A Re-Assessment of the Importance of Accounting Data to the Corporate Bond Market: What Do Large Block Trades Know?

by

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A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Business Administration

in the

Graduate Division

of the

University of California, Berkeley

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Fall 2015

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Abstract

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Doctor of Philosophy in Business Administration

University of California, Berkeley

Prof. Patricia Dechow, Chair

This dissertation evaluates the importance of the uncapped *Enhanced* TRACE dataset that has previously been rarely used within academic literature. In doing so I answer two important questions, one relevant to academic researchers, and one relevant to financial regulators. First, how economically significant are the differences between the *Enhanced* TRACE dataset and the *Historic* TRACE dataset that has been used previously? Secondly, are these differences a result of informed trading, and thus potentially in need of the protection provided by the caps currently imposed by TRACE? I find striking differences between the two datasets. Hidden volume in the periods preceding earnings announcements occurs frequently and is large in size, often exceeding 30% of total volume in the period. Despite this, I find little evidence to suggest that this trading volume is driven by informed investors. The hidden volume shows little ability to anticipate the news in earnings announcements and appears to be somewhat randomly distributed throughout time. My research suggests that researchers should move away from the *Historic* TRACE dataset and instead utilize the new *Enhanced* TRACE dataset when examining corporate bond markets. In addition, my research, suggests that large block trades typically are not informed. This provides preliminary evidence supporting the view, held by many market participants, that regulators should remove the currently imposed TRACE dissemination caps. My research supports the claims of these market participants that the caps simply inhibit investors from accurately assessing the quality of trade execution they have received from broker-dealers.

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Dedication

I would like to thank my parents, Simon and Ellen English, and Jenn Logg for their constant advice, help and support over the years.

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Acknowledgments

I would like to thank my dissertation committee: Patricia Dechow (Chair), Robert Bartlett, Alastair Lawrence, Panos Patatoukas and Richard Sloan. In addition I thank Yaniv Konchitchki, Xiao-Jun Zhang, Korcan Ak, Fernando Comiran, Oscar Olivas, Nils Reuter, James Ryans and Jackie Siriviriyakul for helpful comments and insights. All errors are my own.

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Chapter 1

Introduction

1.1 Outline and Motivation:

"The BDA believes that FINRA should not increase the $1 million and $5 million TRACE volume dissemination caps, which have been in place since TRACE began operating on July 1, 2002... Any research done internally, by and for themselves, is less beneficial if opportunistic investors are afforded the information they need to take advantage of this valuable research by reverse engineering their trading activity... Worse, the capacity of these opportunistic investors to pilfer valuable research may discourage investors from conducting this kind of research at all and may lead them to abstain from investing in securities that they will only invest in with such research."

Bond Dealers of America, Response to FINRA Regulatory Notice 12-39, Nov. 2012

"Market participants, including investors, value the ability to keep their strategies and activities confidential for competitive and other reasons. Broad knowledge of specific sizes and timing of trades is therefore very sensitive information, as is the ability to reverse engineer net flows to or from customers or market makers. Our members believe that an increase to dissemination caps will make such specific knowledge more widespread by increasing the proportion of trades where exact sizes will be made public."

Securities Industry and Financial Markets Association (SIFMA), Response to FINRA Regulatory Notice 12-39, Nov. 2012

Utilizing the recently released *Enhanced* TRACE dataset, which crucially provides previously unavailable *total* trading volume data for the corporate bond market[1], I investigate whether the largest trades in the corporate bond market are driven by informed investors. These trades had previously been shrouded in opacity in a desire to maintain the confidentiality of investors and broker-dealers. By taking advantage of the significantly improved

[1]Full details of the evolution of the Trade Reporting and Compliance Engine (TRACE) and the data available to researchers through WRDS provided in Section 2.1

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TRACE dataset and explicitly focusing on the behavior and information content of large block trades around earnings announcements, I hope to contribute to the existing literature in a number of ways.

First, by re-examining trading patterns around earnings announcements I can gain a clearer picture of whether accounting information is truly relevant for corporate bond holders. Preliminary research has been undertaken in recent years on questions such as the importance of accounting information in the secondary corporate bond market (Easton, Monahan, and Vasvari, 2009; Defond and Zhang, 2014; Han and Zhou, 2014), the presence of accounting based equity market anomalies in the corporate bond market (Bhojraj and Swaminathan, 2009; Wei, Truong, and Veeraraghavan, 2012; Crawford et al., 2014), and the ability of information in the corporate bond market to supplement and subsume well-known accounting anomalies in the equity market (Even-Tov, 2015). Despite this, I believe that a reassessment of some key initial conclusions is important given that researchers can now benefit from the release of a far more comprehensive dataset than was previously available.

In particular, prior research was hindered by the sample limitations that arose due to the data dissemination choices of TRACE. Of particular note was the decision not to report the true volume of any given trade, but rather to cap the reported volume of certain large trades in the reports issued to market participants and researchers. These limitations forced academics to draw inferences from less-than-optimal research designs. Examples of the choices that researchers were forced to make were empirical designs such as the use of the *incidence* of trades around earnings announcements rather than the *size* of trades around earnings announcements to infer the importance of earnings announcements to the corporate bond market (Easton, Monahan, and Vasvari, 2009), or the use of the capped disseminated trading volumes as a proxy for the actual trading volume when considering the levels of buy and sell trading prior to an earnings announcement (Han and Zhou, 2014)[2]. Given these unavoidable difficulties I deem the efforts of prior research to assess the importance of accounting information in the corporate bond market to be important, however that does not negate the need to reassess many of the conclusions previously drawn now that researchers are able to access a far more comprehensive set of information related to trading activity in the secondary corporate bond market.

This need to reconsider previous conclusions drawn without the benefit of the true trading volume measures is particularly important given that I document a sizeable disparity in trading incidence and trading volume. While large block trades make up only a small proportion or the total number of trades in a given month (between 5-10% in a given month, Figure F.3), they make up a disproportionately large percentage of all trading volume[3] (typically between 45 and 60%, Figure F.3). More strikingly, the disparity between trading

[2]Further details provided in Section 2.1.

[3]When referring to trading volume I refer to the raw dollar value of trading volume. In addition, I have calculated an adjusted volume measure where volume is recorded as the percentage of the outstanding issue

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incidence and trading volume between large block trades and non-block trades varies significantly with the credit quality of the bond under consideration. While in a given month investment grade bonds would typically have less than 5% of all trades arising due to block trades and 40-50% of all volume due to these large trades, large trades account for 20-30% of all trades and over 80% of all volume for non-investment grade corporate bonds (Figure F.4). I deem this to be a striking finding especially given the higher likelihood of informed trading driven by asymmetric information occurring in the high yield market relative to the investment grade market. It would appear that in the one market where participants may expect informed trading to occur, participants were prevented from viewing the activities of those trading in size under the old TRACE reporting regime. Given these stark disparities, by focusing only on the relative frequency of trades around earnings announcements researchers may overlook the true economic impact of trading activity. This can only be gleaned from an assessment of the actual *dollar value* of trading activity.

In addition to re-assessing the relationship between accounting information and corporate bond trading activity, I believe that this research can also shed light on an important issue that has been been a recent focus of securities regulators, namely the question of whether large bond trades are in fact more informed and therefore are potentially in need of anonymity through the imposition of a real-time dissemination cap[4]. From an assessment of the comment letters received by FINRA in regards to Notice 12-39 there appears to be widespread disagreement between broker-dealers and investors as to whether the caps should be removed. Some argue that the caps protect market participants from having their trading activity being mimicked by others, while many argue that the dissemination caps simply protect dealers from competition by inhibiting the ability of investors to assess whether they have received good, fairly priced execution to their trade requests[5]. To the best of my knowledge there has not yet been a definitive answer provided for this debate. If I find that these large block trades are in fact more informed, as proxied for by an ability to better anticipate certain accounting and market outcomes around earnings announcements, then this may lend weight to those claiming that the imposition of a dissemination cap is an important form of protection to encourage investors to engage in proprietary research (see quote at beginning of Introduction). However if block trades in the corporate bond market do not exhibit any of the traits of informed trading then those claiming that the TRACE dissemination caps should be removed and all volume data should be provided to the public

that is traded. This is analogous to a measure of corporate bond 'turnover'.

[4]The imposition of caps on the data disseminated by TRACE is a contentious issue with the Financial Industry Regulatory Authority (FINRA) recently reviewing its decision to limit the data released to market participants. FINRA Notice 12-39, issued September 2012, requested market participants' opinions on the current trading volume dissemination caps, in particular "FINRA seeks input on whether it should maintain or modify current TRACE dissemination caps, under which the actual size (volume) of a transaction over a certain par value is not displayed in disseminated real-time TRACE transaction data".

[5]See Appendix D for an example of the difficulty in assessing trade execution under the TRACE dissemination caps.

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in real-time may be given additional evidence to support their claims[6].

A final important contribution of this paper is the comparison it may provide to the extensive literature considering large institutional trades and stealth trading in the equity market (Holthausen, Leftwich, and Mayers, 1987; Admati and Pfleiderer, 1988; Barclay and Warner, 1993; Hasbrouck, 1995; Keim and Madhavan, 1995; Keim and Madhavan, 1996; Chan and Fong, 2000; Chakravarty, 2001; Chordia and Subrahmanyam, 2004). While there has been comprehensive research into the importance and information content of large institutional block trades in the equity markets, to the best of my knowledge there has been no equivalent assessment of the importance of such trades in the corporate bond market. By aiming to retain a sharp focus on the largest trades in the cash corporate bond market, and by being the first to examine the typical characteristics of these trades in depth, I provide the one of the first detailed analyses of a previously under-researched area of the capital markets.

Given the reasons outlined, this paper should provide not just an important contribution to the evolving literature investigating accounting information and the corporate bond markets, but also should speak to an important contemporary industry discussion. For these reasons the topic should be of interest both to academics and practitioners alike.

[6] See Appendix E for examples of responses to FINRA's proposed regulatory notice 12-39.

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Chapter 2

Institutional Background and Related Literature

2.1 Evolution of Trade Reporting and Compliance Engine (TRACE) and its Impact on Academic Research

The introduction of the TRACE reporting system represented an immensely important evolution in the transparency of the corporate bond market and there has been much academic research into its impact on corporate bond market market liquidity (Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2006; Bessembinder and Maxwell, 2008). TRACE is a mandatory automated trade reporting system initiated on July 1st , 2002 by NASD (now FINRA). The system was rolled out in increments but as of the 9th January 2006 substantially all publicly issued bonds were required to be reported. Between 2002 and 2005 the speed at which trades were required to be reported in TRACE was also increased, with it being mandated that a trade in a TRACE-eligible security must be reported within 15 minutes of execution as of the 1st July 2005. Despite the huge changes brought about by the availability of this original dataset to market participants, it had some important limitations for researchers.

One key issue that was particularly crucial in limiting the scope of many academic papers was that prior to the release of the *Enhanced* TRACE dataset (now available through WRDS and used throughout this study) bond market participants and academic researchers were unable to view the true size of a large number of the trades undertaken in the corporate bond market. In an effort to protect the confidentiality of market participants' trading activity (that of both investors and dealers) a dissemination cap was imposed on all trades that exceeded a certain par value volume[7]. In particular, for corporate bond transactions,

[7]Par value volume represents the value of the trade in terms of the par value of the bond, i.e. if an

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caps were imposed on all investment grade trades that were greater than or equal to \$5MM in par value (i.e. 5,000 bonds each with a par value of \$1,000), while a cap of \$1MM (i.e. 1,000 bonds each with a par value of \$1,000) was imposed on non-investment grade trades. Instead of reporting the true par value volume an amount of '\$1MM+' and '\$5MM+' was reported to the market, preventing users of the original *Historic* TRACE dataset from correctly identifying the actual volume of corporate bond activity.

To overcome this restriction researchers typically chose to either refrain from considering the volume of trades in the market (Easton, Monahan, and Vasvari, 2009) or to identify all capped trades as having a volume equal to the imposed cap, i.e. all large non-investment grade trades were deemed to have a par value volume of \$1,000,000 while large investment grade trades were deemed to have a par value volume of \$5,000,000[8] (Han and Zhou, 2014; Even-Tov, 2015). This simplification is non-trivial and economically significant. By artificially recreating the imposed dissemination caps and comparing this to the actual volume traded in a given period I find a striking difference between what market participants were able to see in real-time and what the actual trading volume was. Looking at all trades, both investment grade and non-investment grade in the ten day period prior to an earnings announcement in Figure F.11 I find that on average at least 30% of all trading volume is hidden from the market and thus overlooked by prior research. Even more strikingly, the amount of unobservable volume is highly important across all firm sizes with the smallest firms having nearly 50% of all their pre-earnings announcement bond trading volume being unobserved (Figure F.11). I deem this to be an important finding and a strong justification for an investigation into the importance of this 'hidden' trading activity.

An important improvement in the availability of corporate bond data was made with the introduction of the *Enhanced* TRACE dataset. This was made effective on March 31st, 2010. The dataset documents transaction-level information for all TRACE-eligible securities that have been reported since July 1st, 2002[9]. A crucial addition to this dataset was the availability of *uncapped* trade volume data. There were two key provisions enacted with this increased data release to preserve the confidentiality of market participants:

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investor makes a purchase of 100 bonds which each have a par value of \$1000 (a common par value in the corporate bond market) then the par value volume is \$100,000 irrespective of the price paid. The *dollar value* of this trade depends on the *price* of the bond. If the bond is deeply discounted and has a price of 50, i.e. 0.5 times par value, then the actual dollar amount traded is \$50,000. If however the bond trades at a premium, for example at 102, then the dollar amount traded is \$102,000. In both cases the par value volume will still be recorded as \$100,000.

[8] A significant additional implication of this choice was that without access to the true number of bonds traded, researchers that drew inferences from bond return measures employing a value-weighting methodology would expose themselves to the risk of miscalculating their return measures by applying an equal weighting to all trades over a certain size irrespective of the true value of the trade.

[9] See FINRA Notice 10-14, issued March 2010

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1. There would be an 18 month lag between the date of the transaction and its release in the TRACE dataset[10], and
2. The identity of any broker-dealer that is a party to a transaction will not be released.

It is this improved data availability that has spurred the research presented in this study. By having access to a richer information set, notably around details related to the true volumes traded in the market, researchers can now overcome many of the obstacles that they previously encountered when investigating the cash corporate bond market. It should be noted that the 18-month lag in the release of the data marginally restricts the time-series availability of the sample however I deem the benefits of the improved quality of the *Enhaced* TRACE dataset to outweigh the sample size costs imposed by this restriction. In summary, this study is a first step in establishing the importance of this improved data to researchers, providing preliminary evidence that there may be a case to be made to use the *Enhanced* TRACE dataset as the default sample when studying traded prices in the corporate bond market.

2.2 Related Literature:

My study is closely related to two important strands of academic literature, (i) the role of accounting information in the corporate bond market; and, (ii) the impact of increased transparency in the secondary market for corporate bonds through the introduction of TRACE. I examine each in turn.

Accounting's Role in the Corporate Debt Market

In stark contrast to the equity market, research into the role of accounting information in the corporate bond market is somewhat in it's infancy. Two notable early exceptions were Davis, Boatsman, and Baskin (1978) and Datta and Dhillon (1993) which were some of the first papers to investigate whether earnings announcements convey information to the corporate bond market. Looking at a small sample of 85 bonds from 1968-1972 Davis, Boatsman, and Baskin (1978) find that for some convertible bonds earnings announcements may convey news to the market. Likewise, Datta and Dhillon (1993) find a significant positive (negative) abnormal bond market reaction to positive (negative) earnings surprises calculated from deviations from mean analyst forecasts. This holds even when controlling for the confounding effects of dividend announcements.

[10]This 18-month lag is also currently under review. FINRA has recently issued a request for comment as to whether the current 18-month lag should be reduced to 6 months. Full details in FINRA Notice 15-24, June 2015.

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Research relating accounting information to the corporate bond markets was subsequently limited until Easton, Monahan, and Vasvari (2009) who, using bond transaction data for insurance companies taken from the Mergent FISD dataset, investigate (i) the *incidence* of bond trade around earnings announcements, and (ii) the relation between bond returns and earnings news, both short-term and long-term. The authors find that the incidence of bond trades increases in the two days following an earnings announcement, the trade reaction is larger for bad news than good, and the incidence of trade is higher for riskier bonds. In addition to these important findings, the evidence shows that bond returns appear to react to earnings news and that this reaction is stronger for bad news and speculative bonds. Similar results are found for long-window association studies.

The research by Easton, Monahan, and Vasvari, 2009, allied to the advances in corporate bond market data availability that have occurred in recent years, appeared to spur a renewed interest in this line of literature within the field. In particular Defond and Zhang (2014) sought to re-assess the relative informational efficiency of the stock and bond markets using quoted bond price data from DataStream. While this topic has been extensively researched within the finance literature, with Kwan (1996) providing early evidence that the equity market may be more informationally efficient than the bond market and Hotchkiss and Ronen (2002) providing contradictory evidence when considering intra-day data, Defond and Zhang (2014) explicitly compare the speed with which the equity and bond markets anticipate and react to earnings news. The authors provide evidence suggesting that, in isolation, the corporate bond market is more timely in anticipating good earnings news than bad earnings news. In addition, the corporate bond market appears to be more timely than the equity market when considering bad earnings news. Again, there appear to be important differences between speculative- and investment-grade bonds, with the reported results being more pronounced within the subset of bonds that are deemed to be non-investment grade.

A number of extensions have been made to this recent literature and a particular focus of academics has been the re-assessment of established accounting-based anomalies from the equity market and whether the same anomalies exist within the corporate bond markets. Of particular note was the work by Bhojraj and Swaminathan (2009) who investigate whether the well-known accrual anomaly, first documented in Sloan (1996), is also found within the corporate bond market. Using monthly data from the Lehman Brothers Fixed Income Database (LBFI) for the period between January 1973 and February 1997, the authors find evidence to suggest that high-accrual firms under-perform low-accrual firms in the year following portfolio formation and that this under-performance is robust to a number of return calculations and risk adjustments. Further refinements have been made with researchers investigating another pervasive accounting anomaly, namely the presence of a post-earnings announcement drift (PEAD) in equity returns. An investigation into the presence of his phenomenon was undertaken by Wei, Truong, and Veeraraghavan (2012) who looked at the pricing of corporate bonds in the 30-day period subsequent to an earnings announcement in the years 2002-2010. Consistent with the inferences drawn from Easton, Monahan, and

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Vasvari (2009) and the foundational work into the asymmetric pay-offs of bonds presented by Black and Scholes (1973), the authors find evidence to suggest that the PEAD anomaly is present in the corporate bond market and that this relationship is especially important when considering negative news.

Another interesting recent study is that of Even-Tov (2015). This work investigates whether the bond price reaction around earnings announcements is able to supplement and subsume previously documented accounting-based fundamental anomalies in predicting future stock returns. In line with other studies the paper documents that the announcement period bond return can predict future stock returns and that this relationship is more pronounced within the universe of non-investment grade bonds. Interestingly the author also considers the level of institutional/sophisticated ownership in both the stock and bond markets and finds that the relationship between the bond return and future stock returns is greater for those stocks with lower institutional ownership and for bonds with a higher degree of trading by sophisticated investors (as proxied for by the size of the trade).

A final comprehensive study was undertaken by Crawford et al. (2014). The authors take a high-level approach and examine whether 32 accounting-based fundamental anomalies also exist within the corporate bond market. The authors' key finding is that 18 of the 32 anomalies are significantly related to future abnormal bond returns. In general the authors document that the size of these returns are invariably lower than that documented for the equivalent anomaly in the equity market. However when considering Sharpe ratios, to try to account for any possible differences in the volatility of returns in either market, the study indicates that when the anomaly trading strategies are undertaken in the bond market they often outperform those same strategies carried out in the equity market. A final takeaway is that these results are often amplified when the authors focus on speculative bonds as opposed to those that are deemed investment-grade. This finding that the type of bond issue under investigation is crucial in determining the strength of a hypothesized anomaly appears consistent with some of the preliminary findings outlined above. Despite all of these recent important advances, the literature is still underdeveloped and the importance of accounting information to corporate bond holders is far from conclusive.

The most closely related paper to this study is Wei and Zhou (2012). The authors state that the objective of the paper is to identify the information content of trading activity prior to earnings announcements. Despite initially appearing to tackle a closely related issue to this study, I believe that the paper has a number of limitations that are brought about by the decision to utilize the *Historic* TRACE dataset. If anything, this is exactly the type of paper that this study seeks to improve by bringing to light the obstacles that can be overcome by employing the comprehensive *Enhanced* TRACE dataset when carrying out research within the corporate bond market.

This study is distinct from that of Wei and Zhou (2012) in two clear ways. Of utmost im-

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portance is the decision to employ the *Enhanced* TRACE dataset in this paper. The choice to utilize the augmented *Enhanced* TRACE data enables the research presented here to be significantly more accurate in calculating the true differences between the value of purchases and sales in the periods around earnings announcements. As is clearly documented in this paper, there are important, and often very sizeable, portions of trading activity in the corporate bond market that are completely hidden from a researcher if they are forced to employ the capped values of bond trading volumes given in the *Historic* TRACE dataset. These inaccuracies lead to the very real possibility of inducing large estimation errors throughout a study, possibly calling any findings into question. The second important way in which this paper distinguishes itself is in its clear focus on block trading activity, and in particular the portion of that activity that is not observed by the capital markets in real-time. By maintaining this focus, the paper is able to directly address an important contemporary regulatory discussion, namely whether regulators should increase (or completely remove) the currently imposed TRACE dissemination caps. This is a question that is fundamentally unanswerable without the benefit of the *Enhanced* TRACE dataset and the uncapped volume measures that it provides. To the best of my knowledge no other paper has attempted to address this issue directly.

Corporate Bond Market Disclosures and TRACE

Research looking at the behaviour of corporate bond prices was relatively muted until the advent of TRACE. An exception was Hotchkiss and Ronen (2002) who consider a sample of 20 high-yield bonds whose prices were recorded in the fixed income pricing system (FIPS), a precursor to TRACE, provided by the National Association of Security Dealers (NASD). Reassessing the results documented in Kwan (1996), the authors researched the intra-day efficiency of the equity and bond markets by looking at hourly and daily transactions for 55 bonds over the period running from January 3rd, 1995 to October 1st, 1995. No evidence was found that stocks lead bonds in processing firm-specific information. In contrast to Kwan (1996), Hotchkiss and Ronen (2002) explicitly investigate the market reactions around an event, namely earnings announcements. They claim that the information released is promptly incorporated in security prices by both markets.

The advent of the TRACE dataset was a seismic shift in the level of disclosure in the corporate bond market and prompted a number of research questions. Examples included Downing, Underwood, and Xing (2009) who re-investigate the relationship documented in Hotchkiss and Ronen (2002) and examine the intra-day informational efficiency of the stock and corporate bond markets by using the broader sample made available by TRACE. The authors provide evidence of a lead-lag relationship between the corporate bond market and the equity market, with the stock market demonstrating predictive ability for low-rated corporate bond returns at hourly- and daily- frequencies. It is claimed that this provides further evidence that the corporate bond market is less informationally efficient than the equity mar-

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ket. The relatively high transaction costs associated with trading in corporate bonds are given as an explanation for such a difference in the two securities markets. High costs could prevent only the most informationally-sensitive issues responding to information. While the evidence suggests that stocks are superior to bonds in processing information, the results are far from conclusive. Recent work in by Ronen and Zhou (2013) benefits from the use of TRACE data and counter these findings. The authors claim that the higher informational efficiency of the equity market documented in prior work is no longer found when the unique liquidity and institutional trading features of the corporate bond market are accounted for. In general it would appear that the evidence is mixed as to which of the stock and bond markets (if any) dominates the other in terms of efficiency.

Beyond simply utilizing the TRACE dataset to reassess prior important questions, a number of authors also investigated the impact that the release of the TRACE itself had on the corporate bond market. Early papers included Goldstein, Hotchkiss, and Sirri (2006) and Edwards, Harris, and Piwowar (2007) who documented the impact the introduction of TRACE had on corporate bonds in terms of their liquidity and price respectively[11]. Utilising the early dissemination choices of TRACE, Goldstein, Hotchkiss, and Sirri (2006) carry out a controlled experiment to investigate the changes in liquidity of bonds both before and after the change in transparency brought about by their inclusion in TRACE. Looking cross-sectionally at a sample of BBB-rated bonds, the authors found that the increased transparency brought about by TRACE had either a positive or neutral effect on a bond's trading volume and bid-ask spreads. Edwards, Harris, and Piwowar (2007) investigate transaction costs for corporate bonds and find that these costs vary substantially depending on the size of the trade undertaken. Interestingly the authors also look at the impact that TRACE introduction has on the transaction costs associated with corporate bond trading and find that these costs fall when considering those bonds afforded increased transparency under TRACE.

An additional contemporaneous paper was Bessembinder, Maxwell, and Venkataraman (2006). Similar in spirit to Edwards, Harris, and Piwowar (2007), the authors utilize the data related to corporate bond trading activity by insurance firms provided by the National Association of Insurance Commissioners' database to estimate the trade transaction costs 6 months either side of the introduction of TRACE. These costs appear to fall by approximately half in the period following TRACE relative to the 6 months prior to its introduction. The unique aspect of the paper is the ability to explicitly identify trading cost changes after the introduction of TRACE. While the other papers cited compare those bonds disseminated by TRACE with those that were not, Bessembinder, Maxwell, and Venkataraman (2006) is able to look at a given bond over time to assess how trading costs change with a change in transparency.

[11] A good summary of this literature and the early features of TRACE is also provided in Bessembinder and Maxwell (2008).

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A more recent paper is Asquith, Covert, and Pathak (2013). Benefiting from the decision by TRACE to implement their transparency requirements in phases for different types of bonds, Asquith, Covert, and Pathak (2013) investigate the impact that the implementation of TRACE had on price dispersion and trading activity within the corporate bond market. Looking at all phases of TRACE implementation and employing a difference-in-differences approach the authors undertake a before-and-after comparison of increased transparency regulations. The study finds that none of the phases experience trading activity increases, and that some phases experience reductions of around 40% in the 90 days following the dissemination of trade details. In addition, price dispersion decreases with the implementation of trade reporting requirements. In line with other papers, the credit quality of the bond in question is an important determinant of these effects.

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Chapter 3

Hypothesis

3.1 Hypothesis Development:

From an assessment of anecdotal evidence and prior research I expect large trades in the corporate bond market to fall under one of two classifications:

1. 'Opportunistic' informed trading around information events
2. 'Unopportunistic' trading unrelated to information events

Given the ongoing important debate into the necessity of trade reporting caps to protect those agents possibly acting on proprietary information acquired through expensive research efforts, or whether the imposed caps simply benefit broker-dealers at the expense of investors by limiting the ability of investors to assess the level of trade execution they have received, it is important to empirically identify whether large block trades are predominately of the first 'opportunistic'/informed form or of the second 'unopportunistic'/uninformed form.

I would deem evidence that supports the claim that large block trades are typically of the first 'opportunistic' form as support for the retention of the current trade reporting caps. In contrast, I would deem evidence that supports the claim that large block trades are typically of the second 'unopportunistic' form as support for the removal of the current caps.

To test whether block trades do in fact represent opportunistic informed trades I choose to focus on a firm's earnings announcement as the information event of interest. I make the following hypotheses related to block trading around earnings announcements:

Hypothesis 1. *If hidden trading activity is driven by informed trading then it will exhibit an ability to* anticipate *the relevant news in earnings announcements.*

Given the asymmetric pay-offs of corporate bonds I predict that the incentives for market participants to anticipate the news released around an earnings announcement by acting

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on any proprietary information that they may have would be greater for bad news than good news. Given this, if block trades represented informed trading I would expect pre-announcement block trading activity to be more informative prior to bad news than good news events. Likewise, the importance of the news in an information event should increase as a firm approaches default. These observations lead to the following two hypotheses.

Hypothesis 2. *Corporate bond block trading activity exhibits a greater ability to predict large (or 'extreme') negative news events around earnings announcements than large positive news events around earnings announcements.*

Hypothesis 3. *Corporate bond block trading activity exhibits a greater ability to anticipate news events around earnings announcements for non-investment grade ('high-yield'/'speculative') corporate debt than investment grade corporate debt.*

As an alternative to block trades being the result of informed trading around earnings announcements I hypothesise that block trades could instead be driven by either *a*) forced selling due to bond fund redemptions or risk management protocols; or, *b*) systematic period-end portfolio rebalancing unrelated to information events. To test these alternative explanations for possible 'non-informative' block trading I carry out a number of descriptive tests. In all of the alternative cases I have outlined I would expect that large block trades, or net block trading activity, would cluster either *a*) in the periods directly following a ratings downgrade (especially when from investment-grade to high-yield); or, *b*) in calendar-time (i.e. at the beginning or end of the year/month/week). I investigate each in turn.

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Chapter 4

Data and Research Design

4.1 Data Sources and Restrictions

This study incorporates data from a wide variety of sources, utilizing data predominately from five key data providers - the Trade Reporting and Compliance Engine (TRACE) for secondary corporate bond market transaction price data, the Center for Research in Security Prices (CRSP) for equity markets stock return data, Mergent Fixed Income Securities Database (Mergent FISD) for both credit rating data and individual corporate bond characteristics data, Compustat for quarterly financial statement data, and I/B/E/S for earnings announcement timing data.

The base of my sample consists of the intersection of the quarterly Compustat dataset and the CRSP stock returns file. In addition, I require that all firms in my sample have at least one bond that is traded (as inferred from the TRACE Enhanced dataset) in the sample period. Unlike prior studies (Easton, Monahan, and Vasvari, 2009; Even-Tov, 2015) that rely on the Historical TRACE dataset I am less limited in the earlier time periods that I can consider. These studies typically restrict their analysis to post-January 2005 due to the bond coverage restrictions employed by TRACE. This limitation is not present in the Enhanced TRACE dataset, enabling me to investigate trading activity from the first quarter of 2004 onwards[12].

Given this paper's focus on trading activity in the weeks leading up to a quarterly earnings announcement it is imperative to accurately identify when the earnings announcement was released to the market. To do this I utilize data from both Compustat and I/B/E/S. Following prior research (DellaVigna and Pollet, 2009; Even-Tov, 2015) and the recommendation of WRDS I utilize the earnings announcement date recorded in Compustat as my

[12]Note however that the *Enhanced* TRACE dataset is truncated earlier than the *Historical* TRACE dataset due to the 18-month lag imposed on the release of the uncapped data to protect market participants positioning. This results in my sample running until the fourth quarter of 2011.

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default announcement date when I/B/E/S and Compustat agree. This date is then compared to the reported announcement date in I/B/E/S. If there is a difference of between 1 and 5 working days between the recorded dates then the earlier of the two recorded dates is employed. If the difference is greater than 5 days then I again employ the reported date from Compustat.

While the equity market is highly standardized with only one security typically trading for any given company, the corporate bond market is very different and highly non-standardized. It is very common for a given company to have a large number of corporate bond issues trading at the same time. In turn, these bonds can vary widely in their coupon, maturity and payment characteristics amongst other things. This unique aspect of the secondary corporate bond market creates a number of issues for a researcher and necessitates a series of judgement calls to be made, and data restrictions to be imposed, before arriving at a final sample. Given this, I follow prior literature and impose a number of standard data restrictions. These are outlined below.

As a first pass I implement the TRACE cleaning procedure of Dick-Nielsen (2013)[13]. Among other restrictions, this removes trades that are known errors, agency transactions, and double counted inter-dealer transactions. The filter deletes approximately 40% of the raw transactions provided in the *Enhanced* TRACE dataset available on WRDS. Following this data cleaning process, I assess the bond characteristic data from Mergent FISD and choose to exclude all bonds with option-like characteristics (convertible, putable, callable, exchangeable) due to the unique pricing of such issues. In addition, I exclude all bonds that do not have fixed coupons, those that do not have a par value per bond of $1,000, and those where the coupon payment is not semi-annual. Bonds with a remaining maturity (i.e. a tenor) of less than one year or greater than 50 years are excluded, as are all bonds that are not denominated in US dollars. Finally, I choose to exclude all regulated and financial services firms (those with SIC codes between 4400-5000 and 6000-6999) from my analysis. In addition to this I consider the Compustat data provided and remove all firms with missing financial statement data and those with a quarter-end stock price less than $1.

My final sample consists of 12,410 firm-quarter observations for 722 unique firms (Compustat gvkeys). The sample runs from Q1 2004 to Q4 2011. A full analysis of the descriptive statistics and industry composition for the sample is provided in Section 4.3

4.2 Key Variable Construction

This project utilizes two key variable constructs from prior research to assess the level of informativeness of trading in the cash corporate bond market, and in particular the

[13] The SAS code for this procedure was kindly provided in the cited paper.

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informativeness of the portion of that trading that is not observed by the market in real-time, around earnings announcements. These measures are 1. the trading imbalance measure of Wei and Zhou (2012) and, 2. the earnings per share forecast measure derived from the So (2013) characteristic forecast methodology. I outline the construction of each measure, and the rationale for employing each measure, next.

Wei and Zhou (2012) Imbalance measure

A key component of the *Enhanced* TRACE dataset is the classification of the type of trade that occurs. Broadly, TRACE provides an indicator of whether the recorded trade is either a 'Buy' or a 'Sell' while also indicating whether the trade type is 'Inter-Dealer' or 'Customer'. Following prior research, and given that the objective of this paper is to investigate the possible proprietary private information that may be driving corporate bond trading volume, I choose to eliminate from my research all inter-dealer trades. These are more likely to be non-information driven trades, instead motivated by the need to either increase or decrease their corporate bond inventory holdings to satisfy the needs of their customers. Given these exclusions a buy trade represents a purchase on the part of the customer, whilst a sell trade represents a sale on the part of the counterparty deemed to be the customer.

Prior research into the corporate bond trading activity around earnings announcements was potentially limited by its reliance on the aggregate trading volume that occurred within a period, without being able to distinguish between the type of trading that was occurring. Although buy and sell data has been included in the standard *Historic* TRACE dataset since November 2008 it has been lightly used. I seek to leverage the information inherent in the type of trade that occurs by following Wei and Zhou (2012) and employing their 'trading imbalance' measure[14]. The base of this measure is given as:

$$VolImb_{i,t}(-10,-1) = \frac{Vol\_BUY_{i,t}(-10,-1) - Vol\_SELL_{i,t}(-10,-1)}{Vol\_BUY_{i,t}(-10,-1) + Vol\_SELL_{i,t}(-10,-1)} \tag{4.1}$$

In this setup $Vol\_BUY_{i,t}(-10,-1)$ represents the aggregate dollar volume of all trades that are classified as buys in the ten day period that begins 10 days prior to an earnings announcement and ends the day prior to an earnings announcement. $Vol\_SELL_{i,t}(-10,-1)$ is analogous. This measure was employed for each of the three elements of the total trading volume on a day. The three fundamental components I considered in my decomposition of

[14] Similar imbalance measures have been employed in studies investigating the relationship between daily stock market returns and order imbalances (Lee, 1992; Chordia, Roll, and Subrahmanyam, 2002), the propensity of individual investors to buy attention-grabbing stocks (Barber and Odean, 2008), the ability of retail trades to convey information about future stock prices (Kelley and Tetlock, 2013), and investigations into institutional order flows (Hendershott, Livdan, and Schürhoff, 2015).

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trading volume were:

1. the 'non-block' trading volume (i.e. the total volume of all trades that were not block trades);
2. the 'reported block' trading volume (i.e. the volume of all the trades that would have had to have been reported to the market as either '\$1MM+' or '\$5MM+' under the *Historic* TRACE dataset); and
3. the 'hidden block' trading volume (i.e. the total difference between the actual volume that is reported in the *Enhanced* TRACE dataset for block trades, and the volume that would have been to reported to the market as either '\$1MM+' or '\$5MM+' for these block trades under the *Historic* TRACE dataset).

A clear breakdown of this relationship is provided in Figure F.1

It is important to note that due to the very infrequent nature of bond trading it is prudent to consider a relatively large window of aggregate activity to accurately capture any possible information-driven trading. The decision to implement the 10-day window was a trade-off between having a large enough window to capture trading activity in the face of the illiquidity of the market, and not having a window that is so large as to capture trades that are unrelated to the possible news embedded in the earnings announcement. Moreover, if one were to consider the mean value of daily trading across the same ten day period the very high proportion of days where there are no trades swamps the information from any day in which a trade occurs, strongly biasing the measure towards zero. For these reasons I deemed it unwise to consider mean daily levels of pre-announcement trading activity and settled on a ten-day pre-announcement window[15]

Having created the base imbalance measure for the 10-day period these are then normalized by subtracting the same imbalance measure from Equation (4.1) but calculated over a different time period. To achieve this, for each bond I identify the aggregate level of buy and sell trades respectively across the firm's entire history. I then subtract all trading activity that falls within the (-20,20) trading window around *any* earnings announcement for that firm. This gives 'non-event' aggregate measures of trading volumes for both buy and sell trades. From these two aggregate measures I calculate a 'non-event' imbalance measure that I use to normalize my (-10,-1) trading volume imbalance measure[16]. It is results for this normalized 'imbalance' measure that are documented throughout this study unless otherwise

[15] An alternative window that ran from day $t - 20$ to $t - 1$ was also investigated. The results were unchanged when this was employed.

[16] For robustness, an alternative normalization adjustment was also carried out using the imbalance measure for the (-50,-21) day trading period prior to an earnings announcement. This measure was not employed due to the high level of instances in which there was no trading activity in the (-50,-21) day period, and thus no adjustment applied. These untabulated results however were comparable to the main reported results.

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specified.

To assess the validity of the imbalance measure, in Figure F.13 I consider the time series properties of each of the three key imbalance calculations - non-block, reported block, and hidden block volume. The mean value of the imbalance measure across all earnings announcements in a given quarter is plotted over time. We can clearly see that there is a reassuring level of variance in each of the measures quarter-over-quarter. This suggests that the different types of trades may vary their buy/sell activity over time. Encouragingly, despite this variance the measures also appear to be relatively tightly bounded around zero. In any given month there do not appear to be any extreme outliers, with the most positive mean imbalance measure in any quarter only approaching 0.12. Finally, it should be noted that in a typical quarter the imbalance measure for non-block trades is positive, while the imbalance measure for the (-10,-1) day period for the hidden portion of block trades is negative. This may suggest that the hidden portion of block trades is more heavily weighted towards sell trades in the (-10,-1) trading period before an earnings announcement than buy trades.

In addition to assessing the time series property of the measure I also look at the distribution of each of the three variables across all earnings announcements. Results are reported in Figure F.14. We can clearly see that for all three measures the peak density falls around a value of zero. Non-block imbalance measures appear to be more positive in general and also more variable, with greater mass falling in the tails of the distribution. In addition, for all three calculations there are spikes of mass at the -1/+1 values. These would represent occurrences where either there is no trading in the (-10,-1) day period and all other trading is either solely attributed to either buys or sells. Alternatively they would be instances where there is no volume in the non-event period and all trading in the (-10,-1) period is solely attributable to either buys or sells. I deem this to be less likely given that it would require the firm to have no activity (or *exactly* equal buy/sell activity) in it's entire non-event history.

So (2013) EPS Forecasts

A fundamental objective of this study is to understand whether the portion of block trading that is hidden from the market in real-time due to the dissemination choices of TRACE is 'informed'. My key research design choice to attempt to answer this question is to consider whether this corporate bond trading is able to anticipate the news released around earnings announcements. To do this I employ the following two measures of the news around earnings announcements:

1. the earnings per share surprise at the announcement, as inferred from the difference between the recorded earnings per share and the ex-ante earnings per share that would

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have been predicted if employing the So (2013) characteristic forecast procedure for expected earnings; and,

2. the cumulative abnormal return in the three day window that spans the earnings announcement.

The advantage of employing the So (2013) procedure is that, in contrast to the ex-post nature of the cumulative abnormal return as a measure of the news in the earnings announcement, it provides the researcher with an ex-ante earnings expectation that can then be directly applied to the earnings result itself. This is the principal measure of earnings announcement news I consider in this paper, however by investigating both measures one can alleviate concerns that any results are driven solely by a misspecification of the news in an earnings announcement.

The So (2013) EPS prediction measure uses historically estimated relationships to anticipate earnings per share. One unique element of the procedure is the choice to employ cross-sectional regressions of lagged values of a series of fundamental predictors of future profitability on current earnings per share. These estimated coefficients are then applied to the current values of those fundamental predictors to forecast the next period's earnings per share. This cross-sectional regression utilizes firm characteristics that have been established in the prior literature as robust predictors of future earnings (Fama and French, 2006). The exact linear relationship that is estimated each quarter is given below, with full variable descriptions provided in Appendix A:

$$\begin{aligned} EPS_{i,t} = \alpha &+ EPS\_POS_{i,t-1} + EPS\_NEG_{i,t-1} \\ &+ ACCR\_POS_{i,t-1} + ACCR\_NEG_{i,t-1} \\ &+ AT\_GRWTH_{i,t-1} + Zero\_DIV_{i,t-1} \\ &+ MTB_{i,t-1} + Price_{i,t-1} \\ &+ DIV_{i,t-1} \end{aligned} \tag{4.2}$$

Originally designed as a methodology with which to predict analyst forecast errors, the So (2013) EPS prediction measure was shown to be especially accurate in forecasting EPS. A particular advantage is this methodology is the decision to eschew the time-series models that have been employed in prior research to estimate future earnings (Foster, 1977; Watts and Leftwich, 1977; O'Brien, 1988). This choice reduces the need for extensive availability of historical data, a particular advantage in a study such as this that is only able to call upon 8 years (32 quarters) of data. In addition, the cross-sectional characteristic forecast approach has been shown to outperform not only time-series models of earnings forecasts, but also *analyst forecast* models. These analyst forecast models had previously been shown to outperform time-series models of earnings. Given the comprehensive outperformance of

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the So (2013) model, and the data requirement advantages that it offers, I deem it appropriate to use the forecasted earnings per share generated by the quarterly models as the default measure of ex-ante earnings expectations throughout this study.

It should be noted that the original paper employed annual cross-sectional regressions to arrive at EPS forecast for the following fiscal year. Given the choice in this paper to employ quarterly earnings announcements I investigate the nature of my regressions in more detail to confirm the validity of the forecasts as my chosen proxy. Table G.4 provides a first step. Here I consider consider the mean values of both the estimated coefficients and the t-statistics for these coefficients across all of the quarterly cross-sectional regressions that I run. In general the results conform closely with those documented in So (2013). For nearly all variables the the average coefficient has the same sign as that reported by in So (2013). Typically, these directions are also intuitively appealing. For instance, the results suggest that those firms that report a loss in the prior quarter should have a lower earnings per share in the current quarter. Likewise, firms with a higher prior price are predicted to have a higher current earnings per share. Interestingly the direction of the coefficients in this study related to accruals have the opposite sign to those in So (2013). The accrual figures reported in Table G.4 do not appear to be significant however and may simply indicate that the importance of a high accrual component of firm earnings in predicting poor future performance may be diminished in a quarterly setting of firms that have outstanding corporate bonds (Livnat and Lopez-Espinosa, 2008). Finally, it should be noted that the same variables that on average are statistically significant in this study are also statistically significant on average in the original paper[17].

As an additional check I also confirm the ability of my *ex-ante* earnings per share predictions to explain realized earnings per share. These results are provided in Table G.5. This presents the pooled regression of realized EPS on the predicted EPS. The coefficient on the characteristic-forecast-generated predicted earnings per share is positive and highly significant as expected. Interestingly the presence of a statistically significant positive intercept suggests that the forecasts may marginally under-predict the realized earnings. Taken as a whole however the results help to reassure that the earnings prediction model employed in this study is performing well and is in line with that recorded in the original research carried out in So (2013).

[17]The reported significant variables are not exactly the same however across the two studies. So (2013) records more variables whose average t-statistic across all annual cross-sectional regressions are above the threshold for statistical significance. Namely these variables in So (2013) are absolute negative accruals (ACC_NEG_{-1}), year-over-year percentage total asset growth (AT_GRWTH_{-1}), and dividends per share (DIV_{-1}).

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4.3 Descriptive Statistics and Correlations

In Table G.1 I provide descriptive statistics for the sample. I find that both of my measures proxying for the news around earnings announcements are on average small. Interestingly the measure derived from the So (2013) model ($EPS\_Surp_{i,t}$) has a mean surprise that is positive, indicating that the measure may somewhat underestimate quarterly EPS. The $CAR_{i,t}(-10,-1)$ meanwhile has a mean value very close to zero which is reassuring. Both measures exhibit good dispersion with no clear outliers[18]. 44% of the sample is comprised of announcements for high-yield issues, while none of the trading volume imbalance measures exhibit worrying tendencies. In general the mean imbalance measure for all components of trading volume calculated from the 10-day period prior to an announcement is close to zero, suggesting little systematic buy or sell activity. All other variables appear reasonable and in line with prior research suggesting that the sample is well formed and free from any errors or systematic biases.

Tables G.2 to G.3 outline both Pearson and Spearman rank correlations between key variables of interest. Interestingly, none of the volume imbalance components appear to be statistically significantly correlated with either the So (2013) earnings surprise or the quarterly reported earnings per share. They do however exhibit some small negative correlation with the three day abnormal returns around earnings announcements. The imbalance measures themselves do though exhibit some correlation. This association is somewhat unsurprising given that for a firm to have 'hidden' block volume it must first have had to have recorded a level of reported volume that was sufficiently large as to have been capped. Interestingly there does not appear to be any correlation between the non-block imbalance measure and the two components of the block volume imbalance measure, possibly indicating that the two components of the market do not anticipate the same announcements. All other variables are correlated as expected and the results appear to be consistent across both the Pearson correlation measures outlined in Table G.2 and the Spearman rank measures recorded in Table G.3.

Table G.6 outlines the breakdown of the earnings announcements by the industry of the firm that they are associated with. Industries are partitioned on their 2-digit SIC code and the mean earnings surprise (derived from the So (2013) model), firm size, degree of leverage, and fraction of high-yield announcements are reported. While there appear to be a few industries that are particularly well represented, notably Oil and Gas Extraction and Chemicals and Allied Products, I deem the spread of industries to be un-troubling. It is unsurprising to see certain industries having a higher quantity of earnings announcements represented as certain business models are more suited to the use of debt in their capital structure. Almost all industries have some high-yield earnings announcements, whilst the

[18]Note that all variables were trimmed at the 1% level. Comparable results were found when this process was not performed.

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size of the earnings surprise, the firm sizes, and the degree of leverage do not appear to vary systematically across industries. All of these factors suggest that the final sample employed is representative and unaffected by serious sample selection biases.

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Chapter 5

Empirical Results

5.1 Importance of 'Hidden' Block Trades and the *Enhanced* TRACE Data

An important contribution of this paper is the comprehensive comparison of the *Enhanced* TRACE data employed in this study and the capped TRACE data employed in much prior research. Here I carry out a thorough examination of the economic significance of the differences between the two datasets and the possible implications this may have for academic research.

Given that some prior research (Easton, Monahan, and Vasvari, 2009) was constrained to consider the incidence of trade, as opposed to the volume of trade, to assess the relationship between earnings news and activity within the corporate bond market, I first document the stark differences that exist between trade incidence and trade size for block and non-block trades[19]. This is documented in Figure F.3 and Figure F.4. Figure F.3 considers all trading volume in the sample and documents the proportions of total trading incidence and trading volume in a given month that is attributable to either block or non-block trades. The top panel outlines the results for the total *number* of trades and clearly shows that the vast majority of trades in a given month, typically 90% or more, are non-block trades, i.e. they were not recorded as either '\$1mm+' or '\$5mm+' under the original TRACE reporting requirements. Strikingly this stands in marked contrast to the bottom panel which outlines the results for the total *dollar volume* of trades in a given month for the pooled sample. Block trades are a highly important proportion of all trading volume, typically accounting for over 50% of all trading volume and often exceeding 60% of all volume in a month. Given the importance of distinguishing between investment grade and speculative bonds that has been documented in prior research, in Figure F.4 I further repeat this analysis, partitioning my

[19]To be clear, I classify all trades that were previously capped as block trades throughout the paper, while all trades that fell below the dissemination cap, and thus had their true par value volume reported, are classified as non-block.

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sample on the investment grade/high yield classification. The results show that the disparity between trade incidence and trade volume is present in both segments of the market. For investment grade bonds approximately 5% of trades in a month are block trades, and thus capped by TRACE. The trading volume associated with these trades can reach 50% of all volume in a month though. Likewise, for the high yield market (documented in the bottom panels) the trading incidence of block trades is typically between 20 and 30%, with the total volume arising due to block trades invariably exceeding 80%. There are clearly huge disparities between trade incidence and trade volume across the corporate bond market, and this is likely to be driven by the market being dominated by institutional investors (Ronen and Zhou, 2013). I find these results to be an important preliminary justification for the need for researchers to focus on the volume of trading activity, as opposed to its incidence, as the preferred means to assess bond market activity.

Following this I consider the explicit importance of the fraction of corporate bond trading that was unseen by the market in real-time. This is the portion of a given trade that is larger than the imposed '\$1mm+' and '\$5mm+' caps. If this 'hidden' volume is small then the disparity between trading volume and trading incidence just outlined may be less important as researchers would have been able to simply use the capped value as a proxy for the true volume with little implications for their inferences (Wei and Zhou, 2012; Even-Tov, 2015). First in Figure F.5 I identify all 'hidden' trading volume and consider what fraction of all volume this amounts to for an individual firm. This fraction is calculated across all trading days in the (-10,-1) period before an earnings announcement and is aggregated across all earnings announcements reported by a firm. From the figure it is clear that only a small fraction of firms (58/732) never report any hidden volume in the (-10,-1) period. The vast majority of firms never disclose between 15-40% of their total volume in the (-10,1) period and almost 10% of firms (72/732) have between 40 and 45% of their total trading volume hidden in the pre-announcement period. To ensure that there are no systematic differences across trade types I repeat this analysis in Figure F.6, separating the volume aggregation across buy and sell trades. The results are very consistent. This further indicates that a very sizeable portion of bond trading activity is never reported in real-time and thus would have been excluded from the research of those using the original TRACE dataset.

To further confirm the importance of the size of the trading volume that was not previously captured in the TRACE dataset, and to ensure that it was not confined to a small number of individual earnings announcements, the previous analysis was repeated to assess the percentage of trading volume around individual earnings announcements that was hidden. These results are presented in Figure F.7. It can be seen that nearly 60% of all earnings announcements have some volume that was hidden from the market and that around 15% of all announcements have 40% or more of all the trading volume in the (-10,-1) period being unreported. When breaking this analysis down by buy and sell trades in Figure F.8 it is shown that the results are very similar. There does not appear to be a systematic difference across trade types and only around 46% of earnings announcements have no hidden volume

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in both samples. Important differences have been documented between the universe of investment grade corporate bonds and high-yield bonds and therefore Figure F.9 investigates whether the documented levels of hidden volume around earnings announcements vary by credit rating. Again, hidden volume can be a very sizeable fraction of all volume in the (-10,-1) trading period before an earnings announcement for both high-yield and investment grade bonds. Interestingly the figures show that hidden volume is in fact even more important for speculative grade issues. Almost 60% of all earnings announcements for high-yield issues have some hidden volume prior to the announcement, whereas this figure is closer to 50% for investment grade issues. Nearly 20% of high-yield announcements have 40%+ of their trading volume hidden. I deem this to be extremely significant. Once again, when comparing whether there are major differences across buy and sell trades (Figure F.10), I find significant percentages of earnings announcements containing hidden volume for both types of trades. The results appear strong, consistent and economically meaningful.

Finally, in Figure F.11 I consider whether these relationships vary across firm size. The figure clearly shows that the the hidden volume is an economically important fraction of all trading volume in the 10-day pre-announcement period and that this holds across all firm sizes. For the largest firms approximately 30% of all volume in the (-10,-1) trading day window is hidden from the market, while for the smallest firms (as measured by total assets) this 'hidden' volume accounts for nearly 50% of all activity. In sum, the evidence presents a compelling case that there are significant differences between the TRACE dataset that has been used historically and the *Enhanced* TRACE dataset employed in this research. There are frequent and very sizeable portions of corporate bond trading activity that were obscured from researchers in the past, and these differences were even greater in the high-yield universe of bonds, suggesting that it is prudent for researchers to focus on using the uncapped trading volume data recorded in the *Enhanced* TRACE dataset going forward.

5.2 Anticipation of Earnings Surprises

Portfolio Sorts and the Relative Occurrence of Block Trades

Having established that the fraction of volume that was previously hidden from the market and prior researchers is large and systematic, I proceed to investigate whether it exhibits the traits of informed trading. As a preliminary investigation I carry out a series of nonparametric tests.

If corporate bond block trading is indeed related to accounting-focused information events then it may be reasonable to assume that this trading would cluster around those events, namely quarterly earnings announcements. To see whether this is the case, I investigate the proportion of annual trading volume and annual trading incidence that falls around the

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release of quarterly earnings news. These results are reported in Table G.7. Panel A documents the the average percentage of annual block trading volume (incidence) that falls in various trading windows around earnings announcements. If trading volume (incidence) is evenly distributed throughout the year then we would unconditionally expect that 4.8% of annual volume (incidence) would fall in any 3-day window, or 16% would fall in any 10-day window. I find little evidence to suggest that there are elevated levels of either trading incidence or trading volume in the period before an earnings announcement. In both the (-10,-1) and the (-20,-11) trading period the level of block volume (incidence) is approximately 14%. Using one sided t-tests, I find no evidence that these levels are statistically significantly different from the unconditional expectation of 16%. There does however appear to be an elevated level of activity in the 3-day window immediately around the announcement date. The percentage of total block trading incidence (volume) that falls in the (-1,1) trading days around an announcement is 5.5% (5.6%) and this is statistically significantly higher than that unconditionally expected.

When partitioning by whether the issue in question is investment grade or high yield, as reported in Panel B, I find the results to be very similar. In the pre-announcement periods of (-10,-1) and (-20,-11) the level of activity is lower than that which would be unconditionally expected. In addition, when employing t-tests to investigate potential differences in means between the two samples, I fail to reject the null hypothesis that the mean volume (incidence) is the same in both the high yield and investment grade partitions. When considering the (-1,1) period immediately surrounding an earnings announcement, I again find that the volume and incidence is higher than that which would be unconditionally expected. There also appear to be systematic differences across the samples. When testing the differences in means across the samples it can be seen that the high-yield sample has a greater level of block trading incidence and volume in the 3-day window when tested at the 10% level of significance. To ensure that these results were not driven by a particular anomalous year the process was also repeated on an annual basis, as reported in Panel C. The results are consistent. There appears to be little evidence of elevated trading in the periods immediately preceding an earnings announcement, while the 3-day window bracketing the announcement does appear to exhibit elevated levels of activity.

An important consideration that was overlooked in Table G.7 was the type of news that was released in the announcement period. I consider this by carrying out portfolio sorts each quarter based on the level of the realized earnings surprise and documenting the mean values of various measures of bond trading activity in the 10-day period prior to the announcement in each quintile portfolio. The results for measures of earnings surprises derived from the implementation of the So (2013) model are reported in Table G.8. Panel A considers whether there are differences between the true volume that was traded (DolVolImb) and the capped volume that was reported to the market (CapVolImb) in anticipating earnings news. In general it does not appear that there are systematic differences across portfolios of earnings news for either measure. In all cases the presence of negative values for the respective

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mean imbalance measures would suggest marginally more selling activity than buying activity in the 10-day period before the event. This level of imbalance does not appear to vary consistently across portfolios though, with the portfolio of the best quarterly news events (Rank 5) having very similar mean imbalance measures to that portfolio containing the worst news (Rank 1). In Panel B, I decompose the total volume into its three components - non-block volume (NonBVolImb), the reported portion of block volume (RepBVolImb), and the hidden portion of block volume (HidVolImb) and repeat the analysis. Interestingly the presence of positive values across all portfolios for the non-block trades indicates net buying in all portfolios prior to an announcement, while this purchasing is greater prior to good news (0.018) than bad news (0.005). Both partitions of block trading activity exhibit negative values for the imbalance measure across nearly all portfolios. Of particular interest is whether this varies by portfolio for the hidden portion of block trading. It does not appear to do so, possibly indicating that the hidden block trading does not anticipate earnings news.

OLS Regression

While the evidence so far suggests that large trades in the corporate bond market are not systematically related to earnings announcements, or the news released in earnings announcements, I investigate this further through a series of parametric tests. To achieve this I employ the following OLS models to investigate the relative explanatory power of bond trading imbalance measures to explain quarterly earnings surprises ($EPS\_Surp_{i,t}$)[20] derived from the So (2013) characteristic forecast model procedure.

$$EPS\_Surp_{i,t} = CapVolImb_{i,t}(-10,-1) \tag{5.1a}$$

$$EPS\_Surp_{i,t} = NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \tag{5.1b}$$

$$\begin{aligned} EPS\_Surp_{i,t} = &NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \\ &+ HidVolImb_{i,t}(-10,-1) \end{aligned} \tag{5.1c}$$

$$\begin{aligned} EPS\_Surp_{i,t} = &NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \\ &+ HidVolImb_{i,t}(-10,-1) + HY_{i,t} + Log\_AT_{i,t} + Lev_{i,t} \\ &+ MTB_{i,t} \end{aligned} \tag{5.1d}$$

$$\begin{aligned} EPS\_Surp_{i,t} = &NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \\ &+ HidVolImb_{i,t}(-10,-1) + HY_{i,t} + Log\_AT_{i,t} + Lev_{i,t} \\ &+ MTB_{i,t} + CAR_{i,t}(-10,-1) \end{aligned} \tag{5.1e}$$

To account for possible systematic differences occurring in different quarters or industries I employ both quarter and year fixed effects in all regressions. As a preliminary investigation

[20] Robustness checks related to 3-day announcement window abnormal returns are presented in Section 6.1.

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I first employ Equation (5.1a) to investigate whether the originally reported total volume under the *Historic* TRACE dataset is able to anticipate earnings surprises. I find little evidence that this is the case. It is entirely possible that large block trades are dominated by sophisticated, large institutions (Bessembinder and Maxwell, 2008) while non-block trades are likely to have a far higher presence of (possibly unsophisticated) retail investors. Given this I decompose the originally reported trading volume into its block and non-block components in Equation (5.1b) before supplementing this with the block trading volume that was hidden from the market and only available through the *Enhanced* TRACE dataset in Equation (5.1c). In neither instance do I find any incremental ability of block trading to be able to explain the news in earnings announcements. In Equations (5.1d) to (5.1e) I include additional control variables that should help to explain earnings surprises. In particular I include whether the issuer was high-yield or investment grade, the size of the firm, the firm's leverage, the market to book value of the firm, and the pre-announcement period stock return of the firm. Of particular interest is the pre-announcement stock return of the firm. This is positive and highly statistically significant, possibly indicating that the equity market outperforms the corporate bond market in anticipating news events around earnings announcements (Kwan, 1996; Bittlingmayer and Moser, 2014). In general the evidence would indicate that the trading volume in corporate bonds prior to an earnings announcement has little, if any, ability to anticipate the news in the announcement.

5.3 'Extreme' Event Antcipation

Logistic Regression

A possible reason for the limited evidence of systematic corporate bond trading prior to earnings announcements could be the the asymmetry in bond pay-offs outlined in Black and Scholes (1973). Given that the pay-offs to corporate bonds are capped and that the the likelihood of incurring a loss on your investment is low except in the case of low quality bonds or particularly poor news events, it is likely that only the most 'extreme' news realizations are relevant to corporate bond holders. Given this, I investigate just the largest earnings surprises, both positive and negative, to see whether the previous OLS regression results exhibit little ability of corporate bond markets to anticipate earnings events due to the presence of a large number of small, possibly immaterial, earnings surprises.

I employ four models to test the ability of bond trading imbalance measures to anticipate extreme events. I carry out logistic regressions to see whether corporate bond trading (and other control variables) can predict an indicator variable representing the occurrence of a particularly large positive or negative earnings surprise. I define two such indicator variables to achieve this. In both cases I rank earnings surprises each quarter on their magnitude and assign these into decile portfolios. I define those surprises that fall into the portfolio of the

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largest positive surprises to be extreme positive events ($EPS\_Surp\_POS_{i,t}$), while the portfolio of the largest negative surprises is defined as extreme negative event ($EPS\_Surp\_NEG_{i,t}$) and given an indicator value of 1, and zero otherwise. The exact models utilised to assess the ability of the corporate bond market to predict these events are outlined below with industry fixed effects employed in all specifications:

$$EPS\_Surp\_POS_{i,t} = CapVolImb_{i,t}(-10,-1) \tag{5.2a}$$

$$EPS\_Surp\_POS_{i,t} = NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \tag{5.2b}$$

$$\begin{aligned} EPS\_Surp\_POS_{i,t} = &NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \\ &+ HidVolImb_{i,t}(-10,-1) \end{aligned} \tag{5.2c}$$

$$\begin{aligned} EPS\_Surp\_POS_{i,t} = &NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \\ &+ HidVolImb_{i,t}(-10,-1) + HY_{i,t} + Log\_AT_{i,t} + Lev_{i,t} \\ &+ MTB_{i,t} \end{aligned} \tag{5.2d}$$

$$\begin{aligned} EPS\_Surp\_POS_{i,t} = &NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \\ &+ HidVolImb_{i,t}(-10,-1) + HY_{i,t} + Log\_AT_{i,t} + Lev_{i,t} \\ &+ MTB_{i,t} + CAR_{i,t}(-10,-1) \end{aligned} \tag{5.2e}$$

Table G.12 and Table G.13 report the results using extreme positive earnings surprises and extreme negative earnings surprises respectively as the dependent variables in eqs. (5.2a) to (5.2e). In general I find no ability of corporate bond trading to explain extreme positive earnings surprises. None of the decomposed imbalance measures are statistically significant while the control variables I employ load in intuitively appealing directions. For large negative earnings the coefficients on the three imbalance measures load, however considering their odds ratios (the exponential of the coefficient and the standard way to interpret logistic regressions) we can see that for small increases in the hidden imbalance measure the odds of recording a severe negative surprise are marginally reduced. In general the results appear to be somewhat mixed and inconclusive.

Receiver Operating Characteristic (ROC) Curves

To gain a greater insight into the ability of the bond market to anticipate an extreme positive or negative earnings surprise I look at the classification performance of eqs. (5.3a) to (5.3d) below by examining their respective receiver operating characteristic (ROC) curves. The four models I employ to test the ability of bond trading imbalance measures to anticipate extreme events are:

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$$EPS\_Surp\_POS_{i,t} = CapVolImb_{i,t}(-10,-1) \tag{5.3a}$$

$$EPS\_Surp\_POS_{i,t} = NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \tag{5.3b}$$

$$\begin{aligned} EPS\_Surp\_POS_{i,t} = & NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \\ & + HidVolImb_{i,t}(-10,-1) \end{aligned} \tag{5.3c}$$

$$\begin{aligned} EPS\_Surp\_POS_{i,t} = & NonBVolImb_{i,t}(-10,-1) + RepBVolImb_{i,t}(-10,-1) \\ & + HidVolImb_{i,t}(-10,-1) + CAR_{i,t}(-10,-1) \end{aligned} \tag{5.3d}$$

The base results are shown in Figure F.17 which presents the respective ROC curves and details the area under the curve (AUC) for each model for both positive and negative extreme earnings surprises. These models are pooled across observations and do not discriminate between the quality of the bond issue at the time of the earnings announcement.

ROC curves are the standard method of assessing the ability of a model to assign higher probabilities to an outcome, in this case $EPS\_Surp\_POS_{i,t} = 1$, than to a control ($EPS\_Surp\_POS_{i,t} = 0$). The AUC measures the ability of a model to discriminate between those observations that experience an event and those that do not. A higher AUC signals that a model has greater ability to detect different outcomes. Each line in Figure F.17 represents the ROC curve for each of the models outlined in Equations (5.3a) to (5.3d). It should be noted that an AUC of 0.5 represents that the model is effectively unable to distinguish between outcomes. AUC scores of between 0.5-1.0 represent some ability to distinguish, with a score of 1.0 represents a perfect prediction model[21]. While the models presented show some ability to distinguish between outcomes it should be noted that this ability is very minor, to the point of being negligible. In general it appears that the volume traded in the corporate bond market, and the hidden volume that was previously unavailable in TRACE, has little if any ability to anticipate extreme earnings surprises, be they either positive or negative.

When partitioning on whether the issue in question was either speculative or investment grade at the time of the earnings announcement (Figure F.18) I find the results to be similar in both subsamples to those outlined for the pooled sample. Again, for both positive extreme surprises and negative extreme surprises the models outlined in Equations (5.3a) to (5.3d) appear to have little ability to forecast the outcome of the earnings announcement. The evidence points to the decomposed reported trading volume, the hidden trading volume, and even the pre-announcement abnormal returns having little ability to forecast extreme events. These results could lend further weight to the belief that the previously hidden volume in TRACE was not in fact related to informed, proprietary research-driven trading thus potentially supporting the argument to raise or remove the dissemination caps.

[21] A graphical illustration of the quality of AUC curves is provided in Figure F.2

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Chapter 6

Robustness Tests

6.1 Alternative Surprise Measure

To ensure that my results are not simply a consequence of a poorly specified measure of news around an earnings announcements, I repeat a number of my analyses, utilising the cumulative abnormal returns in the three day trading window around a quarterly earnings announcements ($CAR_{i,t}(-1,1)$)[22]. These abnormal returns are calculated as the raw return of the firm less the year-end size decile-matched portfolio return for the same period. If the measure of earnings surprise derived from So (2013) that has been utilised throughout the analysis up to this point is a poor proxy for the news around an earnings announcement then it may be unsurprising that little, if any relationship is found between the surprise and the pre-announcement bond trading volume. Given the strong and intuitive positive relationship between pre-announcement stock returns and the earnings surprise measure, it is unlikely to be poorly specified however it is prudent to check.

As a first pass, I rerun the portfolio sorting procedure. I create 5 quarterly portfolios formed on the size of the quarterly abnormal return and assessing the pre-announcement bond volume patterns. The results appear similar to those found for the earnings surprise measure, i.e. relatively inconclusive (Table G.9). Interestingly the non-block imbalance measure suggests that in the period immediately before a poor earnings announcement non-block trades are larger net buyers than immediately before particularly good announcements. I then re-run the OLS regressions outlined in Equations (5.1a) to (5.1e), using the 3-day abnormal return as the dependent variable. Again, there appears to be little ability of block trades, and specifically the hidden portion of block trading, to explain the news inferred from 3-day abnormal returns. Finally, I consider extreme realizations of return news and re-run the logistic regressions of Equations (5.2a) to (5.2e) (for both extreme positive and

[22] In unreported analyses I also assess whether corporate bond trading anticipates *volatility* around earnings announcements by repeating all analyses outlined with the absolute level of $CAR_{i,t}(-1,1)$ as the dependent variable. In all instances the results are qualitatively similar to those reported here, again indicating minimal ability of corporate bond trading activity to anticipate volatility.

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negative news) and the ROC curves of Equations (5.3a) to (5.3d). For extreme negative news, and for all ROC curves, whether partitioned by investment grade or high-yield, I find minimal evidence to suggest that bond trading volume, and block volume in particular, has any significant ability to explain the extreme realization. All of these results are in essence consistent with the findings for the earnings surprise measure and indicate that 1. the original model was well specified, and 2. there is insufficient evidence to suggest that corporate bond trading is informed (at least as how defined in this study).

6.2 Systematic Monthly/Annual Portfolio Re-alignment

A key possible alternative explanation for the lack of evidence for earnings announcement-induced bond activity is that the corporate bond market is very different in nature to the equity market. The market may simply consist of buy-and-hold investors who rarely make news-driven trading decisions but simply rebalance their portfolios systematically to achieve a desired yield (that can essentially be guaranteed if portfolio securities are held to maturity).

To test this I follow the methodology of Dechow and Shakespeare (2009) and assess whether there is any systematic buying or selling activity that occurs throughout points in time. The periods of time I consider likely candidates for sytematic trading are the day of the week, the day of the month, the day of the year, and the month of the year. The results are plotted in Figure F.19 and Figure F.20. Plots are provided for both the aggregate difference between total buy volume and total sell volume (Figure F.19), and for the the aggregate imbalance measures at any point in time (Figure F.20). The results appear to be extremely consistent over both measures of trading patterns, notably that there does not appear to be any systematic element to the observed volume. In all cases the non-block and reported block volumes appear to be net sellers while the hidden block volume is a net buyer. There appears to be relatively heavier selling activity at the end of the week but other than that there does not appear to be any clear pattern in the net trading activity of the bond market. In general it would appear that the trading is somewhat random and I see little clear evidence to suggest that market participants are rebalancing their portfolios in a pre-determined and structured manner.

6.3 Forced Redemptions

The final possible reason I consider for block trading volume is the possible presence of forced redemptions by the holders of corporate bonds (Ellul, Jotikasthira, and Lundblad, 2011). It is well known that many bond funds (and particularly insurance companies) are

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prohibited from holding non-investment grade corporate bonds in their portfolios. Given this, any observed large trades, and therefore large volumes of hidden trading, may simply be a reaction by bond funds to imminent, or recently occurred, downgrades where they are forced to sell in size to quickly unload their holdings. This is likely to be particularly pronounced when the downgrade in question takes a bond issue from an investment grade to a speculative classification. I investigate this in Table G.16 and Table G.17. In all case I classify a downgrade as occurring if at least one of the three major credit rating agencies downgrades the issue. If multiple rating agencies downgrade the issue in a short space of time the date of the downgrade is taken to be the date on which the first of these downgrades occurs. Further credit rating details are provided in Appendix B. Note that I focus on the total net volume, as opposed to the imbalance measure, in these analyses and compare the pre-downgrade activity to the post-downgrade activity.

Table G.16 considers all ratings downgrades for an issue. For all downgrades I don't find many striking patterns. Again, I observe that non-block activity is typically classified as a net sale while block trading is typically a net buy. There do not appear to be any stark differences between these values in the pre- and post-downgrade periods however. If anything, for block trading there appears to be larger net purchases immediately prior to a downgrade which at first glance is somewhat puzzling. When considering just those downgrades in which the issue goes from investment grade to speculative grade (Table G.16), I find marginally stronger preliminary results. In the ten day period immediately prior to the downgrade there appears to be heavy net selling by block trades and heavy net buying in the 10 day period immediately following a downgrade. This difference is not as large for non-block trades but is still present (see bottom panel). While very preliminary in nature these results may provide some evidence that the corporate bond market in fact displays some ability to anticipate severe rating downgrades. This could be an important avenue of future research.

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Chapter 7

Conclusions

This paper had two important objectives. A primary focus was to provide a thorough examination of the recently available *Enhanced* TRACE dataset and to rigorously establish the size of the difference between between this dataset and the capped TRACE dataset that had been widely used in prior research. In addition to this, an important second objective was to assess whether the portion of block trading that was previously hidden from market participants and researchers was in fact informed. In doing so I sought to address the important ongoing regulatory discussion as to whether the currently imposed TRACE dissemination caps should be altered (or even removed).

In summary, I find there to be significant differences between the data available under the old TRACE reporting regime and the newly issued uncapped TRACE data. The portion of data that was previously obscured from market participants is large and occurs frequently. The vast majority of firms have hidden trading volume at some point in their life cycle and well over half of all earnings announcements have some hidden volume in the days preceding them. The size of this hidden volume can also be highly economically significant, often exceeding 30% of all volume in the pre-announcement period. These differences could carry real importance for researchers, not least when it comes to calculating trade-weighted return measures as is common in the literature, and I believe that it should be investigated further.

In addition to this I find little evidence to suggest that the 'hidden' block volume displays the traits of informed trading. Through a comprehensive series parametric and non-parametric tests I find no support for the claim that the largest block trades are any more informed than of trades in the market, calling into question the need to impose the real-time dissemination caps currently imposed by TRACE. There appears to be some evidence that the corporate bond market does however anticipate and react to important credit rating events, possibly indicating that the information typically contained in quarterly earnings is less relevant to corporate bond holders than that contained within ratings changes.

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Appendix A

Variable Definitions

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Table A.1 – Important Variables

Variable	Description	Data Source
CapVolImb$_i$(-10,-1)	The volume imbalance measure (Wei and Zhou, 2012) calculated from the total dollar volume reported to the market in the (-10,-1) window for a firm prior to an earnings announcement. This real-time disseminated volume is the combination of all non-block trading volume and all capped block trading volume across all bonds the firm has outstanding at the time. The imbalance measure is given as $(Buy - Sell)/(Buy + Sell)$ in the (-10,-1) period. This is then normalized by the same imbalance measure calculated in either the (-50,-21) day period or by the imbalance measure calculated from the aggregate of all activity that does not fall in the (-20,20) day period around any observed earnings announcement across the entire period of a bond's life. Full details are provided in Section 4.2;	TRACE
NonBVolImb$_i$(-10,-1)	The volume imbalance measure (Wei and Zhou, 2012) calculated from the total *non-block* volume reported to the market in the (-10,-1) window for a firm prior to an earnings announcement. Non-block volume is defined as all trades that are not given as '\$1mm+' or '\$5mm+' in the original capped TRACE dataset. Calculation and alternative normalization options are as given in the *CapVolImb$_i$(-10,-1)* definition;	TRACE
RepBVolImb$_i$(-10,-1)	The volume imbalance measure (Wei and Zhou, 2012) calculated from the total *reported block* volume reported to the market in the (-10,-1) window for a firm prior to an earnings announcement. The reported block volume is the capped disseminated volume reported to the market in real-time under TRACE reporting requirements. This caps the reported par value volume of high-yield issues at \$1,000,000 and investment-grade issues at \$5,000,000. Calculation and alternative normalization options are as given in the *CapVolImb$_i$(-10,-1)* definition;	TRACE
HidVolImb$_i$(-10,-1)	The volume imbalance measure (Wei and Zhou, 2012) calculated from the total *hidden* volume that is *not reported* to the market in the (-10,-1) window for a firm prior to an earnings announcement. The hidden block volume is the difference between the actual par value volume traded at the time (as reported in the TRACE enhanced dataset) and the capped disseminated volume reported to the market in real-time under TRACE reporting requirements. This caps the reported par value volume of high-yield issues at \$1,000,000 and investment-grade issues at \$5,000,000. Calculation and alternative normalization options are as given in the *CapVolImb$_i$(-10,-1)* definition;	TRACE

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$HY_{i,t}$	"1" if any one of the bond issues of the firm is classified as high-yield/speculative at time t, "0" otherwise. Full details of numeric ratings conversion provided in Appendix B;	Mergent
$Log\_AT_{i,t}$	The natural logarithm of total assets (Compustat item ATQ);	Compustat
$MTB_{i,t}$	Market capitalisation, defined as the product of quarter close price (Compustat item PRCCQ) and common shares outstanding (Compustat item CSHOQ), divided by book value of equity (Compustat item CEQQ);	Compustat
$LEV_{i,t}$	Total liabilities divided by total assets (Compustat data item: LTQ / ATQ);	Compustat
$EPS_{i,t}$	Adjusted earnings per share as given by basic quarterly earnings per share (EPSPXQ) less recorded special items (SPIEPSQ). This adjustment is made to maintain consistency with both IBES reported earnings and analyst forecasts and the characteristic forecast procedure documented in So, 2013;	Compustat
$EPS\_Pred_{i,t}$	The predicted adjusted-EPS for quarter t for firm i as given by the So, 2013 characteristic forecast procedure. Full details of the procedure, and the variables used to reach the prediction, are provided in Section 4.2;	Compustat
$EPS\_Surp_{i,t}$	The ex-ante earnings surprise for quarter t as given by $\text{EPS}_{i,t}$ - $\text{EPS\_Pred}_{i,t}$;	Compustat
$EPS\_Surp\_POS_{i,t}$	"1" if firm's earnings surprise, $\text{EPS\_Surp}_{i,t}$ (defined above), is in the top decile of all firms in quarter t, "0" otherwise;	Compustat
$EPS\_Surp\_NEG_{i,t}$	"1" if firm's earnings surprise, $\text{EPS\_Surp}_{i,t}$ (defined above), is in the bottom decile of all firms in quarter t, "0" otherwise;	Compustat
$CAR_{i,t}(-1,1)$	The cumulative abnormal return, adjusted for year-end size-decile matched portfolio returns in the same period, calculated from days t-1 to days t+1 relative to the firm's earnings announcement;	CRSP
$CAR_{i,t}(-10,-1)$	The cumulative abnormal return, adjusted for year-end size-decile matched portfolio returns in the same period, calculated from days t-10 to days t-1 relative to the firm's earnings announcement;	CRSP
$XCAR\_POS_{i,t}(-1,1)$	"1" if firm's cumulative abnormal return in the 3-day earnings announcement period, $\text{CAR}_{i,t}$(-1,1) (defined above), is in the top decile of all firms in quarter t, "0" otherwise;	CRSP
$XCAR\_NEG_{i,t}(-1,1)$	"1" if firm's cumulative abnormal return in the 3-day earnings announcement period, $\text{CAR}_{i,t}$(-1,1) (defined above), is in the top bottom of all firms in quarter t, "0" otherwise;	CRSP

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$EPS\_POS_{i,t}$	Adjusted-EPS in quarter t when adjusted-EPS is positive, "0" otherwise;	Compustat
$EPS\_NEG_{i,t}$	"1" if adjusted-EPS in quarter t for firm i is is negative "0" otherwise;	Compustat
$ACCR\_POS_{i,t}$	Accruals per share in quarter t when accruals are positive, "0" otherwise. Accruals are defined as in So, 2013 as the change in current assets (ACTQ), plus the change in debt in current liabilities (DCLQ), minus the change in cash and short-term equivalents (CHEQ) and minus the change in current liabilities (LCTQ). All changes are quarter-over-quarter.	Compustat
$ACCR\_NEG_{i,t}$	Absolute accruals per share in quarter t when accruals are negative, "0" otherwise;	Compustat
$AT\_GRWTH_{i,t}$	The quarter-over-quarter percentage change in total assets (ATQ);	Compustat
$Zero\_DIV_{i,t}$	"1" if the firm reports a dividend in quarter t, "0" otherwise;	Compustat
$DIV_{i,t}$	Dividends per share in quarter t (DVPSPQ);	Compustat
$Price_{i,t}$	Share price at the end of quarter t (PRCCQ);	Compustat

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Appendix B

Credit Rating Classification

The decision as to how to assign a credit rating to firm-quarters is non-trivial. A history of all credit rating changes for a given bond is taken from the Mergent FISD database. As a first step I assign an indicator variable to each *bond issue* at a given point in time to classify whether the issue is speculative/high-yield. There are two feasible options for this classification:

1. Take the average of all possible ratings for a bond issue at that point in time and assign it a non-investment grade (i.e. high-yield) classification if the average rating (in numeric terms) is above the threshold for non-investment grade (i.e. scores 11+, see table below); or,
2. Classify the issue as being non-investment grade if any one of the three possible rating agencies classifies the issue as high-yield.

I deem the second option to be a more conservative measure and thus choose to use this classification throughout (near identical classifications are found when choosing the first option).

A given company (issuer) may have a large number of bond issues outstanding at any one time. Therefore, having classified each bond issue at a point in time, I choose to classify a firm (issuer) as being non-investment grade if *any one of it's bonds* is classified as non-investment grade at that point in time.

Table B.1 – Overview of Ratings Schemes Definitions

Classification	Credit Risk	Moody's	S&P	Fitch	Code Assigned
Investment Grade	Highest Grade	Aaa	AAA	AAA	1
		Aa1	AA+	AA+	2
	High Grade	Aa2	AA	AA	3
		Aa3	AA-	AA-	4
		A1	A+	A+	5

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	Upper Medium Grade	A2	A	A	6
		A3	A-	A-	7
		Baa1	BBB+	BBB+	8
	Medium Grade	Baa2	BBB	BBB	9
		Baa3	BBB-	BBB-	10
Speculative Grade		Ba1	BB+	BB+	11
	Lower Medium Grade	Ba2	BB	BB	12
		Ba3	BB-	BB-	13
		B1	B+	B+	14
	Low Grade	B2	B	B	15
		B3	B-	B-	16
		Caa1	CCC+	CCC+	17
		Caa2	CCC	CCC	18
		Caa3	CCC-	CCC-	19
		Ca	CC	CC	20
		C	C	C	21
Defaulted	Default	D	D	D	22
				DD	22
				DDD	22

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Appendix C

TRACE Key Dates

Table of key dates taken from the TRACE Fact Book 2014 - `http://www.finra.org/sites/default/files/2014-TRACE-Fact-Book.pdf`

Table C.1 – TRACE Implementation Timeline

Date	Action
1 Jul, 2002	TRACE launched with Phase I dissemination and 75-minute transaction reporting requirement
3 Mar, 2003	Phase IIa dissemination: dissemination of additional AAA, AA, A rated bonds
14 Apr, 2003	Phase IIb dissemination: dissemination of 120 BB rated bonds
1 Oct, 2003	45-minute transaction reporting requirement effective
1 Oct, 2004	Phase IIIa dissemination: dissemination of all bonds not qualified for delayed dissemination; 30-minute transaction reporting requirement effective
7 Feb, 2005	Phase IIIb dissemination: dissemination of all public transactions subject to delayed dissemination
1 Jul, 2005	15-minute transaction reporting requirement effective
9 Feb, 2006	Immediate dissemination of all public TRACE-reportable transactions
3 Nov, 2008	TRACE-eligible securities with equity CUSIPs are reportable to TRACE.
1 Mar, 2010	Agency debentures and primary market transactions are reportable to TRACE.
16 May, 2011	Transactions in asset-backed and mortgage-backed securities are reportable to TRACE.
12 Nov, 2012	Transactions in Mortage-Backed securities traded to be announced are subject to dissemination

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22 Jul, 2013	Transactions in Mortage-Backed securities traded in specified pools are subject to dissemination
30 Jun, 2014	Transactions executed pursuant to SEC Rule 144A are subject to dissemination

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Appendix D

Capped TRACE Example

Here I provide an example of two very different trades that would be reported exactly the same under the dissemination rules imposed in the original *Historic* TRACE dataset. In both instances the investor requests $20,000,000 par value of the same investment-grade issue from a dealer.

Investor A receives their full request from dealer A at a price of 100. Investor A is delivered $20,000,000 par value of the issue.

Investor B's order is only partially fulfilled by dealer B also at a price of 100. Investor B is only delivered $5,000,000 par value of the issue. $15,000,000 par value of investor B's order is left unfilled.

In both instances, under the previous dissemination cap rules TRACE would have reported a trade occurring. The recorded price for each trade would be 100. The recorded volume for each trade would be '$5m++'. Under the uncapped *Enhanced* TRACE dataset both trades would be recorded correctly. Investor A's order would have a price of 100 and a par value of $20,000,000 recorded. Investor B's order would have a price of 100 and a par value of $5,000,000 recorded.

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Appendix E

Comment Letter Examples

Some responses to the request for comments on FINRA Regulatory Notice 12-39 (TRACE Dissemination Issues) are outlined below:

"Full disclosure of trade size will help market participants make more informed trading and risk management decisions.In most asset classes, trading activity is a closely watched indicator of market sentiment. Heavy buying or selling activity helps investors interpret news reports and other forms of market research and commentary. Based upon the information currently available through TRACE, it is not possible to accurately assess the level of intraday activity in specific bonds."

Benchmark Solutions, October 4th, 2012

"An incremental increase in the dissemination caps may be a reasonable middle ground approach that takes into consideration the clear benefits of the increased transparency along with any other commentators' concerns regarding a potential reduction in liquidity."

Dimensional Fund Advisors, November 6th, 2012

"Competition is an essential component of a free and open market in securities. In turn, the wide dissemination of information about securities prices and transactions costs is necessary for the creation and maintenance of free, open and competitive markets... Dissemination caps are an impediment to free and open markets. Without the benefit of complete information about trades, investors are unable to accurately gauge the quality of executions received from bond dealers and end up paying higher execution costs than competitive markets would allow."

The Nelson Law Firm, LLC, October 9th, 2012

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Appendix F

Figures

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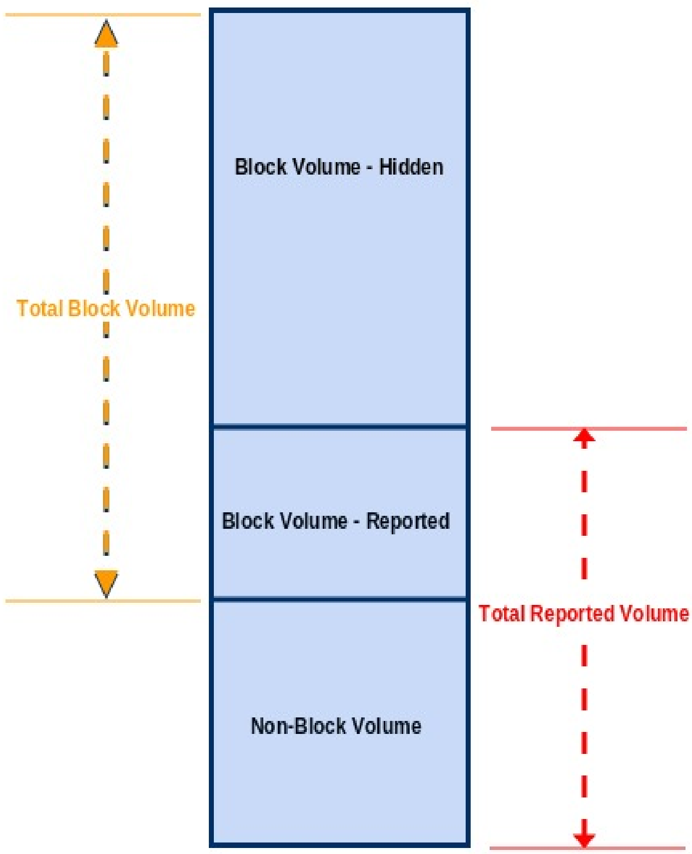
Figure F.1 – Block and Non-Block Volume as Components of Total Volume



This diagram provides an overview of the three components total trading volume for a firm on a given day. Total volume consists of the sum of non-block volume, the portion of block volume that is disseminated to the market, and the portion of block volume that is above the TRACE-imposed dissemination caps and is hidden from the market in real-time. The dissemination caps for large block trades are imposed at a par value volume of \$1,000,000 for non-investment grade (speculative/high-yield) issues and at \$5,000,000 for investment grade issues.

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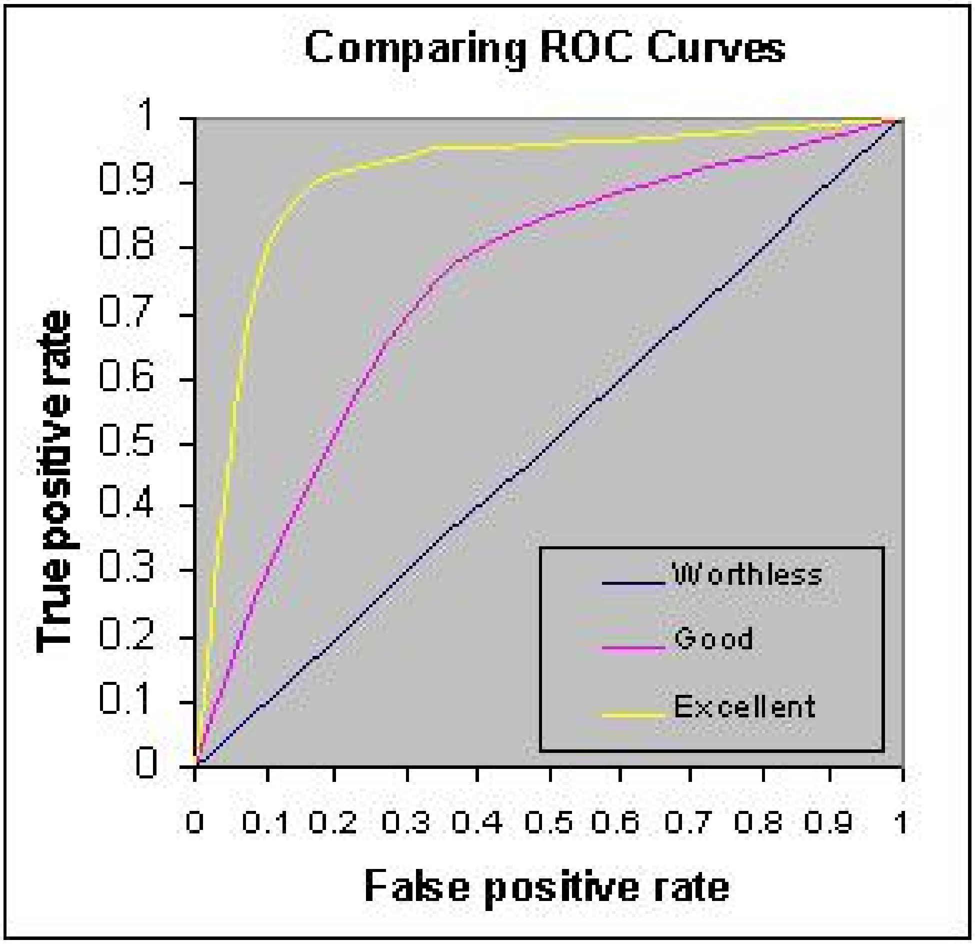
Figure F.2 – ROC Curve Quality Comparison



This diagram provides examples of three theoretical AUC curves. The inferences drawn from each of the three curves into their relative ability to predict an outcome are outlined.

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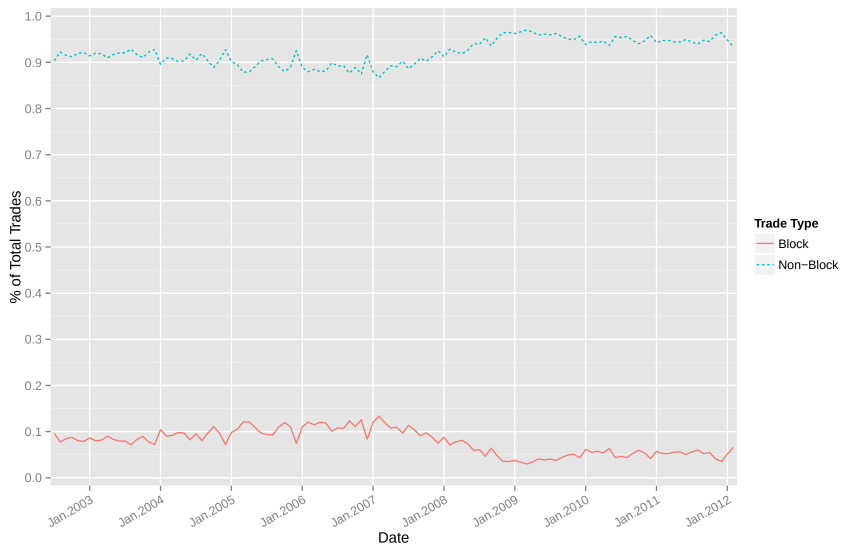
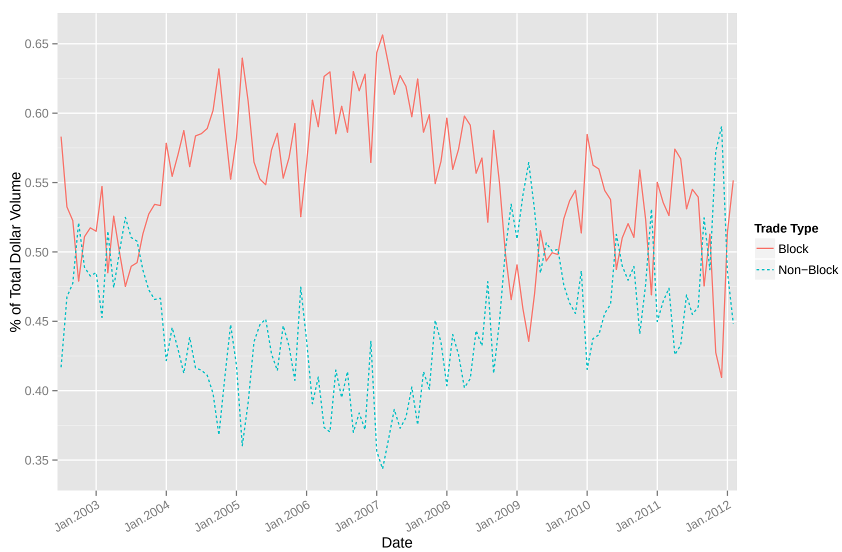
Figure F.3 – Block/Non-Block Percentages of Total Trades and Volume by Month



Percent of Total Trades by Block/Non-Block



Percent of Total Volume by Block/Non-Block

The top panel documents the percentage of total trades in a given month that are classified as either block trades or non-block trades. The bottom panel documents the percentage of total volume in a given month that is due block trades or non-block trades. Note that all trades in the entire sample, and hence all volume, are either classified as block or non-block.

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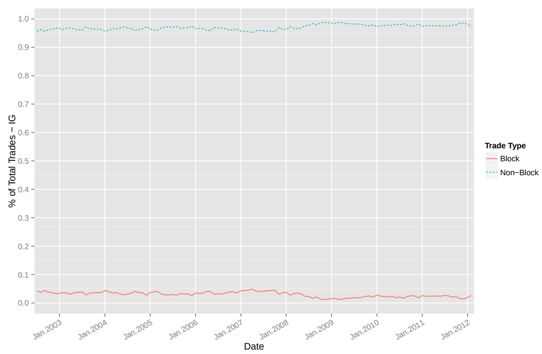
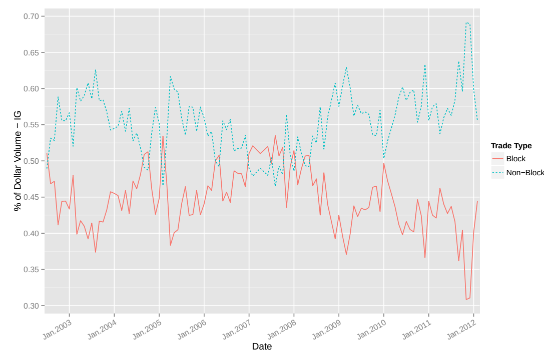
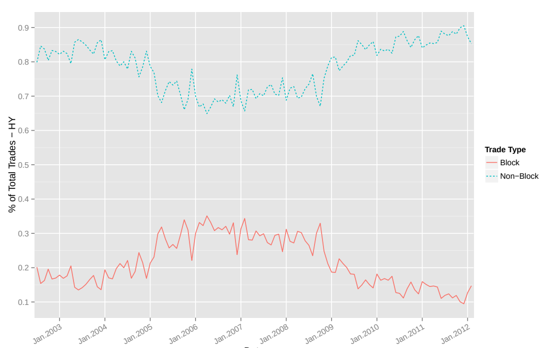
Figure F.4 – Block/Non-Block Percentages - High-Yield/Investment Grade Split



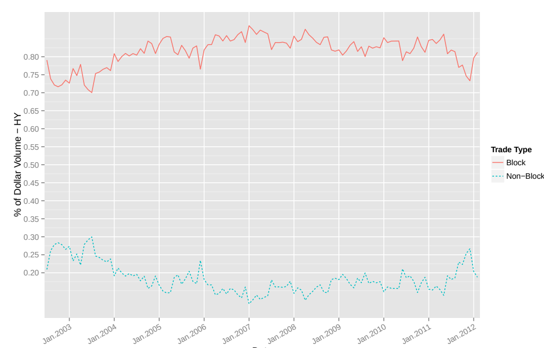
IG - Trade Percentages



IG - Volume Percentages



HY - Trade Percentages



HY - Volume Percentages

The top two panels document the percentage of total trades (volume) in a given month that are classified as either block or non-block for investment-grade (IG) issues. The bottom panels documents the percentage of total trades (volume) in a given month that are classified as either block or non-block for non-investment grade (HY) issues. Note that all trades in the entire sample, and hence all volume, are either classified as block or non-block. Block trades are represented by the red lines while non-block trades are represented by the blue lines.

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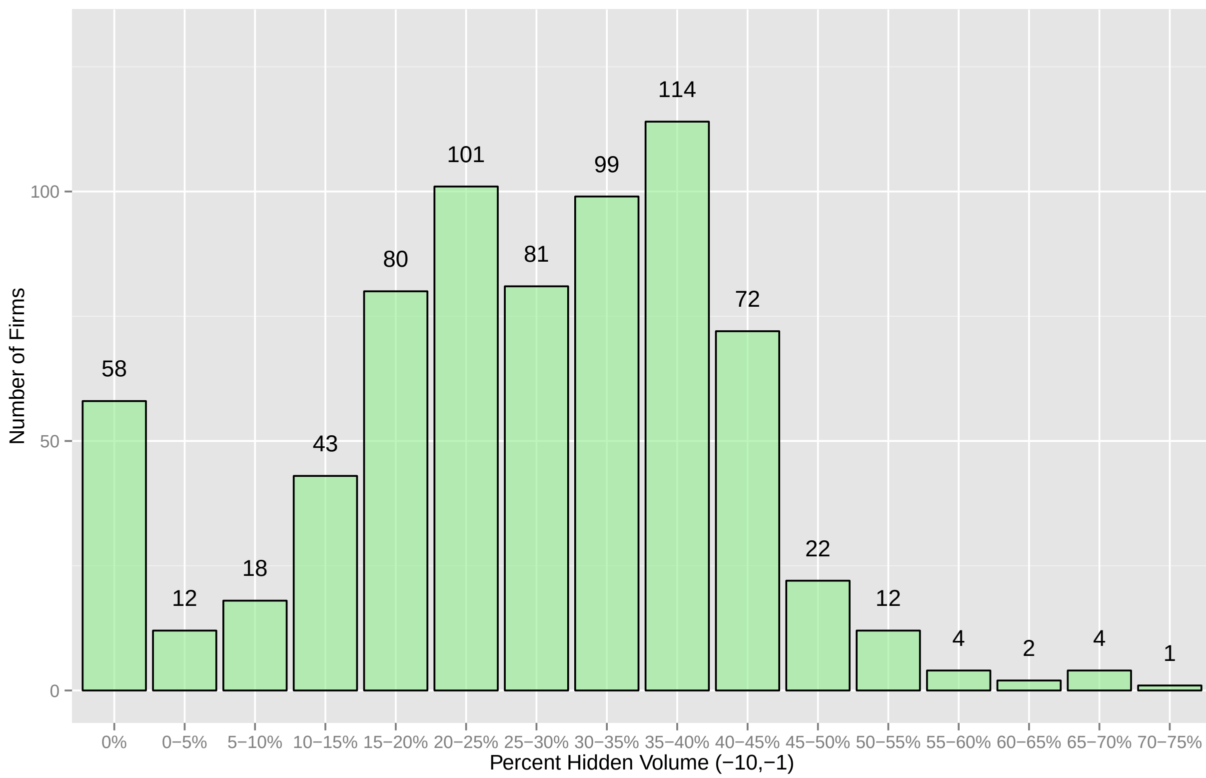
Figure F.5 – Firm Distribution by Percent of Hidden Volume



This figure presents a breakdown of the number of firms that have trading volume hidden from the market in the (-10,-1) trading day period before an earnings announcement. Firms are grouped into buckets based on the relative proportion of all trading volume in the (-10,-1) day period (i.e. aggregated across all earnings announcements for a given firm) that is not disseminated to the market.

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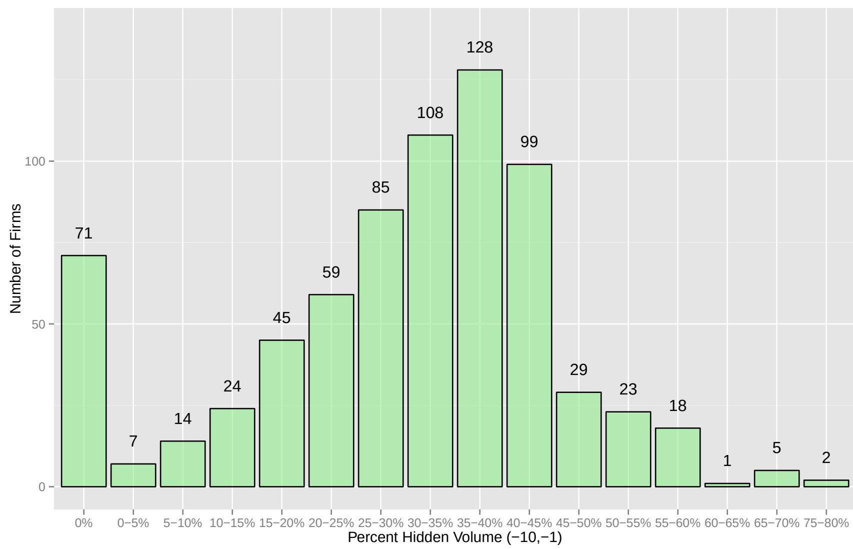
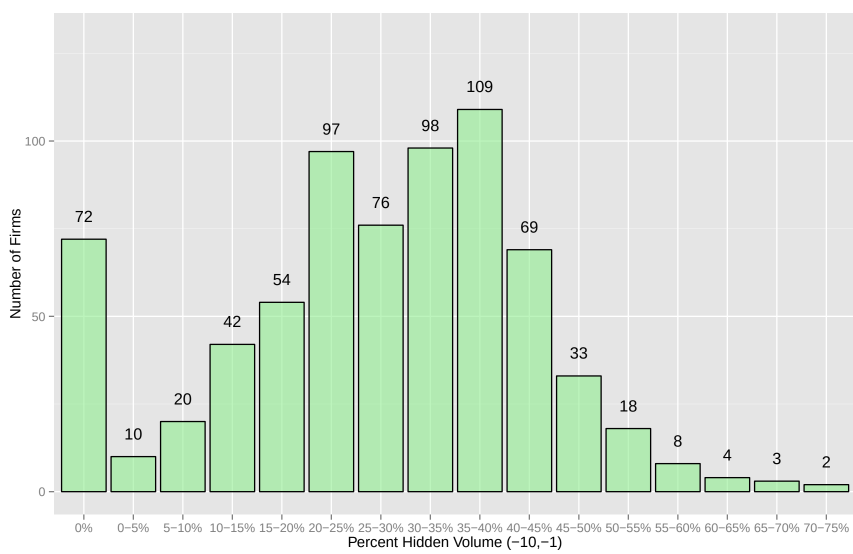
Figure F.6 – Firm Distribution by Percent of Hidden Volume - Buy and Sell Trade Breakdown



Buy Trades



Sell Trades

This figure presents a breakdown of the number of firms that have trading volume hidden from the market in the (-10,-1) trading day period before an earnings announcement. Firms are grouped into buckets based on the relative proportion of total buy or sell trading volume in the (-10,-1) day period (i.e. aggregated across all earnings announcements for a given firm) that is not disseminated to the market. The top panel presents a breakdown for trading volume attributed to buy trades. The bottom panel presents the distribution for sell trades.

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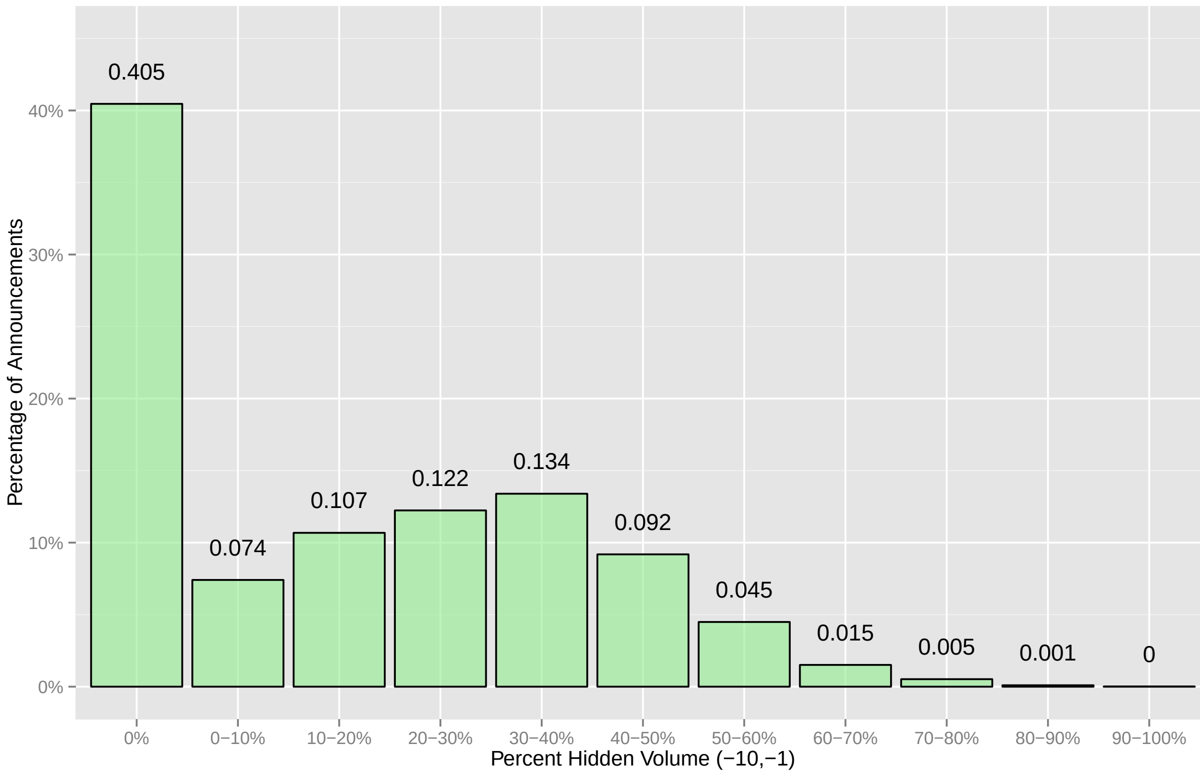
Figure F.7 – Distribution of Earnings Announcements by Percent of Hidden Volume



This figure presents a breakdown of the percentage of earnings announcements that have trading volume hidden from the market in the (-10,-1) trading day period prior to the announcement. Earnings announcements are grouped into buckets based on the relative proportion of trading volume in the (-10,-1) day period that is not disseminated to the market.

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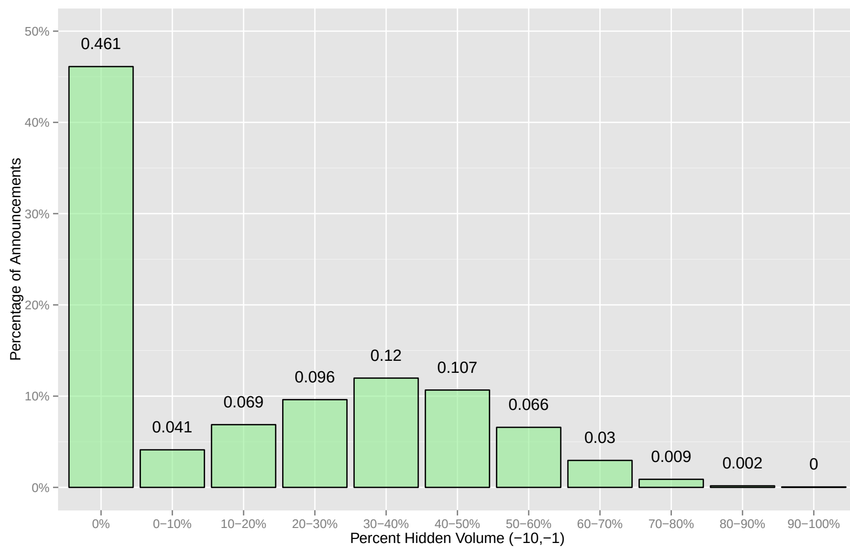
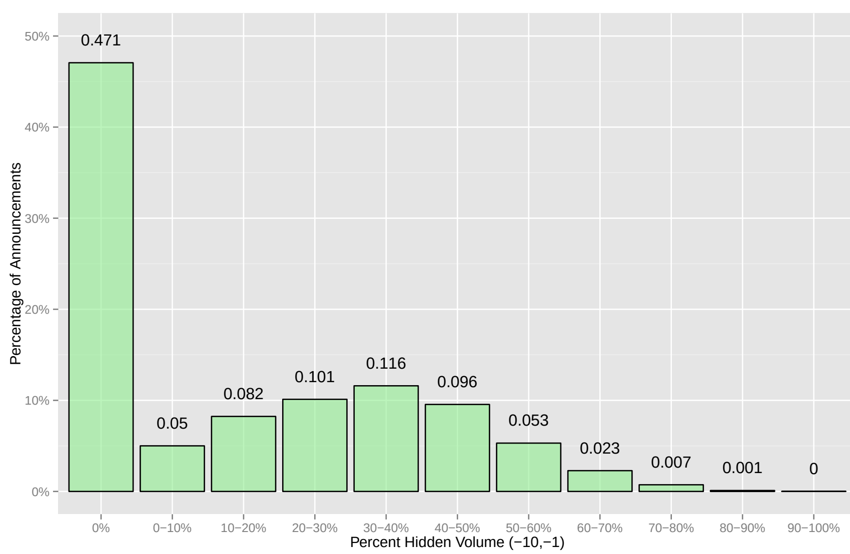
Figure F.8 – Distribution of Earnings Announcements by Percent of Hidden Volume - Buy and Sell Trade Breakdown



Buy Trades



Sell Trades

This figure presents a breakdown of the percentage of earnings announcements that have trading volume hidden from the market in the (-10,-1) trading day period prior to an earnings announcement. Firms are grouped into buckets based on the relative proportion of total buy or sell trading volume in the (-10,-1) day period that is not disseminated to the market. The top panel presents a breakdown for trading volume attributed to buy trades. The bottom panel presents the distribution for sell trades.

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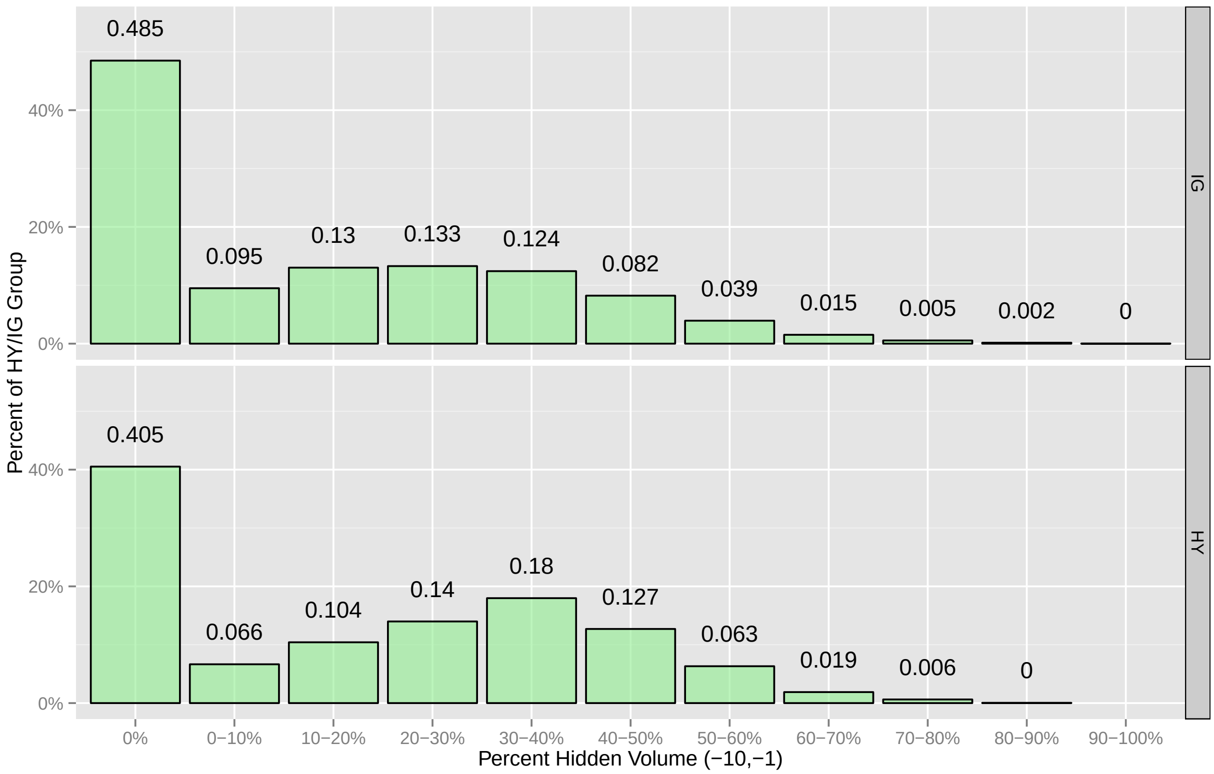
Figure F.9 – Distribution of Earnings Announcements by Percent of Hidden Volume - High-Yield/Investment Grade Split



This figure presents a breakdown of the percentage of earnings announcements that have trading volume hidden from the market in the (-10,-1) trading day period prior to an earnings announcement. Firms are grouped into buckets based on the relative proportion of total trading volume in the (-10,-1) day period that is not disseminated to the market. This is then partitioned on whether at the time of the earnings announcement the firm in question was classified as either high-yield (HY) or investment-grade (IG), as outlined on the right hand side of each panel. The top panel presents a breakdown for investment-grade (IG) earnings announcements. The bottom panel presents a breakdown for high-yield (HY) earnings announcements.

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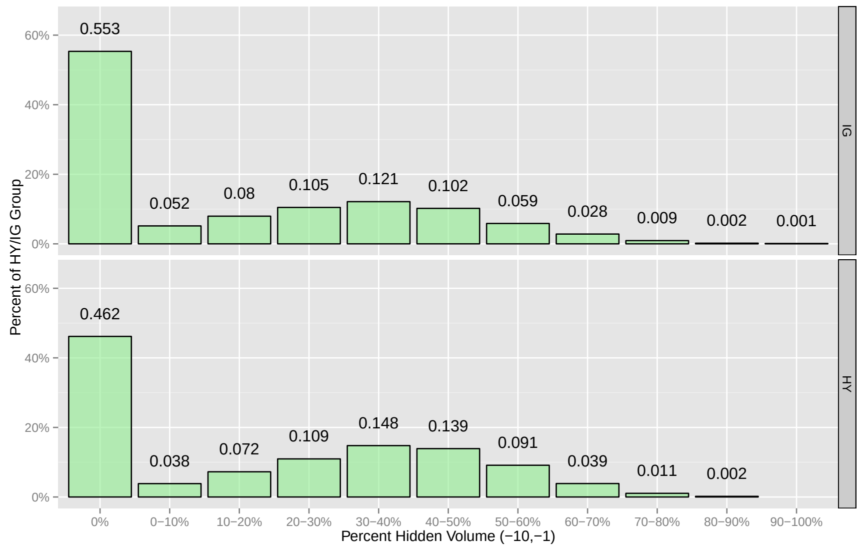
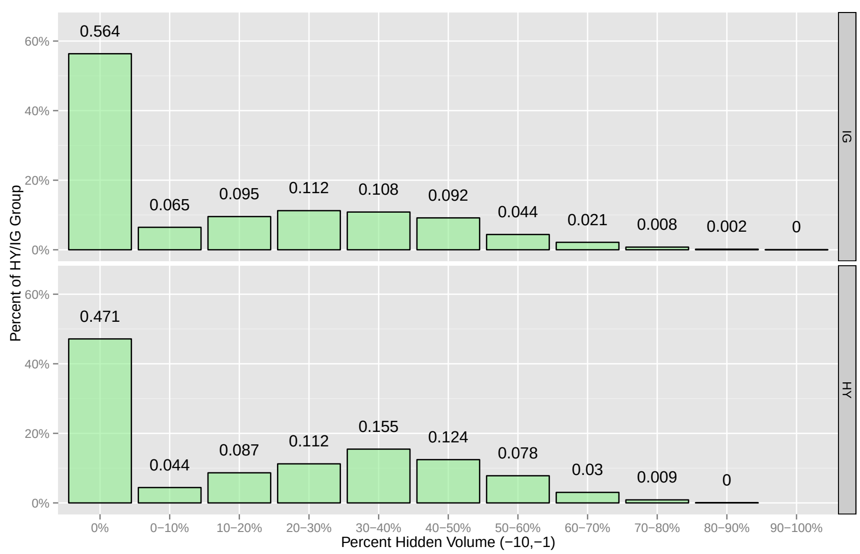
Figure F.10 – Distribution of Earnings Announcements by Percent of Hidden Volume - Buy and Sell Breakdown across Issuer Quality



Buy Trades



Sell Trades

This figure presents a breakdown of the percentage of earnings announcements that have trading volume hidden from the market in the (-10,-1) trading day period prior to an earnings announcement. Firms are grouped into buckets based on the relative proportion of total trading volume in the (-10,-1) day period that is not disseminated to the market. This is partitioned on whether the firm in question was classified as high-yield (HY) or investment-grade (IG). The top panel presents a breakdown of the investment grade (IG)/non-investment grade (HY) split for buy trades. The bottom panel presents a breakdown for sell trades.

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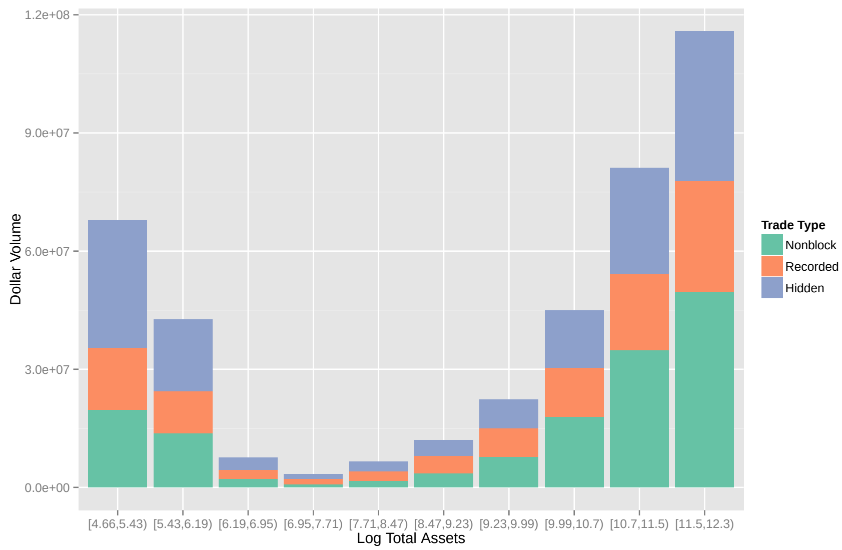
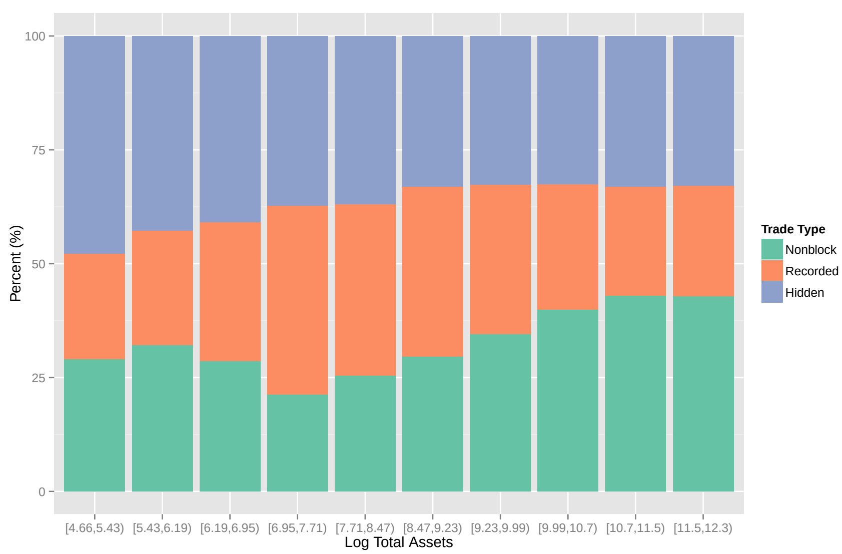
Figure F.11 – Importance of Trade Components across Firm Size Groupings



Total Dollar Volume by Total Asset Groupings



Relative Percent of Dollar Volume by Total Asset Groupings

The top panel documents the total dollar volume of trades in the (-10,-1) trading days before an earnings announcement. The reported sizes are the mean values across all earnings announcements. This is decomposed into the three components of total volume - non-block, reported block, and hidden block volume. This is grouped by firm size, as given by the natural log of total assets. The bottom panel repeats the analysis and outlines the relative percent of total volume across firm size groupings that each trade component accounts for.

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Figure F.12 – Plots of Important Earnings Metrics Over Time

This figure presents a temporal plot of the mean values each quarter across all earnings announcements of the three key earnings metrics employed - adjusted quarterly EPS ($\text{EPS}_{i,t}$), predicted quarterly EPS ($\text{Pred\_EPS}_{i,t}$), and the quarterly EPS earnings surprise ($\text{EPS\_Surp}_{i,t}$). The quarterly EPS earnings surprise is given as the difference between the adjusted quarterly EPS and the predicted quarterly EPS. The predicted quarterly EPS measure is calculated following the cross-sectional procedure outlined in So, 2013. Full variable details are provided in Section 4.2 and Appendix A.

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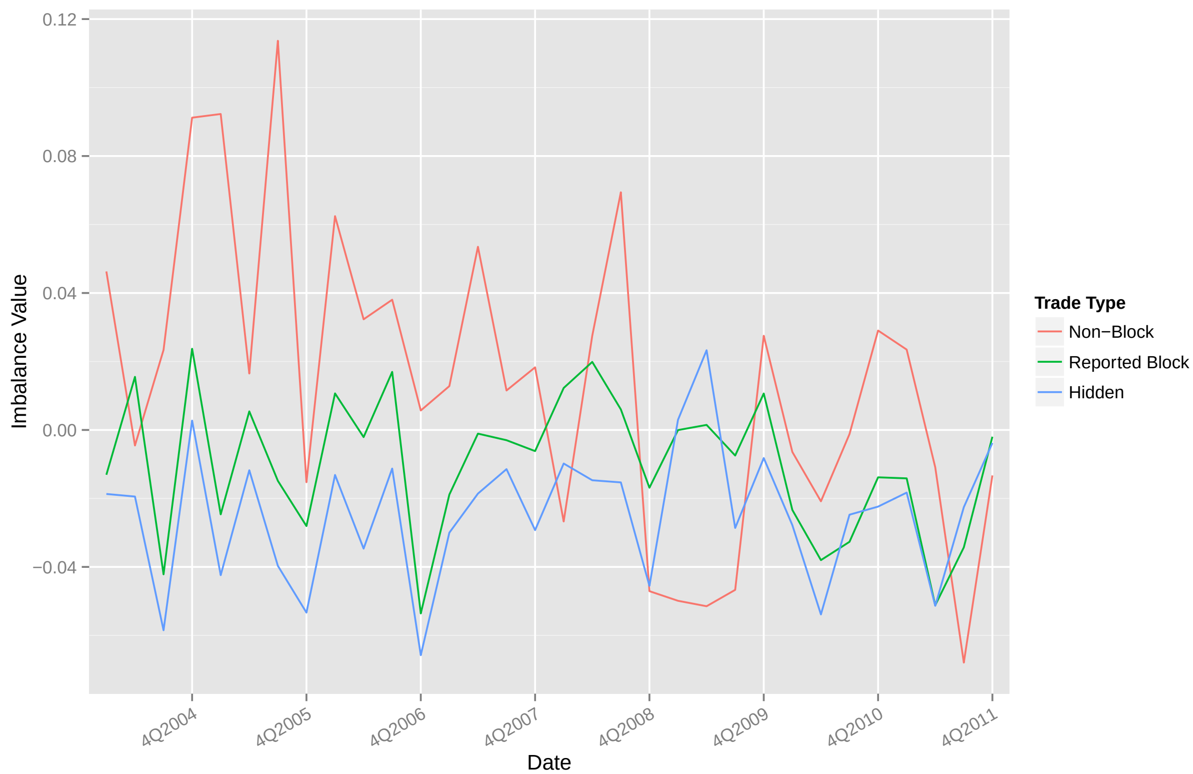
Figure F.13 – Time-Series Plot of Average Decomposed Imbalance Measures



The figure presents a temporal plot of the mean value across all earnings announcements each quarter of the trading imbalance measures for the three key components of total trading volume - non-block volume (NonBVolImb$_i$(-10,-1)), the reported block volume (RepBVolImb$_i$(-10,-1)), and the hidden block volume (HidVolImb$_i$(-10,-1)). The imbalance measure is calculated as in Wei and Zhou, 2012 and is calculated from the relevant dollar volume (i.e. either non-block, reported, or hidden) in the (-10,-1) window for a firm prior to an earnings announcement. The imbalance measure is given as $(Buy - Sell)/(Buy + Sell)$ in the (-10,-1) period. This is then normalized by the same imbalance measure calculation using the aggregate of all activity that does not fall in the (-20,20) day period around any observed earnings announcement across the entire period of a bond's life. Full details are provided in Section 4.2 and Appendix A.

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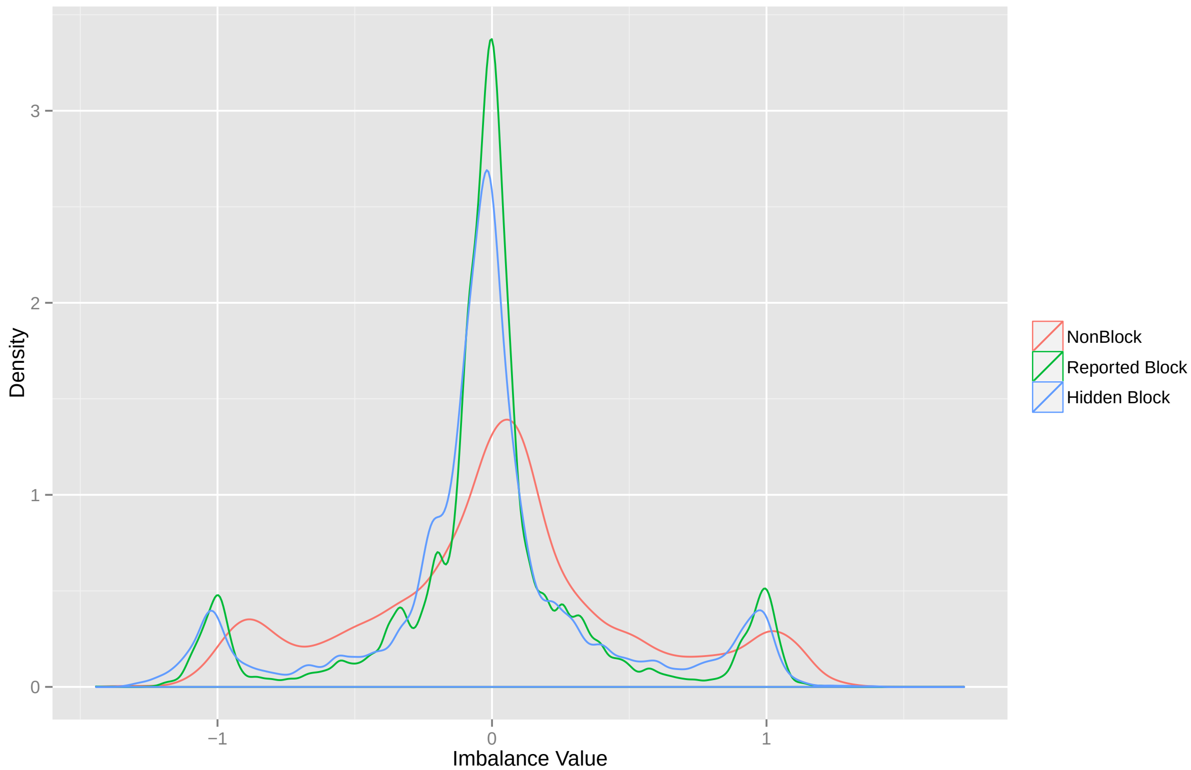
Figure F.14 – Imbalance Measure Calculation Distributions



The figure presents a density plot of all of the quarterly trading imbalance measures for the three key components of total trading volume - non-block volume (NonBVolImb$_i$(-10,-1)), the reported block volume (RepBVolImb$_i$(-10,-1)), and the hidden block volume (HidVolImb$_i$(-10,-1)). The imbalance measure is calculated as in Wei and Zhou, 2012 and is calculated from the relevant dollar volume (i.e. either non-block, reported, or hidden) in the (-10,-1) window for a firm prior to an earnings announcement. The imbalance measure is given as $(Buy - Sell)/(Buy + Sell)$ in the (-10,-1) period. This is then normalized by the same imbalance measure calculation using the aggregate of all activity that does not fall in the (-20,20) day period around any observed earnings announcement across the entire period of a bond's life. Full details are provided in Section 4.2 and Appendix A.

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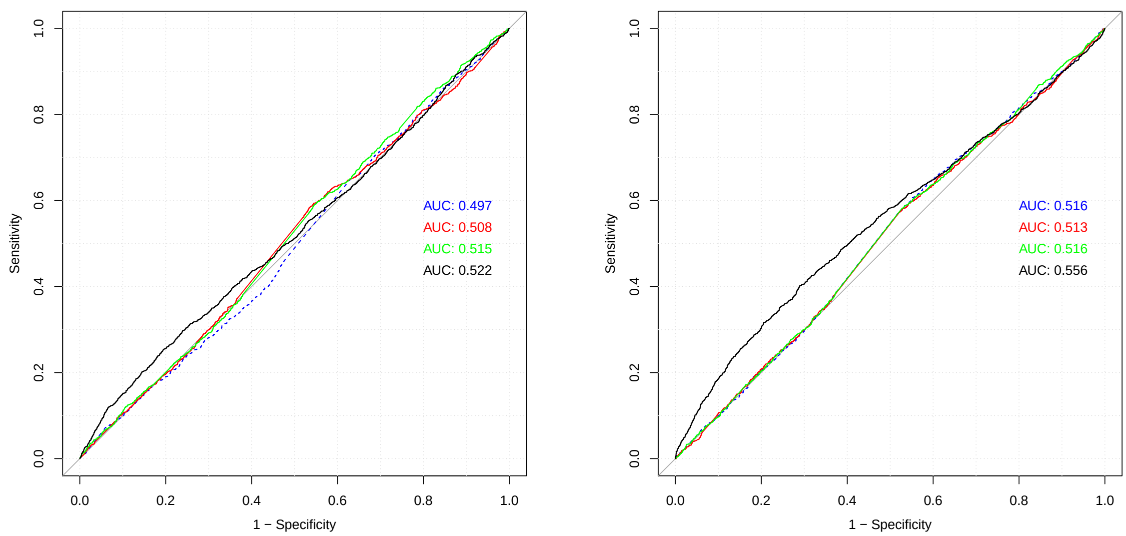
Figure F.15 – ROC Curves - Extreme Abnormal Return Events - Pooled Data



Extreme Positive Return   Extreme Negative Return

This figure presents receiver operating characteristic (ROC) curves for the prediction of either an extreme positive or extreme negative 3-day abnormal return around an earnings announcement. An ‘extreme’ positive abnormal return is classified as when the firm’s cumulative abnormal return, $\text{CAR}_{i,t}$(-1,1) is in the top decile of all firms in quarter t. Negative surprises are those in the bottom decile in a quarter. The ROC curves are calculated from running the four logistic regressions presented in Equations (5.3a) to (5.3d), but replacing the dependent variable of $\text{EPS\_Surp}_{i,t}$ with $\text{CAR}_{i,t}$(-1,1).

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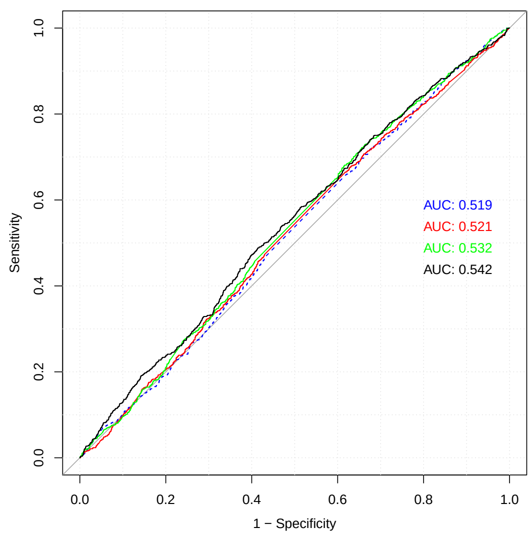
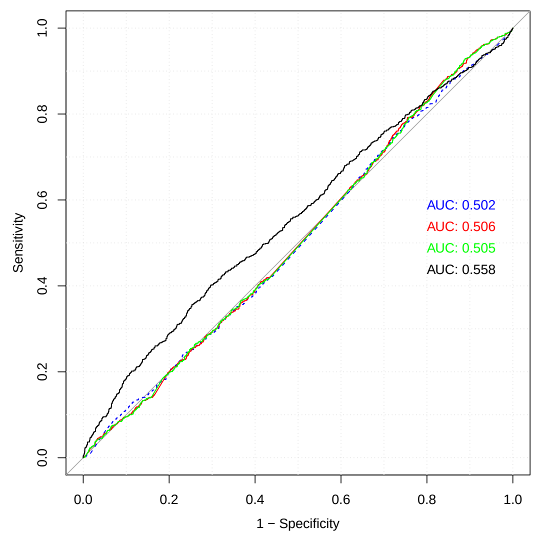
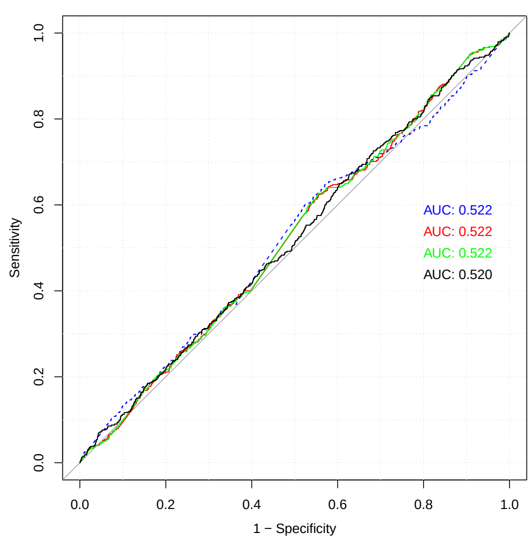
Figure F.16 – ROC Curves - Extreme Abnormal Return Events - High-Yield/Investment Grade Split



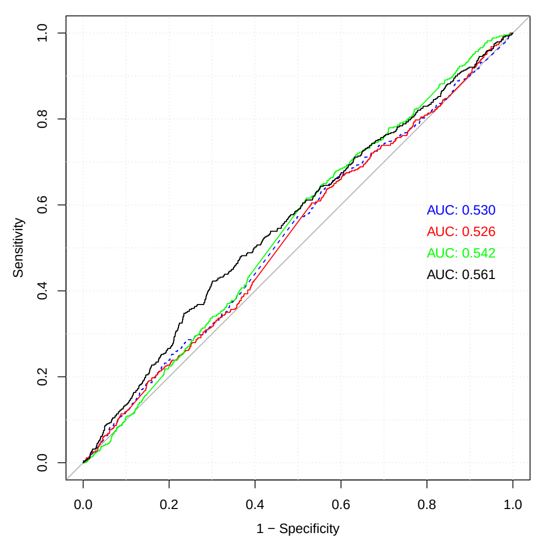
Extreme Positive Return - HY



Extreme Negative Return - HY



Extreme Positive Return - IG



Extreme Negative Return - IG

This figure presents receiver operating characteristic (ROC) curves for the prediction of either an extreme positive or extreme negative 3-day abnormal return around an earnings announcement. This is further split into investment grade (IG) and high-yield (HY) issuers. An 'extreme' positive abnormal return is classified as when the firm's cumulative abnormal return, $\text{CAR}_{i,t}(-1,1)$ is in the top decile of all firms in quarter t. Negative surprises are those in the bottom decile in a quarter. The ROC curves are calculated from running the four logistic regressions presented in Equations (5.3a) to (5.3d), but replacing the dependent variable of $\text{EPS\_Surp}_{i,t}$ with $\text{CAR}_{i,t}(-1,1)$.

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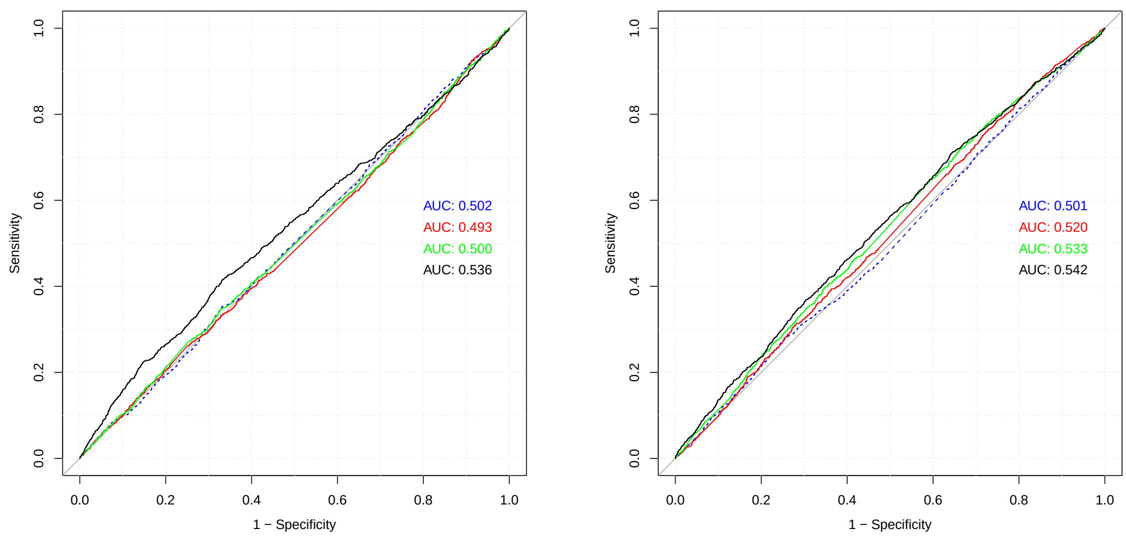
Figure F.17 – ROC Curves - Extreme EPS Surprise Events - Pooled Data



Extreme Positive EPS Surprise | Extreme Negative EPS Surprise

This figure presents receiver operating characteristic (ROC) curves for the prediction of either an extreme positive or extreme negative EPS earnings surprise. An 'extreme' positive EPS surprise is classified as when the firm's earnings surprise, $\text{EPS\_Surp}_{i,t}$ is in the top decile of all firms in quarter t. Negative surprises are those in the bottom decile in a quarter. The ROC curves are calculated from running the logistic regressions presented in Equations (5.3a) to (5.3d).

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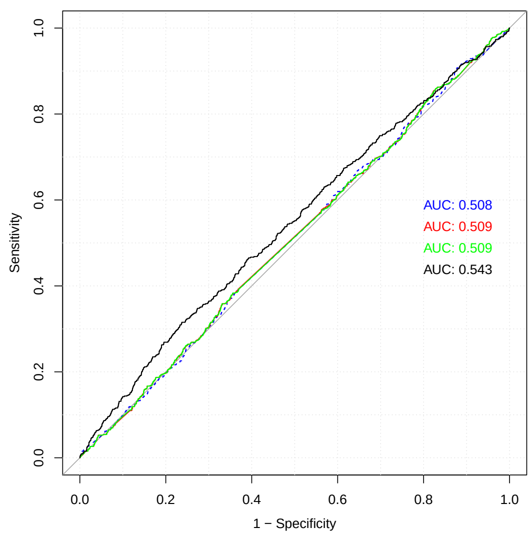
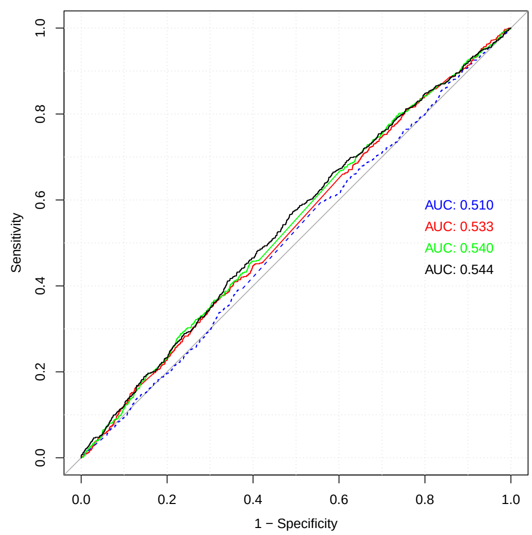
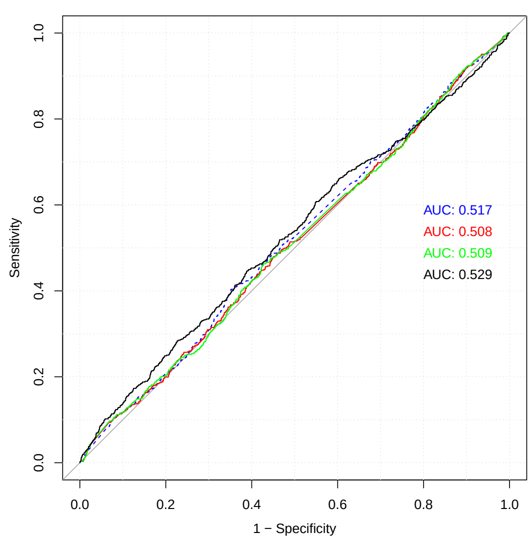
Figure F.18 – ROC Curves - Extreme EPS Surprise Events - High-Yield/Investment Grade Split



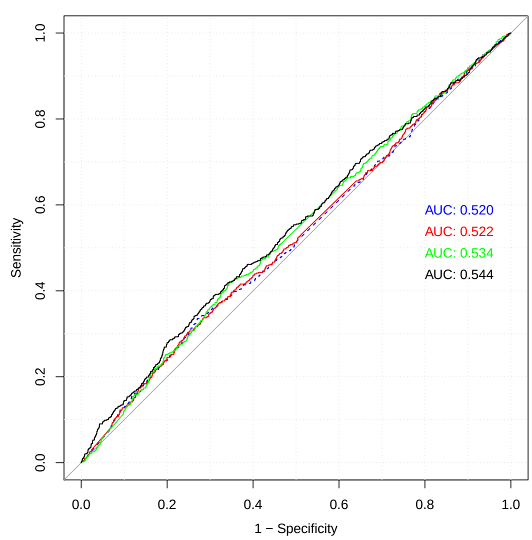
Extreme Positive EPS Surprise - HY



Extreme Negative EPS Surprise - HY



Extreme Positive EPS Surprise - IG



Extreme Negative EPS Surprise - IG

This figure presents receiver operating characteristic (ROC) curves for the prediction of either an extreme positive or extreme negative EPS earnings surprise. This is further split into investment grade (IG) and high-yield (HY) issuers. An 'extreme' positive EPS surprise is classified as when the firm's earnings surprise, $EPS\_Surp_{i,t}$ is in the top decile of all firms in quarter t. Negative surprises are those in the bottom decile in a quarter. The ROC curves are calculated from running the logistic regressions presented in Equations (5.3a) to (5.3d).

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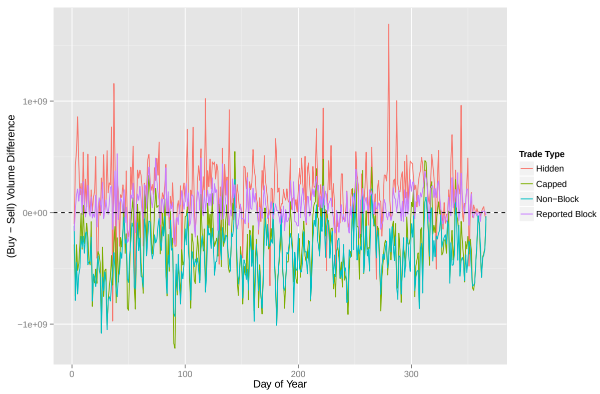
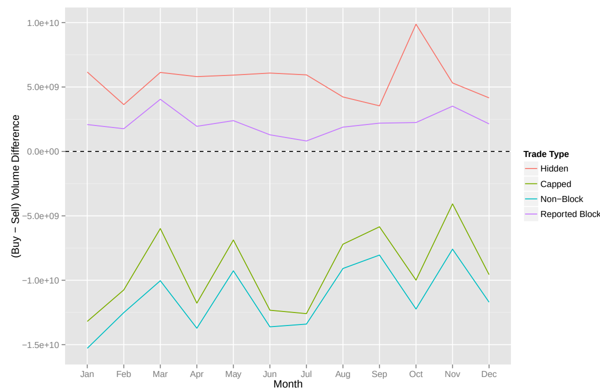
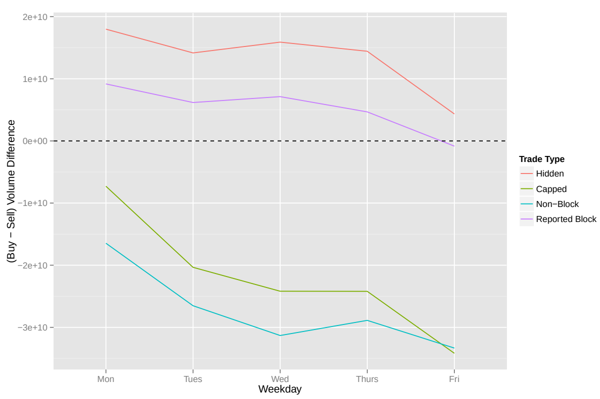
Figure F.19 – Buy less Sell Volume over Various Systematic Time Horizons



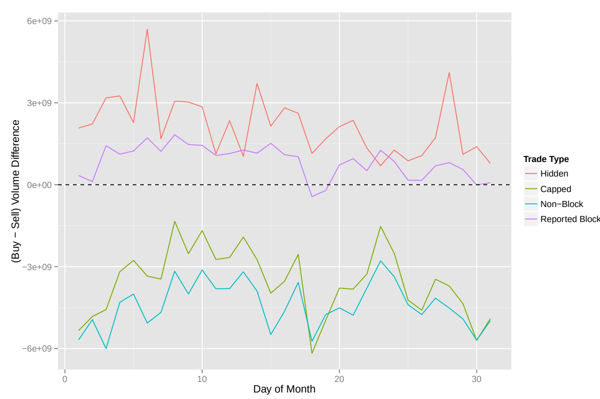
Day of the Year Activity



Month of the Year Activity



Day of the Week Activity



Day of the Month Activity

The figures provide plots of the size of the difference between the total volume of *Buy* trades and the total volume of *Sell* trades across different time horizons. The reported figures represent the total sum of ($Buy - Sell$) activity across all earnings announcements across time for a given analysis period, e.g. the total sum of all *Buy* trades less the total sum of all *Sell* trades that fall on a Wednesday. The analysis considers the day of the year that a trade falls on, the month of the year that a trade falls in, the day of the week that a trade occurs on, and the day of the month that a trade occurs on.

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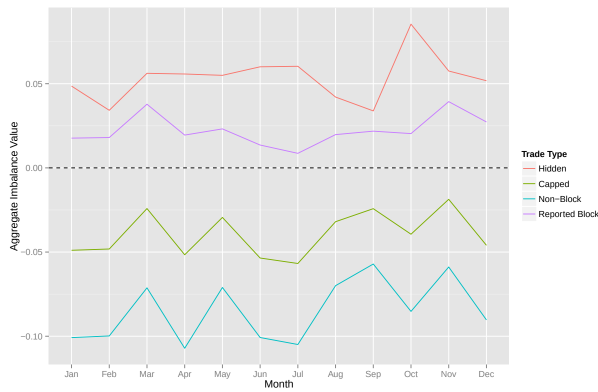
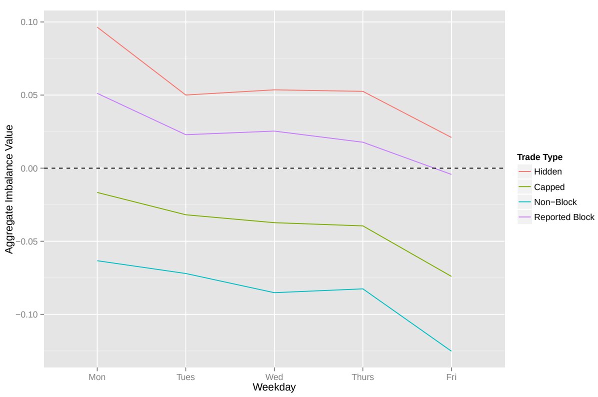
Figure F.20 – Aggregate Imbalance Measures over Various Systematic Time Horizons

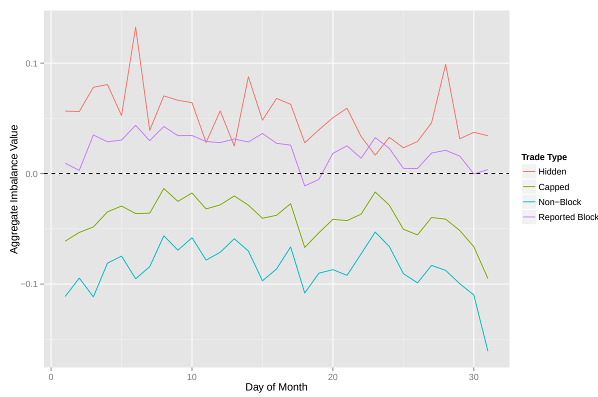
Day of the Year Activity



Month of the Year Activity



Day of the Week Activity



Day of the Month Activity

The figures provide plots of the size of the imbalance measure across different time horizons. The imbalance measure is defined as the difference between the total volume of *Buy* trades and the total volume of *Sell* trades across different time horizons, scaled by the total volume of *Buy* and *Sell* trades, i.e. $Buy + Sell$. The reported figures represent the aggregate imbalance measure calculated from the total amount of *Buy* or *Sell* activity across all earnings announcements across time for a given analysis period, e.g. the total sum of all *Buy* trades less the total sum of all *Sell* trades that fall on a Wednesday, scaled by the total amount of $Buy + Sell$ trades that occur on a Wednesday. The analysis considers the day of the year that a trade falls on, the month of the year that a trade falls in, the day of the week that a trade occurs on, and the day of the month that a trade occurs on.

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Appendix G

Tables

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Table G.1 – Descriptive Statistics

Variable	N	Min	Q10	Q25	Median	Mean	Q75	Q90	Max	StdDev
EPS_Surp$_{i,t}$	12284	-3.350	-0.450	-0.171	0.036	0.070	0.287	0.695	2.709	0.595
EPS$_{i,t}$	12284	-5.520	-0.070	0.210	0.510	0.568	0.870	1.340	8.440	0.724
CAR$_{i,t}$(-1,1)	12284	-0.557	-0.073	-0.033	0.001	0.003	0.038	0.081	1.642	0.075
CapVolImb$_{i,t}$(-10,-1)	12284	-2.000	-0.778	-0.244	0.000	-0.024	0.163	0.735	2.000	0.527
NonBVolImb$_{i,t}$(-10,-1)	12284	-2.000	-0.890	-0.333	0.000	-0.043	0.192	0.812	2.000	0.563
RepBVolImb$_{i,t}$(-10,-1)	12284	-2.000	-0.405	-0.001	0.000	0.011	0.000	0.499	2.000	0.436
HidVolImb$_{i,t}$(-10,-1)	12284	-2.000	-0.535	0.000	0.000	0.018	0.000	0.650	2.000	0.461
HY$_{i,t}$	12284	0.000	0.000	0.000	0.000	0.443	1.000	1.000	1.000	0.497
Log_AT$_{i,t}$	12284	4.671	6.962	7.732	8.558	8.614	9.477	10.305	12.269	1.263
LEV$_{i,t}$	12284	1.008	1.262	1.429	1.675	1.784	1.969	2.353	14.965	0.613
MTB$_{i,t}$	12284	0.109	1.134	1.597	2.364	3.110	3.616	5.480	26.264	2.759
CAR$_{i,t}$(-10,-1)	12284	-0.737	-0.069	-0.031	0.004	0.006	0.040	0.084	1.102	0.077

Descriptive statistics for key variables in the analysis are outlined. Full details of all variables are provided in Appendix A.

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Table G.2 – Pearson Correlation Coefficients

Variables	$EPS\_Surp_{i,t}$	$EPS_{i,t}$	$CAR_{i,t}$(-1,1)	$CapVolImb_{i,t}$(-10,-1)	$NonBVolImb_{i,t}$(-10,-1)	$RepBVolImb_{i,t}$(-10,-1)	$HidVolimb_{i,t}$(-10,-1)	$HY_{i,t}$	$Log\_AT_{i,t}$	$LEV_{i,t}$	$MTB_{i,t}$
$EPS\_Surp_{i,t}$											
$EPS_{i,t}$	0.58***										
$CAR_{i,t}$(-1,1)	0.12***	0.08***									
$CapVolImb_{i,t}$(-10,-1)	0.01	0.00	-0.01								
$NonBVolImb_{i,t}$(-10,-1)	0.01	0.01	-0.01	0.79***							
$RepBVolImb_{i,t}$(-10,-1)	0.00	0.00	0.01	0.42***	0.01						
$HidVolImb_{i,t}$(-10,-1)	0.01	0.01	0.00	0.35***	0.00	0.88***					
$HY_{i,t}$	0.00	-0.30***	-0.01	0.03***	0.03***	-0.01	-0.02**				
$Log\_AT_{i,t}$	0.03***	0.27***	-0.02**	-0.02***	-0.04***	0.02**	0.03***	-0.52***			
$LEV_{i,t}$	0.01	0.13***	0.01	0.00	0.00	0.01	0.01	-0.19***	0.01		
$MTB_{i,t}$	-0.06***	0.07***	-0.02**	0.00	0.00	0.00	0.01	-0.19***	0.06***	-0.18***	
$CAR_{i,t}$(-10,-1)	0.08***	0.03***	0.07***	-0.02**	-0.02**	-0.02*	-0.02*	0.01	-0.01	-0.01	-0.03***

Pearson correlation coefficients for key variables in the analysis are outlined. Full details of all variables are provided in Appendix A.

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Table G.3 – Spearman Correlation Coefficients

Variables	EPS_Surp$_{i,t}$	EPS$_{i,t}$	CAR$_{i,t}$(-1,1)	CapVolImb$_{i,t}$(-10,-1)	NonBVolImb$_{i,t}$(-10,-1)	RepBVolImb$_{i,t}$(-10,-1)	HidVolImb$_{i,t}$(-10,-1)	HY$_{i,t}$	Log_AT$_{i,t}$	LEV$_{i,t}$	MTB$_{i,t}$
EPS_Surp$_{i,t}$											
EPS$_{i,t}$	0.45***										
CAR$_{i,t}$(-1,1)	0.12***	0.09***									
CapVolImb$_{i,t}$(-10,-1)	0.00	-0.01	-0.01								
NonBVolImb$_{i,t}$(-10,-1)	0.00	0.00	0.00	0.76***							
RepBVolImb$_{i,t}$(-10,-1)	-0.02**	-0.01	0.00	0.44***	0.00						
HidVolImb$_{i,t}$(-10,-1)	-0.01	0.01	-0.01	0.31***	-0.02**	0.69***					
HY$_{i,t}$	0.03***	-0.38***	-0.02**	0.04***	0.04***	-0.03***	-0.03***				
Log_AT$_{i,t}$	0.01	0.30***	-0.01	-0.04***	-0.06***	0.02***	0.04***	-0.53***			
LEV$_{i,t}$	-0.01	0.18***	0.01	0.01	0.01	0.02***	0.00	-0.23***	0.06***		
MTB$_{i,t}$	-0.10***	0.23***	0.00	-0.01	0.00	0.00	0.01	-0.33***	0.15***	-0.18***	
CAR$_{i,t}$(-10,-1)	0.07***	0.05***	0.06***	-0.03***	-0.02***	-0.03***	-0.02**	-0.01	0.00	0.01	-0.03***

Spearman rank correlation coefficients for key variables in the analysis are outlined. Full details of all variables are provided in Appendix A.

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Table G.4 – Coefficients and Significance of So, 2013 Replication

	Mean Coef	Mean t-stat
Intercept	-0.041	0.065
EPS_POS$_{-1}$	0.247	2.535
EPS_NEG$_{-1}$	-0.390	-3.478
ACCR_POS$_{-1}$	0.003	0.255
ACCR_NEG$_{-1}$	-0.040	-0.780
AT_GRWTH$_{-1}$	0.026	0.018
Zero_DIV$_{-1}$	-0.086	-0.750
MTB$_{-1}$	-0.001	-0.215
Price$_{-1}$	0.012	6.458
DIV$_{-1}$	-0.010	0.511

The mean coefficient values and t-statistics across all quarterly cross-sectional regressions that are employed under the So, 2013 characteristic EPS forecast measure are outlined. Each quarter Equation (4.2) is run. Variable descriptions are provided in Appendix A.

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Table G.5 – Explanatory Power of So, 2013 Predicted EPS

	Dependent variable:
	$\text{EPS}_{i,t}$
$\text{Pred\_EPS}_{i,t}$	0.724^{***}
	(0.008)
(Intercept)	0.207^{***}
	(0.007)
Observations	12,284
Adjusted R^2	0.379

*p<0.1; **p<0.05; ***p<0.01

The table documents the pooled regression of the realised adjusted-EPS in a quarter on the predicted adjusted-EPS derived from the characteristic forecast procedure outline in So, 2013. The predicted EPS for quarter t is generated from the application of the variables from quarter $t-1$ to the estimated coefficients generated from the implementation of Equation (4.2) using $EPS_{i,t-1}$ as the dependent variable and the $t-2$ values of the explanatory variables.

***, **, and * represent significance levels of 0.01, 0.05, and 0.1, respectively. Standard errors are reported in parentheses. Variable definitions provided in Appendix A.

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Table G.6 – Industry Distribution and Key Variables

SIC2	Industry	N	EPS_Surp	HY	Log_AT	LEV
1	AGRICULTURAL PRODUCTION - CROPS	62	-0.065	0.516	8.736	1.869
7	AGRICULTURAL SERVICES	13	-0.001	0.077	8.052	1.527
10	METAL MINING	91	0.328	0.242	9.415	2.333
12	COAL MINING	100	-0.111	1.000	8.285	1.444
13	OIL AND GAS EXTRACTION	1323	0.141	0.563	8.695	2.032
14	MINING AND QUARRYING OF NONMETALLIC MINERALS, EXCEPT FUELS	70	-0.294	0.157	8.133	1.881
15	BUILDING CNSTRCTN - GENERAL CONTRACTORS & OPERATIVE BUILDERS	4	0.138	1.000	8.037	1.782
16	HEAVY CNSTRCTN, EXCEPT BUILDING CONSTRUCTION - CONTRACTORS	50	0.155	0.980	6.721	1.662
17	CONSTRUCTION - SPECIAL TRADE CONTRACTORS	6	-0.297	1.000	6.314	1.470
20	FOOD AND KINDRED PRODUCTS	853	0.017	0.204	9.073	1.645
21	TOBACCO PRODUCTS	64	0.114	0.266	10.165	1.460
22	TEXTILE MILL PRODUCTS	65	0.025	0.723	7.883	1.732
23	APPAREL, FINISHED PRDCTS FROM FABRICS & SIMILAR MATERIALS	225	0.098	0.644	7.583	1.975
24	LUMBER AND WOOD PRODUCTS, EXCEPT FURNITURE	75	-0.115	0.453	7.811	1.763
25	FURNITURE AND FIXTURES	148	0.012	0.541	8.296	1.763
26	PAPER AND ALLIED PRODUCTS	465	0.005	0.512	8.272	1.569
27	PRINTING, PUBLISHING AND ALLIED INDUSTRIES	188	0.074	0.521	8.293	1.581
28	CHEMICALS AND ALLIED PRODUCTS	1466	0.045	0.299	8.812	1.811
29	PETROLEUM REFINING AND RELATED INDUSTRIES	225	0.383	0.302	9.476	1.771
30	RUBBER AND MISCELLANEOUS PLASTIC PRODUCTS	154	0.037	0.396	8.529	1.676
31	LEATHER AND LEATHER PRODUCTS	2	-0.047	1.000	7.161	1.463
32	STONE, CLAY, GLASS, AND CONCRETE PRODUCTS	90	0.025	0.911	8.219	1.585
33	PRIMARY METAL INDUSTRIES	380	0.117	0.500	8.219	1.844
34	FABRICATED METAL PRDCTS, EXCEPT MACHINERY & TRANSPORT EQPMNT	299	0.149	0.502	8.182	1.613
35	INDUSTRIAL AND COMMERCIAL MACHINERY AND COMPUTER EQUIPMENT	848	0.082	0.329	8.633	1.753
36	ELECTRONIC, ELCTRCL EQPMNT & CMPNTS, EXCPT COMPUTER EQPMNT	548	0.090	0.352	8.782	1.979
37	TRANSPORTATION EQUIPMENT	512	0.093	0.426	8.805	1.619
38	MESR/ANLYZ/CNTRL INSTRMNTS; PHOTO/MED/OPT GDS; WATCHS/CLOCKS	484	-0.024	0.302	8.852	2.198
39	MISCELLANEOUS MANUFACTURING INDUSTRIES	121	0.074	0.413	7.280	1.861
40	RAILROAD TRANSPORTATION	133	0.138	0.098	10.152	1.579
42	MOTOR FREIGHT TRANSPORTATION	126	-0.113	0.325	8.645	1.449
50	WHOLESALE TRADE - DURABLE GOODS	253	0.197	0.617	8.103	1.727
51	WHOLESALE TRADE - NONDURABLE GOODS	201	0.066	0.463	8.797	1.491
52	BUILDING MATRIALS, HRDWR, GARDEN SUPPLY & MOBILE HOME DEALRS	81	0.068	0.210	9.734	2.008
53	GENERAL MERCHANDISE STORES	269	0.023	0.346	9.680	1.793
54	FOOD STORES	140	0.085	0.436	8.990	1.366
55	AUTOMOTIVE DEALERS AND GASOLINE SERVICE STATIONS	191	0.227	0.890	7.821	1.375
56	APPAREL AND ACCESSORY STORES	164	0.069	0.488	8.347	1.866
57	HOME FURNITURE, FURNISHINGS AND EQUIPMENT STORES	51	0.123	0.510	8.537	1.793
58	EATING AND DRINKING PLACES	195	0.037	0.308	8.263	1.745
59	MISCELLANEOUS RETAIL	249	0.046	0.578	8.501	1.945
70	HOTELS, ROOMING HOUSES, CAMPS, AND OTHER LODGING PLACES	102	-0.099	0.608	8.713	1.522
72	PERSONAL SERVICES	85	0.061	1.000	7.300	1.553
73	BUSINESS SERVICES	568	0.104	0.405	8.670	1.980
75	AUTOMOTIVE REPAIR, SERVICES AND PARKING	31	0.111	0.000	8.771	1.319
78	MOTION PICTURES	32	-0.330	1.000	7.318	1.367
79	AMUSEMENT AND RECREATION SERVICES	245	-0.095	0.853	8.287	1.492
80	HEALTH SERVICES	256	0.085	0.609	8.111	1.620
87	ENGINEERING, ACCOUNTING, RESEARCH, MANAGEMENT & RELATED SVCS	80	0.069	1.000	7.286	1.797
99	NONCLASSIFIABLE ESTABLISHMENTS	27	-0.019	0.000	7.556	2.101

The table presents the count of earnings announcements attributable to each of the industries under the 2-digit SIC code classification. Average values of key variables across each industry are also provided. Variable descriptions provided in Appendix A.

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Table G.7 – Percentage of Total Annual Block Volume and Trading Incidence by Event Windows

Panel A: Announcement Period Activity - All Data

	Vol(-1,1)	Vol(-10,-1)	Vol(-20,-11)	Trd(-1,1)	Trd(-10,-1)	Trd(-20,-11)
Mean	0.056	0.137	0.140	0.055	0.136	0.139
p-value	(0.000)	(0.260)	(0.953)	(0.000)	(0.155)	(0.659)

Panel B: Announcement Period Activity - Investment Grade/High-Yield Partition

	Vol(-1,1)	Vol(-10,-1)	Vol(-20,-11)	Trd(-1,1)	Trd(-10,-1)	Trd(-20,-11)
Mean - IG	0.058	0.147	0.148	0.057	0.148	0.152
Mean - HY	0.066	0.151	0.157	0.065	0.151	0.152
p-value	(0.082)	(0.550)	(0.205)	(0.038)	(0.643)	(0.971)

Panel C: Announcement Period Activity by Year

Year	Vol(-1,1)	Vol(-10,-1)	Vol(-20,-11)	Trade(-1,1)	Trade(-10,-1)	Trade(-20,-11)
2004	0.048	0.117	0.115	0.048	0.122	0.113
2005	0.056	0.135	0.136	0.056	0.136	0.134
2006	0.064	0.145	0.144	0.064	0.147	0.142
2007	0.060	0.148	0.146	0.060	0.151	0.144
2008	0.061	0.143	0.154	0.060	0.138	0.147
2009	0.056	0.135	0.145	0.054	0.129	0.147
2010	0.056	0.139	0.149	0.053	0.136	0.149
2011	0.056	0.136	0.146	0.056	0.136	0.142

This table provides a breakdown of the average percentage of total block trading volume - Vol(x,y) - and trade count - Trade(x,y) - that falls in a given window around an earnings announcement date. An 'artificial' year is created for each firm in the sample that runs from February 1st until January 31st of the following year. The total number of block trades and the total dollar volume of all block trades is then calculated for each firm-year. All quarterly announcement dates are then identified for a firm in each year. The total number of block trades and the total dollar value of block trades are then calculated for various windows around all of the announcements in a given firm-year and the percent of total annual trading incidence and volume that this represents is calculated for each firm-year. The average across all companies and years is reported above. To account for the possibility that the choice of artificial year end causes firms to have more or less than 4 announcements in a year I standardize the total announcement period volume (trade count) by the number of announcements recorded in the year and multiply this by 4. Near identical results are found when I consider only those firm-years with 4 announcements.

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Table G.8 – Average Pre-event Imbalance Measures by EPS Surprise Groupings

Panel A: Total Dollar and Capped Dollar Breakdown

Rank	N	EPS Supr	DolVolImb(-10,-1)	CapVolImb(-10,-1)
1	2496	-0.624	-0.019	-0.011
2	2476	-0.103	-0.013	-0.004
3	2474	0.060	-0.020	-0.011
4	2476	0.243	-0.008	-0.002
5	2488	0.779	-0.017	-0.008

Panel B: Non-Block, Reported-Block and Hidden Breakdown

Rank	N	EPS Supr	NonBVolImb(-10,-1)	RepBVolImb(-10,-1)	HidVolImb(-10,-1)
1	2496	-0.624	0.005	0.000	-0.017
2	2476	-0.103	0.018	-0.014	-0.026
3	2474	0.060	0.016	-0.018	-0.033
4	2476	0.243	0.013	-0.008	-0.017
5	2488	0.779	0.018	-0.012	-0.026

Panels A and B report the average imbalance measure (Wei and Zhou, 2012) for different types of trades in the (-10,-1) trading period before an earnings announcement. Each quarter all firms are ranked on the size of the earnings surprise they announce and assigned into quintile portfolios. For each individual announcement the earnings surprise is calculated as the difference between a firm's announced earnings per share and the ex-ante forecasted earnings per share as given by the characteristic forecast methodology outlined in So, 2013.

Panel A shows imbalance results for the total dollar volume as reported to the market at the time (CapVolImb(-10,-1)) and the actual total dollar volume in the 10 day period (DolVolImb(-10,-1)). Panel B shows results for the total dollar volume of non-block trades (NonBVolImb(-10,-1)), block trades as reported to the market (RepBVolImb(-10,-1)), ièthe capped amount of block trading, and the total dollar value of trading hidden from the market (HidVolImb(-10,-1)). Full variable descriptions provided in Appendix A.

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Table G.9 – Average Pre-event Imbalance Measures by 3-Day Abnormal Return Groupings

Panel A: Total Dollar and Capped Dollar Breakdown

Rank	N	CAR(-1,1)	DolVolImb(-10,-1)	CapVolImb(-10,-1)
1	2496	-0.090	-0.005	0.004
2	2476	-0.026	-0.012	-0.006
3	2474	0.001	-0.021	-0.014
4	2476	0.031	-0.013	-0.004
5	2488	0.098	-0.027	-0.016

Panel B: Non-Block, Reported-Block and Hidden Breakdown

Rank	N	CAR(-1,1)	NonBVolImb(-10,-1)	RepBVolImb(-10,-1)	HidVolImb(-10,-1)
1	2496	-0.090	0.027	-0.007	-0.019
2	2476	-0.026	0.023	-0.018	-0.025
3	2474	0.001	0.002	-0.008	-0.026
4	2476	0.031	0.015	-0.009	-0.023
5	2488	0.098	0.002	-0.009	-0.028

Panels A and B report the average imbalance measure (Wei and Zhou, 2012) for different types of trades in the (-10,-1) trading period before an earnings announcement. Each quarter all firms are ranked on the size of the earnings surprise they announce and assigned into quintile portfolios. For each individual announcement the earnings surprise is calculated as the difference between a firm's announced earnings per share and the ex-ante forecasted earnings per share as given by the characteristic forecast methodology outlined in So, 2013.

Panel A shows imbalance results for the total dollar volume as reported to the market at the time (CapVolImb(-10,-1)) and the actual total dollar volume in the 10 day period (DolVolImb(-10,-1)). Panel B shows results for the total dollar volume of non-block trades (NonBVolImb(-10,-1)), block trades as reported to the market (RepBVolImb(-10,-1)), i.e. the capped amount of block trading, and the total dollar value of trading hidden from the market (HidVolImb(-10,-1)). Full variable descriptions provided in Appendix A.

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Table G.10 – OLS Repressions - Earnings Surprises and Imbalance Measures

	Dependent variable:				
	$EPS\_Surp_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
$CapVolImb_i$(-10,-1)	0.003				
	(0.011)				
$NonBVolImb_i$(-10,-1)		0.006	0.006	0.007	0.008
		(0.010)	(0.010)	(0.010)	(0.010)
$RepBVolImb_i$(-10,-1)		−0.010	−0.012	−0.016	−0.013
		(0.012)	(0.023)	(0.023)	(0.023)
$HidVolImb_i$(-10,-1)			0.003	0.005	0.005
			(0.022)	(0.022)	(0.022)
HY_i				0.005	0.007
				(0.013)	(0.013)
Log_AT_i				0.009*	0.010*
				(0.005)	(0.005)
Lev_i				0.002	0.002
				(0.009)	(0.009)
MTB_i				−0.008***	−0.007***
				(0.002)	(0.002)
CAR_i(-10,-1)					0.431***
					(0.068)
Observations	12,410	12,410	12,410	12,410	12,410
R^2	0.100	0.100	0.100	0.102	0.105
Adjusted R^2	0.094	0.094	0.094	0.095	0.098

*p<0.1; **p<0.05; ***p<0.01

Table documents results from running Equations (5.1a) to (5.1e). Standard errors are reported in parentheses. Quarter and Industry fixed effects applied. Variable definitions provided in Appendix A.

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Table G.11 – OLS Repressions - Cumulative Abnormal Returns and Imbalance Measures

	Dependent variable:				
	CAR_i(-1,1)				
	(1)	(2)	(3)	(4)	(5)
$CapVolImb_i$(-10,-1)	-0.001				
	(0.001)				
$NonBVolImb_i$(-10,-1)		-0.002	-0.002	-0.002	-0.002
		(0.001)	(0.001)	(0.001)	(0.001)
$RepBVolImb_i$(-10,-1)		0.002	0.005^{*}	0.005^{*}	0.006^{*}
		(0.002)	(0.003)	(0.003)	(0.003)
$HidVolImb_i$(-10,-1)			-0.004	-0.003	-0.004
			(0.003)	(0.003)	(0.003)
HY_i				-0.003^{*}	-0.003^{*}
				(0.002)	(0.002)
Log_AT_i				-0.002^{**}	-0.002^{**}
				(0.001)	(0.001)
Lev_i				0.001	0.001
				(0.001)	(0.001)
MTB_i				-0.001^{**}	-0.001^{**}
				(0.0003)	(0.0003)
CAR_i(-10,-1)					0.064^{***}
					(0.009)
Observations	12,410	12,410	12,410	12,410	12,410
R^2	0.012	0.012	0.012	0.013	0.017
Adjusted R^2	0.005	0.006	0.006	0.006	0.010

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table documents results from running Equations (5.1a) to (5.1e). Standard errors are reported in parentheses. Quarter and Industry fixed effects applied. Variable definitions provided in Appendix A.

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Table G.12 – Conditional Logistic Regressions - Large Positive Earnings Surprises and Imbalance Measures

	Dependent variable:				
	EPS_Surp_POS$_i$				
	(1)	(2)	(3)	(4)	(5)
CapVolImb$_i$(-10,-1)	−0.019				
	(0.058)				
NonBVolImb$_i$(-10,-1)		−0.001	−0.001	−0.002	0.001
		(0.054)	(0.054)	(0.054)	(0.054)
RepBVolImb$_i$(-10,-1)		0.022	0.047	0.041	0.043
		(0.070)	(0.140)	(0.136)	(0.136)
HidVolImb$_i$(-10,-1)			−0.027	−0.018	−0.017
			(0.133)	(0.129)	(0.128)
HY$_i$				0.197**	0.200**
				(0.081)	(0.081)
Log_AT$_i$				0.040	0.042
				(0.031)	(0.031)
Lev$_i$				−0.318***	−0.311***
				(0.074)	(0.074)
MTB$_i$				−0.068***	−0.066***
				(0.016)	(0.016)
CAR$_i$(-10,-1)					1.169***
					(0.366)
Observations	12,410	12,410	12,410	12,410	12,410

*p<0.1; **p<0.05; ***p<0.01

This table documents the results from running Equations (5.2a) to (5.2e). Standard errors are reported in parentheses. Industry fixed effects applied. Variable definitions provided in Appendix A.

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Table G.13 – Conditional Logistic Regressions - Large Negative Earnings Surprises and Imbalance Measures

	Dependent variable:				
	$EPS\_Surp\_NEG_i$				
	(1)	(2)	(3)	(4)	(5)
$CapVolImb_i$(-10,-1)	−0.063				
	(0.057)				
$NonBVolImb_i$(-10,-1)		-0.114^{**}	-0.115^{**}	-0.122^{**}	-0.127^{**}
		(0.054)	(0.054)	(0.054)	(0.054)
$RepBVolImb_i$(-10,-1)		0.100	0.376^{***}	0.348^{**}	0.347^{**}
		(0.069)	(0.141)	(0.136)	(0.137)
$HidVolImb_i$(-10,-1)			-0.298^{**}	-0.264^{**}	-0.267^{**}
			(0.133)	(0.129)	(0.129)
HY_i				0.277^{***}	0.272^{***}
				(0.080)	(0.080)
Log_AT_i				−0.016	−0.017
				(0.031)	(0.031)
Lev_i				-0.396^{***}	-0.397^{***}
				(0.079)	(0.079)
MTB_i				-0.024^{*}	-0.025^{*}
				(0.013)	(0.013)
CAR_i(-10,-1)					-1.301^{***}
					(0.376)
Observations	12,410	12,410	12,410	12,410	12,410

*p<0.1; **p<0.05; ***p<0.01

This table documents the results from running Equations (5.2a) to (5.2e). Standard errors are reported in parentheses. Industry fixed effects applied. Variable definitions provided in Appendix A.

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Table G.14 – Conditional Logistic Regressions - Large Positive Returns and Imbalance Measures

	Dependent variable:				
	XCAR_POS$_i$(-1,1)				
	(1)	(2)	(3)	(4)	(5)
CapVolImb$_i$(-10,-1)	-0.007				
	(0.057)				
NonBVolImb$_i$(-10,-1)		0.028	0.027	0.005	0.007
		(0.053)	(0.053)	(0.054)	(0.054)
RepBVolImb$_i$(-10,-1)		-0.015	0.269*	0.227	0.228
		(0.070)	(0.142)	(0.140)	(0.140)
HidVolImb$_i$(-10,-1)			-0.309^{**}	-0.257^{*}	-0.254^{*}
			(0.134)	(0.133)	(0.133)
HY$_i$				0.539***	0.540***
				(0.081)	(0.081)
Log_AT$_i$				-0.288^{***}	-0.287^{***}
				(0.032)	(0.032)
Lev$_i$				-0.037	-0.035
				(0.054)	(0.054)
MTB$_i$				-0.047^{***}	-0.046^{***}
				(0.014)	(0.014)
CAR$_i$(-10,-1)					0.723**
					(0.347)
Observations	12,284	12,284	12,284	12,284	12,284

*p<0.1; **p<0.05; ***p<0.01

This table documents the results from running Equations (5.2a) to (5.2e). Standard errors are reported in parentheses. Industry fixed effects applied. Variable definitions provided in Appendix A.

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Table G.15 – Conditional Logistic Regressions - Large Negative Returns and Imbalance Measures

	Dependent variable:				
	XCAR_NEG$_i$(-1,1)				
	(1)	(2)	(3)	(4)	(5)
CapVolImb$_i$(-10,-1)	0.054				
	(0.057)				
NonBVolImb$_i$(-10,-1)		0.013	0.013	-0.010	-0.017
		(0.053)	(0.053)	(0.054)	(0.054)
RepBVolImb$_i$(-10,-1)		-0.021	0.061	0.033	0.026
		(0.070)	(0.142)	(0.137)	(0.138)
HidVolImb$_i$(-10,-1)			-0.089	-0.051	-0.054
			(0.134)	(0.130)	(0.131)
HY$_i$				0.633^{***}	0.625^{***}
				(0.081)	(0.081)
Log_AT$_i$				-0.221^{***}	-0.222^{***}
				(0.031)	(0.031)
Lev$_i$				-0.137^{**}	-0.138^{**}
				(0.064)	(0.064)
MTB$_i$				-0.017	-0.018
				(0.013)	(0.013)
CAR$_i$(-10,-1)					-1.994^{***}
					(0.364)
Observations	12,284	12,284	12,284	12,284	12,284

*p<0.1; **p<0.05; ***p<0.01

This table documents the results from running Equations (5.2a) to (5.2e). Standard errors are reported in parentheses. Industry fixed effects applied. Variable definitions provided in Appendix A.

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Table G.16 – Trading Volume Around Ratings Downgrades - All Downgrades

Variable	Mean Tot Vol	Mean Net Vol
TotVol(-30,-21)	12.688	-0.181
TotVol(-20,-11)	12.078	0.054
TotVol(-10,-1)	15.646	-0.027
TotVol(1,10)	17.333	0.035
TotVol(11,20)	12.568	-0.177
TotVol(21,30)	11.032	-0.307

Variable	Mean Tot Vol	Mean Net Vol
BVol(-30,-21)	8.288	0.200
BVol(-20,-11)	7.799	0.365
BVol(-10,-1)	10.164	0.225
BVol(1,10)	12.026	0.310
BVol(11,20)	8.586	0.156
BVol(21,30)	7.465	0.075

Variable	Mean Tot Vol	Mean Net Vol
NonBVol(-30,-21)	4.400	-0.380
NonBVol(-20,-11)	4.279	-0.311
NonBVol(-10,-1)	5.481	-0.252
NonBVol(1,10)	5.307	-0.274
NonBVol(11,20)	3.982	-0.334
NonBVol(21,30)	3.567	-0.382

This table reports the trading activity around all credit rating downgrades. A total of 6334 such downgrades were identified in the sample period. For each trading period both the average total volume (Mean Tot Vol), calculated as the sum of all buy and sell volume, and the average net volume (Mean Net Vol), calculated as the buy volume less the sell volume, is recorded. TotVol(-30,-21) represents the volume from both block and non-block trades that occurs in the trading period that runs from 30 trading days prior to the downgrade to 21 trading days prior to the downgrade. BVol(-30,-21) is analogous but only considers trading volume associated with block trades. NonBVol(-30,-21) is analogous but only considers trading volume associated with non-block trades.

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Table G.17 – Trading Volume Around Ratings Downgrades - Investment Grade to High-Yield

Variable	Mean Tot Vol	Mean Net Vol
TotVol(-30,-21)	12.831	-0.046
TotVol(-20,-11)	9.768	-0.207
TotVol(-10,-1)	14.392	-0.675
TotVol(1,10)	20.402	1.777
TotVol(11,20)	17.131	0.998
TotVol(21,30)	12.071	-0.042

Variable	Mean Tot Vol	Mean Net Vol
BVol(-30,-21)	6.298	0.023
BVol(-20,-11)	4.014	0.184
BVol(-10,-1)	5.373	-0.396
BVol(1,10)	18.474	1.742
BVol(11,20)	15.909	1.079
BVol(21,30)	11.129	0.062

Variable	Mean Tot Vol	Mean Net Vol
NonBVol(-30,-21)	6.533	-0.069
NonBVol(-20,-11)	5.754	-0.391
NonBVol(-10,-1)	9.019	-0.279
NonBVol(1,10)	1.928	0.035
NonBVol(11,20)	1.222	-0.082
NonBVol(21,30)	0.942	-0.104

This table reports the trading activity around credit rating downgrades in which the rating changes from investment grade to high yield. A total of 328 such downgrades were identified in the sample period. For each trading period both the average total volume (Mean Tot Vol), calculated as the sum of all buy and sell volume, and the average net volume (Mean Net Vol), calculated as the buy volume less the sell volume, is recorded. TotVol(-30,-21) represents the volume from both block and non-block trades that occurs in the trading period that runs from 30 trading days prior to the downgrade to 21 trading days prior to the downgrade. BVol(-30,-21) is analogous but only considers trading volume associated with block trades. NonBVol(-30,-21) is analogous but only considers trading volume associated with non-block trades.

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