days before and after an event to calculate event window returns (while giving greater weight to trades closer to the event), substantially increases the power of the tests. It also brings more small firms into the sample. Of course, the window width choice also depends on other factors, such as how likely it is that other important contaminating information is released in the window. As an example of the increase in test power which results from expanding the event window, we find that using transaction price observations over three days before and three days after the event to calculate event window returns reduces the t-test's likelihood of Type II error for a 15 basis point event in a sample of 300 firms to only 11.8% compared with 31.5% for standardized returns (and 78.4% for unstandardized returns) based on trades on single days before and after the event. For the signed-rank test, the likelihood of Type II error falls from 44.1% for tests based on unstandardized (t- 1,t+1) abnormal bond returns to 20.0% for tests based on standardized (t-1,t+1) returns to only 5.6% when the event window is expanded.[26]

We also explore several sampling and calculation issues – to wit: which trades to include when calculating daily bond prices and how to weight different trades in calculating average bond prices and returns. Restricting the sample to trades of 100 or more bonds, as BKMX recommend, reduces the noise in trade prices but sharply reduces the number of observations. Considering both noise and the sample size effects, we find that test power is roughly the same whether trades of fewer than 100 bonds are included or not. On the other hand, we find that test power is reduced if the sample is restricted to inter-dealer trades. Since small trades have more noise than large trades, a related issue is how to weight various size trades in calculating average prices. We find that test powers differ little depending on whether average bond/day prices are calculated by weighting individual transaction prices: (1) by trade size, (2) by the square root of trade size, or (3) equally - with the square root weighting giving slightly more powerful tests. Comparing the power of different test statistics, we find that the signed-rank test is generally more powerful than the t-test or sign test. Finally we explore the

[26] Based on the average powers for negative and positive events from Tables 2, 4 and 9 using figures for ABSR{t-3,t+3} in Table 9 as explained below.

possible bias in test statistics caused by cross-sectional correlation among bond returns of different firms when their event dates overlap. Our results indicate that cross sectional correlations among abnormal standardized bond returns are slight when abnormal returns are calculated relative to bonds of the same rating and maturity suggesting that Type I errors are likely less in appropriately constructed bond event studies with overlapping event dates than in equity event studies. Nonetheless, even minor cross-correlations can lead to biased t, signed-rand, and sign tests. Importantly, we find that a bond market adaption of the Kolari-Pynnönen (2010) correction yields unbiased t-statistics. The remainder of the paper is organized as follows. In the next section, we describe our data and return calculations. In section 3, we explore the size, i.e. the probability of Type I error, and power, i.e., the probability of not committing Type II error, of various test statistics for returns calculated over a (t-1, t+1) event window following existing bond market event study procedures. In section 4, we develop our heteroskedasticity correction procedure and show how it improves the power of the test statistics. Issues of trade sampling, in particular whether it is better to calculate returns from all trades, only institutional size trades or only inter-dealer trades, are considered in section 5. In section 6, we explore how individual trade prices are best weighted in calculating daily bond prices. In section 7, we consider the consequences for the power of the tests of broadening the event window. In section 8, we explore the possible bias created by cross-correlation in bond returns when event dates overlap and extend the Kolari and Pynnönen (2010) t-test correction to bond markets. Section 9 concludes. Our analysis is conducted using bond transaction prices from non-enhanced TRACE. Our results concerning the need to correct for heteroskedasticity by standardizing returns in section 4, and the possible bias when event dates overlap in section 8 should apply equally well to tests based on dealer price estimate databases, such as Datastream, and on credit default swap spread data. The results in sections 5, 6, and 7 are specific to transaction data sources, such as TRACE and NAIC.

2. Data and measures

From TRACE we obtain bond trade data from January 1, 2005 to December 31, 2011. Bond attributes, such as coupon, maturity, and ratings, are obtained from Mergent's FISD database. Statistics on issuer total assets are obtained from COMPUSTAT and internet searches. Like BKMX (2009), we restrict our sample to industrial, non-convertible, non-putable, and non-zero coupon bonds. In addition, we require that the bonds be denominated in US dollars, have $1000 par value, make semi-annual coupon payments, mature in 50 years or less, be rated by Moody's and/or S&P, and neither be in default nor have a tender offer outstanding. Since price changes on short maturity debt are small unless default is imminent, we only include bonds and notes with at least one year to maturity. 7296 bonds issued by 2206 firms meet these requirements.

A number of bonds in this sample are very rarely traded. To obtain a workable sample, we further require that a bond trades at least 100 times over the 2005-2011 period and that 2-day returns are calculable for at least 10 days over this period. Bonds are dropped from the sample when they default, are called or retired, or maturity drops below one year. We clean the TRACE data following the suggestions of Dick-Nielsen (2009) and BKMX (2009) dropping canceled, corrected, reversed, and commission trade observations.4 We also eliminate: (1) trades with settlement dates more than a week in the future, (2) "when issued" or "special price" trades, (3) trades with special sale conditions attached, (4) irregular trades as indicated by TRACE's "as of" flag, or (5) trades at less than $25 per $100 par value (which we regard as effectively in default). Finally, as a check, we compare the yield-to-maturity (YTM) reported on TRACE to the YTM calculated from the trade price reported on TRACE and coupon and maturity date from FISD. While generally the two YTM's are virtually identical, in 1.77% of trades they differ by ten or more basis points. A difference indicates that: (1) either the TRACE price or YTM is incorrect, (2) a CUSIP mismatch between TRACE and FISD, (3) the FISD coupon or maturity date is incorrect (in a few cases TRACE reports trades after the FISD maturity date), or (4) there was a commission (which is included in the TRACE YTM but not the price) on the trade despite the fact that the TRACE data indicates no commission. Eliminating these trades leaves a sample of 15,247,340 trades, 5507 bonds, and 1495 firms.

Bond returns from day t-1 to day t+1 are calculated as:

$$R(t-1, t+1)_n = \frac{P_{n,t+1} - P_{n,t-1} + \Delta AI_n}{P_{n,t-1} + \Delta AI_n}, \tag{13}$$

where $P_{n,t}$ is the trade-size-weighted average "clean" price of bond n on day t, $AI_{n,t}$ is accrued interest on bond n on day t, and ΔAI_n is the change in accrued interest from day t-1 to day t+1.[27] While BKMX measure 1-day returns from t-1 to t, we have chosen to

[27] Note that this symbolism differs from that commonly used in equity market event studies. Here R(t-1, t+1) represents the return from the average price on day t-1 to the average price on day t+1 – an average time of two days. In equity market event studies, R(t-1,t+1), or CAR(-1,+1), represents a 3- day return from the closing price on day t-2 to the closing price on day t+1. Since we are calculating returns from average, rather than closing prices, we think our symbolism is more suitable in our context. While

use returns calculated from the average price on day t-1 to the average price on day t+1 since announcements may occur before, during, or after trading on day t and since all the studies we have seen to date use at least a two-day window. Use of 2-day returns increases slightly the non-event noise vis-a-vis 1-day returns resulting in slightly lower test powers but qualitatively the results are the same for both 2-day and 1-day returns. In section 7, we consider wider event windows. Following the procedure in BKMX (2009), abnormal bond returns are calculated as:

$$ABR(t-1,t+1)_n = R(t-1,t+1)_n - BM(t-1,t+1)_n, \qquad (14)$$

where $BM(t-1,t+1)_n$ is the mean return on a benchmark rating/maturity matched portfolio corresponding to bond n. We utilize 24 benchmark portfolios: six rating classes (Aaa and Aa, A, Baa, Ba, B, and below B) and four maturity groupings (1 to 3 years, 3+ to 5 years, 5+ to 10 years, and over 10 years).[28] Moody's rating is used to assign bonds to portfolios if available. If Standard & Poor's (S&P) rates the bond and Moody's does not, S&P's rating is used. In order to calculate the benchmark return for each rating/maturity group, we require that at least five bonds in that rating/maturity group trade on days t-1 and t+1.

An issue in bond event studies is how to calculate firm returns when a firm has more than one bond outstanding. A few studies (Jayaraman and Shastri (1988); Marais, Schipper, and Smith (1989); Hand, Holthausen, and Leftwich (1992); Warga and Welch

---

TRACE and Datastream report what is known as the "clean" price, a bond purchaser pays the "dirty" price which is the clean price plus accrued interest since the last coupon payment. Both we and BKMX(2009) also calculate returns using clean prices ignoring accrued interest and find that it makes little difference in the size and power tests.

[28] These differ slightly from BKMX's benchmarks in that they do not include bonds rated below B and separate Aaa and Aa rated bonds. Their three maturity classifications are 0 to 5 years, 5+ to 10 years, and over 10.

(1993); and Cook and Easterwood (1994)) treat each bond as a separate observation. As BKMX (2009) observe, this biases the sample toward larger firms. Moreover, returns for bonds of the same firm will be correlated leading to biased test statistics. Hence, BKMX combine a firm's various bond returns into a single firm-bond return weighing each bond return by its volume of bonds outstanding relative to the firm total. We follow their example.[29] Descriptive statistics for bond and firm returns are reported in Panel A of Table 10 and descriptive statistics for bonds in the bond return sample are reported in Panels B and C. Note that this is for the bond return sample so bonds with many observed returns receive a higher weight than rarely traded bonds.

[Insert Table 10]

3. The size and power of existing bond event study test statistics

To test the size and power of various test procedures and statistics, we employ Monte Carlo procedures as in BKMX (2009), Brown and Warner (1980, 1985), Barber and Lyon (1997), Lyon, Barber, and Tsai (1999), Boehmer, Musumeci, and Poulsen (1991), and Kolari and Pynnönen (2010). To test the size (or Type 1 error probability) and bias of the tests, we choose firms and days at random and calculate how often the tests find evidence of an event when none in fact occurred. Specifically, we choose 300 firm/days at random and test whether the t-test, sign test, and signed-rank test find false evidence of an event. Since some of the 300 randomly chosen event dates do not have trades on both days t-1 and t+1, the number of calculable returns is less averaging about

[29] In an earlier version of this paper available on request, we consider other possible weightings including weights based on the size and number of trades and a simple average. We find it makes very little difference in terms of the bias and power of the tests.

120.[30] Repeating this procedure for 10,000 random samples, we record the percentage of the 10,000 samples in which the tests incorrectly find significant evidence of an event.

[Insert Table 11]

Test size results for a two-tailed test at a 5% significance level are reported in Panel A of Table 11. A well-specified test is one in which the test falsely finds evidence of a negative event approximately 2.5% or less of the time and falsely finds evidence of a positive event approximately 2.5% or less of the time when no event occurred. As shown in Panel A, although the sign and signed rank tests display a slight tendency to find false evidence of negative events (due to the small negative median reported in Table 10), all three tests are reasonably well-behaved. Next we explore the power of various bond event study test statistics measured as the likelihood of detecting an event when one actually occurs, i.e., one minus the probability of Type II error. For this, we induce an artificial event in which returns from t-1 to t+1 are shifted upward by 15 basis points for a positive event or downward by 15 basis points for a negative event. Using two tailed tests with a 5% significance level, we record whether each test correctly rejects the no-event null. This is repeated for 10,000 random samples. Results are reported in Panel B of Table 2. Like BKMX (2009), we find that the sign and signed-rank tests are considerably more powerful than the t-test. The t-test correctly

[30] Our procedure differs from BKMX's in that they choose 200 firm days at random from the sub-sample of firm-days with calculable returns, i.e. trades on both days t-1 and t. In later sections, we consider event study methodologies which impact the number of days with observations, such as restricting the sample to large trades or interdealer trades and broadening the event window. In order to consider the impact of these alternatives on test power, we choose firm event days from the sample of all possible firm-days regardless of whether or not trades occurred on days t-1 and t+1. Hence, the number of calculable return observations on which the tests are based is less than 300, initially averaging 120. When we broaden the event window in section 7, the number of events with calculable returns rises.

rejects the no event null less than 23% of the time for both positive and negative shocks. In contrast, the signed rank and sign tests correctly reject the null more than twice as often. The sign test appears slightly more powerful than the signed-rank test.

4. Abnormal return standardization

A likely candidate for the low t-test power observed in Table 11 is a violation of the homoskedasticity assumption. While the t-test assumes that all abnormal returns have the same variance, that is clearly not the case. As BKMX (2009) report, the abnormal return variance is higher for speculative grade than for investment grade bonds. Moreover, prices are more variable on long term bonds than short-term notes. In Table 12, we report bond ABR standard deviations for our 24 rating/maturity classes.[31] Clearly, return volatility rises as the time-to-maturity lengthens and the rating falls. The standard deviation for bonds rated below B maturing in 10+ years is about seven times that for Aaa-Aa rated bonds maturing in 1 to 3 years. In addition, our data indicate that returns on illiquid bonds are more volatile than on heavily traded bonds and that volatility was higher in the financial crisis period, 2008 and early 2009.

[Insert Table 12]

A possible solution to this heteroskedasticity is to standardize each bond's return by an estimated standard deviation for that bond returns and base the event study test statistics on standardized returns – a reasonably common procedure in equity event

[31] In Table 3, standard deviations for each rating/maturity are calculated over a combined sample for that rating/maturity bucket. We also calculated an alternative in which the standard deviation was calculated separately for each firm and then averaged. The average standard deviations are slightly higher but the results are basically the same.

studies. By reporting separate results for investment and speculative grade issues, several bond studies seem to acknowledge and partially ameliorate the problem. However, to our knowledge, to date no bond event studies have standardized returns – including the older studies based on monthly data.

Both standardized and unstandardized return measures are employed in equity event studies. Many equity event studies base their test on unstandardized abnormal returns (ARs), or cumulative abnormal returns (CARs) in which the t-statistic is calculated as T1=AAR/σ_{AAR} where the average abnormal return AAR=(1/N)$\sum_{i=1}^{N} AR_i$, AR_i is the abnormal return around an event for stock i, and σ_{AAR} is a measure of the standard error of the mean return AAR. σ_{AAR} may be either the cross-section standard deviation of the AR_i or an estimate based on a time series standard deviation for each firm i. The former estimate of σ_{AAR}, which we use for the tests in Table 2, has the advantage of allowing the event to impact volatility. An alternative, suggested by Jaffe (1974), Mandelker (1974) and Patell (1976) is to calculate standardized abnormal returns as $SAR_i = AR_i / \sigma_i$ where σ_i is an estimate of the standard deviation of AR_i based on the time series of returns over a non-event estimation period. The alternative t-statistic, T2, suggested by Jaffe (1974), Mandelker (1974) and Patell (1976) is then calculated as $(1/N)^{.5}\sum_{i=1}^{N} SAR_i$. While T2 assumes that the event does not induce a change in the variance, Boehmer et al. (1991) show that this is easily corrected by marrying the standardization technique of Patell (1976) with the cross-sectional standard deviation suggested by Charest (1978) and Penman (1982) and calculating the t statistic as:

$$T3 = \frac{1}{N}\sum_{i=1}^{N}\frac{SAR_i}{SD(SAR)}, \tag{15}$$

where $SD(SAR)$ is the cross-sectional standard deviation of the SAR_i . In this paper, we employ this T3 t-statistic. Comparing the power of tests based on standardized and unstandardized returns, Brown and Warner (1985) find (their Table 8) that tests based on standardized returns are more powerful. However, after presenting both test statistics, Campbell, Lo, and MacKinlay (1997) assert, "In most [stock market event] studies, the results are not likely to be sensitive to the choice of J_1 [tests based on CARs] versus J_2 [tests based on SCARs] because the variance of the CAR is of a similar magnitude across securities" (p162). Similarly, according to Kothari and Warner (2006), "While a test using standardized abnormal returns is in principle superior, under certain conditions, especially in short-horizon event studies, it typically makes little difference" (their footnote 5). While violations of the homoskedasticity assumption may be minor for equities, it is serious for bonds as Table 12 indicates. Whether return standardization makes much difference to the power of bond market test statistics is the issue to which we now turn.

4.1 Bond return standardization

To estimate the standard deviation of returns, $\sigma_{n,t}$, for each bond n and possible event date t, we calculate the standard deviation of 2-day returns using bond n's observed 2-day returns from t-55 to t-6 and from t+6 to t+55.[32] For this, we require at least six return observations over this time period which reduces the 2-day bond return sample from 1,672,685 to 1,621,093 observations. We utilize two different standardized

[32] Since 2-day returns overlap, they tend to be positively correlated. Thus, while consistent, the sample standard deviation is biased slightly downward in small samples. These problems become more serious later when we lengthen the return window.

return measures which we label standardized abnormal returns (SABR) and abnormal standardized returns (ABSR). SABR(t-1,t+1)$_n$ is calculated by dividing the abnormal return, ABR(t-1,t+1) $_n$, by the standard deviation of abnormal returns over the (t-55, t-6) and (t+6, t+55) periods where abnormal returns are calculated as described in section 2. For ABSR (t- 1,t+1)$_n$, we first calculate standardized raw returns, SRR(t-1,t+1)$_n$ by dividing each raw return by the standard deviation of raw returns over the (t-55, t-6) and (t+6, t+55) periods. For each rating/maturity group we calculate a standardized benchmark SBM (t-1, t+1)$_n$ as an average of the SRR(t-1,t+1)n for all bonds in the same rating/maturity group as bond n. Finally, we calculate the abnormal standardized return ABSR(t-1,t+1)$_n$ = SRR(t-1,t+1)$_n$ - SBM(t-1,t+1)$_n$. Since the ABSR procedure gives lower volatility bonds more weight in calculating benchmark returns than the SABR procedure, we prefer ABSR conceptually but, as seen below, both yield basically the same results. To reduce the impact of outliers, we winsorize both the standard deviations (within each rating/maturity category) and standardized return measures at the 1% level.

[Insert Table 13]

For both ABSR and SABR, we calculate standardized firm returns as a weighted average of the standardized bond returns on all the firm’s bonds where, as before, the weights are based on the amount of bonds outstanding. An average of a firm’s unstandardized ABRs tends to be dominated by the firm’s most volatile bonds. Since a firm’s ABSR and SABR are averages of standardized returns, the influence of less volatile notes and bonds on the firm average is effectively increased. Statistics for firm SABRs and ABSRs are reported in Panel A of Table 13. Standardization reduces the excess kurtosis in firm returns from 21.50 for ABRs in Panel A of Table 10 to 1.64 for SABR and 1.68 for ABSR in Panel A of Table 13. This indicates that most (but not all) of the excess kurtosis in ABRs in Table 1was due to the heteroskedasticity in unstandardized returns.

4.2 Size and power results

Size and power test results are presented in Panels B and C of Table 13 for standardized returns. These tests are structured the same as in Table 2, i.e., 10,000 random samples of 300 firm/days each with 15 basis point shocks for the power tests. For ease in comparing standardized and unstandardized results, the ABR results from Table 11 are repeated in Table 13. As reported in panel B, all three tests are reasonably well-behaved with type I error rates close to 2.5%.

As reported in Panel C, the improvement in the power of the t-test when returns are standardized is dramatic. The likelihood of detecting a 15 basis point (bp) negative event jumps from 22.67% for ABR to 71.89% for SABR and 68.90% for ABSR. Clearly the t-test's relatively low power which we and BKMX observe for unstandardized returns is at least partially due to the violation of the homoskedasticity assumption. Interestingly standardization also leads to a sizable increase in the power of the signed-rank test for which the likelihood of detecting a 15 bp negative event increases from 60.03% for unstandardized returns to 82.37% for SABR and 81.02% for ABSR. Note that this means that the likelihood of Type II error is cut roughly in half. Results for a positive event are similar.

While less than that for the t-test and signed-rank test, the increase in the power of the sign test is noteworthy. Since standardization does not change the sign of a return, the power of the sign test is unchanged by standardization at the bond level. However, the weightings of different bonds in calculating firm return averages differ with standardization giving relatively greater weight to less volatile bonds. Thus some firm returns switch signs leading to a modest improvement in the power of the sign test as well. While the sign test appeared to be the most powerful of the three tests when testing unstandardized returns, the signed-rank test is clearly more powerful for standardized returns. Powers differ little between standardized abnormal returns, SABR, and abnormal standardized returns, ABSR. For the t-test, SABR's power appears slightly higher while results are mixed for the sign and signed-rank tests. Since results are approximately the same and conceptually we prefer standardized benchmarks, henceforth we present results for ABSR only to save space. Both ABSR and SABR are standardized using standard deviations over the (t-55,t+55) period excluding the 10 days around the event. It is possible that the event changes the firm in some way so that post-event volatility is not representative of volatility at the time of the event. In this case, researchers may wish to estimate the return volatility for standardization using returns from the pre-event period only. In the final row of panels B and C, we present results (labeled ABSR-Pre) where event day returns are standardized using volatilities estimated from the (t-101, t-6) period only. As shown there, it makes little difference in terms of test power which period is used to estimate the standard deviation though for most tests test power is slightly lower for ABSR-Pre. In Panel D, we present test power results for stronger and weaker events, specifically 10 and 25 basis point events, for tests based on both unstandardized (ABR) and standardized (ABSR) returns. Even standardized, all three tests have difficulty finding evidence of the 10 basis point event. The signed-rank and sign tests generally find evidence of the stronger event even using unstandardized returns. Excepting the sign test for a 10 basis point positive event, standardization yields stronger tests.

In summary, while, to our knowledge, all bond event studies to date have utilized tests based on unstandardized returns, we find that bond return volatilities differ greatly so that standardizing each bond's event window returns by its estimated return standard deviation leads to much more powerful t-tests and signed-rank tests and slightly more powerful sign tests. While our tests are based on the TRACE data, results should be similar for tests based on quote databases, such as Datastream, or credit default swap databases since bond volatilities differ by time-to-maturity, rating, liquidity, etc. regardless of the database.

4.3 Proportional shocks

In our power tests, we have tested the effect of an across-the-board return shock. According to Table 12, 15 bp represents .361 standard deviations for an Aa rated bond maturing in 1 to 3 years but only .049 standard deviations for a bond rated below B maturing in 10 or more years. Consequently, the likelihood of Type II error is much less for the former as illustrated in Table 14, where we report powers by rating/maturity category for the signed-rank test based on ABSRs for across-the-board 15 bp return shocks averaging powers for positive and negative return shocks. Since conducted by term-to-maturity and rating, these tests are conducted at the bond level, rather than the firm level as in Table 13. Clearly the likelihood of Type II error varies greatly by both maturity and rating from 0.0% for Aa rated bonds maturing in less than 3 years to 86.46% (100%- 13.54%) for bonds rated below B maturing in more than 10 years. Results for the t-test and sign test show the same pattern.

[Insert Table 15]

This raises the issue whether it is realistic to model an event as impacting all bond prices equally. An event which causes a given shift in the yield-to-maturity has a much greater impact on prices of a bond maturing in 20 years than on prices of a note maturing in 2 years. As an alternative to across-the-board shocks, in the remainder of the paper we also present results for a proportional shock where the proportions are based on the standard deviations in Table 12. Specifically, $SHOCK_{r,m}$ = $.0015[SD_{r,m}/.015397]$ where $SD_{r,m}$ is the standard deviation of abnormal returns of bonds of rating r and maturity m as reported in Table 3 and 1.5397% is the standard deviation of all abnormal returns. So the shocks vary from a low of .0015(.00416/.015397) = 4.05 bps for 1-3 year Aa rated bonds to a high of .0015(.03036/.015397) = 29.58 bps for 10-30 year bonds rated below B. Under this proportional event shock format, type II errors are roughly the same across all rating/maturity categories.

5. Trade sampling

Next we turn attention to the issue of trade sampling. To this point we have included all trades in calculating bond returns. However, many trades reported on TRACE are quite small. In our sample, 69.4% are for less than 100 bonds and 53.5%

are for 25 bonds or less and returns based on these small trades are likely noisy. It is clear that there is more bid-ask bounce in smaller trades. For instance, Edwards, Harris, and Piwowar (2007) estimate the roundtrip spreads on trades of 20 bonds at 1.24% but only 0.48% for trades of 200 bonds. Ederington, Guan, and Yadav (2014) estimate a spread of 2.25% on trades of 10 bonds and 0.55% on 500 bond trades. Also, retail investors may be less informed so deviations from equilibrium prices may be larger on small trades. Consistent with more noise in smaller trades, in our sample, the standard deviation of 2-day firm ABRs is 1.10% when calculated using only trades of 100 or more bonds versus 1.55% using all trades.

Reasoning that prices on institutional size trades are more reliable, BKMX calculate test powers: (1) including all trades, and (2) restricting the sample to trades of 100 bonds or more. They find higher test power by restricting the sample to the larger trades if the number of return observations is unchanged. They note that restricting the sample to larger trades is likely to reduce the sample size which may reduce test power but do not test this effect. This is the issue to which we now turn. Restricting the sample to trades of 100 or more bonds reduces the number of firm days t with calculable (t-1,t+1) returns in our sample from 40.2% to 22.1%. To explore how the power of event studies is affected by restricting the sample to trades of 100+ bonds taking into account both the noise and sample size reductions, we recalculate bond and firm returns based only on trades of 100 or more bonds. Again choosing 300 firm/days at random, average sample size is reduced from an average of 120.5 days with calculable returns to 66.4 for the 100+ sample.

In Panel A of Table 15, test powers are reported both for an across-the-board 15 bp return shock and for shocks proportional to the relative standard deviations for that rating and maturity as described in section 4.3.[33] Results for all trades are repeated for easier comparison. As reported in Panel A, the t-test and signed-rank tests are slightly more powerful when the sample is restricted to trades of 100+ bonds, whereas the sign test is slightly less powerful. In other words, it appears that for the t-test and signed-rank test, the noise reduction effect slightly outweighs the sample size reduction effect and that this is reversed for the sign tests. However, for all three tests, the power differences are fairly small so researchers can safely make this sampling choice depending on their event and sample, and what they are most interested in testing.[34] Limiting the sample to trades of 100+ bonds tends to restrict the sample to heavily traded bonds and to eliminate smaller firms from the sample. When the sample is restricted to trades of 100+ bonds, median total assets of the firms in the sample is $26.2 billion. In contrast, for the firm days in the broader sample, but not in the 100+ sample, median total assets is $21.6 billion.[35]

---

[33] In unreported size tests, Type I error is approximately 2.5% in each tail for all tests in Panels A and B.

[34] A caveat is in order here. Like Brown and Warner (1980, 1985), Barber and Lyon (1997), Lyon, Barber, and Tsai (1999), Boehmer, Musumeci, and Poulsen (1991), BKMX (2009), and Kolari and Pynnönen (2010), we calculate test size and power by choosing event-dates at random. Thus, the power calculations presume that trading volume is unaffected by the event - though our tests do allow the event to impact volatility. However, it seems likely that the event could induce increased trading, especially after the event. In that case, the decrease in sample size when the sample is restricted to larger trades would be less than estimated here and power results would be higher. This applies also to our results on broadening the event window in section 7.

[35] Matching bond data from TRACE and Mergent FISD with firm COMPUSTAT data is complicated by the fact that COMPUSTAT's header CUSIP changes over time (as for instance firms merge) whereas TRACE and Mergent FISD use the bond's CUSIP which is normally unchanged from the offering date. When possible, we match each bond to the issuer's company identifier, PERMCO, using CRSP's history name file. For the remaining public U.S. firms, we matched bonds and firms using tickers, S&P Bond Guide, and other sources manually verifying these matches on the basis of company name. Many publicly traded bonds are issued by firms not covered by Compustat. Various firms, such as Dun and Bradstreet, collect or estimate balance sheet figures for some, but not all, of these firms. We searched for these on the internet. Similarly we searched on the internet for the total assets of foreign firms issuing public debt in

Since November 2008, TRACE reports whether a trade is between a dealer and a non-dealer customer or an interdealer trade. Edwards, Harris, Piwowar (2007) and Ederington, Guan, and Yadav (2014) show that bid-ask spreads are considerably smaller in interdealer trades. Moreover, dealers may be more informed so deviations from equilibrium prices could be less. Hence, we expect less non-event noise in returns calculated from interdealer trades only and indeed the standard deviation of firm ABR returns based on only interdealer trades is 1.37% versus 1.53% for all trades. On the other hand, since only 43.5% of the trades in our 2008-2011 sample are interdealer trades, restricting the sample to interdealer trades sharply reduces sample size. Power results based on data from November 2008 (when TRACE started identifying interdealer spreads) through December 2011 are reported in Panel B of Table 6. Results for tests using all trades for this same subperiod are shown for comparison. As shown there, restricting the sample to interdealer trades reduces the power of the tests somewhat. Since test powers are approximately the same whether or not the trade sample is restricted to trades of 100 or more bonds while restricting the trade sample to inter-dealer trades reduces tests' powers slightly, we continue to employ all trades in our analyses below.

6. Calculating average prices

As discussed in the previous section, for the same firm, standardized returns calculated from small trades tend to have a higher variance than returns calculated from

---

the U.S. converting to dollars using the exchange rate at the time. If possible, we collected total asset figures as of December 31, 2009. If only available for a different date, we adjusted to a 12/31/2009 basis using the producer price index. We were unable to obtain total asset figures for 5.6% of the firms but, since their bonds trade infrequently, this amounted to only 1.44% of the firm return sample.

large trades so that even after standardization some heteroskedasticity likely remains. This raises the issue of how best to weight different trades in calculating the average price on a given day. Theoretically, if returns calculated from trades of size x have a standard deviation of s(x) and trades of size y on the same day have a standard deviation of s(y), then the weight attached to trade size x should be s(y)/s(x) times y's weight in calculating the average price that day. However, this becomes very difficult to apply in practice since a return involves prices from two different days. Nonetheless, it seems clear that in calculating average prices for either day, larger trades should get more weight than small trades but how much more and does it matter? This is the issue to which we now turn. Specifically we compare test powers for three weightings: (1) equal, (2) trade size, and (3) square root of trade size.

Comparing test power when bond returns are calculated from only the last trade price of the day and when returns are calculated from the bond's average daily trade prices, BKMX (2009) find that average prices yield more powerful tests. In calculating these daily average prices, BKMX weight each trade by trade size which is the procedure we have followed to this point. Note that this weighting scheme gives a trade of 10,000 bonds a weight 100 times that of a trade of 100 bonds. Since it seems implausible that the return standard deviation on trades of 100 bonds is 100 times the standard deviation of trades of 10,000 bonds, we explore test powers for this and two alternative weighting schemes: equal and square root of trade size weights.

[Insert Table 16]

Test powers for the three different weighting schemes are reported in Table 16. Since no Type I errors rates exceed 3% for the 2.5% tail, we do not report size results.

While powers for all three test statistics are slightly higher for the square root of trade size weighting, the power differences are small. We continue with trade size weightings in the remainder of the paper but results for the other two are available on request.

7. The event window choice

The next issue we consider is the event window choice when working with transaction databases, such as TRACE. Of the possible firm-event days in our sample, only about 40.2% have trades on both t-1 and t+1 so that standardized returns over the (t-1, t+1) event window can be calculated. The problem is likely to be even more severe for less comprehensive databases, such as the NAIC database, or if the sample is restricted to large trades. Relatedly, there may be only a trade or two on days t-1 or t+1, so the calculated returns may contain considerable noise if restricted to trades on those dates. Thus a question is whether more powerful and representative tests can be constructed by incorporating trades over a longer event window, such as (t-2, t+2) or (t-3, t+3) and, if so, how. Of course, the longer the window, the greater the likelihood that there will be events or information flows other than the event of interest which will induce fluctuations in bond returns. This added noise will tend to reduce test power.

Within wider event windows, there are several possible return calculations. For instance, within the (t-2, t+2) window, returns could be calculated from t-2 to t+2 , from t-2 to t+1, from t-1 to t+2, and from t-1 to t+1. One possibility is to use returns calculated using the days with trading closest to the event before and after. For the (t-2,t+2) window for instance, this would mean using ABSR(t-1,t+1) (and ignoring trades on days t-2 and t+2) if trades occur on both days t-1 and t+1; using ABSR(t-2,t+1) if there are trades on t-2 and t+1 but not t-1; using ABSR(t-1,t+2) if there are trades on t-1 and t+2 but not t+1; and using ABSR(t-2,t+2) if there are trades on days t-2 and t+2 but not t-1 and t+1. We calculate this measure, which we label ABSR-Short(t-2,t+2), standardizing ABSR(t-1,t+2) and ABSR(t-2,t+1) by the standard deviation of 3-day returns, and ABSR(t-2,t+2) by the 4-day return standard deviation. Without standardization, this is the procedure followed by Chava, Ganduri, and Ornthanalai (2012) who expand the window out to t-7 and t+7.

In our TRACE dataset, expanding the dataset in this way from (t-1,t+1) to (t-2,t+2) increases the number of possible firm-events for which ABSR is calculable by 31.4%.[36] While this increased sample size will tend to raise the power of the tests, the wider the event window, the greater the likelihood that some news or event other than the event being tested will impact returns which will tend to lower the power of the tests. Confirming the latter, the standard deviation of non- standardized returns is 1.67% for ABR(t-2,t+2) and that of ABR-Short(t-2,t+2) is 1.58% versus 1.46% for ABR(t-1,t+1). Since it is not clear a priori whether test power is increased or decreased, this is the issue we now consider. Size and power results for ABSR-Short(t-2,t+2) are reported in Table 8 where we repeat results for ABSR(t-1,t+1) for comparison. While still very close to zero, the mean of ABSR-Short(t-2,t+2) is negative resulting in a slight tendency to find false evidence of a negative event as reported in Panel A.

---

[36] This also tends to increase coverage of smaller firms. For the 720,742 firm/day observations for which ABSR(t-1,t+1) is calculable, median total firm assets are $14.4 billion (as of December 2009); for the 226,128 firm/days added due to trades on days t-2 and/or t+2, median total assets are $6.5 billion.

Importantly, we see that expanding the event window in this manner leads to an increase in test power. For a 15 bp negative event, the likelihood of correctly finding evidence of the event using a t-test is 81.44% for ABSR-Short(t-2,t+2) versus 68.90% for ABSR(t-1,t+1). For a 15 bp positive event, the powers are 74.36% versus 68.04%. Similar results are observed for the signedrank and sign tests. Power is increased further by expanding the window to (t-3,t+3) and (t-4,t+4). Due to infrequent trading, there may be an advantage to bringing in trade observations on other days even if the bond trades on days t-1 and t+1. As an extreme case, suppose a bond's bid and ask prices don't change and there is a single trade at the bid on day t-1 and a single trade at the ask on day t+1. In this case, ABSR(t-1,t+1) will be large and positive even though prices have not changed. Bringing in trades on days t-2 and t+2 may average out some of this noise and thus increase test power. Of course, widening the event window increases the likelihood that prices move due to something other than the event of interest which will tend to reduce test power.

Hence we next consider the alternative of basing the return calculations on average trade prices over several trading days before and after the event. If a bond trades on both days t-1 and t-2, we wish to include both but clearly the observed trades on day t-1 should get greater weight since they are closer to the event and thus have less non-event noise. Thus, our approach is to average all ABSRs within the event window. For instance, for a (t-2, t+2) event window, we average ABSR(t- 1,t+1), ABSR(t-1,t+2), ABSR(t-2,t+1), and ABSR(t-2,t+2) or as many of the four as are calculable. Suppose for instance that the bond trades on three of the four days: t-2, t-1, and t+1, but not t+2. In this case, what we call the composite ABSR, which we label as ABSR{t-2,t+2}(note the braces replacing the parentheses), is an average of ABSR(t-1,t+1) and ABSR(t-2,t+1). In calculating ABSR(t-1,t+1), the abnormal return over the (t-1,t+1) window is divided by the standard deviation of 2-day returns for that bond. In calculating ABSR(t-2,t+1), the abnormal return over the (t-2,t+1) window is divided by the standard deviation of 3-day returns. Since the standard deviation of 3-day returns exceed that of 2-day returns, this effectively means that the trades on day t-2 receive a lower weight than those on day t-1 in calculating this composite return. Size and power results for this composite return ABSR{t-2,t+2} are reported in Table 17. As shown there, the power of ABSR{t- 2,t+2} consistently exceeds that of both ABSR(t-1,t+1) and ABSR-Short(t-2,t+2).

[Insert Table 17]

In summary, as compared with tests based on trades on just days t-1 and t+1, expanding the sample to utilize trades on days t-2 and t+2 leads to an increase in test power even when there are trades on days t-1 and/or t+1. While trades further from the event have more noise than those close to the event, they tend to average out some of the noise in individual trade observations.

The finding that event studies based on the 4-day event window composite returns ABSR{t- 2,t+2} are significantly more powerful than those based on ABSR(t-1,t+1) raises the issue of whether test power could be increased more by further broadening the event window. To explore this issue, we consider 6-, 8-, and 10-day composite returns: ABSR{t-3,t+3}, ABSR{t-4,t+4}, and ABSR{t- 5,t+5} respectively. As before, these are measured as averages of all ABSR returns within the expanded window. For example ABSR{t-3, t+3} is an average of ABSR returns over the windows (t-3, t+1), (t-3,t+2), (t-3,t+3), (t-2,t+1), (t-2,t+2), (t-2,t+3), (t-1,t+1), (t-1,t+2), and (t-1,t+3). Again we would point out that since the standard deviation of ABR returns increases with the length of the event window, the use of standardized returns effectively assigns returns over the shorter windows a greater weight in calculating composite ABSRs.

As the event window is widened, sample size increases since some bonds which do not trade within two days of the event may trade sooner and later. For instance, average sample size for ABSR{t-3,t+3} is 11.5% larger than that for ABSR{t-2,t+2} and 46.4% higher than that for ABSR(t- 1,t+1). This increase in sample size tends to increase test power. In addition, even for bonds which trade in the (t-2,t+2) window, bringing in more trades may average out some of the noise in individual trade prices which also will tend to increase test power. On the other hand, trades further away from the event date are more likely to be influenced by factors other than the event of interest which will tend to reduce test power. Confirming the latter, the variance of unstandardized returns from t-3 to t+3 is 45.0% higher than unstandardized returns from t-1 to t+1. Thus further widening the event window may either increase or reduce test power.

[Insert Table 18]

Size and power results for tests based on composite ABSRs for expanded event windows are reported in Table 18. As reported in Panel A, as the event window is widened, the t and signed-rank tests show a slight bias toward finding false evidence of negative events due to very small negative return means and medians. As reported in Panels B and C, all three tests show further increases in test power as the event window is broadened, albeit at a decreasing rate. For a negative 15 bp event, the likelihood of Type II error for the signed-rank test falls from 18.98% for ABSR(t-1,t+1) to 4.53% for ABSR{t-3,t+3}, to 2.83% for ABSR{t-5,t+5}. For a positive 15 bp event, the likelihood of Type II error for the signed-rank test falls from 21.06% for ABSR(t-1,t+1) to 6.56% for ABSR{t-3,t+3}, to 4.67% for ABSR{t-5,t+5}. The implication is that on balance widening the event window increases test power due to increasing the number of bonds and firms for which returns are calculable and to averaging out some of the noise in individual trade prices. However, the increase in power as the window is expanded beyond three days before and after is slight. Of course, the increase in power as the event window is broadened must be balanced against other considerations. For instance, if one is interested in testing for information leakage before the event or how quickly and efficiently the information is impounded, a 10-day event window is likely too long. Moreover, while our evidence indicates that in general the additional non-event noise over the longer periods is out-weighted by the increased sampling, this may not be the case surrounding all events.

8. Event date clustering and cross-sectional correlation

In our Monte Carlo simulations above, we have followed Brown and Warner (1980, 1985), Barber and Lyon (1997), Lyon, Barber, and Tsai (1999), Boehmer, Musumeci, and Poulsen (1991), and BKMX (2009) in choosing firms and event dates at random. Consequently, there is little event date overlap. Often however an event impacts a number of firms in which case the usual tests, which assume independence, are biased if returns are cross-sectionally correlated. Suppose, for instance, one is interested in testing how a single regulatory change impacts firms in a particular industry. The usual tests are biased toward finding false evidence that the regulatory change has an effect since if some other event or news affecting all or most firms in the industry occurs during the event window all firms will tend to have positive (or negative) returns which the tests will wrongly attribute to the regulatory change being tested. Our proposal in the previous section to increase the number of trade observations by widening the event window using composite returns, increases the likelihood of overlapping events potentially worsening this problem.

Kolari and Pynnönen (2010) show that the bias in the usual t-test can be expressed as a function of the average pairwise correlation between standardized abnormal returns of all firms in the sample assuming that the correlations are constant over time. For the most extreme case when the event date is the same for all firms, Kolari and Pynnönen (2010) show that the variance of the mean standardized abnormal return, equivalent to our ABSR, can be expressed as:

$$Var\ (\overline{ABSR})= [\text{Var (ABSR)/n}][1+(\text{n-1})\ (\bar{\rho})\ ]$$

where Var (ABSR) is the cross-sectional variance of the event window ABSRs, n is the number of firms in the sample and is the average pairwise correlation between any two ABSRs. If $\bar{\rho}$=0, $Var\ (\overline{ABSR})$= [Var (ABSR)/n], and the usual t-test is unbiased. However, according to equation 4, even small cross-sectional correlations can lead to a substantial bias toward falsely finding evidence of an event. If for instance, there are 101 firms with an average pairwise correlation of .05, according to equation 4, the true variance is six times the variance calculated assuming independence. Kolari and

Pynnönen (2010) propose calculating an adjusted t-statistic by multiplying the usual t by the square root of $[(1 - \bar{r} + (1 + (n - \bar{r})]$ where $\bar{r}$ is an estimate of $\bar{\rho}$.

8.1 Testing for bias

Having shown above that our proposed bond event study tests are unbiased when event dates are unique, we now test for Type I error when all firms share a common event date and apply Kolari and Pynnönen's (2010) suggested t-test correction. Estimating $\bar{r}$ for the Kolari and Pynnönen bias correction creates a challenge in bond market event studies due to infrequent trading since it requires that both bonds trade on the same days. Hence, in this section, we restrict the sample to bonds that have a calculable ABSR(t-1,t+1) on at least 10% of the days between 2005 and 2011 inclusive. In order to construct samples in which the firms share some attribute, we further require data on CRSP or Compustat. These requirements reduce our sample to 915 firms.

In order to test for bias, we seek subsamples in which firms share some characteristic so that their bond returns are likely correlated. Note that since we define a bond's abnormal return relative to the average return for bonds of that approximate rating and maturity, rating and maturity are eliminated as correlation sources.[37] Hence, we explore other similarities that might lead to correlated returns. One possibility is that, like equity returns, bond returns for firms in the same industry might be correlated. Hence, we calculate average pairwise correlations 2005-2011 for the six two-digit SIC

[37] If we calculate abnormal returns by subtracting from the raw return, the average return over all bonds instead of the average return for bonds of that rating and approximate maturity, the average pairwise correlations within a rating maturity group range from .0237 for Baa rated bonds maturing in 3 to 5 years to .2084 for Aaa-Aa bonds maturing in 3 to 5 years. Correlations are positive for all eighteen rating/maturity subsamples.

codes with at least 40 firms in our sample.[38] The two industries with the highest average pairwise correlations for ABSR(t-1,t+1) are SIC28, chemicals and allied products, =.00327 , and SIC 67, investment companies, holding companies, and trusts, = .00485. In addition, we divide the sample into quintiles based on total assets, leverage measured as total debt divided by total assets (book value), and total bonds outstanding. As reported in Panel A of Table 10, the average pairwise ABSR(t-1,t+1) correlation for the smallest bonds outstanding quintile is .00523. Thus, despite our attempt to construct subsamples with correlated returns, the resulting average ABSR(t-1,t+1) correlations are all miniscule. None exceed .006. To construct the size test, we choose a day from 2005-2011 at random. Then apply the t, signed-rank, and sign tests to the SIC and quintile subsamples. This simulation is repeated 1000 times and we record how often each test incorrectly finds significant evidence of an event using a 5% significance level. An unbiased test should find false evidence of a positive event on that date about 2.5% of the time and false evidence of a negative event about 2.5% of the time.

8.2 Test size results

Results for tests based on ABSR(t-1,t+1) returns are reported in Panel A of Table 10 for our SIC and quintile subsets where we also report results for samples of 100 randomly chosen firms (which should be unbiased) for comparison. As expected, since the average pairwise correlations shown in column 2 are quite small, in Panel A there is only minor bias in any of the three tests. Of course these are only eight of the innumerable possible subsamples, and it is possible that there are some with much higher correlations and therefore more bias. Nonetheless, these results suggest that by

[38] We also divided the 915 firms into nine broader industry groups based on SIC codes but the average correlations were all very close to zero so these results are not presented here.

calculating abnormal returns separately by rating and maturity, as we and BKMX propose, two of the major sources of correlation in bond returns are eliminated so that there is much less cross sectional correlation in bond ABSR(t-1, t+1) returns than in stock returns and hence less test bias when event dates overlap.

Results for composite ABSR{t-3, t+3} returns are reported in Panel B. While still low (none exceed .02), the average pairwise correlations reported in column 2 are considerably higher than those observed for ABSR(t-1,t+1) in panel A. This appears due to a slight correlation between returns on different bonds on different days. Consequently, as predicted by Kolari and Pynnönen (2010), the t-test is biased toward finding false evidence of an event in those subsamples with higher correlations. This is especially true for the smallest quintiles in terms of total assets and bonds outstanding for which several of the Type I errors exceed 5%.[39] This confirms Kolari and Pynnönen (2010) argument that even small cross-sectional correlations can result in substantial bias. While Kolari and Pynnönen's analysis was restricted to the t-test, we observe a similar bias in the signedrank and sign tests. In the final two columns of Panel B, we present results of tests using Kolari and Pynnönen's corrected t-test. As described above, this requires estimation of correlations between all firm pairs on day t. These are estimated using ABSR{t-3, t+3} over the (t-200, t+200) period excluding (t-6, t+6) requiring at least five return pair observations. As reported in Panel B, this test is pretty well-behaved with Type I errors distributed around 2.5%.

[39] Like the two smallest quintiles, the average pairwise correlation in SIC28 also exceeds .01 but its bias is considerably less. This is apparently because the subsample size is smaller. According to the Kolari and Pynnönen (2010) model, the bias in the estimated variance of the mean is approximately proportional to the number of firms. SIC28 consists of 67 firms versus about 161 in the quintiles.

In summary, when abnormal standardized returns are calculated relative to bonds of the same rating and maturity, cross-sectional correlations appear much less serious in the bond market than for equities. Consequently, when event dates overlap, the bias toward finding false evidence of an event is less severe. Nonetheless, as predicted by Kolari and Pynnönen's model, we find that even small average correlations in the range of .02 produce biased t-tests in samples between 60 and 200 firms. We find similar biases in the signed-rank and sign tests and higher correlations for wider window composite returns than for ABSR(t-1,t+1). Fortunately, we find that the Kolari and Pynnönen t-test correction yields tests with little, if any, bias.

9. Summary and conclusions

Bond market event studies to date have employed tests with relatively low power to detect bond price reactions to announcements and events. We show that much more powerful tests can be obtained by standardizing returns and widening the event window. Unstandardized returns are highly heteroskedastic because bond volatility differs substantially by term-to-maturity, rating, and other characteristics. Return standardization removes this heteroskedasticity leading to a considerable increase in the powers of the t-test and signed-rank test and slight for the sign test. In addition, due to very thin trading, basing bond and firm returns on trades on single days before and after an event leads to: (1) many event dates without a calculable return, and (2) noisy event date returns for the events with observed returns. Calculating composite returns based on price observations on several days before and after the event (while putting more weight on returns based on trades on days closer to the event) results in a substantial increase in test power despite the greater non-event noise over the wider window. Some of the increase in test power from widening the event window arises from the increase in sample size since some firms with no bonds which trade on both the day before and the day after the event do have bonds that trade on other days close to the event. However, we find that most of the increase in test power arises from averaging out more of the noise (including bid-ask bounce) in individual bond trade prices.

The resulting improvement in test power vis-a-vis current state-of-the-art bond event study methods is dramatic. For instance, using a 5% significance level, the power of the t-test to detect an event which lowers event day returns by 15 basis points rises from 22.7% for tests based on unstandardized abnormal bond returns from day t-1 to day t+1 for a random sample of 300 possible firm/event days (Table 4) to 68.9% for tests based on standardized (t-1,t+1) returns (Table 4) to 90.2% for tests based on standardized composite returns over the t-3 to t+3 window (Table 9). For negative 15 basis point events, the power of the signed-rank test rises from 60.0% for tests based on unstandardized abnormal bond returns from day t-1 to day t+1 to 81.0% for tests based on abnormal standardized returns from day t-1 to day t+1 to 95.l% for tests based on composite abnormal standardized returns over the t-3 to t+3 window. For positive 15 basis point events, the power of the t-test rises from 20.6% to 68.0% to 86.3% while the power of the signed-rank test rises from 51.9% to 78.9% to 93.4%. We find that restricting the sample to institutional size trades has little net impact on test power but that restricting the sample to trades between dealers slightly reduces test power. We further find that the signed-rank test is somewhat more powerful than the t-test and sign test.

Exploring test bias when event dates overlap, we find in the subsamples we examine that cross-sectional correlations among abnormal standardized returns are small when the benchmark for the abnormal return calculation is the return on other bonds of the same rating and approximate maturity. This suggests that cross-correlations are likely less of a problem in bond market than in equity market event studies. Nonetheless, we find some evidence of bias in the t, signed-rank, and sign tests toward falsely finding evidence of an event when the event date is the same for all firms in the subsample using composite returns over a t-3 to t+3 window. However, we also find that an adaptation to the bond market of the t-test correction proposed by Kolari and Pynönnen (2010) removes this bias.

We hope bond market researchers find the procedures we suggest helpful. While we have utilized the TRACE data, our findings on heteroskedasticity, standardization and on test bias when event dates overlap should equally apply to tests based on dealer quotes or credit default swap data.

Chapter 3: Essay Three

Bond Market Post-Earnings-Announcement Drift

Abstract

Exploiting a large sample of daily bond transactions from TRACE, we examine bond market reaction to earnings surprises and post-announcement return patterns. We find 1) significant bond price responses to both positive and negative earnings surprises, 2) evidence of bond market post-earnings announcement drifts driven by drifts following positive earnings surprises. Our results suggest that while both positive and negative earnings surprises have informational content for bond prices, negative earnings gets impounded into bond prices more efficiently than positive information. Further, we find that the absolute magnitude of both the initial bond price responses and the post-announcement drifts are greater for firms with noninvestment-grade debt, suggesting that prices of riskier bonds are more sensitive to earnings news and adjust to information less efficiently.

1. Introduction

Beginning with the seminal work by Ball and Brown (1968), extensive studies have documented that stock prices are strongly responsive to quarterly earnings news and that stock returns continue to drift in the same direction as earnings surprises, up to months after the announcements.[40]The apparent predictability of cross sectional returns based on past earnings news seems to be an enduring feature of stock returns and is among the most controversial aspects of the debate on market efficiency.

We investigate whether the extensive evidence of the significant post-announcement drift in the stock market extends to the bond market and explore the implications for bond market efficiency. During the decade 2005 to 2011, U.S. corporations issued a total of $6.6 trillion in corporate bonds, compared to $1.3 trillion in equity through common stock offerings.[41] Given that corporate bonds are an important source of external financing for U.S. firms and that earnings announcement is the primary public information about firm's performance, examining the behavior of bond prices around earnings announcements provides evidence of the impact of unexpected earnings on the wealth of a group of nontrivial claimholders and gives an opportunity to test bond market efficiency.

In general, the extent of market efficiency of corporate bonds has not been established in the literature. While Hotchkiss and Ronen (2002) and Ronen and Zhou (2008) find that the bond market is efficient, Downing, Underwood, and Xing (2009)

[40] Empirical studies trying to provide the evidence and explanations include Bernard and Thomas (1989), Bhushan (1994), Ng,Rusticus, and Verdi (2008), Bartov, Radhakrishnan, and Krinsky (2000), Mendenhall (2004), Battalio and Mendenhall (2006), and Chordia, Goyal, Sadka, Sadka, and Shivakumar (2009) who find that stocks with lower stock price, less liquidity, higher arbitrage costs and risks tend to have greater drifts. Livnat and Mendenhall (2006) and Doyle, Lundholm, and Soliman (2006) serve as benchmarks for the recent PEAD literature, which document significant PEAD using analyst consensus forecasts as the earnings expectation benchmark.

[41]Source: Thomson Reuters.

find that the corporate bond market is less informationally efficient than the stock market. In the specific case of earnings announcement, though several studies provide initial evidence that the bond market is responsive to earnings surprises in terms of bond returns and trading activities (Datta and Dhillon (1993), Easton Monahan and Vasvari (2009), and Hotchkiss and Ronen (2002)), the pattern in post-announcement bond returns and thus market efficiency remain unexplored.

Bonds, like stocks, are claims on a firm's assets so that information that affects the value of the firm will impact prices of both the firm's bonds and stocks. However, to the extent that the bond market has different features from the equity market, strong evidence of equity market response to earnings announcement and Post-Earnings-Announcement Drift (PEAD) does not preclude that bond prices will behave in the similar way. First, bondholders are not residual claimaints and a bond's payoff structure is asymmetric. Changes in accounting earnings may not translate to changes in bondholders' wealth like they do for shareholders. Under this assumption, bond prices may not be sensitive to earnings surprises, especially for positive earnings news. However, it is also possible that earnings surprises reveal information about changes in the probability of default. An unexpected impairment of a firm's operating performance which results in a higher default probability will clearly have a negative effect on bondholders while a large positive earnings surprise may resolve or alleviate uncertainty about a firm's financial distress and therefore move bond prices upward. Under assumption of earnings surprises revealing information about default probability, bond prices are responsive to earnings surprises.

Second, the price adjustment of bonds is likely to be constrained by the relative illiquidity and higher transaction costs of bond market, compared to the equity market. For instance, Bessembinder, Kahle, Maxwell, and Xu (2009) report that the average bond only trades 52 days a year with just a few bonds being actively traded. Ederington, Guan, and Yang (2012) document that during January 2005-December 2011 in TRACE sample, the median (mean) number of trades per day is only 3 (6.3) conditional on trading. The lower trading frequency of corporate bonds may reflect their relatively large trading costs. Actually, Edwards, Harris, and Piwowar (2007) report that effective spreads in corporate bond is 124 basis points for trades of $20,000, which triples the size of equity markets for retail-sized trades. If low market liquidity and higher trading costs constrain the informed trades that are necessary to incorporate new information into bond prices, then bond market may react sluggishly to the information, and in this case, earnings news.[42]

A possibly delayed reaction to earnings announcements due to the relative illiquidity of the bond market may further implicate a less efficient market and thus increase the likelihood of post-announcement drifts. Coupled with equity market evidence from Chordia et al (2009) and Ng et al (2008), who find weaker return responses at the time of the earnings announcement and greater subsequent return drift for firms with higher transaction costs, this suggests that post-announcement drifts might be greater in the bond market.

While lack of liquidity likely deteriorates bond market efficiency, being dominated by large institutions might improve market efficiency as institutions are

[42]A line of finance literature studying the relation between liquidity and market efficiency finds that higher liquidity enhances market efficiency (see Chordia, Roll, Subrahmanyam (2008) for a review).

assumed to be skilled information processors.[43] In general, Boehmer, Kelly, and Pirinsky (2005) observe a positive impact of institutional investors on intraday price efficiency. Evidence has also shown that there is a greater tendency for return drifts among stocks with less institutional ownership (Ng, Rustigus, and Verdi (2008) and Bartov, Radhakrishnan, and Krinsky (2000)).Therefore, it is not clear apriori whether and to what extent bond prices drift following earnings news, depending largely on the tradeoff among favorable or adverse factors affecting bond market efficiency.

Further, we expect that investment grade and noninvestment grade bonds may behave differently. On the one hand, earnings news may have a stronger effect on speculative-grade bonds than higher rated bonds. This is because a bond investment can be viewed as a long position in a risk-free debt in combination of a short position in a put option on the issuer's assets. As the put option is deep out-of-the-money for investment-grade bonds and in the money for speculative-grade bonds, investors should be more sensitive to firm-specific news for speculative bonds. On the other hand, bond price adjustments to earnings information may be less efficient for lower rated bonds due to higher transaction costs (Edwards et al (2007)) and greater uncertainty about their financial conditions. As such, how bond returns with different riskiness behave differently remains an open question.

Despite the unclear pattern of bond returns in response to earnings surprise, empirical work on the bond return patterns around earnings news remain somewhat sparse. There are no studies examining the post-announcement return patterns in the

[43]Bessembinder et al (2009) report that trades of $100,000 or more account for 96.7% of bond trading volume. However, Ederington et al (2012) find that 69.4% (46.5%) of bond trades are less than $100,000 ($25,000). This may imply that there are considerable amount of small investors on the bond market and that many bond price observations are determined by non-institutional size trades.

bond market. One possible obstacle that researchers face is data availability. Because most bond transaction prices have never been published until recently, extant studies providing early step towards understanding bond price behavior have relied on quotes at either monthly (weekly)frequency or data that covers only a subset of bonds.[44] For example, Datta and Dhillon (1993) give early evidence that earnings announcements have information content for the bond market with a relatively small sample. Using Mergent FISD insurance company bond trades database, Easton et al (2009) investigate the role of earnings in the bond market and find that the incidence of bond trade during the days surrounding earnings announcements increases and some evidence of initial bond price responses to unexpected earnings, albeit with some exceptions. Wei and Zhou (2012) find that the direction of pre-announcement bond trading is significantly related to earnings surprises. Using a dataset of intraday transaction prices of a sample of 55 most liquid bonds, Hotchkiss and Ronen (2002) find that the bond market reacts quickly to earnings surprises within shorter time windows. These studies provide evidence that short-window trading and returns do react to announcements, but still leave open the question of whether there is post announcement drift and in turn the implication for bond market efficiency.

Another obstacle comes from the estimation of abnormal bond returns, which can account for the unique issues with bond returns. Specifically, how to treat the multiple bonds issued by the same firm, how to deal with the constantly changing sensitivity to risk factors as a bond moves closer to its maturity date, how to determine

[44] The main source of data regarding corporate bond trades pre-TRACE is the National Association of Insurance Commissioners, who required insurance companies to report prices and volumes for their bond trades (Bessembinder and Maxwell (2008)). Insurance companies are estimated to hold between 33%-40% of corporate bonds and have completed 12.5% of the dollar trading volume in TRACE-eligible securities during second half of 2002 (Campbell and Taksler (2003)).

the appropriate price and model used since few bonds trade on a continuous basis, and how to account for the considerable heteroskedasticity in bond returns. All these issues are found to make existing methods used to test abnormal stock returns not well specified in testing bond returns (Bessembinder et al (2009) and Ederington et al (2012)). Moreover, few bond pricing models have been developed to focus on noninvestment grade bonds until recently. As observed by Bessembinder et al (2009), lower rated bonds are less likely to detect an "event" by extant event study methodologies. Ederington et al (2012) propose that the low power observed for low rated firms is due to violation of the homoskedasticity assumption. As such, remedies are critical to get more reliable inference for riskier bonds.

In light of the difficulties faced by prior bond event studies, we use a comprehensive record of U.S. over-the-counter corporate bonds from Trade Reporting and Compliance Engine (TRACE) database and apply event study methodologies developed by Bessembinder et al (2009) and Ederington et al (2012) to investigate the bond price behavior around earnings announcements. When calculating bond abnormal returns, we base benchmark returns on the portfolios based on the same maturity and rating groups instead of treasury bonds to account for the constantly changing sensitivity to risk factors as suggested by Bessembinder et al (2009). We then derive test statistic as proposed by Ederington et al (2012), which overcomes considerable cross-sectional heteroskedasticity in bond returns and simultaneously account for event-induced increases in the variance. Specifically, we standardize each individual bond return by its estimated volatility and get the standardized individual bond returns. We then get inference based on the cross sectional standard deviation of these standardized returns during the event window.

We test the bond market reaction to earnings news by examining firms' bond abnormal returns over the short interval surrounding earnings announcement dates and find a significant bond price response to both positive and negative earnings surprises. We then separate sample firms into firms with investment- versus speculative-grade bonds. Investment-grade bond returns are responsive to negative earnings surprises but not to positive earnings surprises. This is consistent with the implications of the non-linear payoff structure of bonds. Specifically, for an investment-grade firm, better performance does not lend much upside potential to bondholders' payoff while an unexpected bad performance triggers the concern for the issuer's financial condition. Therefore, investment-grade bond prices move quickly in response to negative earnings surprises but not to positive earnings surprises. In contrast, speculative-grade bond returns are strongly responsive to both negative and positive earnings surprises. We interpret this finding to be consistent with the fact that speculative-grade bonds behave more like stocks and that the probability of default is highly sensitive to changes in earnings. Though good news may not have much impact on higher-rated bond, it has a relatively large impact on speculative-grade bonds as it alleviates the concerns of financial distress. Overall, our findings of a significant bond price reaction to earnings surprises compliments the findings of Easton et al. (2009) and Wei and Zhou (2012), who document that the incidence of bond trade increases during the days surrounding earnings announcements, suggesting that earnings news has informational content for bond market.

Next, we examine whether there exits PEAD in the bond market. To estimate the drift, we calculate the cumulative abnormal returns over the period from the fourth day through the 63rd trading day after earnings announcement as well as the short interval abnormal bond returns around subsequent announcement date. We find evidence of PEAD, which is driven by drifts following positive earnings surprises and speculative-grade firms. Interestingly, while we find strong evidence of PEAD for the universe of common stocks during our sample period year 2005 to 2011, there is no indication of stock PEAD among the firms with a matched bond. Combined together, these findings may imply that firms in our sample are firms with relatively efficient information dissemination environment in the equity market and that it is lack of liquidity in the bond market that makes bond prices adjust sluggishly to earnings news. In addition, little evidence of PEAD for high rated bonds and observed PEAD for lower-rated bonds are also consistent with Edwards et al's (2007) finding that highly rated bonds have lower transaction costs, such that earnings news is impounded into bond prices more efficiently.

To justify our argument that bond market PEAD is driven by market illiquidity, we separate samples into high versus low liquidity firms based on their bond trading activities. Consistent with our prediction, the post-announcement drift in the bond market is driven by firms with low liquidity, even after controlling for firms' riskiness.

Our study contributes to the literature by studying the bond price behavior around one of most prominent firm-specific information events with a comprehensive database that covers all the U.S. over-the-counter corporate bonds. We interpret our findings as evidence that accounting earnings information is value relevant to bond market and that bond market efficiency is likely hampered by illiquidity. To the extent that the complete record of corporate bond transactions from TRACE system begins in 2005, our study represents one of the first empirical studies on the daily behavior of bond prices in response to firm-specific information. We use methodologies that accounts for the liquidity and other institutional characteristics specific to bond market (Bessembinder et al. (2009) and extended by Ederington et al. (2012)). Our study may have implication for market reaction timeliness for other firm-specific information release and possibly other forms of underreaction in bond market and thus the current study helps inform the controversy about bond market efficiency.

The remainder of this paper is organized as follows. Section 2 describes the data and the variables construction. Section 3 presents the research design and empirical results, and Section 4 provides discussions of the robustness tests and further examinations. Section 4 concludes the paper.

2. Data and Methodology

2.1 Sample Selection

Our sample consists of firms with bond trading observations in TRACE that have a matched common stock (share code equals 10, 11) listed on the NYSE, AMEX and NASDAQ (exchange code equals 1, 2, or 3) when needed data on analyst earnings expectations from Institutional Brokers Estimate System (I/B/E/S)and accounting information from COMPUSTAT are available. Our sample period begins from the first quarter of 2005, when TRACE extended its coverage from a subset to almost the entire corporate bond markets, and ends in the fourth quarter of 2011.We merge each bond to the issuer's stock identifier, PERMNO, using CRSP's historical name file.[45]

We gather bond characteristics such as coupon, maturity, and ratings from Mergent's FISD database. Moody's rating is used if it is available; otherwise Standard &Poor's rating is adopted. Particularly, bonds are designated as "investment grade" (rated BBB or better by Standard &Poor's or Baa or better by Moody's respectively), or "noninvestment grade." To calculate the corresponding return measure for stocks, we obtain daily stock returns from the Centre for Research in Security Prices (CRSP) daily tape.

Criteria for inclusion of a bond and a trade are the same as those used in Bessembinder et al (2009) and Ederington et al (2012). We restrict the sample to industrial, non-convertible, non-putable, and non-zero coupon bonds, and bonds that have at least one year to maturity but mature in 50 years. We drop canceled, corrected, and commission trade observations. Very thinly traded bonds are also eliminated as we require that the bond be traded at least 100 times over the 2005-2011 period and that 2-day returns be calculable for at least 10 days over this period. After implementing standard deletion criteria in PEAD literature and for bond return calculation, the remaining sample has 6,409 firm-quarters, involving 3,074 bonds issued by 549 underlying firms.[46]

---

[45]We match bond's issuer CUSIP with CRSP historical CUSIP instead of CRSP header CUSIP. Because Mergent FISD database keeps the issuer's CUSIP as of the offering date, merging by header CUSIP which is the current CUSIP in WRDS will lose many bond observations. In addition, a few bonds have a different CUSIP with the CUSIP of their prospective issuer, thus we manually match these bonds to their prospective issuer's stock.

[46]As suggested by Livnat and Mendenhall (2006), we require that the price per share be available from Compustat as of the end of quarter t, and be greater than $1 to reduce the noise caused by small deflators to calculate earnings surprise measure. This eliminates very small firms with low liquidity, as well as

2.2 Earnings Surprise Measure- Standard Unexpected Earnings (SUE)

We define earnings surprises as actual earnings per share from the I/B/E/S detail file minus expected earnings based on analyst consensus forecasts, scaled by stock price at the end of prior quarter. In line with Livnat and Mendenhall (2006), the measure of analysts' expectations is the median of forecasts reported to I/B/E/S. We only adopt individual analyst's forecastsmade after the previous quarter's earnings announcement and within 90 days of the current quarter's earnings announcement. If a single analyst provides multiple forecasts during the 90-day pre-announcement period, we consider only the most recent forecast (or revision) for each analyst (Rees and Thomas (2010)). The standard unexpected earnings (SUE) are defined as follows:

$$SUE_{it} = \frac{E_{it} - FE_{it}}{P_{it-1}}, \tag{16}$$

Where Eit is actual quarterly earnings per share for firm i in quarter t, FEit is the median of analysts' forecasts of quarterly earnings per share, and Pit-1 is the stock price at the end of prior quarter.[47]

2.3 Estimation of Bond Abnormal Returns

***Raw returns*.** Largely following Ederington et al (2012), we calculate bond return from m days prior to and n days subsequent to earnings announcement date t as follows,

$$\text{Bond Ret}_{m,\,n} = \text{Ln}\,(P_{t+n}) - \text{Ln}\,(p_{t-m}) \tag{16}$$

firms at their initial stages or close to liquidation. However, merging with bond data has effectively removed tiny firm observations.

[47]Our major conclusions are insensitive to whether we use analyst-based SUE measure or seasonal random walk measure. As such, we take Livnat and Mendenhall's (2006) suggestion and use analyst-based SUE measure.

P_{t+n} is the price of bond n days following event day t, and p_{t-m} is the price m days prior to event day t. When a bond trades several times on a day, a volume weighted price is calculated by weighting each transaction price by logarithm of its trade size. Since Bessembinder et al (2009) report a slight tendency to find false evidence of negative events if using percentage returns, we use log returns as a remedy, as we suspect that the problem was due to positive skewness in percentage returns.

Abnormal bond returns. We use a companion portfolio approach designed to control for risk effect that is specific to bonds. To account for the constantly changing sensitivity to risk factors as a bond moves closer to its maturity date, we assign bonds into portfolios on the basis of maturity and rating and estimate the mean returns on the matched portfolio as the benchmark returns. Specifically, bond abnormal returns are calculated as follows:

$$ABR_{m,\,n} = \text{Bond Ret}_{m,\,n} - \text{BM Ret}_{m,\,n} \tag{17}$$

Bond $\text{Ret}_{m,\,n}$ is raw bond return, and BM $\text{Ret}_{m,\,n}$ is the mean return on a rating/maturity matched benchmark portfolio corresponding to each bond. We assign bonds into one of the 24 benchmark portfolios based on rating and maturity – six rating classes (Aaa and Aa, A, Baa, Ba, B, and below B) and four maturity groupings (1 to 3 years, 3+ to 5 years, 5+ to 10 years, and over 10 years).

Standardizing bond returns. As observed by Ederington et al (2012), bond returns are characterized by considerable cross-sectional heteroskedasticity. Prices of long-term, low-rated, and illiquid bonds are much more volatile, ceteris paribus. Further, bond prices are more volatile during periods of financial crisis. Since the t-test assumes bond returns are identically distributed, failure to control for this heteroskedasticity results in mis-specified t-tests. To overcome this issue, we standardize event window returns by a bond's estimated return volatility as proposed by Ederington et al (2012). We estimate return volatility slightly differently for short-window and longer-window returns (which we will describe below) for practical purposes.

Short-window returns. We construct two alternative short-window bond abnormal returns. The first is standardized abnormal return (SABR), where we standardize abnormal bond return by its estimated standard deviation. We calculate the standard deviation of a n-day bond return using observed n-day returns over 25 days prior to and after the announcement date. For example, we standardize (t-1, t+1) return by standard deviation estimated by observed two-day returns over (t-25, t+25) window. The second approach is abnormal standardized return (ABSR), where we standardize the bond raw return by its time series standard deviation and minus the mean standardized return on its benchmark portfolio.

Extant PEAD literature for equity examines three-day or two-day returns around earnings announcement date, i.e., cumulative return (-1, +1) or (0, +1). If we calculate bond returns in the same way, then bond price observations are required on day -1 and day +1. However, due to infrequent trading, use of transaction price observations on only day t-1 and t+1 as in most equity market event studies, will eliminate many bond observations and tends to bias the sample toward larger firms with more actively traded bonds.[48] Ederington et al (2012) show that enlarging the event window from (-1,+1) to (-3,+3) , i.e., exploiting transaction prices on days t-2, t-3 in addition to t-1, and t+2, t+3in addition to day t+1, in calculating event window returns increases the number of observations and thus yields more powerful tests, while false rejection rate is not inflated. As such, we calculate the short window returns as the average of (-1, +1), (-1, +2), (-1,+3), (-2, +1), (-2, +2), (-2,+3),(-3, +1), (-3, +2), (-3,+3) returns, whenever calculable. For example, if a bond has price observations on day t-1, t+1, t+2, and t+3 only, then returns for (-1, +1), (-1, +2), and (-1, +3) are calculable. We average the three window returns as {-3, +3} for this bond. As such, we get averaged returns the short window standardized abnormal returns as SABR {-3, +3} and short window abnormal standardized returns as ABSR {-3, +3}.

Longer-window returns. Most PEAD studies examine post earnings announcement drift by estimating cumulative abnormal returns over one quarter after the announcement date. We therefore calculate bond returns from the 4th trading day subsequent to earnings announcement to the 63rd trading day (one quarter). Due to infrequent trading, we use trades from the closest day after the 4th day post-announcement, and the closest day before the 63rd day. The longer-window abnormal return is calculated by subtracting the mean return on the maturity and rating matched

[48] Ederington et al (2012) estimate that on any day t during the sample period, two day returns from day t-1 to day t+1 can only be calculated for 31.3% of the bond/days even after eliminating the least traded bonds. Since some firms have multiple bonds outstanding, the percentage of firm/days for which returns for the (t-1, t+1) window are calculable is somewhat higher but is still only 38.6%.

portfolio from the raw return. We then standardize abnormal returns by the cross sectional standard deviation of the abnormal returns within each rating/maturity group.

Firm-level bond returns. Returns of multiple bonds issued by the same firm are combined into firm level returns for two reasons. First, treating each bond as a separate observation biases the sample toward larger firms with many bonds. Another reason is that returns for bonds of the same company will be correlated leading to biased test statistics (Bessembinder et al. (2009) and Ederington et al. (2012)).

3 Research Design and Empirical Findings

In this section, we investigate bond market reaction to earnings announcement and post-earnings announcement drift using two approaches: mean tests with SUE-ranked portfolios as well as cross-sectional regressions. We explore initial bond market reaction by examining bond return patterns during the short interval around earnings announcement dates. We study post-earnings- announcement drift by examining 1) bond return patterns over the 63 trading days subsequent to an earnings announcement and 2) short window returns around next earnings announcement date.

3.1 Sorting and Means Tests

SUE portfolios. Each calendar quarter, we form ten portfolios based on the level of earnings surprise (SUE). To investigate bond market reaction to earnings news, we calculate {-3,+3} bond return at the firm level around the earnings announcement date. We then calculate the mean returns for each SUE decile and get the statistic inferences. To investigate post-earnings announcement drifts, we estimate the longer-window mean returns for each SUE decile, and also calculate the mean {-3, +3} returns around subsequent earnings announcement date for each SUE decile sorted during current quarter. We eliminate the observations if the next earnings announcement date is missing or more than 90 days after the current announcement date. Due to the fat tail of SUE, we conduct alternative tests by breaking sample firms into 20 groups based on SUE each quarter, and present mean returns for the top and bottom two vigintiles.

Partition by Risk. To investigate how risk affects the initial response to earnings announcement and post-announcement drift, we separate firms into investment-grade and speculative-grade. Bonds are designated as "investment grade" if rated BBB or better by Standard & Poor's (or Baa or better by Moody's), or as "noninvestment grade" otherwise. A firm is rated by the highest rating of all its bonds. Within each credit risk group, we then sort stocks into portfolios based on the level of earnings surprise (SUE).

3.2 Variable Transformation and Regression Tests

We then adopt a regression approach to test bond market reaction to earnings news. To address outliers and potential nonlinearities in the relation between abnormal returns and explanatory variables in the regression tests, we transform SUE into coded scores based on their rank within each calendar quarter. This method was adopted by Bernard and Thomas (1990), followed by Bhushan (1994) and modified by Mendenhall (2004). Specifically, we rank earnings surprise into vigintiles, resulting in ranks from 0 to 19. We then divide the rank by 9.5 and subtract 1. For example, the coded vigintile rank for extreme negative earnings surprise is –1 (=0/9.5 – 1). As such, a coded score on SUE of

–1 represents extreme negative earnings surprise while +1 represents positive earnings surprise. We define RISK as a dummy variable that takes on the value one if the firm is rated as speculative and zero if rated as investment grade.

To test initial bond market reaction to earnings announcement, we then regress the abnormal return bond variables on the ranked SUE variable and an interaction term of ranked SUE with RISK dummy as follows:

$$SABR\ \{-3, +3\}_q = a + b_1 RSUE_q, \tag{18}$$

$$SABR\ \{-3, +3\}_q = a + b_1 RSUE_q + b_2 RSUE_q * RISK, \tag{19}$$

where SABR $\{-3, +3\}_q$ is standardized abnormal return during the short interval of earnings announcement date at quarter q. RSUE is the ranked SUE variable, and RISK is the dummy variable that takes on the value one if the firm is rated as speculative grade and zero if rated as investment grade.

To investigate the post-earnings announcement drift, we first regress longer-window cumulative abnormal returns on coded SUE variable and an interaction term of ranked SUE with RISK dummy as follows,

$$SABR\ (4,63) = a + b_1 RSUE_q, \tag{20}$$

$$SABR\ (4,63) = a + b_1 RSUE_q + b_2 RSUE_q * RISK, \tag{21}$$

where SABR (4,63) is standardized abnormal return over one quarter subsequent to the earnings announcement date of quarter q. RSENT is the ranked SUE variable, and RISK is the dummy variable that takes on the value one if the firm is rated as speculative grade and zero if rated as investment grade.

We then regress the short interval abnormal return bond variables around next quarter's earnings announcement on the ranked SUE variables as follows

$$SABR\ \{-3, +3\}_{q+1} = a + b_1 RSUE_q, \tag{22}$$

$$SABR\ \{-3, +3\}_{q+1} = a + b_1 RSUE_q + b_2 RSUE_q * RISK, \tag{23}$$

where SABR $\{-3, +3\}_{q+1}$ is standardized abnormal return during the short interval of earnings announcement date in quarter q+1. RSUE is the ranked SUE variable, and RISK is the dummy variable that takes on the value one if the firm is rated as speculative grade and zero if rated as investment grade.

3.3 Initial Bond Market Reaction to Earnings Surprises

3.3.1 Initial Bond Market Reaction to Earnings News

We first conduct means tests to provide straightforward evidence of the bond market reaction to earnings surprises across SUE portfolios. Specifically, we calculate mean standardized abnormal returns (SABRs {-3, +3}) and abnormal standardized returns (ABSR {-3, +3}) for each portfolio based on sorts of SUE. As a robustness check, we also provide 3-day stock returns CAR (-1,+1) around earnings announcement date.

[Insert Table 19]

Table 19 presents the results for initial bond market response to earnings surprises by means tests. The results suggest that bond market responses strongly to earnings surprises. Panel A shows results for SUE portfolios sorted into decile portfolios based on SUE for the current quarter and Panel B presents SUE portfolios sorted into 20 portfolios (vigintiles) based on SUE for the current quarter. We find a significant negative price response to extreme negative earnings surprises and positive response to extreme positive earnings surprises. The bond return pattern is almost monotonically increasing when moving from the extreme negative surprise to the extreme positive surprise decile. As shown in Table 19 Panel A, the mean short-window bond return (SABR) is -.24 for negative earnings surprises, and the mean SABR is .35 for positive earnings surprises. We get very qualitatively similar results for alternative abnormal return measures (ABSRs). The magnitudes of our unexpected earnings proxies SUE (analyst consensus forecast error standardized by stock price at the end of prior quarter) are also small. The mean SUE is -4.12% for negative surprises and 2.02% for positive surprises. And not surprisingly, stock market reaction is also strong for the sample period. Equity market reaction is consistent with extant literature, as the cumulative abnormal return of stock from 1 day before to 1 day after earnings announcement date is -4.26% for negative earnings news and 4.62% for positive earnings surprises.

In order to explore the possible fat tail distributions in the extreme decile portfolios, we separate the bottom and top deciles into 4 portfolios and the results are shown in Table 19 Panel B. We find that the strong initial bond market responses to earnings surprises still hold for this sorting. Though vigintile 2 has a much smaller SUE in absolute value than vigintile 1, the negative response is strongly significant.

[Insert Table 20]

Table 20 provides additional evidence of initial bond market reaction to earnings surprises by regressions. Specifically, we regress short-window bond returns on the coded SUE ranks (based on 20 sorting). Column (1) shows the result for a regression of the magnitude of earnings surprises (SUE) in the current quarter on the magnitude of SUE from the prior quarter. The significant positive coefficient of 0.1535 suggests that SUE measures are positively serial correlated, which is consistent with Chan, Jegadeesh, and Lakonishok (1996) who find that security analysts' earnings forecasts also respond sluggishly to past news. Column (2) further confirms that a firm's SUE ranking are serial correlated. Column (4) confirms our mean test finding that bond market responds significantly to earnings surprises. The estimate of the coefficient on RSUE, the coded SUE ranking variable is 0.21 and statistically significant.

Overall, both the mean test and regression results suggest that both positive and negative earnings surprises have informational content for the bond market so that bond prices react strongly to earnings surprises. Our results compliments Easton et al (2009) who find that the incidence of bond market trading volume is strongly responsive to earnings surprises, suggesting the information content of earnings announcement announcements is significant to bond market.

3.3.2 Initial Reaction to Earnings News by Firm Riskiness

To assess the impact of earnings surprises to firms with different risk level, we separate sample firms into investment and noninvestment grade firms. Specifically, bonds are designated as "investment grade" if rated BBB or better by Standard & Poor's (or Baa or better by Moody's), or as "noninvestment grade" otherwise. A firm is rated by the highest rating of all its bonds. Within each of the two credit risk group, we then sort stocks into portfolios based on the level of earnings surprise (SUE) each calendar quarter.

[Insert Table 21]

The means tests results are presented in Table 21 and Table 22, which are based on decile sorting and vigintile sorting respectively. We find that both investment and speculative grade bond are strongly responsive to earnings surprises. However, the magnitude of absolute return responses is larger for non-investment grade firm, especially to positive earnings surprises. Actually, noninvestment grade bonds are responsive to both positive and negative earnings surprises, while investment grade bonds are only responsive to negative earnings surprises. Specifically, in Table 3 the standardized abnormal return (SABR) is -0.1772 to negative earnings surprises in investment grade firms and -0.1627 in noninvestment grade firms. For positive earnings surprise, the mean SABR is 0.4285 for noninvestment grade firm and statistically significant while there is no indication of significant response in investment-grade firms.

In addition, the absolute magnitude of earnings surprises for the extreme portfolios are also much larger in the riskier firms. The mean SUE for negative surprises is only -.4% for investment grade firms but is -9.26% for noninvestment grade firms. Likewise, the mean SUE for positive earnings surprises is only .63% for investment grade firms and 3.87% for noninvestment grade firms. This result suggests that the information is more ambiguous for analysts to forecast the performance of riskier firms.

[Insert Table 22]

Table 22 suggests that the returns pattern we find in Table 21 is not affected by vigintile sorting on SUE. We find significantly negative responses to negative earnings surprises for both investment-grade and noninvestment-grade bonds. In contrast, only noninvestment-grade bonds are sensitive to positive earnings surprises.

Table 20 provides more results via regression approach. Column (3) suggests that while ranking of SUE is positively correlated, but the negative coefficient estimation on the interaction term of last quarter's SUE ranking (RSUE_last) and RISK suggests that correlation is reduced for riskier firms. This may suggest that riskier firms' performance is less persistent compared to low risk firms and that analysts' forecast is less consistent. Column (5) confirms the finding of our mean test that bond market reaction to earnings surprises is stronger for noninvestment grade firms. The estimated coefficient on the interaction term of RSUE and RISK is 0.299 and statistically significant.

We interpret these results as consistent with the implications of bond's nonlinear payoff structure. In general, a negative earnings surprise aggravates the concern of default and thus causes negative bond price response, while a large positive earnings surprise may resolve or alleviate uncertainty about a firm's financial distress and therefore move bond prices upward. However, since bond payoff is capped above, for a firm with stable financial condition, there is little concern about default and therefore a positive earnings surprise is not that valuable for investors. On the other hand, for a financially risky firm, both good and bad news convey relevant information to change expectations of default risk. As such, bond prices respond strongly to both negative and positive surprises for risky firms.

3.4 Bond Market Post-Earnings Announcement Drift

3.4.1 Post-announcement drift in bond market

We have provided evidence that earnings news has significant information content for bond market, we then explore whether and to what extent there exists post-earnings announcement drift in the bond market. Exploring bond market PEAD gives the opportunity to examine the bond market efficiency. We first conduct means tests to determine if subsequent bond cumulative abnormal returns drift in the same direction with earnings surprises.

[Insert Table 23]

Table 23 reports the overall results from means tests. We find evidence of post earnings announcement drift, which is concentrated after extreme positive earnings surprises. To save space, we only report results for standardized abnormal returns (SABRs) and the results for abnormal standardized return are qualitatively unchanged. The SABR over 4 days to 10 days subsequent to earnings announcement is 0.0918 and statistically significant for extreme positive decile and continue to be significant for returns until one-month and one-quarter after the announcement date. In contrast, there is little evidence of post-announcement drift following negative earnings surprises.

We then examine the short-window abnormal returns around the subsequent earnings announcement. Bernard and Thomas (1989) suggest that if market prices fail to reflect the full implications of current quarterly earnings for future quarterly earnings, then the full implications of quarter t earnings might not be assimilated until (in the extreme) earnings for quarter t+1 are announced. We identify SUE ranks based on SUE from quarter t, and then examine the bond market reaction to announcement of quarter t+1 earnings.

[Insert Table 24]

Table 6 column (1)-(3) summarizes the results for short-window abnormal return around subsequent earnings announcements for overall bonds. We find that bond returns around subsequent earnings announcement date largely confirms the pattern with longer-window bond abnormal result from Table 23, in that post-announcement drift is driven by drifts following positive earnings surprises. Specifically, the short-window standardized abnormal return (SABR {-3,+3}) is 0.1 and statistically significant for positive earnings surprises but there is no indication for negative earnings surprises.

These results may suggest that bond market reaction to earnings surprises is relatively more complete and immediate for negative earnings surprises than for positive earnings surprises.As a result, there is little evidence of post-announcement drift following negative earnings surprises but indication of post-announcement drift following positive earnings surprises.

3.4.2 Post-announcement drift and firm risk

To assess the potential difference in post-announcement return pattern for lower-rated and higher-rated firms, we partition firms into investment and non-investment firms and present results from means tests in Table 23. We find that the absolute magnitude of post-earnings announcement drift is greater for speculative grade firms, and the drift is still concentrated in drifts following positive earnings surprises. Among non-investment grade firms, the firm-level bond return SABR over 4 days to 10 days subsequent to earnings announcement date is 0.1254 following positive earnings surprises and continues to be significantly positive over one quarter subsequent to earnings announcement. In contrast, the corresponding SABR is only 0.0651 for (4,10) and just marginally significant for investment grade firms.

Table 24 column (4) through (6) present the mean short-window returns (SABR {-3,+3}) around subsequent earnings announcement. We show that short-window returns around subsequent earnings announcement are significant for speculative grade firms but not for investment grade firms. Combined, the post-announcement drift in the bond market is driven by incomplete initial response to positive earnings announcement among speculative-grade firms.

[Insert Table 26]

Table 26 provides supplemental results for longer-window abnormal returns via regression approach. The positive coefficient estimation on the coded SUE rank (RSUE) of 0.0399 from the regression of SABR (4,10) and 0.0497 from the regression of SABR (4, 63) suggest that post-earnings announcement bond return drift in the same direction of earnings surprises. The interaction term of SUE ranking (RSUE) and RISK is positive but insignificant. Table 2 column (6) through (10) presents additional results for short-window returns around subsequent earnings announcement date. Column (6) suggests that short-window return around subsequent announcement date is significantly positively correlated with earnings rank determined in current quarter. However, Column (7) suggests that the impact of prior quarter's earnings information is subsumed by current quarter's information, as the estimated coefficient on Rsue_last becomes insignificant when Rsue is included. And consistent with our above finding, the short window return is stronger in absolute value for riskier firms.

Overall, we find evidence of post-earnings announcement drift in the bond market. And the drift is driven by drift following positive earnings surprises particularly among speculative-grade firms. Combined with the finding that initial reaction to positive earnings surprises are observed for only speculative-grade firms, this finding suggests that initial responses of speculative-grade firms to positive earnings surprises are not complete.

3.5 Stock Market Reaction to Earnings Announcement and PEAD

We have shown that the bond market is strongly responsive to earnings surprises and that there is evidence of post-announcement drift in the market. In this section, we check the robustness of equity market PEAD during our sample period and for sample firms with matched bonds.

We examine equity market PEAD by regression post-announcement return on the coded SUE rank variable and RISK dummy. We calculate cumulative abnormal returns starting from 3 days (day +3) after the current quarter's earnings announcement until the day after the next earnings announcement, which is typically adopted by the extant PEAD literature (Livnat and Menhenhall (2006)).

[Insert Table 27]

Table 27 summarizes the results for equity market PEAD. Not surprisingly, there is significant evidence of post-earnings announcement drift for all common stocks during our sample period 2005 to 2011. The estimated coefficient on coded SUE rank (Rsue) is 0.0119 and statistically significant. However, there is no indication of drifts for firms with matched bonds. The estimated coefficient on RSUE for regression (1) is

0.002 and statistically insignificant, and regression (2) shows that firm riskiness does not affect the extent of post-announcement equity return patterns.

This finding suggests that the stock price adjustment to earnings surprises is efficient for matched firms and thus there is no evidence of post-announcement drift. As such, firms with matched bonds seem to have a good information assimilation environment. Then the evidence of PEAD in the bond counterparty might be caused by the substantial transaction costs and illiquidity that inhibit a complete and immediate response to earnings news.

3.6 Bond market PEAD and Liquidity

Since we suspect that bond market PEAD is driven by the relative illiquidity of bond market. In this section, we conduct additional tests to investigate whether bond market PEAD is affected by bond liquidity. We investigate how post-announcement bond return pattern differs with varying degree of liquidity, where the liquidity of a bond and in turn its issuer is determined based on trading activities of the bond.

To measure the liquidity, we calculate the daily average trade size. We first calculate the total trade size and total days of a bond over the entire period from the first day the bond trades to the last day (including days that a bond does not trade). We then divide the total trade size by total days as the average trade size per day. For a firm with multiple bond issuances, we take the mean of the daily average trade sizes across its bonds. After a firm has be determined the daily average trade size and matched with earnings surprises, we then partition firms into two groups with high versus low trading activity.

[Insert Table 28]

Table 28 provides results for means tests on post-announcement return patterns based on liquidity partition within investment- and noninvestment- grade firms. Panels A and B present means tests results for high versus low liquidity firms within investment-grade firms, and Panels C and D present results for high versus low liquidity firms within noninvestment-grade firms. We find that after controlling for firms' riskiness, bond returns have greater drifts for those with lower liquidity. According to Panels A and B, the standardized bond return SABR (4, 10) is 0.2288 and statistically significant and SABR (4, 21) is 0.103 and marginally significant following positive earnings surprises for lower liquid firms while it is not significant for higher liquid firms. Panels C and D indicate that the PEAD for speculative-grade firms is largely driven by those with low liquidity. The SABR (4, 21) for low liquid firms is 0.1976 and statistically significant while it is insignificant for higher liquid firms. The SABR (4, 63) is 0.164 and statistically significant.

Overall, the tests provide some supportive evidence to our argument that bond market PEAD is driven by its relative illiquidity than equity market. This evidence is robust even after controlling for firm riskiness.

4. Conclusion

The phenomenon that post-earnings announcements returns tend to drift in the same direction as the earnings surprises (PEAD) has been documented as a robust and persist equity market anomaly. However, in light of the difficulties faced by researcher as to data availability and implementable methodologies specific to bond market, research has not yet investigated whether and to what extent there is a PEAD in the bond market. Examining the bond return behavior at earnings announcements and post-announcements provides a good opportunity to examine the sensitivity of bond market to certain kind of value-relevant information as well as the extent of bond market efficiency.

In this paper, we utilize a comprehensive record of daily transactions for OTC bonds from TRACE, and apply bond event study methodologies developed by Bessembinder et al (2009) and Ederington et al (2012) to investigate how cross-sectional bond return behaves around earnings announcements and find three major findings. First, bond prices respond positively to positive earnings surprises and negatively to negative earnings surprises, and both reactions are statistically significant, suggesting earnings news has information content for the bond market. Second, there is indication of post-announcement drifts, which is driven by positive earnings surprise among speculative-grade firms. The evidence of a slightly delayed response to positive surprises is consistent with the implication of non-linear payoff structure of bonds. Third, we find evidence of post-announcement drift in the bond market which is not observed for equity returns for the matched sample of firms with bond returns. This finding may suggest that bond market efficiency is limited by its considerable illiquidity, unlike its equity counterparty. We justify this argument by showing that bond PEAD exists in less liquid firms.

Reference

Aggarwal, Reena, 2003, Allocation of initial public offerings and flipping activity, *Journal of Financial Economic* 68,111-135.

Altinkilic, Oya and Robert S. Hansen, 2003, Discounting and underpricing in seasoned equity offers, *Journal of Financial Economics* 69, 285–323.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Ball, R.; and P. Brown.1968. "An Empirical Evaluation of Accounting Income Numbers", Journal of Accounting *Research* 6, 159-178.

Barber, B., and J. Lyon. 1997. Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. Journal of Financial Economics 43:341–72.

Bartov, E., S. Radhakrishnan, and I. Krinsky. 2000. "Investor sophistication and patterns in stock returns after earnings announcements". The Accounting Review 75, 43–63.

Baron, David P., 1982, A model of the demand for investment banking advising and distribution services for new issues, *Journal of Finance* 37, 955–976.

Battalio, R. and R. Mendenhall. 2006."Post-Earnings Announcement Drift: Timing and Liquidity Costs." working paper, University of Notre Dame.

Beatty, Randolph P., and Jay R. Ritter, 1986, Investment banking, reputation, and the underpricing of initial public offerings, *Journal of Financial Economics* 15, 213–232.

Benveniste, Lawrence M., and Paul A. Spindt, 1989, How investment bankers determine the offer price and allocation of new issues, *Journal of Financial Economics* 24, 343–361.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring abnormal bond performance, *Review of Financial Studies* 22, 4219–4258.

Bessembinder, Hendrik, William F. Maxwell, and Kumar Venkataraman, 2006, Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds, *Journal of Financial Economics* 82, 251-288.

Bessembinder, H., and W. F. Maxwell, 2008. "Markets: Transparency and the Corporate Bond Market," *Journal of Economic Perspectives*22, 217-234.

Bernard, V. L., and J. K. Thomas. 1989. "Post-Earnings-Announcement-Drift: DelayedPrice Response or Risk Premium."*Journal of Accounting Research* 27 (supplement):1-36.

Bhushan, R. 1994. "An Informational Efficiency Perspective on the Post-Earnings-Announcement Drift."*Journal of Accounting and Economics* 18: 45-65.

Billingsley, R. S., and T. Kovacs. 2011. The 2008 short sale ban: Liquidity, dispersion of opinion, and the cross-section of returns of US financial stocks. Journal of Banking & Finance 35.9: 2252-2266

Boehmer, E., J. Musumeci, and A. B. Poulsen. 1991. Event-study methodology under conditions of event induced variance. Journal of Financial Economics 30:253–72.

Brown, S., and J. Warner. 1980. Measuring security price performance. Journal of Financial Economics 8:205– 58.

Brown, S., and J. Warner. 1985. Using daily stock returns: The case of event studies. Journal of Financial Economics 14:3–31.

Biais, Bruno, Peter Bossaerts, and Jean-Charles Rochet, 2002, An optimal IPO mechanism, *Review of Economic Studies* 69, 117-146.

Cai, Nianyun, Jean Helwege, and Arthur Warga, 2007, Underpricing in the corporate bond market, *Review of Financial Studies* 20, 2021–2046.

Campbell, J. Y., A. W. Lo, and A. C. MacKinlay. 1997. The Econometrics of Financial Markets, Princeton University Press, Princeton, New Jersey.

Campbell J.Y. and G. B. Taksler, 2003."Equity Volatility and Corporate Bond Yields," *Journal of Finance*58, 2321-2350.

Chan, L.K., N. Jegadeesh and J. Lakonishok, 1996, "Momentum Strategies," *Journal of Finance*51, 1681-1713.

Chemmanur, Thomas J., 1993, The pricing of initial public offerings: A dynamic model with information production, *Journal of Finance* 48, 285–304.

Charest, G. 1978. Dividend information, stock returns, and market efficiency. Journal of Financial Economics 6:265-96.

Chava, S., R. Ganduri, and C. Ornthanalai. 2012. Are credit ratings still relevant? Working paper available on SSRN.

Chordia, T., R. Roll, and A. Subrahmanyam, 2008, "Liquidity and Market Efficiency", *Journal of Financial Economics* 87, 249-268.

Chordia T., Goyal A., Sadka G., Sadka R. and Shivakumar L. (2009), "Liquidity and the postearnings-announcement-drift*", Financial Analysts Journal* 65, 18-32.

Clayton, M. 2011. The valuation effect of IPOs: evidence from the bond market. Working paper available on SSRN.

Cook, D. and J. Easterwood. 1994. Poison put bonds: An analysis of their economic role. Journal of Finance 49: 1905-1920.

Corwin, Shane, 2003, The determinants of underpricing for seasoned equity offers, *Journal of Finance* 58, 2249–2279.

Datta, Sudip, Mai Iskandar-Datta, and Ajay Patel, 1997, The pricing of initial public offers of corporate straight debt, *Journal of Finance* 52, 379–96.

Datta, S., and U. S. Dhillon, 1993, “Bond and Stock Market Response to Unexpected Earnings Announcements”,*Journal of Financial and Quantitative Analysis*28, 565-577.

DeFond, M. and J. Zhang. 2008. The information content of earnings surprises in the corporate bond market. Working paper available on SSRN.

DeFond, M. and J. Zhang. 2014. The timeliness of the bond market reaction to bad news earnings surprises. forthcoming Contemporary Accounting Research.

Deng, X., J. Kang, and B. S. Low. 2013. Corporate social responsibility and stakeholder value maximization: Evidence from mergers. *Journal of Financial Economics* 110.1: 87-109.

Dick-Nielsen, Jens, 2009, Liquidity biases in TRACE, *Journal of Fixed Income* 19, 43–55.

Dick-Nielsen, Jens, Peter Feldhutter, David Lando, 2012, Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics* 103, 471–492.

Downing, C., S. Underwood, and Y. Xing, 2009, “The Relative Informational Efficiency of Stocks and Bonds: An Intraday Analysis”, *Journal of Financial and Quantitative Analysis* 44, 1081-1102.

Doyle,J. T., R. J. Lundholm and M.T. Soliman. 2006. “The Extreme Future Stock Returns Following I/B/E/S Earnings Surprises.” *Journal of Accounting Research*44, 849-887.

Eckbo, Espen B., Ronald W. Masulis, and Oyvind Norli, 2007, Security Offerings, published in: *Handbook of Corporate Finance: Empirical Corporate Finance*, edited by B. Espen Eckbo, North Holland, Amsterdam, 233–373.

Edelen, Roger.M., and Gregory B. Kadlec, 2005, Comparable-firm returns, issuer surplus, and the pricing and withdrawal of IPOs, *Journal of Financial Economics* 77, 347–373

Easton, P.D., S.J .Monahan, and F. Vasvari. 2009. Initial evidence on the role of accounting earnings in the bond market. Journal of Accounting Research 47: 721-766.

Ederington, Louis H., 1974, The yield spread on new issues of corporate bonds, *Journal of Finance* 29, 1531–43.

Ederington, L., W. Guan, and P. Yadav. 2014. Dealer Spreads in the Corporate Bond Market: Agent vs. Market-Making Roles, working paper available on SSRN.

Ederington, Louis H., Wei Guan, and Lisa Z. Yang, 2014, Bond market event study methodology, Working paper, University of Oklahoma.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate bond market transaction costs and transparency, *Journal of Finance* 62, 1421–1451.

Easton, P.D., S.J .Monahan, and F. Vasvari.2009, "Initial Evidence on the Role of Accounting Earnings in the Bond Market", *Journal of Accounting* 47, 721-766.

Edwards, A., L. Harris, and M. Piwowar. 2007. Corporate bond market transactions costs and transparency. Journal of Finance 62:1421–51.

Ellul, Andrew, and Marco Pagano, 2006, IPO underpricing and after-market liquidity, *Review of Financial Studies* 19, 381–421.

Ellul, A., C. Joptikasthira, and C. Lundblad. 2011. Regulatory pressure and fire sales in the corporate bond market. Journal of Financial Economics 101.3: 596-620.

Gao, Y., S. Liao, and X. Wang. 2011. The economic impact of the Dodd Frank Act of 2010: evidence from market reaction to event surrounding the passage of the act. Working paper available on SSRN.

Fang, Lily, 2005, Investment bank reputation and the price and quality of underwriting services, *Journal of Finance* 60, 2729 – 2761.

Fernando, Chitru S., Vladimir A. Gatchev, and Paul A. Spindt, Wanna Dance? How Firms and Underwriters Choose Each Other, *Journal of Finance* 60, 2437–2469.

Frankel, Richard, S. P. Kothari, and Joseph Weber, 2006. Determinants of the informativeness of analyst research. *Journal of Accounting and Economics* 41, 29–54.

Fung, W. K. H., and Andrew Rudd, 1986. Pricing new corporate bond issues: An analysis of issue cost and seasoning effects. *Journal of Finance* 3, 633–643.

Goldreich, David, Bernd Hanke, Purnendu Nath, 2005, The price of future liquidity: Time-varying liquidity in the U.S. Treasury market, *Review of Finance* 9, 1–32.

Grinblatt, Mark, and ChuanYang Hwang, 1989, Signaling and the pricing of new issues, *Journal of Finance* 44, 393-420.

Goldreich, David, 2007, Underpricing in discriminatory and uniform-price treasury auctions, *Journal of Financial and Quantitative Analysis* 42, 443–466

Goldstein, Michael, and Edith Hotchkiss, 2007, Dealer behavior and the trading of newly issued corporate bonds, Working paper, Babson College and Boston College.

Hand, J., R. Holthausen, and R. Leftwich. 1992. The effect of bond rating agency announcements on bond and stock prices. Journal of Finance 47:733–52.

Heckman, J. James, 1979, Sample selection bias as a specification error, *Econometrica* 47, 153–161.

Hotchkiss, Edith, and Tavy Ronen.2002.“The Informational Efficiency of the Corporate Bond Market: An Intraday Analysis”, *Review of Financial Studies* 15, 1325-1354.

Hwang, Franklin, and Gerald R. Faulhaber, 1989, Signaling by underpricing in the IPO market, *Journal of Financial Economics* 23, 303-324.

Jaffe, J. 1974. Special information and insider trading. Journal of Business 47 :410-428.

Jayaraman, N. P., and K. Shastri. 1988. The valuation impacts of specially designated dividends. Journal of Financial and Quantitative Analysis 23:301–12.

Klein, A., and E. Zur. 2011. The impact of hedge fund activism on the target firm’s existing bondholders. Review of Financial Studies 24: 1735-1771.

Kozhanov, Igor and Joseph P. Ogden, 2012, The pricing and performance of new corporate bonds: Sorting out underpricing and liquidity effects, Working paper, University at Buffalo−SUNY.

Kolari, J., and S. Pynnönen. 2010. Event study testing with cross-sectional correlation of abnormal returns. Review of Financial Studies 23: 3996-4025.

Kothari, S., and J. Warner. 2006. Econometrics of event studies. Chapter 1 in Handbook of Corporate Finance: Vol 1 Empirical Corporate Finance, E. Eckbo (ed.), Elsevier, North Holland.

Krigman, Laurie, Wayne H. Shaw, and Kent L. Womack, 1999, The persistence of IPO mispricing and the predictive power of flipping, *Journal of Finance* 54, 1015–1044.

Li, Kai and Nagpurnanand Prabhala, 2007, Self-selection models in corporate finance, published in Handbooks in Finance: Empirical Corporate Finance, edited by B. Espen Eckbo, North Holland, Amsterdam, 37-86.

Lindvall, John, 1977, New issue corporate bonds, seasoned market efficiency and yield spreads, *Journal of Finance* 32, 1057–67.

Liu, Xiaoding, and Jay R. Ritter, 2010, The economic consequences of IPO spinning, *Review of Financial Studies* 23, 2024–2059.

Ljungqvist, Alexander, 2004, IPO Underpricing, published in *Handbooks in Finance: Empirical Corporate Finance*, edited by B. Espen Eckbo, North Holland, Amsterdam, 375–422

Ljungqvist, Alexander, and William J. Wilhelm, 2003, IPO Pricing in the Dot-Com Bubble, *Journal of Finance* 58, 723-752.

Loughran, Tim, and Jay R. Ritter, 2004, Why has IPO underpricing increased over time? *Financial Management* 33, 5–37.

Lowry, Michelle, Micah S. Officer, and G. Willaim Schwert, 2010, The Variability of IPO initial returns, *Journal of Finance* 65, 425-465.

Livnat, J., and R. Mendenhall.2006. "Comparing Post-Earnings Announcement Drift for Surprises Calculated from Analyst and Time-Series Forecasts." *Journal of Accounting Research,* 44, 177-205.

Lyon, J. D., B. Barber, and C. Tsai. 1999. Improved methods for tests of long-run abnormal stock returns. Journal of Finance 53: 165-201.

Mandelker, G. 1974. Risk and return: The case of merging firms. Journal of Financial Economics 1: 303-335.

Marais, L., K. Schipper, and A. Smith. 1989. Wealth Effects of Going Private for Senior Securities. Journal of Financial Economics 23:155–91.

May, Anthony. 2010. The impact of bond rating changes on corporate bond prices: New evidence from the over-the-counter market. Journal of Banking and Finance 34: 2822-36.

Mendenhall, R. 2004."Arbitrage Risk and Post-Earnings-Announcement Drift."*Journal of Business*, 77, 875-894.

Michayluk, D. and R. Zhao. 2010. Stock splits and bond yields: isolating the signaling hypothesis. Financial Review 45: 375-386.

Muscarella, Chris J., and Michael R. Vetsuypens, 1989, A simple test of Baron's model of IPO underpricing, *Journal of Financial Economics* 24, 125–135.

Ng, J., T. Rusticus; and R. Verdi, 2008."Implications of Transaction Costs for the Post-Earnings Announcement Drift."*Journal of Accounting Research* 46, 661-696.

Patell, J. M. 1976. Corporate forecasts of earnings per share and stock price behavior: Empirical tests. Journal of Accounting Research 14:246-76.

Rees, L.; and W. Thomas. 2010. "The stock price effects of changes in dispersion of investor beliefs during earnings announcements." *Review of Accounting Studies* 15, 1-31.

Penman, S. 1982. Insider trading and the dissemination of firms' forecast information. Journal of Business 55:479–503.

Plunus, S., R. Gillet, and G. Hübner. 2012. Reputational damage of operational loss on the bond market: evidence from the financial industry. International Review of Financial Analysis 24:66-73.

Ritter, Jay R., and Ivo Welch, 2002, A review of IPO activity, pricing, and allocations, *Journal of Finance* 57, 1795–1828.

Rock, Kevin, 1986, Why new issues are underpriced, *Journal of Financial Economics* 15, 187–212.

Reuter, Jonathan, 2006, Are IPO allocation for sale? Evidence from the mutual fund industry, *Journal of Finance* 61, 2289–2324.

Ronen, T., and X. Zhou, 2008, "Where Did All The Information Go? Trade in The Corporate Bond Market", working paper, Rutgers University.

Wei J. and X. Zhou, 2012, "Informed Trading in Corporate Bonds Prior to Earnings Announcements", working paper.

Scholes, Myron S., 1972, The market for securities: Substitution versus price pressure and the Effects of information on share prices, *Journal of Business* 45, 179–211.

Smith, Clifford W. Jr., 1977, Alternative methods for raising capital: Rights vs. underwritten offers, *Journal of Financial Economics* 5, 273–307.

Sorensen, Eric H., 1982, On the seasoning process of new bonds: Some are more seasoned than others. *Journal of Financial and Quantitative Analysis* 42, 195–208.

Warga, A., and I. Welch. 1993. Bondholder losses in leveraged buyouts. Review of Financial Studies 6:959–82.

Weinstein, Mark I., 1978, The seasoning process of new corporate bond issues, *Journal of Finance* 33, 1343–54.

Wei, C., and D Yermack. 2011. Investor reactions to CEOs' inside debt incentives. Review of Financial Studies 24: 3813-40.

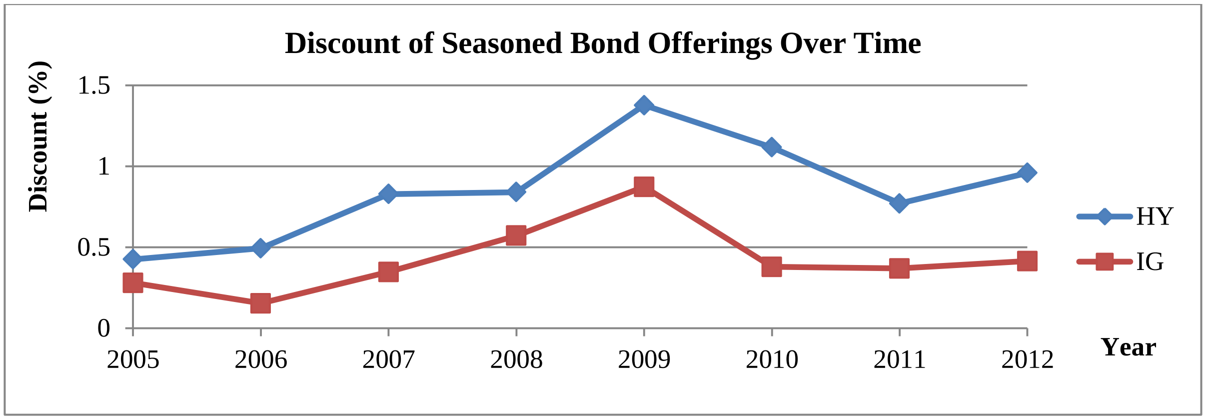
Wei, J. and X. Zhou. 2012. Informed trading in corporate bonds prior to earnings announcements. Working paper available on SSRN.

Welch, Ivo, 1989, Seasoned offerings imitation costs, and the underpricing of initial public offerings, *Journal of Finance* 44, 421-449.

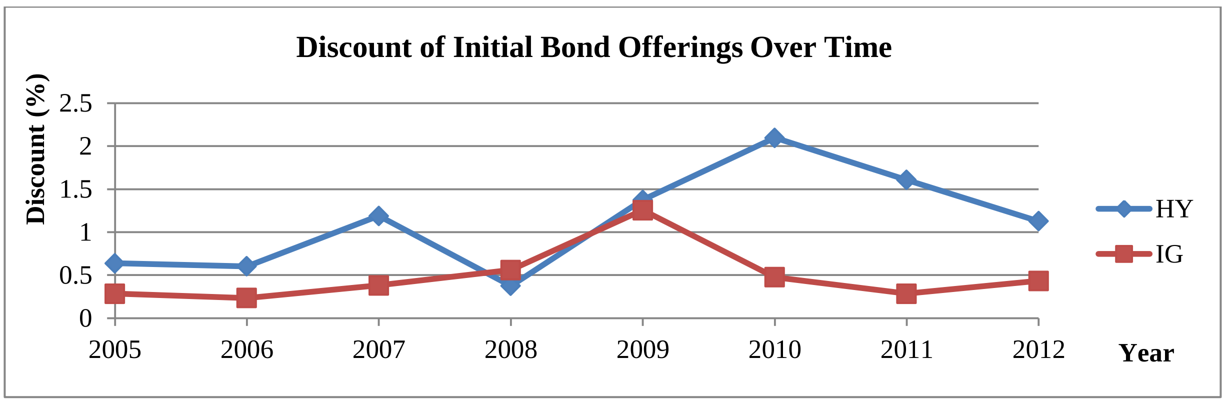
Yeoman, John C., 2001, The optimal spread and offering price for underwritten securities, *Journal of Financial Economics* 62, 169–198

Figure 1. Magnitude of Underpricing Measured as Discount (%) over Time

Panel A: Seasoned Bond Offerings



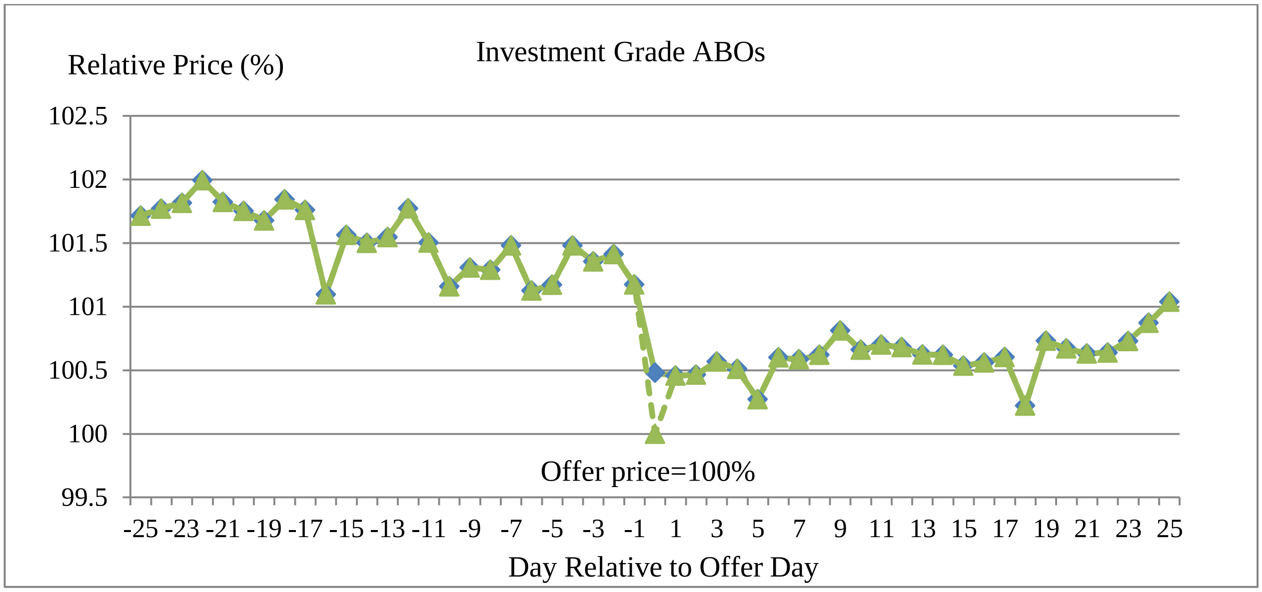
Panel B: Initial Bond Offerings



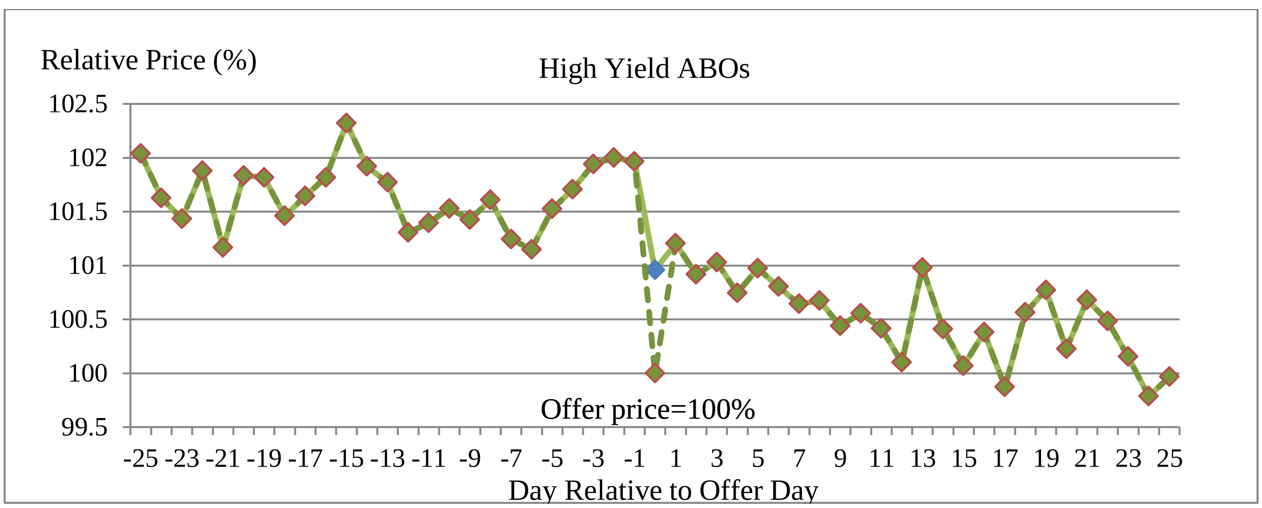
The figure plots corporate bond underpricing by year, from February 2005 through September 2012. *Discount* is calculated as the return from the offer price to the second-day average trade price on the post-offer secondary market. Initial bond offerings (IBOs) are bonds issued by firms with no publicly traded bonds outstanding. Seasoned bond offerings (SBOs) are bonds issued by firms with publicly traded bonds. The sample includes 2046 investment grade and 334 high yield issues that meet the sample restrictions described in Section 2.

Figure 2. Secondary Market Price Relative to Offer Price around Additional Bond Offerings

Panel A: Investment Grade Issues



Panel B: High Yield Issues



The figure plots relative bond price for additional bond offerings to an existing indenture (ABOs). *Relative Price* is measured as the weighted average secondary market trade price on day t (relative to issue date) expressed as a percentage of the offer price, adjusted by market movement based on same period rating-matched index returns. Both the offer price (dashed line) and secondary market price (solid line) are shown for the offer date. The sample includes 62 investment grade ABOs and 22 high yield ABOs that meet the sample restrictions described in Section 2.

Appendix: Tables

Table 1 Summary Statistics for Bond Offerings

Bond issues characteristics are reported for 2,380 corporate bond offerings from February 2005 through September 2012 that meet the sample restrictions described in Section 2. *Initial bond offerings (IBOs)* are bonds issued by firms with no publicly traded bonds outstanding. *Seasoned bond offerings (SBOs)* are bonds issued by firms with publicly traded bonds. *Additional bond offerings (ABOs)* are additional offerings to an existing indenture (with the same terms and CUSIP). Moody's rating is used if available; otherwise Standard &Poor's or Fitch rating is adopted. *Offer Amount* is the proceeds raised in the issue. *Existing debt outstanding* is the issuer's debt outstanding as of the day prior to the offer. *Relative offer size* is calculated as offer amount divided by total debt outstanding.

Panel A – Number of Observations

Maturity	N. Total	SBOs	IBOs	ABOs
1<=years to maturity <= 5	616	537	63	16
5 < years to maturity <= 10	1242	1089	110	43
Years to maturity > 10	522	473	24	25
Rating				
AA or above	211	179	22	10
A	842	770	52	20
BBB	1008	883	93	32
BB	186	160	18	8
B	123	98	12	13
CCC or below	10	9	0	1

Panel B – Summary Statistics : Investment Grade Issues

	SBOs (excl. ABOs) N=1832		IBOs N=167		ABOs N=62	
Variable	Mean	Median	Mean	Median	Mean	Median
Offer amount ($mil)	701.16	500.00	707.96	500.00	429.44	375.00
Years to maturity	11.96	10.00	10.32	10.00	15.52	10.00
Offer price	99.58	99.72	99.69	99.79	100.28	100.07
Existing bonds outstanding (mil)-firm level	6860.02	3379.23	0.00	0.00	11546.14	6350.00
Relative offer size (%)	33.57	16.74	.	.	10.59	6.67
N. lead managers	3.69	3.00	3.44	3.00	3.37	3.00
Gross spread (%)	0.57	0.60	0.58	0.6	0.62	0.65
Days from Pricing to Issue	0.45	0.00	0.53	0.00	0.53	0.00

Panel C – Summary Statistics : High Yield Issues

	SBOs (excl. ABOs) N=267		IBOs N=30		ABOs N=22	
Variable	Mean	Median	Mean	Median	Mean	Median
Offer amount ($mil)	527.46	450.00	383.50	350.00	179.86	150.00
Years to maturity	9.10	10.00	8.97	10.00	8.23	7.50
Offer price	99.29	100.00	99.43	100.00	101.77	101.78
Existing bonds outstanding (mil)-firm level	1991.41	1100.00	0.00	0.00	1876.53	1512.50
Relative offer size (%)	61.72	40.00	.	.	18.74	12.70
N. lead managers	3.68	3.00	3.10	3.00	2.55	1.00
Gross spread (%)	1.67	1.75	1.95	2.00	1.65	1.63
Days from Pricing to Issue	0.42	0.00	0.50	0.00	0.18	0.00

Table 2 Bond Underpricing by Issue Type

The table reports bond underpricing measures (discounts) for corporate bonds issued between February 2005 and September 2012. *IBOs* are Initial bond offerings, issued by firms with no publicly traded bonds; *SBOs* are seasoned bond offerings, issued by firms with publicly traded bonds; and *ABOs* are additional bond offerings to an existing indenture. Panel A reports investment grade issues and Panel B reports high yield issues, respectively. *Discount* is measured as the weighted average secondary market trade price on the first day or second day of trading minus the offer price expressed as a percentage of the offer price, where trade prices are weighted by trade size. *Adjusted Discount* is calculated by subtracting from the raw discount the same period index return corresponding to the same rating category. *Diff* is defined as difference between the discounts measured from the first trading day to the second trading day. T-statistics are given in parentheses below the mean value. The significance level of the median is based on a Wilcoxon signed-rank test. The difference in means T-statistic assumes unequal variances across groups when a test of equal variances is rejected at the 10 percent level. The significance level of the difference in medians is based on a Wilcoxon rank-sum test. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively.

	N.	SBOs Mean (%)	Median (%)	N.	IBOs Mean (%)	Median (%)	N.	ABOs Mean (%)	Median (%)
Panel A: Investment Grade Issues									
Discount – 1st day	1832	0.46***	0.28***	167	0.55***	0.35***	58	0.48***	0.28***
Discount – 2nd day	1729	0.58***	0.38***	154	0.59***	0.46***	58	0.45***	0.29***
Diff: 2nd – 1st day		0.12***	0.10***		0.04**	0.11**		-0.03	-0.01
Adj. Discount – 1st day	1832	0.46***	0.28***	167	0.52***	0.32***	58	0.48***	0.28***
Adj. Discount – 2nd day	1729	0.57***	0.37***	154	0.52***	0.36***	58	0.46***	0.18***
Diff Adj. 2nd – 1st day		0.11***	0.09***		0.00	0.04		-0.02	-0.04
Panel B: High Yield Issues									
Discount – 1st day	267	0.95***	0.77***	30	1.50***	1.33***	22	0.96***	0.88**
Discount – 2nd day	262	1.10***	0.87***	29	1.68***	1.72***	22	1.31***	1.14***
Diff: 2nd – 1st day		0.16***	0.10***		0.19**	0.39**		0.35**	0.26**
Adj. Discount – 1st day	267	0.93***	0.79***	30	1.45***	1.33***	22	0.96***	0.88***
Adj. Discount – 2nd day	262	1.04***	0.84***	29	1.60***	1.76***	22	1.20***	1.04***
Diff Adj. 2nd – 1st day		0.11***	0.05***		0.15*	0.43*		0.24*	0.16*

Table 3 Bond Underpricing by Issue Type and Trading Side

Underpricing measures based on investor sell and investor purchase prices are reported, respectively. *Investor Sell* is a trade from a non-dealer customer sell order (at the dealer bid price) and *Investor Buy* is a trade from a non-dealer customer buy order (at the dealer ask price). *IBOs* are initial bond offerings, issued by firms with no publicly traded bonds; *SBOs* are seasoned bond offerings, issued by firms with publicly traded bonds; and *ABOs* are additional bond offerings to an existing indenture. *Discount* is measured as the weighted average secondary market trade price (where trade prices are weighted by trade size) on the first day or second day of trading minus the offer price expressed as a percentage of the offer price. *Adjusted Discount* is calculated by subtracting from the raw discount the same period index return corresponding to the similar rating category. *Diff* is defined as difference between the discounts measured from the first trading day to the second trading day. Panels A and B report investment grade and Panels C and D report high yield offerings. T-statistics are given in parentheses below the mean value. The significance level of the median is based on a Wilcoxon signed-rank test. The difference in means T-statistic assumes unequal variances across groups when a test of equal variances is rejected at the 10 percent level. The significance level of the difference in medians is based on a Wilcoxon rank-sum test. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively.

Variable	SBOs N. Issues	SBOs N. Trades	SBOs Mean (%)	SBOs Median (%)	IBOs N. Issues	IBOs N. Trades	IBOs Mean (%)	IBOs Median (%)	ABOs N. Issues	ABOs N. Trades	ABOs Mean (%)	ABOs Median (%)
Panel A: Underpricing Measures Based on Investor Sell Prices – Investment Grade Issues												
Discount – 1st day	1662	22851	0.42***	0.24***	155	1994	0.53***	0.38***	56	755	0.44***	0.22***
Discount – 2nd day	1629	26385	0.51***	0.32***	142	2178	0.56***	0.44***	57	555	0.37***	0.17***
Diff: 2nd – 1st day			0.09***	0.08***			0.03**	0.06**			-0.07	0.05**
Adj. Discount – 1st day			0.42***	0.24***			0.50***	0.36***			0.43***	0.22***
Adj. Discount – 2nd day			0.49***	0.31***			0.48***	0.32***			0.47***	0.28***
Diff Adj. 2nd – 1st day			0.07***	0.07***			-0.02	-0.04			0.04**	0.06

Panel B: Underpricing Measures Based on Investor Purchase Prices – Investment Grade Issues

Discount – 1st day	1482	11747	0.51***	0.32***	134	1353	0.64***	0.42***	55	611	0.72***	0.40***
Discount – 2nd day	1634	28792	0.69***	0.46***	143	2498	0.69***	0.51***	55	2147	0.63***	0.38***
Diff: 2nd – 1st day			0.18***	0.14***			0.05	0.09			-0.09**	-0.02
Adj. Discount – 1st day			0.51***	0.33***			0.63***	0.37***			0.69***	0.40***
Adj. Discount – 2nd day			0.67***	0.45***			0.62***	0.42***			0.71***	0.37***
Diff Adj. 2nd – 1st day			0.16***	0.12***			-0.01	0.05			0.02	-0.03

Panel C: Underpricing Measures Based on Investor Sell Prices –High Yield Issues

Discount – 1st day	248	5941	0.90***	0.74***	29	685	1.46***	1.26***	20	142	0.79***	0.80***
Discount – 2nd day	254	5723	1.05***	0.80***	27	532	1.68***	1.66***	18	127	0.96***	1.00***
Diff: 2nd – 1st day			0.15***	0.06***			0.22***	0.40***			0.17	0.20***
Adj. Discount – 1st day			0.89***	0.73***			1.44***	1.26***			0.80***	0.77***
Adj. Discount – 2nd day			1.00***	0.80***			1.61***	1.65***			0.95***	0.88***
Diff Adj. 2nd –1st day			0.11***	0.07***			0.17***	0.39***			0.15	0.11***

Panel D: Underpricing Measures Based on Investor Purchase Prices –High Yield Issues

Discount – 1st day	233	3499	1.07***	0.96***	27	361	1.64***	1.46***	21	87	1.37***	1.03***
Discount – 2nd day	252	5843	1.20***	1.01***	29	369	1.78***	1.83***	19	143	1.56***	1.46***
Diff: 2nd – 1st day			0.13	0.05			0.14	0.37			0.19	0.43
Adj. Discount – 1st day			1.06***	0.97***			1.59***	1.46***			1.38***	0.97***
Adj. Discount – 2nd day			1.14***	0.97***			1.70***	1.80***			1.48***	1.33***
Diff Adj. 2nd –1st day			0.08	0.00			0.11	0.34			0.10	0.36

Table 4 Determinants of Underpricing

Results are reported from regressions of underpricing on explanatory variables proposed to test alternative hypotheses. The dependent variable is *Adjusted Discount. Discount* is measured as the weighted average secondary market trade price (where trade prices are weighted by trade size) on the second day of trading minus the offer price expressed as a percentage of the offer price. *Adjusted Discount* is calculated by subtracting from the raw discount the same period index return corresponding to the same rating category. *"A", "BBB", "BB", and "B and below"* are dummies, equal to one if an issue is rated as "A", "BBB", "BB", or "B and below", respectively by Moody's. *"5-10 Years"* and *"Above 10 Years"* are dummies, equal to one if an issue's maturity is between 5 to 10 years, and above 10 years, respectively. The omitted category is rated as "AA and Above" with maturity of 1-5 years. *"Call Option"* equals one if the issue has a call option built in. *"Rating Disagreement"* equals one if the specific issue is rated as investment grade by one rating agency but as speculative by another. *"Bond Price Volatility"* is defined as the standard deviation of daily bond price changes over the one month period after the offer. *"Days from Pricing to Issue"* measures the number of days between the day when offer is priced and the first day with trading. "*IBO"* equals one if the bond is issued by firms with no publicly traded bonds outstanding. "*Private Firm"* equals to one if the issuer has no publicly traded stocks. "*N. Analysts*" represents number of analysts following the issuing firm. "*MOVE Index"* is Merrill Lynch's measure of implied volatility of US Treasury markets. *"VIX index"* is CBOE's measure of the implied volatility of S&P 500 index options. *"Bid-Ask Spread"* measures the average of daily bid-ask spread over the one month period after the offer. *"Bid-Ask Volatility"* measures the standard deviation of daily bid-ask spread over the one month period after the offer. *"ABO"* is an indicator for additional offerings to an existing indenture. "*Relative offer size*" is calculated as offer amount divided by total debt outstanding of the issuer prior to the offer. Model (1) shows baseline analysis; Model (2) through (5) report tests for each alternative hypothesis and Model (6) reports the full set regression. Model (1) to (5), T-values are calculated from White's heteroscedasticity consistent standard errors. ***, ** indicate significance level at 1% and 5%, respectively.

Variable	(1) Baseline Analysis	(2)Uncertainty & Information Asymmetry	(3)Uncertainty & Information Asymmetry	(4) Liquidity	(5) Price Pressure	(6) Full set regression
Intercept	0.369***	-0.560***	-0.541***	0.250***	0.239***	-0.591***
	(6.62)	(-6.71)	(-5.61)	(5.14)	(4.47)	(-4.74)
A	0.073	0.112*	0.110*	0.089	0.142**	0.129*
	(1.22)	(2.28)	(2.21)	(1.73)*	(2.66)	(1.87)
BBB	0.229***	0.242***	0.233***	0.200***	0.192***	0.229***
	(3.65)	(4.66)	(4.36)	(3.74)	(3.51)	(3.07)
BB	0.666***	0.815***	0.819***	0.622***	0.519***	0.708***
	(7.37)	(10.14)	(9.99)	(7.44)	(5.94)	(7.21)
B and below	0.723***	0.812***	0.812***	0.678***	0.632***	0.729***
	(5.66)	(7.54)	(7.43)	(6.17)	(5.44)	(5.49)
5-10 Years	0.083*	0.050	0.047	0.072*	0.087*	0.039
	(1.87)	(1.17)	(1.09)	(1.70)	(1.97)	(0.98)
Above 10 Years	0.219***	0.179***	0.174***	0.205***	0.284***	0.212***
	(3.55)	(2.77)	(2.65)	(3.46)	(4.67)	(3.06)
Call Option	-0.139**	0.004	0.007	-0.082	-0.064	0.023
	(-2.41)	(0.07)	(0.14)	(-1.51)	(-1.14)	(0.36)
Rating Disagreement		0.093	0.094			0.100
		(0.65)	(0.65)			(0.51)
Bond Price Volatility		26.112**	27.387***			21.081**
		(2.49)	(2.55)			(2.25)
Days from Pricing to Issue		0.060***	0.060***			0.102***
		(2.80)	(2.77)			(2.53)
IBO		0.095	0.100*			
		(1.62)	(1.70)			
ABO		-0.011	-0.014			0.100
		(-0.13)	(-0.16)			(1.10)
Private Firm		-0.073				
		(-0.39)				
N.Analysts			-0.001			0.001
			(-0.68)			(0.46)
MOVE Index		0.002***	0.002**			0.001
		(2.08)	(2.00)			(0.96)
VIX Index		0.022***	0.022***			0.024***
		(6.13)	(6.05)			(5.52)
Bid-Ask Spread				78.177***		-15.412
				(3.86)		(-0.56)
Bid-Ask Volatility				-15.037		-2.069
				(-1.41)		(-0.21)
Relative Offer Amount					0.230***	0.226***
					(4.44)	(3.57)
N.	2256	2238	2222	2216	2072	2016
Adj R-square	0.055	0.177	0.178	0.068	0.066	0.186

Table 5 Post-Offering Trading Activities

Trading activity is reported for the first two trading days and the first week after issuance from February 2005 to September 2012. *Institutional* size trades are trades equal to or greater than 100 bonds ($100,000) and *retail* size trades are trades of fewer than 100 bonds. *Investor Sell* is a trade from a non-dealer customer sell order and *Investor Buy* is a trade from a non-dealer customer buy order. *IBOs* are initial bond offerings, issued by firms with no publicly traded bonds; *SBOs* are seasoned bond offerings, issued by firms with publicly traded bonds; and ABOs are additional bond offerings to an existing indenture. *N.Trades* is the aggregate number of trades during the day (week) and *Trade Size* (in millions) is the average daily (weekly) dollar trading volume. *Turnover* (%) is the average daily (weekly) dollar trading volume divided by the amount of the offer.

			1st Day			2nd Day			First Week-Total		
	Retail	Buy/Sell	N. Trades	Trade Size (Millions$)	Turnover (%)	N. Trades	Trade Size (Millions$)	Turnover (%)	N. Trades	Trade Size (Millions$)	Turnover (%)
Panel A: Investment Grade Bonds											
SBO	Institutional	Customer Sell	13.73	34.24	5.88	16.13	47.11	6.48	39.33	119.35	17.65
		Customer Buy	7.22	30.52	4.70	12.37	34.79	4.97	34.18	104.44	14.84
	Retail	Customer Sell	1.54	0.06	0.01	1.41	0.06	0.01	6.72	0.25	0.04
		Customer Buy	4.78	0.17	0.03	10.26	0.29	0.04	44.86	1.19	0.17
ABO	Institutional	Customer Sell	13.09	61.64	11.87	9.14	29.13	7.01	29.95	122.49	26.13
		Customer Buy	5.44	39.76	7.86	6.76	18.32	4.39	21.74	85.79	18.85
	Retail	Customer Sell	1.69	0.04	0.01	2.00	0.04	0.01	8.95	0.19	0.05
		Customer Buy	12.19	0.23	0.04	49.50	0.85	0.18	115.01	2.14	0.43
IBO	Institutional	Customer Sell	12.82	32.05	5.24	15.23	44.03	6.21	37.69	115.16	16.76
		Customer Buy	8.99	32.04	4.54	10.57	32.02	4.44	33.78	105.16	14.23
	Retail	Customer Sell	2.71	0.09	0.01	1.15	0.06	0.01	7.60	0.27	0.03
		Customer Buy	5.72	0.20	0.04	13.66	0.31	0.05	38.68	1.01	0.16
Panel B: High Yield Bonds											
SBO	Institutional	Customer Sell	23.89	56.33	12.74	22.51	50.14	9.07	59.15	139.62	27.90
		Customer Buy	12.28	36.15	7.52	15.94	102.46	22.18	42.09	166.81	34.94
	Retail	Customer Sell	1.70	0.04	0.01	1.81	0.08	0.02	7.46	0.27	0.06
		Customer Buy	30.38	0.85	0.09	18.03	0.51	0.08	82.17	2.24	0.33
ABO	Institutional	Customer Sell	7.78	14.60	9.12	7.12	17.42	6.54	22.08	47.51	25.44
		Customer Buy	2.95	5.39	3.34	5.18	10.30	7.07	16.13	27.64	19.00
	Retail	Customer Sell	1.00	0.01	0.04	1.50	0.04	0.03	7.94	0.21	0.21
		Customer Buy	2.82	0.06	0.05	6.11	0.13	0.08	28.76	0.64	0.31
IBO	Institutional	Customer Sell	23.59	439.49	110.55	19.41	37.44	11.15	54.29	501.00	129.53
		Customer Buy	12.89	338.93	85.17	11.96	29.61	8.81	33.94	393.35	100.59
	Retail	Customer Sell	1.00	0.03	0.00	1.60	0.08	0.02	6.10	0.22	0.07
		Customer Buy	6.50	0.26	0.09	4.86	0.21	0.05	41.00	1.51	0.35

Table 6 Summary Statistics for Bond Offerings of Financial Firms

Offer characteristics are reported for 1186 financial firm bond offerings from February 2005 through September 2012 that meet the sample restrictions described in Section 2. *IBOs* are initial bond offerings, issued by firms with no publicly traded bonds; *SBOs* are seasoned bond offerings, issued by firms with publicly traded bonds; and ABOs are additional bond offerings to an existing indenture. Moody's rating is used if it is available; otherwise Standard &Poor's or Fitch rating is adopted. *Offer Amount* is the proceeds raised in the issue. *Existing debt outstanding* is issuer's debt outstanding as of the day prior to the offer. *Relative offer size* is calculated as offer amount divided by total debt outstanding. *Self-marketed* refers to bond issues where banks serve as lead managers while marketing their own bond offerings and *Non Self- marketed* issues are managed by other banks.

Panel A N. Observations

Maturity	N.	SBOs	IBOs	ABOs
1<=years to maturity <= 5	494	423	21	50
5 < years to maturity <= 10	478	408	24	46
Years to maturity > 10	214	197	5	12
Rating				
AA or above	441	387	9	45
A	520	453	21	46
BBB	194	163	20	11
BB	14	12	0	2
B	16	12	0	4
CCC or below	1	1	0	0

Panel B: Investment Grade, Non self-marketed

	SBOs (excl. ABOs) N=536		IBOs N=42		ABOs N=41	
Variable	Mean	Median	Mean	Median	Mean	Median
Offer amount ($mil)	700.10	500.00	532.74	500.00	384.27	250.00
Years to maturity	9.88	10.00	8.95	10.00	7.54	5.00
Offer price	99.63	99.81	99.62	99.78	101.09	100.43
Existing bonds outstanding (billion)-firm level	40.629	5.356	0.00	0.00	139.483	17.756
Relative offersize (%)	24.45	11.70	.	.	3.79	0.76
N. lead managers	2.98	3.00	3.07	2.50	1.88	1.00
Days from Pricing to Issue	0.83	0.00	0.33	0.00	0.22	0.00

Panel C: Investment Grade, Self-marketed

	SBOs (excl. ABOs) N=467		IBOs N=8		ABOs N=61	
Variable	Mean	Median	Mean	Median	Mean	Median
Offer amount ($mil)	844.96	550.00	906.25	875.00	599.90	350.00
Years to maturity	9.56	7.00	12.00	7.50	9.95	9.00
Offer price	99.85	99.97	99.78	99.83	101.14	100.81
Existing bonds outstanding (billion)-firm level	98.276	87.089	0.00	0.00	115.261	102.105
Relative offersize (%)	6.75	5.93	.	.	2.11	0.70
N. lead managers	1.34	1.00	1.63	1.50	1.21	1.00
Days from Pricing to Issue	0.23	0.00	0.63	0.00	0.00	0.00

Table 7 Self-marketed Vs Non Self- marketed Seasoned Bond Issues

The table reports underpricing of investment grade seasoned bond issues by financial firms from February 2005 through September 2012. *Self-marketed* refers to bond issues where banks serve as lead managers while marketing their own bond offerings and *Non Self-marketed* issues are managed by other banks. *Discount* is measured as the weighted average secondary market trade price on the second day of trading minus the offer price expressed as a percentage of the offer price, where trade prices are weighted by trade size. *Adjusted Discount* is calculated by subtracting from the raw discount the same period index return corresponding to the same rating category. T-statistics are given in parentheses below the mean value. The significance level of the median is based on a Wilcoxon signed-rank test. The difference in means T-statistic assumes unequal variances across groups when a test of equal variances is rejected at the 10 percent level. The significance level of the difference in medians is based on a Wilcoxon rank-sum test. ***, **, and * indicate significance level at 1%, 5%, and 10% respectively.

Variable	N	Mean (%)	Median (%)
Discount – 1st day			
Non Self-Marketed	519	0.35***	0.18***
Self-Marketed	405	0.08***	0.01***
Diff: Non Self - Self		0.27***	0.17***
Adj. Discount – 1st day			
Non Self-Marketed	519	0.36***	0.19***
Self-Marketed	405	0.08***	0.01**
Diff: Non Self - Self		0.28***	0.18***
Discount – 2nd day			
Non Self-Marketed	489	0.43***	0.23***
Self-Marketed	273	0.23***	0.14***
Diff: Non Self - Self		0.20***	0.09***
Adj. Discount – 2nd day			
Non Self-Marketed	489	0.46***	0.27***
Self-Marketed	273	0.20***	0.15***
Diff: Non Self - Self		0.26***	0.12***

Table 8 Self-marketed Vs Non Self-marketed Bond Issues

The table reports OLS regression of investment grade financial seasoned bond offerings for public firms only. The dependent variable is *Adjusted Discount*. *Discount* is measured as the weighted average secondary market trade price on the second day of trading minus the offer price expressed as a percentage of the offer price, where trade prices are weighted by trade size. *Adjusted Discount* is calculated by subtracting from the raw discount the same period index return corresponding to the similar rating category. *"A" and "BBB"* are dummies, equal to one if an issue is rated as "A" or "BBB", respectively. *"5-10 Years"* and *"Above 10 Years"* are dummies, equal to one if an issue's maturity is between 5 to 10 years or above 10 years, respectively. The omitted category is rated as "AA and Above" with maturity of 1-5 years. *"Call option"* equal to one if the issue has a call option built in. *"Rating Disagreement"* equals to one if the specific issue is rated as investment grade by one rating agency but as speculative by another. *"Bond Price Volatility"* is defined as the standard deviation of daily bond price changes over the one month period after the offer. *"Days from Pricing to Issue"* measures how many days in between the day when offer is priced and the first day with trading. "*N. Analysts*" represents number of analysts following the issuing firm. "*MOVE Index"* is Merrill Lynch's measure of implied volatility of US Treasury markets. *"VIX index"* is CBOE's measure of the implied volatility of S&P 500 index options. "*Relative offer size*" is calculated as offer amount divided by total debt outstanding of the issuer prior to the offer. *"Bid-Ask Spread"* measure the average of daily bid-ask spread over the one month period after the offer. *"Bid-Ask Volatility"* measure the volatility of daily bid-ask spread over the one month period after the offer. "*Self-Marketed*" equals to one if the issuer is one of the lead underwriters. "*Year2009*" equals one if the issue date is between Oct, 2008 and Oct 2009. T-values are calculated from White's heteroscedasticity consistent standard errors. ***, **,* indicate significance level at 1%, 5%, and 10%, respectively.

Variable	Coefficient	t Value
Intercept	-0.305**	-1.98
A	0.171***	2.84
BBB	0.395***	3.88
5-10 Years	0.095	1.44
Above 10 Years	0.312**	2.26
Call Option	-0.186	-1.64
Rating Disagreement	-0.053	-0.94
Bond Price Volatility	17.598	1.12
Days from Pricing to Issue	-0.031	-0.56
N.Analysts	-0.003	-1.04
MOVE Index	0.003	1.55
VIX Index	0.015**	2.18
Relative Offer Amount	0.106	1.31
Bid-Ask Spread	-10.769	-0.44
Bid-Ask Volatility	-40.799*	-1.86
Self-Marketed	-0.137***	-2.57
Year2009	0.084	0.57
N.	617	
Adj R-square	0.151	

Table 9 Decision to Self-Market

The table reports the results for the switching regressions. Panel A presents the Probit estimation results for the self-market decision for public firms only. The dependent variable is a binary variable equaling one if the issuer serves as one of the lead managers of the issue and zero otherwise. Panel B reports the second stage switching model, where the inverse Mills ratio derived from the first stage is included to control for the decision to self-underwriting and the dependent variable is *Adjusted Discount*. *Discount* is measured from offer price to the weighted price from the second day of trading, where prices are weighted by trade size. *Adjusted Discount* is calculated by subtracting from the raw discount the same period index return corresponding to the similar rating category. Panel C compares the means of actual underpricing with their counterfactuals derived from the switching model. "*Possibility of Self-Underwriting*" equals one if the financial issuer is a commercial or investment bank who has investment banking as its one of its major business. *"A" and "BBB"* are dummies, equal to one if an issue is rated as "A" or "BBB", respectively. *"5-10 Years"* and *"Above 10 Years"* are dummies, equal to one if an issue's maturity is between 5 to 10 years or above 10 years, respectively. *"Call option"* equal to one if the issue has a call option built in. *"Rating Disagreement"* equals to one if the specific issue is rated as investment grade by one rating agency but as speculative by another. *"Bond Price Volatility"* is defined as the standard deviation of daily bond price changes over the one month period after the offer. *"Days from Pricing to Issue"* measures how many days in between the day when offer is priced and the first day with trading. "*N. Analysts*" represents number of analysts following the issuing firm. "*MOVE Index"* is Merrill Lynch's measure of implied volatility of US Treasury markets. *"VIX index"* is CBOE's measure of the implied volatility of S&P 500 index options. "*Relative offer size*" is calculated as offer amount divided by total debt outstanding of the issuer prior to the offer. *"Bid-Ask Spread"* measure the average of daily bid-ask spread over the one month period after the offer. *"Bid-Ask Volatility"* measure the volatility of daily bid-ask spread over the one month period after the offer. The omitted category is rated as "AA and Above" with maturity of 1-5 years. ***, ** indicate significance level at 1% and 5%, respectively.

Panel A: Selection Model — Decision to Self-Market

Parameter	Estimate	t Value
Intercept	-2.800***	-6.17
A	0.213	1.26
BBB	-0.874***	-3.16
5-10 Years	0.283*	1.67
Above 10 Years	0.664**	2.50
Call Option	0.637*	1.85
Bond Price Volatility	-24.760	-1.44
Days from Pricing to Issue	-0.087	-1.51
MOVE Index	-0.007*	-1.86
VIX Index	0.020	1.24
Relative Offer Amount	-0.142	-0.74
Possibility of Self-Underwriting	3.721***	10.72

Panel B: Second Stage Regression — Determinants of Underpricing

Variable	Self-Marketed Coefficient	Self-Marketed t Value	Non Self- Marketed Coefficient	Non Self- Marketed t Value
Intercept	-0.302	-1.42	-0.421**	-2.22
A	0.298***	2.83	0.194**	2.13
BBB	0.115	0.59	0.413***	3.88
5-10 Years	0.138	1.50	0.114	1.39
Above 10 Years	0.509***	3.09	0.339***	2.69
Call Option	0.028	0.18	-0.279*	-1.88
Rating Disagreement	-0.273***	-3.09	0.018	0.23
Bond Price Volatility	-22.633	-1.02	20.022*	1.68
Days from Pricing to Issue	-0.063	-1.39	-0.006	-0.16
N.Analysts	-0.006	-1.36	-0.003	-0.69
MOVE Index	-0.001	-0.27	0.004*	1.93
VIX Index	0.031***	3.40	0.013*	1.8
Relative Offer Amount	-0.127	-0.62	0.088	0.83
Bid-Ask	-57.744*	-1.85	3.116	0.12
Bid-Ask Volatility	-26.511	-1.49	-48.293**	-1.98
Inverse Mills	0.416	1.47	0.063	0.78
Year2009	-0.274*	-1.77	0.203	1.45
N.	222		395	
Adj R-square	0.1095		0.1589	

Panel C: Counterfactual Analysis: Actual versus Counterfactual Underpricing

	No.	Actual mean	Counterfactual mean	Difference
Self-Marketed	222	0.241	0.774	-0.533
		(6.44)	(18.16)	(-23.96)
Non-Self-Marketed	67	0.478	-0.322	0.800
(underwriting is possible)		(4.93)	(-4.29)	(12.71)
Difference		0.237	1.096	
		(2.28)	(12.47)	

Table 10 - The bond and firm return samples

The bond and firm return samples are described. The 2-day bond returns in panel A are calculated from average daily trade prices where individual trade prices reported on TRACE are weighted by trade size. Abnormal bond returns (ABRs) are calculated as the return from t-1 to t+1 minus the mean return for all bonds in the same rating/maturity class. Abnormal firm returns are calculated as an average of the firm's abnormal bond returns weighted by amount outstanding. Descriptive statistics for the sample of 1,672,685 bond returns are reported in Panels B and C. The dataset consists of TRACE trades 2005-2011.

	Mean	Median	Standard deviation	Skewness	Excess kurtosis	% positive	Observa-tions	% days with returns
Panel A - Unstandardized returns								
Raw bond returns	0.001	0.001	0.017	0.197	18.683	54.85%	1,672,685	31.34%
Abnormal bond returns	0.000	0.000	0.015	0.137	19.479	49.38%	1,672,685	31.34%
Abnormal firm returns	0.000	0.000	0.015	0.128	21.500	49.43%	752,220	38.61%
Panel B - Bond characteristics in the bond return sample								
Coupon	6.46%	6.37%	1.64%					
Years to maturity	8.77	6.21	7.77					
Bonds outstanding (000s)	707.7	500	577.3					
Panel C - Rating and maturity distributions for the bond return sample								
Rating			Maturity					
Aaa & Aa	6.9%		1-3 yrs	18.1%				
A	28.5%		3-5 yrs	21.5%				
Baa	34.9%		5-10 yrs	39.9%				
Ba	11.7%		10+ yrs	20.4%				
B	10.3%							
below B	7.8%							

Table 11 - Size and power tests based on unstandardized abnormal returns

In panel A, the percentage of times tests based on the abnormal firm-bond returns (ABRs) described in Table 1 and using a 5% significance level incorrectly find evidence of an event when no event occurred are reported. For 10,000 random samples, 300 firm-days are chosen at random from all days a firm had bonds outstanding and the tests are applied to those observations for which ABR returns from t-1 to t+1 could be calculated. We report separately the percentage of times the tests find false evidence of a negative event (the 2.5% tail) and false evidence of a positive event (the 97.5% tail). In panel B, an artificial event is simulated by increasing or decreasing the (t-1,t+1) return by 15 basis points and the percentage of times a test correctly detects the event based on a 5% significance level is reported.

Panel A - Size tests	t-test		Signed-rank test		Sign test	
Significance level	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
No event null rejection rates	2.37%	2.18%	3.12%	1.68%	2.98%	1.30%

Panel B - Power tests for 15 basis point return shocks	t-test	Signed-rank test	Sign test
Positive shock	20.62%	51.87%	59.33%
Negative shock	22.67%	60.03%	70.23%

Table 12 - Abnormal bond return standard deviations by rating and maturity

Standard deviations of 2-day abnormal bond returns (ABRs) are reported stratified by rating and term-to-maturity. The bonds are classified by Moody's rating if available; if not, by Standard and Poor's rating. Returns are based on average daily prices in which each trade price is weighted by the size of the trade. Abnormal returns are calculated as the difference between the return on the bonds and the average for bonds of the same rating and maturity grouping over the same two-day window.

Rating	Bond term-to-maturity			
	1 to 3 years	3+ to 5 years	5+ to 10 years	Over 10 years
Aaa and Aa	0.416%	0.520%	0.749%	1.551%
A	0.682%	0.828%	1.008%	1.743%
Baa	1.027%	1.313%	1.382%	1.970%
Ba	1.215%	1.374%	1.376%	2.107%
B	1.771%	2.055%	1.798%	2.147%
Below B	2.685%	2.752%	2.450%	3.036%

Table 13 - Size and power of event study tests based on standardized returns

First, descriptive statistics of standardized returns are presented in panel A. SABR is the standardized return calculating by dividing each bond ABR by its standard deviation over the periods (t-55, t-6) and (t+6, t+55) where ABR is the unstandardized abnormal bond return calculated as the bond's return from day t-1 to day t+1 minus the average return for bonds in the same maturity/rating category. ABSR is the difference between the standardized raw return and the average standardized raw return for bonds in the same maturity/rating category. Firm SABRs and ABSRs are calculated as a weighted average of the SABRs and ABSRs over all the firm's bonds. The size (Panel B) and power tests (Panel C) are conducted as described in Table 2 with a 5% significance level. ABSR-Pre is the ABSR standardized using the standard deviation of returns over the (t-101, t-6) period. ABR size and power statistics are repeated from Table 2 for easier comparison.

Panel A - Return	Mean	Median	Standard deviation	Skewness	Excess kurtosis	Observa-tions
Abr. Std. Ret.	-.0006	-.0048	.7900	.0290	1.675	720,742
Std. Abr. Ret. (SABR)	-.0029	-.0068	.8654	.0272	1.636	720,742
Panel B - Size	t-test		Signed-rank test		Sign test	
Significance	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
ABSR	2.62%	2.65%	2.70%	2.46%	2.23%	1.65%
SABR	2.87%	2.23%	3.12%	1.95%	2.64%	1.48%
ABR (unstandardized)	2.37%	2.18%	3.12%	1.68%	2.98%	1.30%
ABSR-Pre	2.57%	2.13%	2.91%	2.00%	2.48%	1.47%
Panel C - Power tests 15 basis point shocks	Negative event			Positive event		
	t-test	Signed-rank test	Sign test	t-test	Signed-rank test	Sign test
ABSR	68.90%	81.02%	76.65%	68.04%	78.94%	71.88%
SABR	71.89%	82.37%	76.27%	68.41%	78.29%	69.81%
ABR (unstandardized)	22.67%	60.03%	70.23%	20.62%	51.87%	59.33%
ABSR-Pre	66.21%	81.30%	76.59%	62.71%	74.84%	67.06%
Panel D - Power tests for 10 and 25 basis point shocks						
10 bp - unstandardized	11.46 %	25.77%	28.76%	12.54%	33.79%	40.76%
10 bp - standardized	38.30 %	50.77%	45.51%	37.38%	46.69%	39.59%
25 bp - unstandardized	47.97 %	90.63%	95.08%	49.54%	92.90%	96.83%
25 bp - standardized	97.55 %	99.30%	98.27%	97.35%	99.05%	97.83%

Table 14 - Test power stratified by bond rating and maturity for a 15 basis point return shock

Based on abnormal standardized returns, ABSR, the percentage of times the signed-rank test, correctly finds evidence of an event which shifts 2-day bond returns by 15 basis points are reported by rating and maturity. The reported percentages are averages of the percentage of times positive and negative return shocks are correctly identified. Results are based on 10,000 simulations at a 5% significance level for each maturity/rating category. Tests are conducted at the bond level. The bonds are classified by Moody's rating if available; if not, by Standard and Poor's rating.

Rating	Bond term-to-maturity			
	1 to 3 years	3+ to 5 years	5+ to 10 years	Over 10 years
Aaa and Aa	100.00%	99.92%	90.76%	31.75%
A	99.98%	97.91%	82.27%	28.76%
Baa	97.33%	80.44%	64.73%	30.81%
Ba	68.28%	59.71%	54.14%	22.95%
B	45.57%	36.78%	43.24%	20.89%
Below B	26.22%	21.82%	25.11%	13.54%

Table 15 - The effect of trade sampling on test power

The power of test statistics based on all trades are compared with (1) samples based on trades of 100 or more bonds (in Panel A) and (2) samples based on interdealer trades only (in Panel B). We report the percentage of times the tests correctly found evidence of an event using a 5% significance level. All are based on 10,000 simulations where 300 firm-days are chosen at random from all possible firm-days when the firm had bonds outstanding. Results are reported both for an across-the-board shock in bond returns of 15 basis points and shocks which are proportional to the average return standard deviation for bonds of that rating and maturity class. Results in Panel A are based on TRACE data 2005-2011. Results in Panel B are based on data starting in November 2008 when TRACE started identifying interdealer trades.

	Negative event			Positive event		
Panel A - Large trades	t-test	Signed-rank test	Sign test	t-test	Signed-rank test	Sign test
Across-the-board 15 bp shocks						
All trades	68.90%	81.02%	76.65%	68.04%	78.94%	71.88%
Trades of 100+ bonds only	73.77%	82.26%	72.90%	72.74%	79.94%	68.12%
Proportional shocks						
All trades	55.75%	68.61%	62.04%	53.91%	65.32%	56.79%
Trades of 100+ bonds only	60.03%	70.43%	59.51%	59.35%	67.92%	54.98%
Panel B - Interdealer trades						
Across-the-board 15 bp shocks						
All trades	75.38%	87.06%	83.47%	74.82%	84.73%	78.20%
Interdealer trades only	74.08%	85.16%	79.45%	70.38%	79.99%	72.30%
Proportional shocks						
All trades	61.57%	74.58%	68.88%	60.58%	70.67%	62.61%
Interdealer trades only	56.93%	69.50%	61.74%	52.72%	62.81%	52.89%

Table 16 - Comparing the power of tests based on different measures of average daily prices

The powers of test statistics based on abnormal standardized returns, ABSR, are compared when average bond prices each day are calculated from: 1) an unweighted average of all transaction prices, 2) transaction prices weighted by trade size (ala BKMX (2009)), and 3) transaction prices weighted by the square root of trade size. In panel A, the percentage of times the tests correctly found evidence of an event at the 5% significance level is reported where event day returns were shocked up or down 15 basis points. The tests in Panel B are identical to those in panel A except the event day shock for bonds of maturity m and rating r is proportional to the average 2-day return standard deviation for bond of the same rating and maturity relative to all bonds. All are based on 10,000 simulations where 300 firm-days are chosen at random from all possible firm-days.

Daily average bond price calculation:	Negative event			Positive event	
	t-test	Signed-rank test	Sign test	t-test	Signed-rank test
Panel A - Power tests - 15 bp across-the-board shocks					
Trade prices weighted by trade size	68.90%	81.02%	76.65%	68.04%	78.94%
Prices weighted by square root of trade size	71.07%	83.24%	79.01%	70.24%	81.07%
Unweighted trade price average	67.31%	80.15%	75.04%	67.48%	77.20%
Panel B - Power tests - proportional shocks					
Trade prices weighted by trade size	55.75%	68.61%	62.04%	53.91%	65.32%
Prices weighted by square root of trade size	57.70%	70.27%	64.19%	56.59%	67.25%
Unweighted trade price average	54.41%	67.02%	60.22%	54.67%	64.01%

Table 17 - Comparing the size and power of tests based on different abnormal standardized return measures over a four-day window

The size and power of test statistics based on different abnormal standardized return measures over the four-day window (t-2, t+2) are compared. ABSR(t-1,t+1) is the abnormal standardized return based on observed prices on days t-1 and t+1. It is not calculable if there are no trades on either date so tests based on this statistic have fewer observations than the other two measures. ABSR-Short(t-2, t+2) is the shortest observable ABSR among the set of ABSR(t-1,t+1), ABSR(t-1,t+2), ABSR(t-2,t+1) and ABSR(t-2,t+2). ABSR{t-2, t+2} return, which we designate the composite return is an average of the ABSR(t-1, t+1), ABSR(t-2, t+1), ABSR(t-1, t+2), and ABSR(t-2, t+2). In panel A, the percentage of times the tests incorrectly found evidence of an event in 10,000 simulations in which 300 non-event firm-days were chosen at random are reported. In panel B, the percentage of times the tests correctly found evidence of a 15 basis point event at the 5% level is reported. The tests in Panel C are identical to those in panel B except the event day shock for bonds of maturity m and rating r is proportional to the average 2-day return standard deviation for bond of the same rating and maturity relative to all bonds.

Panel A - Size tests	t-test		Signed-rank test		Sign test	
Significance level	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
ABSR(t-1,t+1)	2.62%	2.65%	2.70%	2.46%	2.23%	1.65%
ABSR-Short(t-2,t+2)	3.14%	1.92%	3.19%	1.82%	3.02%	1.54%
ABSR{t-2,t+2}	2.60%	2.34%	2.79%	2.25%	2.46%	1.98%

Panel B - Power tests - 15 bp across-the-board shocks	Negative event			Positive event		
	t-test	Signed-rank test	Sign test	t-test	Signed-rank test	Sign test
ABSR(t-1,t+1)	68.90%	81.02%	76.65%	68.04%	78.94%	71.88%
ABSR-Short(t-2,t+2)	81.44%	89.57%	85.34%	74.36%	82.58%	77.65%
ABSR{t-2,t+2}	84.77%	92.23%	88.38%	82.40%	90.22%	85.61%
Panel C - Power tests - proportional shocks						
ABSR(t-1,t+1)	55.75%	68.61%	62.04%	53.91%	65.32%	56.79%
ABSR-Short(t-2,t+2)	71.27%	80.67%	75.41%	62.52%	71.97%	65.20%
ABSR{t-2,t+2}	75.23%	83.69%	78.50%	71.71%	81.14%	74.99%

Table 18 - Comparing the size and power of tests based on 2-day and composite 4-day, 6-day, 8-day and 10-day event windows

The size and power of test statistics based on abnormal standardardized returns over the (t-1, t+1) window, ABSR(t-1,t+1), and composite abnormal standardized returns over the {t-2, t+2}, {t-3,t+3}, {t4,t+4}, and {t-5,t+5} event windows are compared. The composite returns are averages of all ABSR returns surrounding day t within the event window. In panel A the percentage of times the tests incorrectly found evidence of an event in 10,000 simulations in which 300 non-event firm-days were chosen at random are reported. In panel B, the percentage of times the tests correctly found evidence of a 15 basis point event at the 5% level is reported. The tests in Panel C are identical to those in panel B except the event day shock for bonds of maturity m and rating r is proportional to the average 2-day return standard deviation for bond of the same rating and maturity relative to all bonds.

Panel A - Size tests	t-test		Signed-rank test		Sign test	
Significance level	2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
ABSR(t-1, t+1)	2.62%	2.65%	2.70%	2.46%	2.23%	1.65%
ABSR{t-2, t+2}	2.60%	2.34%	2.79%	2.25%	2.46%	1.98%
ABSR{t-3, t+3}	3.14%	2.19%	3.02%	2.24%	2.63%	1.75%
ABSR{t-4, t+4}	3.26%	1.96%	3.15%	1.86%	2.59%	1.86%
ABSR{t-5, t+5}	3.32%	1.81%	3.15%	2.04%	2.58%	1.84%
Panel B - Power tests 15 bp across-the-board shocks	Negative event			Positive event		
	t-test	Signed-rank test	Sign test	t-test	Signed-rank test	Sign test
ABSR(t-1, t+1)	68.90%	81.02%	76.65%	68.04%	78.94%	71.88%
ABSR{t-2, t+2}	84.77%	92.23%	88.38%	82.40%	90.22%	85.61%
ABSR{t-3, t+3}	90.19%	95.47%	93.33%	86.30%	93.44%	90.06%
ABSR{t-4, t+4}	92.28%	96.54%	94.73%	87.87%	94.89%	91.83%
ABSR{t-5, t+5}	93.33%	97.17%	95.58%	88.21%	95.33%	92.86%
Panel C - Power tests - proportional shocks						
ABSR(t-1, t+1)	55.75%	68.61%	62.04%	53.91%	65.32%	56.79%
ABSR{t-2, t+2}	75.23%	83.69%	78.50%	71.71%	81.14%	74.99%
ABSR{t-3, t+3}	82.44%	89.64%	85.22%	77.18%	86.43%	80.43%
ABSR{t-4, t+4}	85.71%	91.93%	87.64%	79.03%	88.33%	83.69%
ABSR{t-5, t+5}	87.40%	93.26%	89.31%	79.46%	89.37%	85.37%

Table 19 - Measures of test bias when firms share a common event day

Size results are presented for various samples when the event day is the same for all firms. In each simulation, an event day is chosen at random from trading days between January 2005 and December 2011. We report below the percentage of times the tests falsely find significant evidence of a positive or negative event that day for various samples based on 1000 simulations. Average pairwise correlations over the 2005-2011 period are shown in the second column. Size results for Kolari and Pynnönen (2010)'s corrected t-test are shown in the final two columns of Panel B. Results for tests based on abnormal standardized returns, ABSR(t-1,t+1) are reported in Panel A and results for tests based on composite abnormal returns, ABSR{t-3,t+3} in Panel B. The dataset consists of the 915 firms with at least 175 ABSR(t-1,t+1) returns in the 2005-2011 period (i.e., at least 10% of the days).

Panel A - ABSR(t-1, t+1) abnormal standardized returns

	Average Correlation	t-test		Signed-rank test		Sign test	
		2.5%	97.5%	2.5%	97.5%	2.5%	97.5%
100 random firms	-.001334	1.6%	1.5%	1.3%	1.7%	1.8%	1.4%
SIC 28	.003269	2.8%	2.6%	2.8%	3.3%	2.2%	2.4%
SIC 67	.004851	3.3%	2.8%	3.1%	2.4%	2.1%	1.7%
Assets - top quintile	-.000553	2.3%	2.6%	3.2%	4.3%	2.4%	4.8%
Assets - bottom quintile	.001798	2.8%	2.3%	3.2%	2.3%	2.9%	1.3%
Leverage - top quintile	-.002796	2.1%	1.6%	2.7%	2.2%	2.0%	1.9%
Leverage - bottom quintile	-.000726	2.2%	2.1%	2.1%	3.3%	2.5%	2.4%
Bonds outstanding - top quintile	.000227	1.9%	3.0%	2.0%	4.0%	1.9%	3.8%
Bonds outstanding - bottom quintile	.005226	3.9%	4.2%	4.6%	3.8%	2.8%	3.1%

Panel B - ABSR{t-3, t+3} composite returns								
	Average Corr.	t-test		Signed-rank test		Sign test		KP corrected t-test
		2.5%	97.5%	2.5%	97.5%	2.5%	97.5%	2.5%
100 random firms	.001247	3.1%	2.0%	3.2%	2.8%	2.2%	1.8%	
SIC 28	.012570	6.0%	3.7%	6.3%	4.0%	5.3%	3.5%	2.4%
SIC 67	.007869	5.3%	3.9%	4.8%	3.0%	3.3%	2.5%	4.0%
Assets - top quintile	.000986	2.0%	2.4%	2.2%	3.7%	2.7%	5.4%	2.0%
Assets - bottom quintile	.010475	9.5%	5.8%	10.3%	6.0%	7.7%	4.5%	3.0%
Leverage - top quintile	-.000459	2.1%	3.0%	2.7%	3.3%	2.1%	3.2%	2.5%
Leverage - bottom quintile	.002575	6.0%	3.3%	5.4%	3.7%	3.5%	3.0%	3.7%
Bonds outstanding - top	.000738	2.8%	3.9%	2.1%	4.6%	1.8%	3.8%	2.5%
Bonds outstanding - bottom	.015170	10.9%	9.2%	11.2%	9.0%	8.7%	6.1%	3.6%

Table 20 Initial Market Response to Earnings Surprises

The table reports mean magnitude of earnings surprises, standardized bond abnormal returns, and stock abnormal returns around earnings announcement date. Earnings surprise (SUE) is standardized unexpected earnings and is calculated as the difference between analyst consensus forecast and the actual earnings deflated by stock price as of the end of last quarter. In Panel A, SUE Ranks are decile portfolios based on SUE for the current quarter. . In Panel B, stocks are sorted into 20 portfolios (vigintiles) based on SUE for the current quarter. Bond ABSR is abnormal standardized return calculated as the standardized bond return minus the average standardized return on a maturity and rating matched portfolio. Individual bond return is standardized by its standard deviation of bond returns over (-25,+25) window around earnings announcement date. Bond SABR is standardized abnormal bond return. Both ABSR and SABR are combined into firm-level returns and estimated during the short interval of earnings announcement window. Stock CAR is cumulative abnormal return during the announcement window, and stock abnormal return is the raw stock return from CRSP minus benchmark returns based on Fama-French size and Book-to -Market assignments.

SUE Rank	firm-quarter	Earnings Surprise (SUE)	t-stat	Bond ABSR {-3,+3}	t-stat	Bond SABR {-3,+3}	t-stat	Stock CAR (-1,+1)	t-stat
Panel A SUE decile rank									
Extreme Negative	630	-4.12%	-8.07	-0.2043	-5.62	-0.2424	-5.54	-0.0426	-9.94
2	648	-0.19%	-21.55	-0.0759	-2.58	-0.1106	-3.15	-0.0279	-10.11
3	712	-0.03%	-11.26	-0.0343	-1.54	-0.0586	-2.1	-0.0155	-7.44
4	578	0.02%	16.15	0.0247	0.98	0.0021	0.06	-0.0086	-4.27
5	629	0.05%	42.88	-0.0027	-0.12	-0.0086	-0.32	-0.0012	-0.58
6	649	0.09%	53.66	0.0477	1.92	0.057	2	0.0051	2.65
7	644	0.14%	56.01	0.0069	0.26	0.0175	0.54	0.0094	4.22
8	642	0.22%	55.39	0.0501	2.07	0.0569	1.95	0.0177	7.67
9	645	0.40%	48.23	0.0737	2.52	0.0864	2.44	0.0277	10.89
Extreme Positive	632	2.02%	12.46	0.2794	8.41	0.3516	8.5	0.0462	11.52
Panel B SUE vigintile rank									
Extreme Negative	309	-7.63%	-7.60	-0.1927	-3.62	-0.2143	-3.47	-0.0535	-8.45
Vigintile 2	321	-0.75%	-16.36	-0.2155	-4.34	-0.2695	-4.34	-0.0321	-5.58
Middle	5147	0.09%	31.17	0.0105	1.16	0.0045	0.40	0.0007	0.87
Vigintile 19	321	0.76%	29.90	0.2238	5.03	0.2829	5.05	0.0387	8.57
Extreme Positive	311	3.33%	10.67	0.3369	6.81	0.4225	6.95	0.0540	8.09

Table 21 Regression of Short-window Abnormal Returns

This table reports the regression results for initial bond returns to earnings surprise at current quarter and prior quarter. SUE_last is magnitude of standardized unexpected earnings of last quarter. Rsue_last is coded SUE rank of last quarter. Rsue is coded SUE rank of current quarter. Rsue_last* RISK is an interaction term of coded SUE rank of last quarter and the dummy variable for speculative-grade firms. Rsue* RISK is an interaction term of coded SUE rank of current quarter and the dummy variable for speculative-grade firms.

	SUE_ current	**Rsue_ current**	**Rsue_ current**	**SABR {-3,+3}**	**SABR {-3,+3}**	**SABR {-3,+3}**	**SABR {-3,+3}**	**SABR {-3,+3}**	**SABR {-3,+3}**	**SABR {-3,+3}**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Intercept	-0.001	0.0028	0.0028	0.0142	0.01427	0.0161	0.0155	0.0165	0.015	0.0152
	-1.83	0.38	0.38	1.35	1.34	1.49	1.45	1.52	1.41	1.43
SUE_last	0.1505									
	13.06									
Rsue_last		0.1973	0.2282			0.0473	0.005	-0.0121	0.004	-0.0295
		16.04	12.21			2.64	0.28	-0.44	0.22	-1.08
Rsue				0.2121	0.0739		0.2144		0.0714	0.0768
				12.03	3.27		11.86		3.13	3.34
Rsue_last* RISK			-0.0632		0.2989			0.1041	0.3146	0.059
			-2.55		8.26			2.89	8.63	1.63
Rsue*RISK										0.30287
										8.16

Table 22 Initial Market Response to Earnings Surprises by Firm Risk

The table reports mean magnitude of earnings surprises, standardized bond abnormal returns, and stock abnormal returns around earnings announcement date, by credit rating. Bonds are designated as "investment grade" if rated BBB or better by Standard &Poors or Baa or better by Moody's respectively, or "Speculative grade" otherwise. A firm's rating is determined by the highest rating of all bonds issued by the same firm

SUE		Earnings		Bond		Bond		Stock	
Decile Rank	**firm-quarter**	**Surprise**	**t-stat**	**ABSR {-3,+3}**	**t-stat**	**SABR {-3,+3}**	**t-stat**	**CAR (-1,+1)**	**t-stat**
Panel A Investment Grade									
Extreme Negative	374	-0.40%	-10.36	-0.1518	-4.18	-0.1772	-3.87	-0.0313	-11.32
2	377	-0.05%	-15.17	-0.0694	-2.20	-0.1120	-2.76	-0.0200	-7.71
3	432	0.00%	1.85	-0.0025	-0.11	0.0000	0.00	-0.0077	-3.67
4	370	0.03%	29.96	0.0073	0.29	-0.0035	-0.11	-0.0042	-1.76
5	389	0.05%	39.28	0.0031	0.11	0.0147	0.45	0.0002	0.08
6	400	0.08%	46.55	0.0046	0.15	0.0286	0.81	0.0049	2.21
7	389	0.12%	50.24	-0.0091	-0.33	-0.0037	-0.11	0.0039	1.60
8	396	0.17%	48.88	-0.0141	-0.53	-0.0168	-0.52	0.0132	5.11
9	391	0.27%	49.40	-0.0144	-0.50	-0.0087	-0.25	0.0216	8.13
Extreme Positive	380	0.63%	23.55	0.0130	0.42	0.0425	0.98	0.0253	8.57
Panel B Speculative Grade									
Extreme Negative	241	-9.26%	-7.32	-0.1553	-2.52	-0.1627	-2.37	-0.0530	-7.07
2	253	-1.01%	-12.70	-0.2522	-4.30	-0.3329	-4.53	-0.0412	-5.67
3	244	-0.27%	-12.81	-0.0353	-0.65	-0.0480	-0.81	-0.0268	-4.76
4	256	-0.06%	-6.01	-0.0327	-0.69	-0.0997	-1.89	-0.0170	-3.63
5	261	0.04%	8.13	0.0893	1.68	0.0547	0.83	-0.0076	-1.68
6	253	0.12%	22.31	0.0764	1.50	0.0367	0.61	0.0048	1.11
7	257	0.22%	27.11	0.1323	2.68	0.1835	2.90	0.0163	3.90
8	249	0.41%	25.86	0.2189	4.10	0.2128	3.59	0.0347	6.93
9	255	0.81%	23.74	0.3528	6.47	0.4461	6.51	0.0444	7.77
Extreme Positive	242	3.87%	9.86	0.3601	6.08	0.4285	5.92	0.0585	7.26

Table 23 Initial Market Response to Earnings Surprises by Firm Risk (Vigintiles)

The table reports mean magnitude of earnings surprises, standardized bond abnormal returns, and stock abnormal returns around earnings announcement date, by credit ratings. We form 20 portfolios based on SUE ranking. Bonds are designated as "investment grade" if rated BBB or better by Standard &Poors or Baa or better by Moody's respectively, or "Speculative grade" otherwise. A firm's rating is determined by the highest rating of all bonds issued by the same firm.

SUE		Earnings		Bond		Bond		Stock	
Vigintile Rank	Firm-quarters	Surprise	t-stat	ABSR {-3,+3}	t-stat	SABR {-3,+3}	t-stat	CAR (-1,+1)	t-stat
Panel A Investment Grade									
Extreme Negative	183	-0.65%	-8.86	-0.1956	-3.50	-0.1803	-2.57	-0.0335	-7.86
Vigintile 2	191	-0.15%	-19.09	-0.1099	-2.36	-0.1744	-2.93	-0.0292	-8.20
Middle	3144	0.09%	44.02	-0.0115	-1.18	-0.0120	-1.00	0.0015	1.73
Vigintile 19	197	0.41%	35.10	-0.0054	-0.14	0.0335	0.75	0.0214	5.86
Extreme Positive	183	0.86%	17.90	0.0328	0.67	0.0521	0.69	0.0296	6.28
Panel B Speculative Grade									
Extreme Negative	115	-5.45%	-5.69	-0.1587	-6.38	-0.0674	-0.80	-0.0341	-0.36
Vigintile 2	126	-5.16%	-4.53	-0.0324	-9.35	-0.2357	-2.65	-0.2801	-2.87
Middle	2028	0.10%	0.53	0.0003	2.19	0.0692	3.65	0.0572	2.50
Vigintile 19	127	5.06%	4.37	0.0176	17.93	0.2705	3.05	0.3334	2.96
Extreme Positive	115	6.72%	6.04	0.0621	8.14	0.4590	5.99	0.5334	6.09

Table 24 Post-Earnings Announcement Longer-window Bond Returns

This table longer-window standardized abnormal returns (SABRs) after earnings announcement, for 2 weeks (10 trading days), one month (21 trading days), two months (42 trading days) and one quarter (63 trading days). SUE Ranks are decile portfolios based on SUE for the current quarter. Bond abnormal returns are calculated as the raw bond returns minus the average return on a rating and maturity matched portfolio and then standardized by the cross sectional standard deviation of bond abnormal returns within the rating and maturity portfolio. The t-stats columns report t values based on two-tailed tests.

SUE3 CQ	Firm-quarters	SABR (4, 10)	t-stat	SABR (4, 21)	t-stat	SABR (4, 63)	t-stat	SABR (22, 63)	t-stat
Extreme Negative	630	-0.0426	-1.16	-0.0025	-0.07	-0.0204	-0.58	0.0193	0.56
2	648	-0.0374	-1.30	-0.0146	-0.55	-0.0369	-1.40	-0.0274	-1.00
3	712	0.0077	0.34	0.0245	1.08	-0.0626	-2.64	-0.0840	-3.57
4	578	-0.0246	-1.04	-0.0194	-0.91	-0.0177	-0.72	-0.0138	-0.58
5	629	0.0202	0.82	0.0133	0.56	-0.0007	-0.03	-0.0464	-1.97
6	649	-0.0085	-0.34	0.0180	0.81	-0.0024	-0.10	-0.0258	-1.11
7	644	-0.0551	-2.08	-0.0200	-0.84	-0.0514	-2.17	-0.0514	-2.19
8	642	-0.0358	-1.35	0.0115	0.49	0.0157	0.68	0.0040	0.16
9	645	0.0476	1.79	0.0683	2.66	0.0326	1.16	-0.0118	-0.42
Extreme Positive	632	0.0918	2.93	0.0517	1.81	0.0590	1.97	0.0264	0.87

Table 25 Post-Earnings Announcement Longer-window Bond Returns by Credit Rating

This table longer-window standardized abnormal returns (SABRs) after earnings announcement, for 2 weeks (10 trading days), one month (21 trading days), two months (42 trading days) and one quarter (63 trading days) , by credit rating. Bonds are designated as "investment grade" if rated BBB or better by Standard &Poors or Baa or better by Moody's respectively, or "Speculative grade" otherwise. A firm's rating is determined by the highest rating of all bonds issued by the same firm. SUE Ranks are decile portfolios based on SUE for the current quarter. Bond abnormal returns are calculated as the raw bond returns minus the average return on a rating and maturity matched portfolio and then standardized by the cross sectional standard deviation of bond abnormal returns within the rating and maturity portfolio. The t-stats columns report t values based on two-tailed tests.

SUE3_CQ	Firm-quarters	SABR (4, 10)	t-stat	SABR (4, 21)	t-stat	SABR (4, 63)	t-stat	SABR (22, 63)	t-stat
Panel A Investment Grade									
0	374	-0.0105	-0.24	0.0115	0.33	-0.0865	-2.25	-0.0573	-1.53
1	377	-0.0189	-0.64	-0.0117	-0.40	-0.0534	-1.89	-0.0622	-2.09
2	432	-0.0045	-0.18	0.0246	1.02	-0.0337	-1.20	-0.0634	-2.31
3	370	-0.0220	-0.83	-0.0164	-0.69	0.0150	0.56	0.0022	0.08
4	389	0.0314	1.03	0.0042	0.15	0.0034	0.12	-0.0226	-0.76
5	400	-0.0295	-0.93	-0.0198	-0.67	-0.0092	-0.31	-0.0325	-1.17
6	389	-0.0515	-1.67	-0.0134	-0.42	-0.0098	-0.32	-0.0408	-1.35
7	396	-0.0179	-0.55	-0.0230	-0.84	-0.0219	-0.80	0.0009	0.03
8	391	-0.0142	-0.45	0.0430	1.51	0.0208	0.67	-0.0052	-0.17
9	380	0.0651	1.72	0.0596	1.84	0.0589	1.58	0.0148	0.39
Panel B Speculative Grade									
0	241	-0.0621	-0.90	0.0354	0.57	0.0112	0.16	0.0350	0.52
1	253	-0.0510	-1.06	-0.0090	-0.18	-0.0163	-0.38	0.0296	0.65
2	244	-0.0249	-0.50	-0.0392	-0.76	-0.0007	-0.01	0.0049	0.11
3	256	-0.0220	-0.45	-0.0497	-1.14	-0.1133	-2.35	-0.0819	-1.68
4	261	0.0419	0.92	0.0551	1.27	-0.0299	-0.70	-0.0831	-2.07
5	253	-0.0728	-1.52	0.0627	1.61	-0.0183	-0.45	0.0004	0.01
6	257	-0.0441	-1.05	0.0069	0.19	0.0168	0.41	-0.0178	-0.38
7	249	0.0627	1.51	0.0681	1.48	0.0253	0.60	-0.0200	-0.46
8	255	0.0738	1.44	0.0280	0.63	-0.0040	-0.08	-0.0302	-0.61
9	242	0.1254	2.46	0.0954	1.90	0.0873	1.71	0.0295	0.58

Table 26 Bond Abnormal Returns around Subsequent Announcement Date

This table reports the short-window bond returns surrounding the subsequent earnings announcement dates. SUE Ranks are decile portfolios based on SUE of the prior quarter. Column (1) through (3) report result for the whole sample firms. Column (4) through (6) report results for investment-grade bonds and Column (7) through (9) for speculative-grade bonds.

		Overall					Investment Grade					Speculative Grade			
SUE3_CQ	firm-quarter	bond ABSR {-3,+3}		bond SABR {-3,+3}		firm-quarter	bond ABSR {-3,+3}		bond SABR {-3,+3}		firm-quarter	bond ABSR {-3,+3}		bond SABR {-3,+3}	
	(1)	(2)		(3)		(4)	(5)		(6)		(7)	(8)		(9)	
Extreme Negative	630	0.0509	1.15	0.0578	1.56	374	-0.08932	-2.22	-0.0868	-2.51	241	0.128805	1.62	0.1102	1.63
2	648	-0.0600	-1.66	-0.0488	-1.52	377	0.037454	1.07	0.0286	1.06	253	0.029219	0.44	0.0526	0.89
3	712	-0.0039	-0.14	0.0017	0.08	432	-0.04517	-1.70	-0.0329	-1.55	244	-0.05208	-0.67	-0.0142	-0.22
4	578	-0.0504	-1.83	-0.0283	-1.28	370	-0.0534	-1.71	-0.0466	-1.83	256	0.034923	0.50	0.0775	1.31
5	629	0.0173	0.49	0.0374	1.50	389	-0.03298	-0.85	-0.0124	-0.44	261	0.162022	2.75	0.1539	2.94
6	649	0.0415	1.31	0.0431	1.72	400	-0.00715	-0.17	-0.0030	-0.10	253	0.106055	1.31	0.1329	2.25
7	644	-0.0078	-0.25	-0.0004	-0.01	389	-0.02476	-0.69	-0.0192	-0.67	257	-0.06113	-0.89	-0.0151	-0.27
8	642	-0.0346	-1.07	-0.0247	-0.90	396	-0.00923	-0.29	-0.0171	-0.64	249	0.194698	2.80	0.1750	2.92
9	645	0.0768	2.23	0.0500	1.74	391	-0.08731	-2.29	-0.0852	-2.85	255	0.182717	2.99	0.1565	2.90
Extreme Positive	632	0.1408	3.47	0.1000	3.02	380	0.050761	1.43	0.0242	0.82	242	0.194321	2.54	0.1222	1.99

Table 27 Regression of Longer-window Returns

This table reports the regression results for post-announcement bond returns. SABR (4, 10) is standardized abnormal returns from 4 trading days to 10 trading days subsequent to earnings announcement date. SABR (4, 21) is standardized abnormal returns from 4 to 21 trading days (1 month) subsequent to earnings announcement date. SABR (4, 63) is standardized abnormal returns from 4 to 63 trading days (1 quarter) subsequent to earnings announcement date.SABR (22, 63) is standardized abnormal returns from 22 to 63 trading days (1 quarter) subsequent to earnings announcement date. Rsue is coded SUE rank of current quarter. RSUE* RISK is an interaction term of coded SUE rank of current quarter and the dummy variable for speculative-grade firms.

	SABR (4, 10)		SABR (4, 21)		SABR (4, 63)		SABR (22, 63)	
Intercept	-0.0040	0.0109	0.0109	0.0109	-0.0095	-0.0095	-0.0206	-0.0205
	-0.46	1.34	1.35	1.34	-1.12	-1.12	-2.42	-2.42
RSUE	**0.0399**	0.0184	**0.0332**	0.0184	**0.0497**	**0.0522**	0.0136	**0.0321**
	2.76	1.08	2.47	1.08	3.52	2.92	0.96	1.8
RSUE*RISK		0.0316		0.0316		0.0007		-0.0369
		1.14		1.14		0.02		-1.27

Table 28 Stock Return Patterns

	stock (whole sample)	stock (with bonds sample)	stock (with bonds sample)
Intercept	-0.0043	0.0044	0.0044
	-5.37	1.79	1.79
RSUE	**0.0119**	0.0020	0.0046
	8.97	0.49	0.89
RSUE*RISK			-0.0068
			-0.81