ESSAYS ON THE MARKET FOR CORPORATE BONDS

SUBMITTED FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY IN ECONOMICS

Aino Levonmaa

St Antony's College

Hilary Term 2017

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Abstract

This thesis contains three empirical studies on the US corporate bond market; each chapter is self-contained and can be read independently. Chapter 1 studies the impact of credit rating changes on corporate bond returns. This study uses a large dataset of corporate bond transactions from the TRACE database for the US corporate bond market, combined with credit rating changes from Fitch, Moody's and Standard and Poor's (S&P), to analyse over 22,000 bonds, coupled with approximately 28,400 rating events over nearly six years. The results show that the bond market responds to news on credit quality asymmetrically: credit rating downgrades, representing bad news for bond holders, produce the strongest response in returns, whilst upgrades do not generate a statistically significant increase in returns. Chapter 2 analyses how order flow (investor "buy" and "sell" trades), impacts corporate bond prices. Order flow plays an important informational role, acting as a conduit through which private information about fundamental value is aggregated into prices. Using intraday transaction data from the TRACE database, I analyse over 1,000 of the most liquid corporate bonds, a total of 9.5 million trades. Drawing on similar studies of other markets, the relationship between returns and order flow is modelled using a vector autoregression, and the information content of a trade is measured as the long-run price impact of a shock to order flow. Price impacts are particularly strong and significant for order flow from institutional investors and for bonds with higher default risk, higher volatility and lower liquidity. Chapter 3 provides novel evidence on the importance of high frequency measures of volatility and correlation for the corporate bond market. Realized measures of volatility have been shown to be important in modelling and forecasting equity, exchange rate, and Treasury bill return volatility. We merge the NYSE's TAQ database of high frequency equity prices with the TRACE database, and show that the information contained in high frequency data is valuable in modelling the dynamics of the firm-level covariance matrix of bond and stock returns, for over 100 individual U.S. firms.

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Chapter 1

The Impact of Credit Rating Events on Corporate Bond Returns

Abstract

This paper answers the question of whether and how credit rating changes impact corporate bond returns. This study uses of a large dataset of corporate bond transactions combined with a large set of credit rating changes from the three dominant rating agencies, Fitch, Moody's and Standard and Poor's (S&P). I analyse the trading history of 22,200 unique bond issues, coupled with 28,466 rating events over 1,577 trading days. The rating events are analysed in distinct categories; rating changes within investment grade, rating changes within speculative grade, and rating changes where this boundary is crossed. The results of this chapter show that the bond market responds to news on credit quality in an asymmetric fashion. Credit rating downgrades, representing bad news for bond holders, particularly within investment grade (companies with low to moderate credit risk) produce the strongest response on abnormal returns, whilst upgrades fail to produce a statistically significant increase in excess return. The significance of these results is tested using a test statistic robust to cross-dependence in individual bond returns. The Wilcoxon signed rank test, often used in the event study literature, is computed and its weaknesses are discussed.

1. Introduction

1.1 Overview

Do we observe a price impact when the credit rating of a bond changes? According to the Efficient Markets Hypothesis (EMH) discussed by Malkiel (1992), efficient capital markets fully and correctly reflect all relevant information in determining security prices. Whether a change in the credit rating of a company or a bond issue impacts security prices depends on if the rating change contains information that is not yet incorporated into prices or if the rating change is unanticipated by market participants. Credit ratings seek to evaluate the credit risk, or the likelihood of default of a company and its debt securities. This assessment is generally based on a subjective evaluation of firm cash flows, profitability and operating environment. If the information revealed by the credit rating change impacts prices, the market is inefficient with respect to that information.

Due to Roberts (1967), market efficiency is generally defined over three information sets. Weak-form efficiency requires that current prices fully reflect all information contained in the sequence of past prices. Semi strong-form efficiency requires that prices fully reflect all publicly available information, including past prices, but also incorporating other variables such as interest rates, news releases, economic data and published financial statements. If markets are strong form efficient, security prices also reflect private information. Moreover, both Roberts and Malkiel argue that the EMH implies the absence of arbitrage opportunities given a particular information set; it is not possible to make economic profits, that is, risk-adjusted profits net of transaction costs, trading on the basis of information contained in this set.

This paper examines the impact of credit rating changes on corporate bond returns. Price impact on the announcement of a rating change is evidence that credit ratings provide information not already incorporated in bond prices, and thus that credit rating agencies provide valuable information to financial market participants. The two main hypotheses about bond price reaction on ratings events examined in this paper are the information content hypothesis and clientele effect: do bond rating changes convey information to the market that has not already been incorporated in prices? Do we observe more significant price reactions for bonds whose primary clientele consists of regulated institutions that have a “forced demand” for a certain credit grade? These two hypotheses are reviewed in more detail below.

A unique feature of this study is the use of a recent and very large data set for bond transactions in the secondary US corporate bond market. The Trade Reporting and Compliance Engine (TRACE) system consists of intraday bond prices and other transaction features published on a contemporaneous basis. The coverage of the sample is comprehensive: the bond transactions are captured between July 2002 and June 2008, consisting of 35,123 bonds issued by 930 different companies. The sample period reflects a unique time for financial markets characterised by the peak of the market in 2007 and the beginnings of the financial crisis.

The time series of credit rating changes is obtained from Mergent’s Fixed Income Securities Database (FISD). The rating changes reported are from all three leading credit rating agencies, Moody’s Investors Service (Moody's), Fitch and Standard and Poor’s (S&P), whilst the existing literature has focused attention on Moody's and S&P. The total number of credit rating events analysed is 28,466. The events are analysed firstly for the entire sample of credit rating changes, which contains bonds from all rating classes. Next, I analyse the rating events in distinct categories; rating changes within investment grade, which, broadly stated, contains bonds with low or moderate credit risk, rating changes within speculative grade, that is, bonds with higher credit risk, and rating changes where this boundary is crossed. The impact of the credit rating changes is measured using an event study methodology focused on the measurement of mean abnormal bond returns. The significance of the results is tested using a test statistic robust to cross-dependence in individual bond returns. The Wilcoxon signed rank test, often used in the event study literature, is computed and its weaknesses are discussed.

1.2 Information Content Hypothesis

The question whether credit rating changes convey pricing-relevant information to the capital markets is inextricably linked to the function of credit rating agencies. Ederington et al. (1984), Holthausen and Leftwich (1986), and Wakeman (1990) provide a discussion on the role of credit rating agencies. According to one view, rating agencies provide no new information to financial markets; they merely assimilate the existing public information, such as financial statements, securities' offering memoranda and market data. If capital markets are semi strong-form efficient, announcements of credit rating changes should not impact security prices. This implies that information contained in credit ratings is already incorporated in security prices, as the information comes from the public domain. In this setting, the existence of credit rating agencies may be justified based on the costs associated with information acquisition, the rating agencies are the most efficient providers of a collection of company information. By incorporating existing public information, rating agencies are perceived to lag the market and to produce credit ratings that are backward looking; ratings that will only change when there is public indication of deteriorating or improving performance. Corroborating this view, Ederington and Yawitz (1987) show that two thirds of ratings can be predicted from publicly available data. Hence, as argued by Wakeman (1990), a bond rating summarises in an "easily communicated" measure all the key determinants of a company's or bond's credit risk.

However, rating agencies claim to have access to confidential inside information during the process of assigning or reviewing credit ratings. This inside information can consist of budgets, forecasts and internal reports or planned mergers and acquisitions. Whether credit rating agencies gain access to private information is hard for an outsider to ascertain, nonetheless, private information should improve the value of credit ratings. If markets are considered to be semi strong-form efficient, the release of a credit rating, based partially on private information, is expected to impact bond prices. In this view, rating agencies are information specialists, who convey relevant aspects of private information from companies to investors without fully revealing specific details, but discretely summarising them in the credit rating. Jorion et al. (2005) examine the informational effect of credit ratings on stock prices before and after fair disclosure regulation was implemented in the US in 2000. Fair disclosure prohibits companies from making "non-public disclosures to favoured investment professionals", such as equity analysts. Surprisingly, credit rating agencies are exempt from this regulation and hence gain a potential informational advantage. The empirical evidence indicates this was indeed the case; the impact of rating changes on stock prices was stronger post fair disclosure regulation, indicating an increased informational content of credit ratings, and a "strategic advantage" for rating agencies serving as conduits of non-public information.

The above discussion regarding the information value of credit rating changes has been based on the premise that credit ratings have changed as a response to changes in company fundamentals, its cash flows and embedded credit risk. In order to examine the value of pure ratings information, that is, to examine rating changes that are not triggered by changes in company fundamentals, Kliger and Sarig (2000), examine bond and stock price reactions to rating changes caused by a refinement in Moody's rating process. Importantly, the finer ratings are based on exactly the same underlying information as the credit ratings before the refinement and as such are just finer partitions of the previous information on credit risk. Kliger and Sarig (2000) find that the incremental value of rating information based on a methodological refinement does not impact the value of firm as a whole, but it does affect how this value is distributed between debt and equity. A change in the assessment of default risks affects the firms' funding opportunities and cost of capital. Shareholders, the residual claimants to the firm's cash flows lose when a firm's credit risk declines (when the credit rating is upgraded) whilst bondholders, the senior claimants, benefit from such reductions in default risks. Based on these results the authors argue that the incremental value of pure ratings information stems from information credit ratings provide about diversifiable risks, as firm value remains unchanged.

1.3 Clientele Effect Hypothesis

Bond price reactions around credit rating events may also be explained by regulatory constraints restricting investors such as pension funds and insurance companies to a particular credit class, most commonly to bonds rated within investment grade or to a subset thereof. These regulatory restrictions can influence bond returns following an unexpected rating change even if the informational content of the change is limited, that is, if the ratings are believed to reflect only a set of publicly available information. When a market is segmented by regulatory constraints, a clientele effect in the demand for corporate bonds is a viable cause for price impact in bond prices.

The clientele effect is concerned with the impact of market imperfections, such as taxes, regulatory restrictions or transaction costs, as conveyed by investor preferences, on security prices. The seminal research of Modigliani and Miller (1961) suggests that the value of the firm is unrelated to its dividend policy, as investors influenced by dividend and capital gains tax policy tend to invest in the equity of companies whose dividend policy matches their preferences, as shaped by their marginal tax rates. Modigliani and Miller termed this tendency a dividend clientele effect. Regulated investors in fixed income markets are governed by an infrastructure where regulatory limits prohibit investment across all credit ratings. In this framework, regulatory restrictions guiding investments are market imperfections dividing investors into clienteles buying bonds whose ratings are consistent with their credit risk appetite and regulatory guidelines. If investors are restricted to certain credit grades, will changes in credit ratings have a more pronounced impact on bond returns?

1.4 Existing Evidence on Security Price Impact

Using bond and equity data, the extant literature on the price impact of credit rating changes reveals mixed results. Katz (1974) examines the impact of "rating reclassifications" on a bond's yield to maturity using 115 investment grade bonds issued by electric utility companies during a seven year period from 1966 to 1972. He finds no anticipation of the event, but a rather long and slow price adjustment process after the rating change, indicating semi strong-form market inefficiency. Conversely, Weinstein (1977), using a more comprehensive sample, finds evidence to contradict these results. Working with monthly holding period returns rather than yields, a slightly larger sample size of 132 bonds from utility and industrial companies over 13 years during 1962 - 1974, he finds no evidence of a price response on the announcement of a rating change. Credit rating changes convey no new information to capital markets, bond prices already incorporate the changes in company performance or credit risk that the new credit rating reflects.

The results from these early studies may suffer from poor data availability. Weinstein (1977) uses bond quotations rather than transaction prices in computing the holding period return and he reports that only between 15% to 30% of the quotes used are actual transaction prices. Hence, a fraction of up to 85% of price data does not reflect actual market pricing. Further, the cross-sectional firm sample, particularly in the case of Katz (1974), is narrow; the investor base of electric utility companies is not likely to provide a good representation of bond investors in the market at large.

Since these early papers, through the introduction of daily price data and better model specifications, more precise measurement of abnormal returns has been possible. As argued by Fama (1991) daily security price data affords more precise measurement of the speed of price response to information, a key factor in evaluating market efficiency. Holthausen and Leftwich (1986) examine the impact of rating changes on daily common stock prices, with a sample of 1014 rating changes, from 1977 to 1982. To prevent the impact of other contemporaneous news announcements confounding the effect of the rating change, Holthausen and Leftwich classify observations as either contaminated or non-contaminated. The contaminated sample contains the observations where an article regarding the company experiencing a rating change was published in the Wall Street

Journal during a four-day period surrounding the credit rating event. For observations in the uncontaminated sample, no such concurrent disclosures were made. They find that downgrades are associated with statistically significant negative stock returns, even after observations containing contemporaneous announcements are removed, whilst in either sample, upgrades are not. The results are consistent with the view that rating agencies, via credit rating downgrades, provide novel information to the capital market.

Using the same methodology of controlling for releases of concurrent information as Holthausen and Leftwich (1986), as well as the same sample of rating changes, Hand et al. (1992) examine the effect of rating agency announcements on daily bond and stock prices during the period from 1977 to 1982. Additionally, they examine the effects of additions to the credit watch list, which is interpreted as a potential change in rating, between 1981 and 1983. The effects of both potential upgrades and potential downgrades on the credit watch list are significant, reflecting perhaps the unexpected nature of the announcement. Actual rating changes produce weaker results, especially for upgrades, which gives an indication that the actual rating changes are to some extent expected by the market, as a particular firm's debt may have been on the credit watch list prior to the rating event. However, it should be noted that rating changes are not always preceded by a watch list announcement. Also notable in these results is the asymmetry in the response of both stock and bond prices to credit rating upgrades and downgrades: announcements of rating downgrades are associated with statistically significant negative excess bond and stock returns, whilst there is some evidence of positive excess bond returns for upgrades, but none for stock returns.

Hite and Warga (1997) examine the impact of bond rating changes announced by Moody's and S&P on bond performance using a rather large monthly dataset of 2,800 industrial bonds during a ten year period of 1985 to 1995. Supporting the existing evidence on asymmetry of the response in bond prices to upgrades and downgrades, returns on upgraded bonds show a very weak response to credit rating changes, with the exception of statistically significant positive returns for bonds upgraded from speculative grade to investment grade. Conversely, results for downgraded bonds are significant across credit grades, with the strongest impact observed for bonds crossing the threshold between investment and speculative grades.

1.5 Structure of the Paper

The structure of this paper is the following: Section 2 provides an introduction to the rating process and the institutional framework behind credit rating agencies. Section 3 outlines the event study methodology employed. Section 4 details the data used in this study, it explains how the databases were merged and provides descriptive statistics. Section 5 discusses the empirical methods used in the analysis, and Section 6 reports the results. Concluding remarks are contained in Section 7.

2. Rating Agencies and the Credit Rating Process

The credit rating industry in the United States is regulated by the Securities and Exchange Commission (SEC). Since 1975 the SEC has restricted entry into the credit rating industry by recognising only a limited number of agencies as “nationally recognized statistical rating organizations" (NRSROs).[1] Since September 2008, there are ten firms registered as NRSROs, however, as documented by Becker and Milbourn (2008), 90% of market share is captured by the three rating agencies studied in this paper: Fitch, Moody's and S&P.

Credit ratings aim to capture the creditworthiness of an institution or a debt security on a forward looking basis. Each rating agency uses its own methodology and rating scale in measuring credit quality, however, broadly stated, they are all concerned with assessing the likelihood of default, or whether financial obligations will be repaid in full and in a timely manner.[2] Rating agencies assign ratings to issuers and their financial obligations using an alphabetical ratings scale ranging from investment grade to non-investment or speculative grade. Investment grade companies and bonds, incorporating low to moderate credit risks are rated by Fitch and S&P use the same scale of: AAA, AA, A, and BBB, whilst speculative grade entities reflecting higher credit risks, are rated using BB, B, CCC, CC, C, and D. Moody's credit ratings for the same categories of investment and speculative grade ratings are: Aaa, Aa, A, Baa and Ba, B, Caa, Ca, C, respectively. As described by Jorion et al. (2005), the rating of an issuer need not be equal to that of a specific debt issue. Other bond characteristics, such as the seniority of the bond, that is, its rank within the firm's capital structure determine the relative ranking of the ratings of the entity and its obligations.

The credit rating agencies play a multifaceted role in the process of financial intermediation, their judgement of the creditworthiness of an institution and its ability to

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[1] See SEC document "Report on the Role and Function of Credit Rating Agencies in the Operation of the Securities Markets" for a discussion.

[2] The rating guides of the three credit agencies used as references in this discussion are listed in the References section of this paper.

meet its financial obligations are used by a wide range of market participants. Firstly, investors, such as pension and mutual funds and insurance companies, use credit ratings as guidelines indicating the credit quality of their fixed income investments or as inputs in proprietary credit research. Often credit ratings are also a component in investors’ internal regulations, which limit credit exposure within different rating grades. Secondly, issuers require credit ratings in order to obtain access to public credit markets. A bond's credit rating has a significant impact on both investor demand for the asset and, as a consequence, to its pricing. Investors will demand a higher return for assets with higher credit risk; hence a lower credit rating, holding constant other factors entering into investment decisions, implies higher costs of financing for the issuing entity. Further, bond pricing and investor appetite for a particular debt issue may also depend on which of the rating agencies has rated the issue. For example, a single-rated debt issue, rated by only one credit rating agency, may obtain less favourable pricing from the issuer's perspective than an issue with two ratings: Some investment funds may, from a regulatory standpoint, require two ratings to invest in a bond issue. Alternatively, the market may perceive a single-rated debt issue as a signal worse of credit quality compared to a bond with two ratings - the issuer may have been unable to obtain a similar quality credit rating from another rating agency.[3] Thirdly, regulators, including the SEC, use credit ratings to monitor credit risks embedded in investments of regulated entities. For example, money market funds, a heavily regulated type of mutual fund, are restricted in their investments to only the highest two rating categories, and credit ratings are used as benchmarks to establish "minimal credit risk".[4]

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[3] See SEC document "Report on the Role and Function of Credit Rating Agencies in the Operation of the Securities Markets" for a discussion.

[4] Money market funds in the US are governed by Rule 2a-7 under the Investment Company Act of 1940.

Periodically, and particularly in time of financial turmoil, the independence, expertise and objectivity of credit rating agencies are called to question. The objectivity of the agencies is shadowed by the inherent conflict of interest in the rating agency business model which stems from issuers paying the agencies for company level ratings as well as for rating their debt securities they issue out to the market. Since credit quality of a company is a major component of the terms of financing it can obtain in the credit markets, issuers naturally prefer higher credit ratings on their debt. Given that these companies are the paying customers, credit rating agencies may find it difficult to remain objective.

3. Event Study Methodology

Event studies are used in a wide range of fields and contexts. The classic example of an event study is that on stock splits by Fama et al. (1969). Event studies measure whether a firm specific or industry-wide event, such as a credit rating change or a change in accounting regulations or capital requirements has any impact on a security's return and hence on the wealth of firms' claimholders. This impact is measured using the notion of abnormal return, defined by Campbell et al. (1997) as the observed return on a security around the event, less the normal or expected return of the security:

$$\varepsilon_{it} = R_{it} - E[R_{it}|X_t] \tag{1}$$

ε_{it} is the unexpected, or abnormal component of the return for security i at time t, R_{it} is the observed return, $E[R_{it}|X_t]$ is the expected or normal return, as predicted by a particular model of security returns, and X_t is the conditioning information for that model. More formally, event studies test the hypothesis that the impact of the event on security returns, as measured by abnormal returns, is zero.

$$H_0: \quad E[\varepsilon_{it}] = 0$$

$$vs. \qquad H_a: \quad E[\varepsilon_{it}] \neq 0$$

The event study methodology provides an important framework for tests of market efficiency. By examining potential abnormal post-event returns, it is possible to gauge the speed at which security prices adjust to new information and the magnitude of the impact of the announcement, and hence gain information on market efficiency. However, tests of market efficiency are subject to the "joint-test problem", also known as the Roll Critique, where testing market efficiency is always also a test of whether the particular pricing model used to estimate securities' normal returns is correct.[5] Thus, in the case where the null hypothesis of zero abnormal returns is rejected, the rejection may be a result of true market inefficiency or the null hypothesis may be rejected simply because the pricing model used to measure expected returns is incorrect.

In order to define and calculate the abnormal return of a security during an event, it is necessary to specify a model for expected returns, as a security's performance can only be considered abnormal relative to a benchmark measure. Two widely used models for expected returns are the "mean adjusted return model" (also known as the "constant-mean-return model") and the "market model". Both of these models are discussed at length in Campbell et al. (1997) and Brown and Warner (1980). In the mean adjusted return model, the expected return, $\bar{R}_i$, can vary across securities, but it is considered constant over time:

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[5] Roll (1977) discusses the problems related to testing the capital asset pricing model (CAPM).

$$\varepsilon_{it} = R_{it} - \bar{R}_i \tag{2}$$

The market model, commonly used in event studies involving equities, relates the return of a security to the return on the market portfolio in a linear fashion:

$$\varepsilon_{it} = R_{it} - \alpha_i - \beta_i R_{mt} \tag{3}$$

R_{mt} is the return on the market portfolio in period t, α_i is the regression intercept, and β_i the slope coefficient. The market portfolio is generally proxied by a stock market index, such as the S&P 500. The advantage of the market model is that by capturing the variability of the market return, the variance in the abnormal return, insofar as it is generated by market-wide factors, is reduced, which allows for more precise inference on abnormal returns.

In order to facilitate the computation of abnormal returns associated with events, the notion of an "event window" is defined. The time period that captures the event, and a number of days surrounding it, is called the event window. The day of the event is labelled day zero, whilst the pre-event day labels run backwards, with the day immediately before the event being day -1 and so forth. The post-event days start from +1, the day after the event. The length of the event window can range from two days (event day zero and day +1) to several months or over a year.[6] As the event study methodology is built on the premise that abnormal returns capture the impact of the event on security holder returns, abnormal returns are calculated over the event window. The subset of the sample period outside the event window and leading up to an event is the estimation period. The parameters of the model for expected returns, the expected return and variance are estimated from this sub-

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[6] Event studies with an event window of a year or more are called "long horizon" event studies as discussed in Kothari et al. (2006).

period. The event window is not included in the estimation period, to prevent the event-driven returns from influencing the parameters for the model for expected returns.

The estimated expected return $\hat{\bar{R}}_i$ and variance $\hat{\sigma}^2$ of security returns are obtained from the data in the estimation period of length T. For the mean adjusted returns model these parameters are estimated using: [7]

$$\hat{\bar{R}}_i = \frac{I}{T}\sum_{t=1}^{T} R_{it} \tag{4}$$

$$\hat{\sigma}^2 = \frac{I}{T-1}\sum_{t=1}^{T}\left(R_{it} - \hat{\bar{R}}_i\right)^2 \tag{5}$$

In order to draw inferences on the impact of the event on claim holders' wealth, the abnormal returns computed for the event window need to be aggregated across securities experiencing events, and across time. The most common method to assess the significance of abnormal returns for a sample of event securities or firms is to compute the cross-sectional average abnormal return for a given day within the event window, which tests the hypothesis of whether, on average, the event is associated with a change in the securities' returns. For a sample of N securities experiencing events, the cross-sectional mean abnormal return, AR_t , for period *t* within the event window is:

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[7] Brown and Warner (1980), Campbell et al. (1997) and Kothari and Warner (2006) contain further details regarding the estimation of the mean adjusted return model.

$$AR_t = \frac{1}{N}\sum_{i=1}^{N} \varepsilon_{it}$$

(6)

Abnormal returns can be aggregated over time in order to examine their behaviour within multiple days of the event window. This is done via the introduction of the cumulative abnormal return (CAR), which is a cumulative sum over the average abnormal returns for a particular interval (t_1, t_2) in the event window.

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_t$$

(7)

The time series aggregation may be particularly useful in examining the joint significance of day 0 and +1, if there is any uncertainty whether the event in question took place during market hours. If the time of the event is known with precision, the potential impact of the event would be captured in the securities' abnormal returns for the event day, otherwise, the statistically significant mean abnormal return for day +1 maybe an indication that the news was only publicly available after market hours, and hence its impact is captured only on day +1.

4. Data

4.1 Description of Sources for Bond Transaction and Ratings Data

The primary data source used for bond transaction information is the Trade Reporting and Compliance Engine (TRACE) extracted through Wharton Research Data Services (WRDS). The TRACE system is a rather novel database for the over-the-counter US corporate bond market providing real-time transaction information for market participants: retail and institutional investors, broker-dealers and regulators. TRACE is supplied and operated by the Financial Industry Regulatory Authority (FINRA).[8] The bond transaction data includes customer and inter-dealer transactions in "TRACE-eligible securities", which are depository-eligible, SEC registered, US dollar denominated securities across all credit grades.

TRACE was initiated in July 2002 in an effort to improve the efficiency and transparency of the corporate bond market. The public reporting (by FINRA member firms, such as broker-dealers) of bond transactions was implemented in three phases, each of which increased the number of securities information was disseminated on and reduced the delay allowed when reporting trades. The final phase was fully effective in February 2005 and since then TRACE captures 99% of all public transactions, representing 95% of the total dollar value traded.[9] Since January 2006 the TRACE system has provided real-time reporting of all transactions. The few trades that fall outside the scope of TRACE are those that occur on exchanges. Edwards et al. (2007) report that less than 5% of bonds are listed on the New York Stock Exchange (NYSE), and for these bonds, less than 40% of trades occur on the NYSE's Automated Bond System.

TRACE reports the time and date of bond transactions, making intra-day price information available, although, many bonds trade infrequently and may only have a few trades per

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[8] FINRA was created in July 2007 through the merger of the National Association of Securities Dealers (NASD) and the member regulation, enforcement and arbitration functions of the New York Stock Exchange. It is a self-regulatory organisation for all securities firms in US that interact with the public.

[9] See TRACE Fact Book 2008.

month or even per year. In addition to the reported price and yield of a bond, TRACE disseminates information on trading volume as transaction par value, however only through an indicator for large transactions. For trades in investment grade bonds with a par value of more than $5 million, TRACE contains an indicator of "5MM+". Similarly, for speculative grade debt, transactions greater than $1 million are reported as "1MM+".

The impact of this real-time database of secondary market transaction information available to investors has been remarkable. In contrast to equities, which are mostly traded on organised exchanges, bond trades commonly amount to transactions between a dealer and a client carried out over the phone or on electronic trading platforms. As a result, the details of the transaction, bond price and traded volume are private information to the transacting parties. Two recent papers by Edwards et al. (2007) and Bessembinder et al. (2006) examine the impact of the introduction of TRACE on transaction costs associated with bond trades in the secondary market. Edwards et al. (2007) find that secondary transactions costs drop by up to 2% when bond prices are disseminated by TRACE. Their estimated round-trip transaction costs range from 150 to 3 basis points (1 basis point is 0.01%), depending on trade size, issue size, the credit quality and time to maturity of the bond.

In addition to latest reported transaction prices being available on FINRA's website, TRACE pricing is also available through Bloomberg, a real-time news and financial information service used extensively by both professional investors and dealers in the corporate bond market. The wide availability of TRACE transaction prices increases information flow into the market - last transaction prices can be verified along with other relevant bond characteristics prior to trading. This level public price information enhances the quality of trade execution. Investors now have a better gauge on pricing, as TRACE provides an alternative pricing source to prices posted by broker-dealers, whose incentives are generally not aligned with those of their customers.

The data from Mergent’s Fixed Income Securities Database (FISD), available through WRDS, serves two distinct purposes. Firstly, I construct the time series of rating information from FISD for each bond issue rated by the three credit rating agencies used in the study. The data available contains the date of the ratings change, but not the time of publication of the rating announcement. Further, FISD contains only an incomplete record of when (if at all) a particular bond was on "credit watch list". If an issuer or a bond is on the watch list, this is a signal to the market that the rating is under review for an upgrade or a downgrade, creating the possibility for partial anticipation of any subsequent rating changes. Secondly, FISD contains information on bond characteristics, such as maturity, coupon and other terms of the offering, which are used to categorise bonds contained in the TRACE database and to filter the sample so that it represents straight corporate debt, that is, bonds that do not carry any conversion privileges or other special features and have a specific maturity date and coupon rate.

The bond transaction data from TRACE is merged with both the credit rating and bond characteristic data from FISD. This is a computational challenge, as the two databases are extremely large in size: The raw data from TRACE from its initiation in July 2002 to June 2008 included approximately 29 million observations of intra-day bond transactions. The time series of rating changes contained 231,588 observations of credit rating reclassifications. The FISD database for bond characteristics was smaller in size, containing information on 24 different issue features for 33,655 unique bonds. The processing of this large quantity of data was a necessary exercise, as the merging of these databases was a crucial initial step toward a comprehensive sample of the US corporate bond market and toward a detailed analysis of the key questions in this paper.

4.2 Sample Selection

The sample period covered in this study is from the first day of TRACE transaction data in July 2002 to June 2008, which amounts to 1,577 trading days. During this period, 35,123 unique bond issues were traded in the corporate bond market. In order to exclude erroneous trade entries, I eliminate trades that were cancelled or corrected. Further, I only include trades that are defined as "regular trades", which excludes trades with non-standard settlements, trades that were reported outside market hours and trades which have a reported transaction price consisting of a weighted average price of some previous trades.

I filter the transactions by imposing restrictions on the minimum trade frequency and by requiring certain characteristics of the issues to be reported in FISD. The corporate bond market is characterised by a paucity of trades - it is common for some bonds to trade at issuance, and then to be dormant until a few trades around maturity. In order to detect abnormal returns around events, frequent trading in the event window is required. I impose two minimum trading frequency requirements: The first restriction specifies a lower bound of 66 trading days for the time between the first and last transaction for a given bond. A bond may not complete this minimum duration requirement because of non-trading or simply due to the fact that it has matured within this time period. The second restriction is placed on the number of days with trades; transactions must be observed for a given bond on at least thirty trading days over the sample period of 1,577 days. These minimum trading frequency restrictions reduce the number of bonds in the sample to 25,990. This 18.4% reduction in the sample size as a response to rather lenient trade frequency criteria gives good indication of the magnitude of infrequent trading in the corporate bond market: Requiring bonds to trade on 2% of the trading days and limiting the time between the first and last observed trades to 4% of the days in the sample removes nearly 20% of the bonds.

I merge the remaining transaction data with the bond characteristic and rating change data from FISD, using bond identification information (the CUSIP[10]) provided in both TRACE and FISD. I require non-missing rating information for a bond to be retained in the sample; this requirement eliminates 3,264 (9.3%) bonds from the TRACE database. I further filter the data to include only straight corporate bond issuance. The preference for a sample of bonds with standard features stems from an attempt to minimise the impact that non-standard characteristics may have on the bond's trading behaviour. I remove convertible bonds, preferred securities, exchangeable bonds and bonds that have a put option or a tender exchange offer embedded. I remove bonds that are in default or bonds issued by companies that are in bankruptcy, as these issues are unlikely to provide a good characterisation of trading behaviour of solvent and liquid bonds in the market. Finally, I remove zero coupon and perpetual bonds, asset backed bonds, which are bonds collateralized by a portfolio of loans or other assets, such as credit card receivables. Jointly these filters remove a further 14.6% of bonds from the sample. Table 1 summarises the filtering process.

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[10] A bond's CUSIP (Committee on Uniform Security Identification Procedures) is a unique 9 digit alphanumeric identifier.

Table 1 Data Filtering

This table describes the effects of the filters used to construct the final sample of 22,200 bonds. The sample period spans from the initiation of TRACE in July 2002 to June 2008, a period of 1,577 trading days.

	Number of Bonds	Percentage of Initial Sample
Bond issues in TRACE during the sample period	35,123	
Subtotal of issues with rating information	31,859	90.7%
Subtotal of issues statisfying trade frequency requirements	25,990	74.0%
Subtotal after filtering on bond characteristics	22,200	63.2%
Final sample to be used in the study	22,200	63.2%

The remaining 22,200 bond issues compose the sample of bonds from the transaction data from TRACE that will be used in the event study to examine the impact of changes in credit ratings on bond returns. Given the filters imposed above, these bonds characterise a relatively liquid sample of standard corporate bonds, and a representative cross-section of the issuers making up the corporate bond market.

4.3 Sample Characteristics

Table 2 summarises the number of bonds and the number of downgrades and upgrades for each credit rating agency during the sample period. The last row of Table 2 reports the number of bonds in the sample for each rating agency, taking into account the fact that some bonds experience both type of events during the sample period. The remaining number of bonds for each agency is remarkably similar - each agency captures roughly a third of the bond rating market in this sample.

Table 2 Number of Rating Events

This table reports the number of bonds and events for each credit rating agency in the sample. The last row details the number of unique bonds rated by each agency, taking into account the fact that a given bond may be both downgraded and upgraded during the sample period.

	Fitch		Moody's		Standard and Poor's	
	Downgrades	Upgrades	Downgrades	Upgrades	Downgrades	Upgrades
Number of						
Bonds	4,538	2,774	4,767	2,213	3,923	3,553
Events	7,548	2,955	8,011	2,364	6,298	3,910
Total number of bonds per agency, accounting for bonds experiencing both events						
	6,232		6,729		6,404	

The three agencies have a potentially large degree of overlap in the institutions and bond issues they rate, which may induce event date clustering. Events are said to be clustered when multiple securities experience an event around the same time causing their event windows to overlap. The statistical implications of event clustering are discussed in Section 5.2. However, in order to limit the impact of event clustering at the outset, I remove the last event for bonds that have two rating changes with overlapping event windows. Further, all bonds in the remaining sample are required to have at least two rating observations, so that the impact of rating changes can be studied. Controlling for these conditions, the number of unique bonds in the sample decreases by 56% to 9,870 compared to the original 22,200 bonds remaining after the filtering process. Clearly, many bonds have very stable ratings. An example of this type of issuer is General Electric, which was downgraded in March 2009 from AAA to AA- by S&P and from AAA to Aa2 by Moody's after more than 40 years with stable ratings.

Tables 3 to 5 below provide details of the frequency of bond trading within the event window, and this information is summarised in Figures 1 and 2. In this study, the length of the event window is 45 days, including day zero, and 22 trading days on either side of the event day. The figures and tables below highlight the paucity of bond trades. The largest proportion of bonds in the sample trade between 1 to 5 days out of the 45 day event window. There are few differences in the trading frequencies between the agencies for downgraded bonds, but for upgrades, the bonds rated by S&P trade most frequently; 9 out of the 11 event day categories, S&P rated bonds have the highest trading frequency. Downgraded bonds generally trade more frequently than upgraded bonds; 47 - 54% of downgrades trade on 10 or more days, in comparison to 37 - 54% for bonds upgraded. The higher relative infrequency of trading for upgrades is also highlighted as a higher proportion of bonds with zero trades in the event window; 6.4 - 18.7% for upgrades compared to 6.7 - 9.4% for downgrades. At the higher trading frequencies, for bonds with 40 or more trades, there is little difference between the two event types. For the analysis in the remainder of this paper, the bonds that have zero trades in the 45 day window are removed, as abnormal returns cannot be measured for such bonds. Hence, the number of bonds in the sample decreases by a further 3.8% to 9,036.

Tables 3 - 5

These tables detail the trading frequencies of bonds within the event window reported separately for Fitch (Table 3), then Moody's (Table 4) and lastly S&P (Table 5). The first column reports the number of event days with trades. The left panel details trading frequency for downgraded bonds and the right hand side panel for upgraded bonds. For example, 79 (1.7%) bonds downgraded by Fitch trade every day in the event window, and 49.7% of the bonds downgraded by Fitch trade on at least 10-15 days in the event window.

Table 3 Event window trading frequencies for bonds downgraded and upgraded by Fitch

	Downgrades			**Upgrades**		
Number of Event Days with Trades	Number of Bonds	Percent of Bonds	Cumulative Percent of Bonds	Number of Bonds	Percent of Bonds	Cumulative Percent of Bonds
45	79	1.7%	1.7%	69	2.5%	2.5%
40-44	236	5.2%	6.9%	120	4.3%	6.8%
35-40	190	4.2%	11.1%	107	3.9%	10.7%
30-35	194	4.3%	15.4%	155	5.6%	16.3%
25-30	269	5.9%	21.3%	189	6.8%	23.1%
20-25	335	7.4%	28.7%	201	7.2%	30.3%
15-20	401	8.8%	37.5%	271	9.8%	40.1%
10-15	553	12.2%	49.7%	376	13.6%	53.6%
5-10	707	15.6%	65.3%	454	16.4%	70.0%
1-5	1,148	25.3%	90.6%	654	23.6%	93.6%
0	426	9.4%	100.0%	178	6.4%	100.0%
Total	4,538	100%		2,774	100%	

Table 4 Event window trading frequencies for bonds downgraded and upgraded by Moody's

	Downgrades			**Upgrades**		
Number of Event Days with Trades	Number of Bonds	Percent of Bonds	Cumulative Percent of Bonds	Number of Bonds	Percent of Bonds	Cumulative percent of Bonds
45	62	1.3%	1.3%	31	1.4%	1.4%
40-44	218	4.6%	5.9%	89	4.0%	5.4%
35-40	184	3.9%	9.7%	90	4.1%	9.5%
30-35	187	3.9%	13.7%	79	3.6%	13.1%
25-30	244	5.1%	18.8%	82	3.7%	16.8%
20-25	339	7.1%	25.9%	127	5.7%	22.5%
15-20	411	8.6%	34.5%	151	6.8%	29.3%
10-15	585	12.3%	46.8%	166	7.5%	36.8%
5-10	796	16.7%	63.5%	288	13.0%	49.8%
1-5	1,358	28.5%	92.0%	697	31.5%	81.3%
0	383	8.0%	100.0%	413	18.7%	100.0%
Total	4,767	100.0%		2,213	100.0%	

Table 5 Event window trading frequencies for bonds downgraded and upgraded by S&P

Number of Event Days with Trades	**Downgrades**			**Upgrades**		
	Number of Bonds	Percent of Bonds	Cumulative Percent of Bonds	Number of Bonds	Percent of Bonds	Cumulative Percent of Bonds
45	99	2.5%	2.5%	116	3.3%	3.3%
40-44	223	5.7%	8.2%	175	4.9%	8.2%
35-40	193	4.9%	13.1%	138	3.9%	12.1%
30-35	197	5.0%	18.1%	184	5.2%	17.3%
25-30	259	6.6%	24.8%	178	5.0%	22.3%
20-25	311	7.9%	32.7%	241	6.8%	29.0%
15-20	358	9.1%	41.8%	279	7.9%	36.9%
10-15	478	12.2%	54.0%	385	10.8%	47.7%
5-10	554	14.1%	68.1%	547	15.4%	63.1%
1-5	989	25.2%	93.3%	947	26.7%	89.8%
0	262	6.7%	100.0%	363	10.2%	100.0%
Total	3,923	100%		3,553	100%	

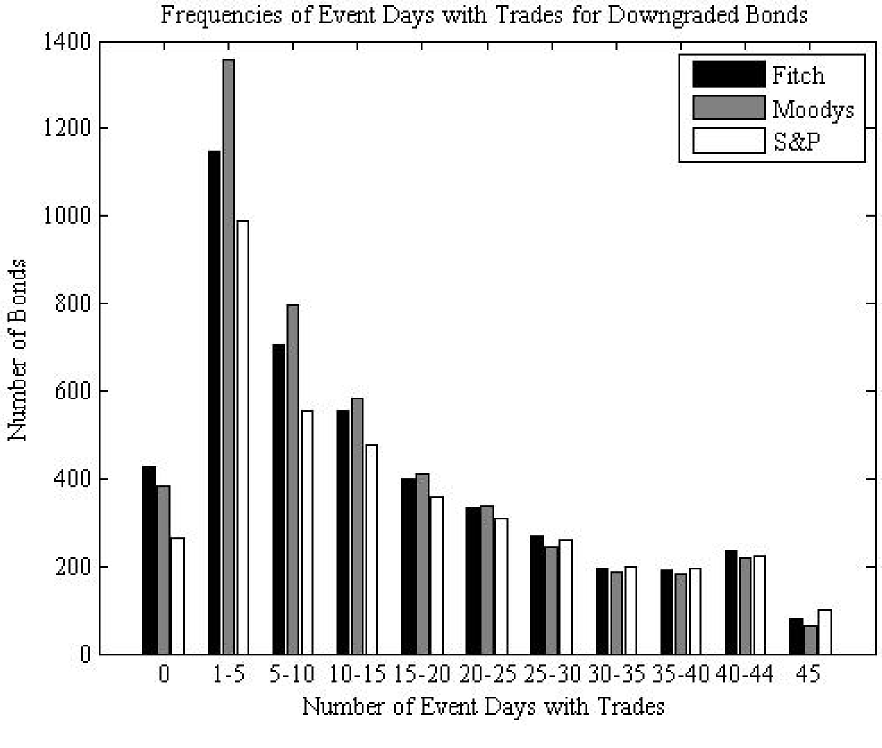

Figure 1 Frequencies of Event Days with Trades for Downgraded Bonds
The distribution of trading frequency in the event window for bonds downgraded by Fitch, Moody's and S&P in the sample period of July 2002 to June 2008.

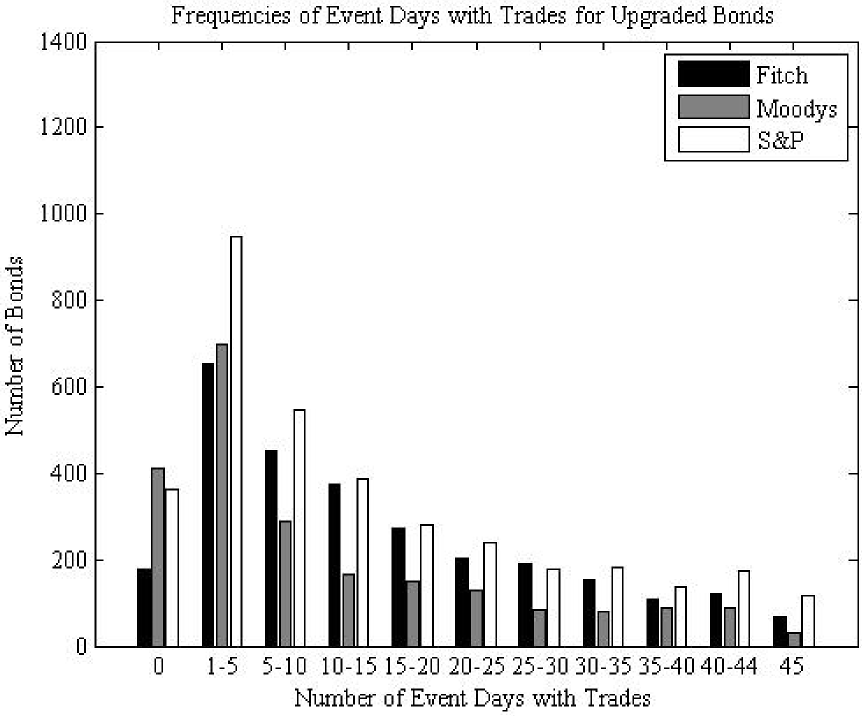

Figure 2 Frequencies of Event Days with Trades for Upgraded Bonds
The distribution of trading frequency in the event window for bonds upgraded by Fitch, Moody's and S&P in the sample period of July 2002 to June 2008.

Table 6 below summarises the distribution of rating changes, that is, the difference between original and revised bond ratings, during the sample period. The table aggregates over the credit rating actions across the three rating agencies, and therefore represents the total number of events across the three agencies. It is clear that for the majority of bonds in the sample a credit rating event consists of a change in the rating of only one grade; 61% of downgrades and 89% of upgrades amount to a change of a single rating category. Further, the number of downgrades is nearly 2.5 times greater than the number of upgrades. Although not detailed separately in Table 6, the number of credit rating events where the boundary between investment and speculative grade is crossed is 4,089 for bonds downgraded into speculative grade and 380 for bonds upgraded to investment grade. At this boundary the number of downgrades is nearly 11 times greater than the number of upgrades, confirming the directional trend of rating changes for the full sample.

Table 6 The distribution of Rating Changes
The distribution of rating changes between the original and revised ratings during the sample period of 1,577 trading days.

Number of Ratings Categories Changed	Downgrades	Upgrades	Total
1	12,385	7,380	19,765
2	4,630	694	5,324
3	2,308	102	2,410
4	638	21	659
5	171	29	200
6	30	13	43
7	27	6	33
8	2	8	10
9	0	7	7
10	0	3	3
11	0	3	3
12	9	0	9
Total	20,200	8,266	28,466

The asymmetry between the number of bonds downgraded compared to the number of bonds upgraded is consistent with earlier research, for example Hand et al. (1992) document a nearly three fold difference in the number of downgrades versus upgrades. Steiner and Heinke (2001), examining the impact of credit rating changes on Eurobonds, report close to twice as many downgrades as upgrades. This difference can be a consequence of the time period chosen, for example, the sample period of this study runs from July 2002 until June 2008, after the financial crisis had already started to take its toll on companies' operating and funding capabilities. Conversely, the disparity may stem from a general trend of deteriorating credit quality in the American financial and corporate sector. This hypothesis was examined for an eighteen year period from 1978 to 1995 by Blume et al. (1998), who argue that rather than exhibiting a decline in absolute credit quality, lower credit ratings are an evidence of more stringent rating standards being in place.

Table 7 below provides details regarding the distribution of bond issuance across the sample of 9,036 bonds. The bonds were issued by 930 companies; however, there is a high concentration in bonds issued by a relatively small number of firms. Only five firms have 250 or more bonds in the sample, and approximately 44% of the firms in the sample only have one bond outstanding. Further, the distribution of bond issuance is skewed to the right; the median issuer has only two bonds in the sample, whilst the average number of bonds per issuer is close to ten. The bonds in the sample have an average time to maturity of 8.2 years.[11] Further, the average coupon in the sample is 5.8%.

Table 7 Bond Issuance across Firms

Statistics describing the distribution of bond issuance across the firms in the sample.

Number of Bonds per Firm	
Max	1,005
Mean	9.7
Median	2
[500,Max]	4
[250,500)	1
[100,250)	11
[50,100)	7
[25,50)	15
[10,25)	62
[5,10)	120
(1,5)	299
1	411
Total number of firms	930

Table 8 below provides more details on the industry and issuer composition of the US corporate bond market. The industry classification is based on the North American Industry Classification System (NAICS), reported in the FISD database. In this paper, I have restricted neither the type of issuers nor the number of bonds per issuer included in the

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[11] The time to maturity was measured in March 2009.

event study. The market is dominated by debt issued by financial institutions and the financial services arms of big corporations, such as that of General Motors (GMAC). Collectively, the biggest ten issuers of corporate bonds, measured by the number of bonds these firms have in the sample of 9,036 bonds, make up 46% of the market. Similarly, the industry sectors of Finance and Insurance and Manufacturing, represent nearly 80% of the total number of bonds trading during the sample period.

Table 8 Top Ten Bond Issuers and Industries

The left panel of this table lists the top ten bond issuers as ranked by the number of bonds in the sample. The right hand side panel details the top ten industry sectors as defined by NAICS.

Rank	Company Name	Number of Bonds	Industry Sector	Number of Bonds
1	General Motors	1,005	Finance and Insurance	6,108
2	Ford	572	Manufacturing	1,084
3	Bank of America	519	Information	517
4	Sallie Mae	518	Utilities	432
5	John Hancock Financial	487	Wholesale & Retail Trade	238
6	Daimler Chrysler	234	Transportation and Warehousing	137
7	CIT Group	231	Mining, Quarrying, and Oil and Gas Extraction	119
8	Bear Stearns	226	Real Estate and Rental and Leasing	112
9	Lehman Brothers	206	Construction	86
10	AIG	196	Accommodation and Food Services	51

5 Empirical Methods

5.1 Measuring Abnormal Bond Performance

Following the majority of papers in the bond market event study literature, I use the mean adjusted return model to measure expected returns, see Bessembinder et al. (2009). First, I compute the daily holding period return for bond i. The bond price reported in TRACE is the traded clean price, that is, the price which excludes accrued interest; hence the corporate bond returns used in this study are likely to underestimate the total return for bonds in the sample.[12] The bond return is defined as:

$$BR_{it} = ln\left(\frac{P_{it}}{P_{it-1}}\right) \tag{8}$$

BR_{it} is the return for bond *i* in period *t*, calculated using the closing price for day *t-1*, P_{it-1}, and the closing price for day *t*, P_{it}.

Handjinicolaou and Kalay (1984) adapt the mean adjusted return model for bond returns by controlling for variations in interest rates. The implicit assumption in this model is that corporate bonds earn a constant premium relative to the Treasury security. As discussed by Bessembinder et al. (2009), this assumption may not be an accurate description of the behaviour the credit spread over treasuries, however, it may be a reasonable approximation over short time periods. The impact of the changes in the term structure of interest rates is accounted for by calculating the premium bond return, PBR_{it} for bond *i* in period *t*, which is defined as the bond's daily holding period return less the return on a Treasury security, TR_t:

$$PBR_{it} = BR_{it} - TR_t \tag{9}$$

Following Hand et al. (1992), a single Treasury security is selected. As discussed by Hand et al. (1992), the use of a single Treasury security as a benchmark for all maturities of corporate bonds takes into account the variations in the term structure of interest rates, but

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[12] Accrued interest is the portion of the next coupon payment the buyer of the bond must compensate the seller for, calculated over the period between the last coupon payment and the settlement date, see Fabozzi (2002).

it does not control for changes in bond returns due to default or term premiums. However, Hand et al. (1992) estimate the impact of this omission to be insignificant for short estimation periods.

The Treasury price information for this study is obtained from the Federal Reserve Economic Data (FRED) database at the Federal Reserve Bank of St. Louis. I use the ten year constant maturity series to overcome the issue of selecting over on- and off-the-run ten year Treasury bonds, as the FRED constant maturity Treasury series are based on the closing bid-side yields on actively traded Treasury securities.[13] The return on the Treasury calculated is using equation (8).

The abnormal and expected returns can now be computed according to the specification of the mean adjusted returns model detailed in Section 3 using the premium bond return as the return measure for bond performance. The expected return, EBR_i, for bond i (in the general notation of section 3 this was labelled $\hat{\hat{R}}_i$) is calculated using bond returns in the estimation window, letting $\mathcal{M}_i$ be the set of days in the estimation window containing a total of $\mathrm{M_i}$ observations.

$$EBR_i = \frac{1}{\mathrm{M_i}} \sum_{t \in M_i} PBR_{it} \tag{10}$$

After the expected return is calculated, the abnormal bond return, ABR_{it}, can be calculated for each bond for every day in the 45 day event window:

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[13] See the Federal Reserve Statistical Release H.15 from the St. Louis Federal Reserve for details on constant maturity treasury data.

$$ABR_{it} = PBR_{it} - EBR_i \tag{11}$$

As discussed in section 3, the performance measure used to test for the existence of abnormal bond returns is the cross-sectional average abnormal return. AR_t in equation (12) below represents the estimated cross-sectional average abnormal return for each day t in the 45 day event window. The number of bonds on each event day, N_t, can vary, as all bonds may not trade every day in the event window:

$$AR_t = \frac{1}{N_t}\sum_{i=1}^{N_t} ABR_{it} \tag{12}$$

5.2 Variance Estimation

In the literature, abnormal returns are generally assumed to be identically and independently normal, see Kothari and Warner (2006) and Campbell et al. (1997). The independence assumption imposes zero covariance terms between individual security returns in the cross-section. Further, if security prices, P_t, are modelled as having a martingale structure:

$$E[P_{t+1} \mid P_t, P_{t-1}, \dots] = P_t \tag{13}$$

then the time series of individual abnormal returns are assumed to have no autocorrelation.

However, the sample composition detailed in Section 4.3 shows that bond issuance is highly concentrated around a few companies, which implies that the rating events will be highly clustered. When events are clustered in calendar time, the independence assumption is violated. Event clustering is an issue that needs further consideration in this paper; as I am examining ratings events at the bond issue level, it is highly likely that bonds of the same issuer have rating changes whose timing overlaps perfectly. Hence, the covariance terms between security returns can not be assumed to be zero. If the variance of the bond returns were estimated according to equation (5) in Section 3, the impact of the cross-correlation would be ignored, and the estimated variance would be biased, likely downward, resulting in the misspecification of test statistics used to test for abnormal returns.

In order to account for the cross-sectional dependence between the bond issues in the sample, the variance of bond returns is estimated using the cross-sectional average abnormal return in equation (12). A further complication is the potential non-trading exhibited by bonds in the sample - any given bond may not trade throughout the duration of the sample. Hence, I adopt an unbalanced panel approach to estimate the variance of bond returns. [14] The cross-sectional dependence in the return series of bond issues is captured since the variability of the average abnormal return through time incorporates any cross-dependence that exists between the individual bond returns. This can be illustrated by computing the variance of the cross-sectional average abnormal return in equation (12):

$$Var(AR_t) = \frac{1}{{N_t}^2}\sum_{i=1}^{N_t} Var(ABR_{it}) + \frac{2}{{N_t}^2}\sum_{j=1}^{N_t}\sum_{k=j+1}^{N_t} cov(ABR_{jt}, ABR_{kt}) \tag{14}$$

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[14] Brown and Warner (1980) use the name "Crude Dependence Adjustment" to describe this method of variance estimation.

where the covariance term in equation (14) is nonzero, due to contemporaneous cross-correlation between individual abnormal bond returns. Further, I define the grand mean $\overline{AR}$, as the average abnormal return over both time and the number of securities:

$$\overline{AR} = \frac{1}{T}\sum_{t=1}^{T} AR_t = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t} ABR_{it} \tag{15}$$

Hence the estimate for the variance of the cross-sectional average, $\widehat{\sigma^2}$, is given by

$$\widehat{\sigma^2} = \frac{1}{T}\sum_{t=1}^{T}(AR_t - \overline{AR})^2 \tag{16}$$

5.3 Test Statistics

I examine the significance of the abnormal bond returns by using a t-test based on the cross-correlation robust variance estimator in equation (16) above. Under the null hypothesis that the cross-sectional average abnormal return is zero for each day, *t*, in the event window, the t-statistic is given by:

$$t - stat \equiv \frac{AR_t}{\hat{\sigma}} \sim N(0,1) \tag{17}$$

I also examine the statistical significance of the abnormal bond returns using the Wilcoxon signed rank test, a non-parametric test statistic widely used in the event study literature, as exemplified by Brown and Warner (1980), Maxwell and Stephens (2003), Steiner and Heinke (2001) and Bessembinder et al. (2009). The Wilcoxon signed rank test assumes a symmetric distribution around the median and a marked weakness of the Wilcoxon signed rank test is that it is not well specified if the distribution is skewed.

The test is used for paired observations; in this event study, the pair is the observed premium bond return, PBR_{it}, and the expected return, EBR_i, used in the calculation of the abnormal bond return. To implement the Wilcoxon signed rank test in practice, the difference between the premium bond return and the expected bond return is computed; this is simply the abnormal return given in equation (11). The absolute value of these differences is then calculated

$$D_{it} = |ABR_{it}| \tag{18}$$

and ranked across bonds according to the value of each difference, the smallest difference on day t is given rank $RNK_{it} = 1$ and the largest rank $RNK_{it} = N_t$. The signs of the original differences, that is, the abnormal returns, are returned to their corresponding ranks, yielding the Wilcoxon signed ranks. Finally, the sum over each signed rank is calculated:

$$W_t^+ = \sum_{i=1}^{N_t} RNK_{it} \cdot \mathbf{1}\{ABR_{it} > 0\} \tag{19}$$

$$W_t^- = \sum_{i=1}^{N_t} RNK_{it} \cdot \mathbf{1}\{ABR_{it} < 0\} \tag{20}$$

where $\mathbf{1}\{A\} = 1$ if A is true, and zero otherwise. The specific null hypothesis tested is whether the differences, that is, the average abnormal returns, have median zero, against the alternative of a nonzero median, under the maintained hypothesis that abnormal returns have a continuous, symmetric distribution.

$$H_0: \quad Med(ABR_{it}) = 0$$

$$vs. \qquad H_a: \quad Med(ABR_{it}) \neq 0$$

The p-value is computed using the normal distribution, as the sample size for all event types and agencies is large enough to warrant the approximation. For a two tailed test, the smaller of W_t^+ and W_t^- is used as the test statistic:

$$W_t = min(W_t^+, W_t^-) \tag{21}$$

$$Z = \frac{W_t - E(W_t)}{\sqrt{V(W_t)}} \tag{22}$$

The expectation and variance of the test statistic[15] under the null hypothesis are known in closed form for this test and are given by $E(W_t) = \frac{n(n+1)}{4}$ and $V(W_t) = \frac{n(n+1)(2n+1)}{24}$.

6. Results

In this section I present and discuss the results of this study. The results are reported separately for the four categories of rating events examined: Section 6.1 examines the full sample results, which consists of credit rating changes for bonds from all rating classes. Section 6.2 discusses the results for the impact of credit rating changes on bonds with both pre- and post-event ratings within investment grade. In Section 6.3 I isolate rating changes where the boundary between investment grade and speculative grade is crossed. Section 6.4 studies bonds which have speculative grade ratings. To conclude the discussion of results, Section 6.5 reports the results for the Wilcoxon signed rank test and discusses its weaknesses in an event study context.

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[15] See Lehmann (1975) for details.

In Sections 6.1 to 6.4, the results are detailed over three tables, one for each credit rating agency, and 4 figures with panels for each agency and event type. The tables are divided into two panels, with the left hand side detailing the results for downgrades, and the panel on the right reporting results for upgraded bonds. The first row details the number of events, that is, the number of downgrades and upgrades for each agency. The first column of each panel reports the event day, the second the average abnormal return, AR, the third the cumulative abnormal return, CAR, and the last column reports the t-statistic robust to cross-correlation. It should be noted that the tables only give the results for the 21 days nearest to the event day 0. Figures 3 to 6 detail the evolution of the mean abnormal return for the full event window of 45 days for each event type and credit agency.

6.1 Full Sample Results

The full sample results are consistent with market efficiency, as no single-day average abnormal return in the event window is statistically significant. Credit rating changes across all credit grades for the US corporate bond market carry no significant informational content. All the information incorporated in the change of a credit rating, such as assessments of credit risk, firm profitability and prospects have already been compounded into bond prices.

Tables 9 to 11 below detail the results for the full sample of bonds for each credit rating agency. The mean abnormal return for days around the event window is not statistically significant (at the 5% level) for the bonds rated by Fitch, Moody's or S&P. Despite the lack of significance, the results for bonds downgraded by Fitch and S&P register the largest (in absolute value) negative mean abnormal returns on days 0 and +1 for Fitch and on days -1, 0, +1 for S&P, indicating some response in bond prices around downgrades. The strongest reaction, that is, the smallest negative single-day mean abnormal return, -0.51% (t-statistic of -1.73) is observed on the event day for bonds downgraded by S&P. The directional trend in the average abnormal return for downgrades is negative; 61-76% of the average abnormal returns are negative for the three rating agencies.

Tables 9-11

Represent the full sample results for each credit rating agency, divided into two panels according to the event type. The first row gives the number of events, N, for both downgrades and upgrades. The first column is the event day, the second the average abnormal return (AR), the third the cumulative abnormal return, (CAR) and the last column gives the t-statistic according to equation (17). Event day zero is highlighted in bold.

Table 9 Full sample results for bonds rated by Fitch

	Downgrades, N = 6,926			**Upgrades, N = 2,750**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	-0.2779	-0.4090	-1.0473	0.1132	0.5110	0.4266
-9	0.2382	-0.1708	0.8976	0.1381	0.6491	0.5205
-8	-0.0437	-0.2145	-0.1648	-0.0360	0.6131	-0.1358
-7	0.0246	-0.1899	0.0928	0.0221	0.6352	0.0832
-6	0.0438	-0.1461	0.1651	-0.0581	0.5771	-0.2190
-5	0.0081	-0.1380	0.0304	0.0550	0.6321	0.2073
-4	-0.0396	-0.1777	-0.1494	0.0141	0.6462	0.0532
-3	-0.1641	-0.3418	-0.6183	0.0048	0.6510	0.0182
-2	-0.1375	-0.4793	-0.5180	0.0507	0.7018	0.1912
-1	-0.1886	-0.6679	-0.7108	0.0144	0.7162	0.0543
0	**-0.4675**	**-1.1354**	**-1.7614**	**0.0277**	**0.7439**	**0.1042**
1	-0.3507	-1.4861	-1.3214	-0.0208	0.7231	-0.0784
2	-0.1187	-1.6048	-0.4471	0.0370	0.7600	0.1393
3	-0.2162	-1.8210	-0.8147	0.1195	0.8795	0.4503
4	-0.1932	-2.0142	-0.7281	0.0922	0.9718	0.3475
5	-0.0750	-2.0893	-0.2827	0.0497	1.0214	0.1871
6	0.0951	-1.9942	0.3582	0.0370	1.0585	0.1395
7	-0.1063	-2.1004	-0.4004	-0.0263	1.0322	-0.0991
8	-0.1479	-2.2483	-0.5572	0.0006	1.0328	0.0023
9	-0.1462	-2.3945	-0.5508	0.1108	1.1436	0.4175
10	-0.0704	-2.4649	-0.2651	0.0424	1.1859	0.1597

Table 10 Full sample results for bonds rated by Moody's

	Downgrades, N = 7,408			**Upgrades, N = 2,016**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	-0.0828	0.5308	-0.2978	0.0264	0.1328	0.0948
-9	-0.0500	0.4808	-0.1798	0.0134	0.1462	0.0483
-8	-0.1040	0.3769	-0.3742	0.0218	0.1680	0.0783
-7	0.0751	0.4519	0.2702	0.0510	0.2190	0.1836
-6	0.0089	0.4608	0.0320	-0.0113	0.2077	-0.0406
-5	-0.0034	0.4574	-0.0122	-0.0269	0.1808	-0.0968
-4	-0.0153	0.4421	-0.0552	0.0143	0.1951	0.0515
-3	0.0179	0.4600	0.0643	0.0177	0.2128	0.0636
-2	-0.0088	0.4511	-0.0318	0.0140	0.2268	0.0504
-1	0.0247	0.4759	0.0890	-0.0155	0.2113	-0.0557
0	**-0.2755**	**0.2003**	**-0.9916**	**0.0191**	**0.2304**	**0.0688**
1	-0.0828	0.1175	-0.2981	0.0122	0.2426	0.0437
2	-0.0372	0.0803	-0.1339	0.0849	0.3275	0.3055
3	-0.0405	0.0397	-0.1459	0.0345	0.3620	0.1241
4	-0.1380	-0.0982	-0.4964	0.0162	0.3782	0.0584
5	-0.1039	-0.2021	-0.3738	0.0082	0.3864	0.0296
6	0.0013	-0.2008	0.0047	0.0274	0.4138	0.0985
7	0.1338	-0.0669	0.4816	0.0000	0.4138	0.0000
8	-0.1341	-0.2010	-0.4826	0.0260	0.4398	0.0934
9	-0.0656	-0.2666	-0.2360	0.0070	0.4468	0.0253
10	-0.0968	-0.3634	-0.3485	0.0489	0.4957	0.1760

Table 11 Full sample results for bonds rated by S&P

	Downgrades, N = 5,866			**Upgrades, N = 3,500**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	0.3076	0.1403	1.0358	0.0230	0.1836	0.0775
-9	0.0455	0.1858	0.1532	0.0299	0.2135	0.1008
-8	-0.0002	0.1856	-0.0007	-0.0124	0.2011	-0.0416
-7	0.0064	0.1920	0.0216	0.0835	0.2846	0.2812
-6	-0.0174	0.1746	-0.0586	0.1004	0.3850	0.3380
-5	0.0029	0.1776	0.0099	-0.0528	0.3323	-0.1777
-4	-0.0564	0.1212	-0.1899	0.0618	0.3941	0.2082
-3	0.0223	0.1434	0.0750	-0.0127	0.3813	-0.0429
-2	-0.0752	0.0682	-0.2532	-0.0124	0.3690	-0.0417
-1	-0.1284	-0.0602	-0.4324	0.0518	0.4208	0.1745
0	**-0.5147**	**-0.5749**	**-1.7334**	**-0.0279**	**0.3928**	**-0.0940**
1	-0.3528	-0.9277	-1.1880	0.0122	0.4050	0.0410
2	-0.0517	-0.9794	-0.1742	0.0545	0.4595	0.1834
3	-0.1231	-1.1025	-0.4145	0.0495	0.5090	0.1668
4	-0.0252	-1.1278	-0.0850	0.0141	0.5231	0.0476
5	0.0395	-1.0883	0.1331	0.0512	0.5743	0.1724
6	-0.0079	-1.0962	-0.0266	0.0712	0.6455	0.2397
7	-0.0262	-1.1224	-0.0883	0.0432	0.6887	0.1455
8	0.0482	-1.0742	0.1624	0.0044	0.6931	0.0148
9	0.0325	-1.0417	0.1094	0.1179	0.8110	0.3970
10	-0.0096	-1.0512	-0.0322	0.0090	0.8200	0.0303

As the exact timing of the rating change announcement within a trading day is not known, this information may arrive before, during or after trading hours, it is appropriate to examine the joint significance of average abnormal returns on the event day and day +1, in order to capture the possibility that the rating change was released after the close of trading. [16] The cumulative average abnormal returns for days 0 and +1 for bonds downgraded by Fitch and S&P are statistically significant at -0.82% and -0.87% (t-statistics of -2.18 and -2.07) respectively. This provides some evidence that bond downgrades offer pricing-relevant information to the bond markets.

Contrasting the results for downgrades, the mean abnormal return for credit rating upgrades, as can be noted by observing Figure 3 below, is particularly stable and close to zero through the length of the event window. This indicates informational efficiency of the bond market with respect to rating upgrades. However, 76-81% of the average abnormal returns for upgraded bonds are positive across the three rating agencies.

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[16] According to S&P, their analysts release credit ratings changes as soon as they have factual evidence that stating that the issuer's or issue's creditworthiness has or is on its way to changing. Further, the releases of ratings are not timed according to any schedule.

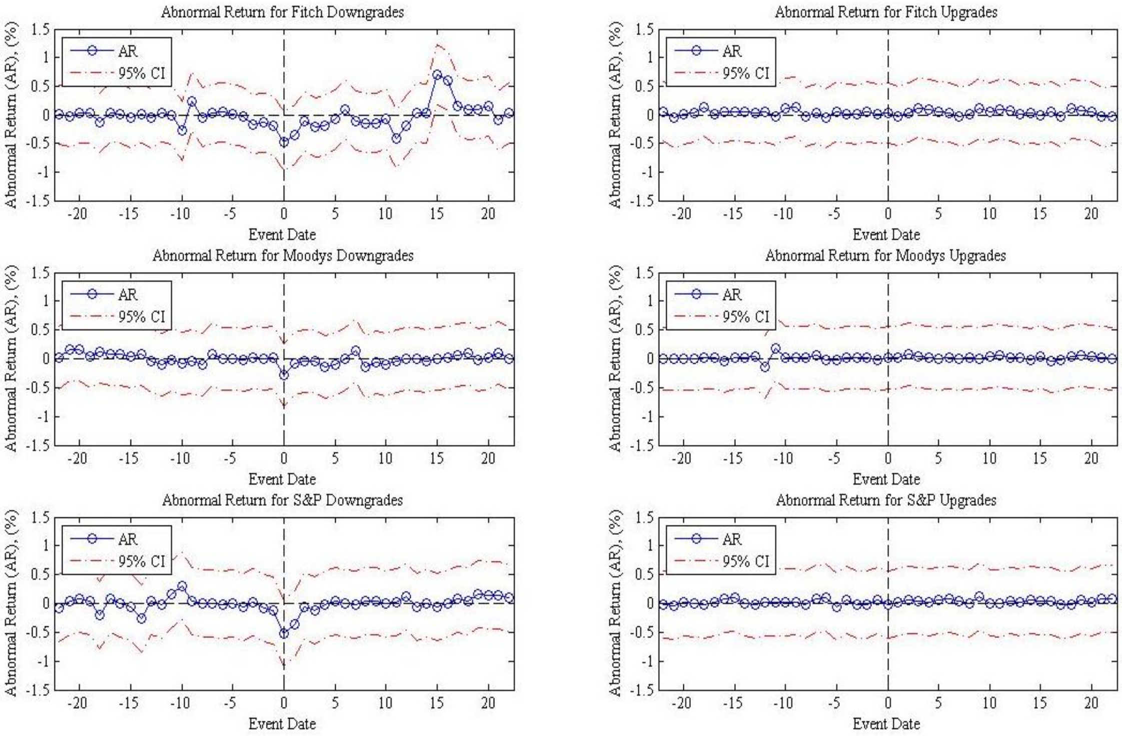

Figure 3 Average Abnormal Returns for Rating Changes for the Full Sample
The evolution of average abnormal returns, AR, for the full sample of rating changes in the event window of 45 days. The left hand side panel contains the figures for downgraded bonds; the first figure is for Fitch, the second for Moody's and the third for S&P. The right hand side panel presents the results for upgraded bonds in the same order for rating agencies, Fitch, Moody's and S&P. The 95% confidence intervals are computed using the variance estimator robust for cross-correlation, given in equation (16), and a 5% significance level.

The subdued response of corporate bond returns to credit rating changes may be an indication that the rating change is anticipated by market participants. Firstly, as discussed in section 1.2, Ederington and Yawitz (1987) show that two thirds of ratings can be predicted from publicly available data. More recently, Hull et al. (2004) investigate the relationship between credit default swaps (CDS) and credit rating changes over a five year period from 1998 to 2002. (A CDS is a contract that provides the buyer of the CDS insurance against the default of a company or a particular financial obligation.) The authors examine to what extent CDS spreads can predict the probability of a rating event. They find that for 43% of downgrades, CDS spreads provided useful information in estimating the probability of the downgrade. For upgrades, no such relationship was found. This recent study of predictability of rating changes from public information lends support for market efficiency in the full sample results. Secondly, due to data availability restrictions in FISD, for this paper, it was not possible to control for credit rating changes that had been placed on the credit watch list to signal a potential change in rating. Thus, the sample may contain a fraction of ratings that were at least partially anticipated by the market; therefore the actual rating change generates a milder reaction in security prices.

6.2 Credit Rating Changes within Investment Grade

Next I analyse just those bonds that were upgraded or downgraded within investment grade. The bonds downgraded within the investment grade category produce the most significant results in this study. For bonds rated by Fitch, both the event day and day +1 are statistically significant, with mean abnormal returns of -0.87% and -0.59% (t-statistics of -3.29 and -2.23) respectively. For bonds downgraded by S&P only the event day average abnormal return is significant at -0.61% (t-statistic of -2.0). Returns for bonds downgraded by Moody's are negative, but not significant. Furthermore, the joint significance test of the cumulative average residual for bonds rated by Moody's over the event day and day +1 is not significant at -0.74% (t-statistic of -1.88). The downgraded bonds for all three agencies experience the most negative abnormal returns around the event date.

Tables 12-14

Represent the results for rating changes within investment grade each credit rating agency, divided into two panels according to the event type. The first row gives the number of events, N, for both downgrades and upgrades. The first column is the event day, the second the average abnormal return (AR), the third the cumulative abnormal return (CAR) and the last column gives the t-statistic according to equation (17). Event day zero is highlighted in bold.

Table 12 Investment grade results for bonds rated by Fitch

	Downgrades, N = 3,329			**Upgrades, N = 1,593**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	-0.5496	-0.0168	-2.0708	0.0081	0.2045	0.0307
-9	0.5553	0.5385	2.0922	0.0418	0.2463	0.1575
-8	-0.0360	0.5025	-0.1356	-0.0117	0.2346	-0.0440
-7	0.0023	0.5048	0.0086	-0.0269	0.2076	-0.1015
-6	0.0259	0.5307	0.0976	-0.0145	0.1931	-0.0546
-5	0.0333	0.5640	0.1256	0.0653	0.2585	0.2461
-4	-0.0517	0.5123	-0.1948	0.0366	0.2951	0.1380
-3	-0.0239	0.4884	-0.0901	0.0322	0.3273	0.1215
-2	-0.1526	0.3358	-0.5749	0.0317	0.3590	0.1194
-1	-0.2606	0.0752	-0.9820	0.0029	0.3619	0.0108
0	**-0.8744**	**-0.7992**	**-3.2946**	**0.0273**	**0.3891**	**0.1028**
1	-0.5930	-1.3922	-2.2343	0.0111	0.4002	0.0418
2	-0.1427	-1.5349	-0.5376	0.0266	0.4269	0.1004
3	-0.2704	-1.8053	-1.0188	0.0219	0.4488	0.0825
4	-0.2010	-2.0063	-0.7575	0.0485	0.4972	0.1826
5	0.1167	-1.8896	0.4397	0.0317	0.5289	0.1194
6	0.2960	-1.5936	1.1154	-0.0066	0.5223	-0.0248
7	0.1300	-1.4636	0.4899	-0.0381	0.4843	-0.1435
8	0.0162	-1.4473	0.0611	0.0292	0.5135	0.1101
9	-0.0215	-1.4689	-0.0812	0.0386	0.5521	0.1456
10	-0.0346	-1.5035	-0.1305	0.0065	0.5587	0.0247

Table 13 Investment grade results for bonds rated by Moody's

	Downgrades, N = 3,171			**Upgrades, N = 1,429**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	-0.1799	-0.6087	-0.6473	0.0110	0.0714	0.0397
-9	-0.0261	-0.6348	-0.0938	0.0191	0.0904	0.0686
-8	-0.0382	-0.6730	-0.1375	0.0402	0.1306	0.1447
-7	0.1167	-0.5563	0.4200	0.0446	0.1752	0.1605
-6	0.0409	-0.5154	0.1470	-0.0025	0.1727	-0.0090
-5	-0.0662	-0.5817	-0.2384	-0.0069	0.1659	-0.0247
-4	-0.0453	-0.6270	-0.1632	0.0208	0.1867	0.0750
-3	-0.1244	-0.7514	-0.4478	0.0388	0.2255	0.1395
-2	-0.1176	-0.8691	-0.4233	0.0344	0.2598	0.1237
-1	-0.1297	-0.9988	-0.4667	-0.0130	0.2468	-0.0468
0	**-0.5128**	**-1.5116**	**-1.8453**	**-0.0201**	**0.2267**	**-0.0725**
1	-0.2270	-1.7386	-0.8169	-0.0030	0.2237	-0.0109
2	-0.1051	-1.8436	-0.3781	0.0563	0.2800	0.2027
3	-0.0686	-1.9123	-0.2470	0.0139	0.2939	0.0502
4	-0.2024	-2.1147	-0.7284	0.0304	0.3244	0.1095
5	0.0343	-2.0804	0.1234	0.0158	0.3402	0.0568
6	0.0592	-2.0212	0.2129	-0.0037	0.3365	-0.0133
7	-0.0040	-2.0252	-0.0143	0.0062	0.3427	0.0224
8	-0.3213	-2.3465	-1.1561	0.0501	0.3928	0.1802
9	-0.0798	-2.4263	-0.2871	0.0120	0.4048	0.0432
10	0.0333	-2.3930	0.1197	0.0368	0.4416	0.1323

Table 14 Investment grade results for bonds rated by S&P

	Downgrades, N = 2,222			**Upgrades, N = 2186**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	0.0115	0.1579	0.0388	-0.0057	0.0515	-0.0191
-9	-0.0719	0.0860	-0.2422	0.0173	0.0688	0.0583
-8	0.0167	0.1027	0.0562	0.0228	0.0915	0.0766
-7	0.0034	0.1060	0.0113	-0.0006	0.0910	-0.0019
-6	-0.0994	0.0066	-0.3348	-0.0199	0.0711	-0.0669
-5	-0.0081	-0.0015	-0.0272	-0.0388	0.0323	-0.1305
-4	-0.1095	-0.1109	-0.3686	0.0411	0.0735	0.1384
-3	0.0751	-0.0359	0.2528	0.0485	0.1220	0.1634
-2	-0.1147	-0.1505	-0.3862	0.0170	0.1390	0.0572
-1	-0.2510	-0.4015	-0.8451	0.0323	0.1713	0.1089
0	**-0.6078**	**-1.0093**	**-2.0467**	**-0.0269**	**0.1444**	**-0.0905**
1	-0.2099	-1.2192	-0.7069	0.0148	0.1592	0.0497
2	-0.1610	-1.3802	-0.5420	0.0152	0.1744	0.0512
3	-0.0683	-1.4485	-0.2300	0.0531	0.2275	0.1789
4	-0.0664	-1.5149	-0.2237	0.0214	0.2489	0.0722
5	0.2521	-1.2628	0.8491	0.0405	0.2895	0.1365
6	0.1855	-1.0772	0.6247	0.0154	0.3049	0.0518
7	0.0822	-0.9950	0.2768	-0.0076	0.2973	-0.0255
8	0.0069	-0.9881	0.0232	-0.0583	0.2390	-0.1962
9	0.0684	-0.9197	0.2304	0.0818	0.3208	0.2756
10	0.0009	-0.9188	0.0031	0.0323	0.3531	0.1087

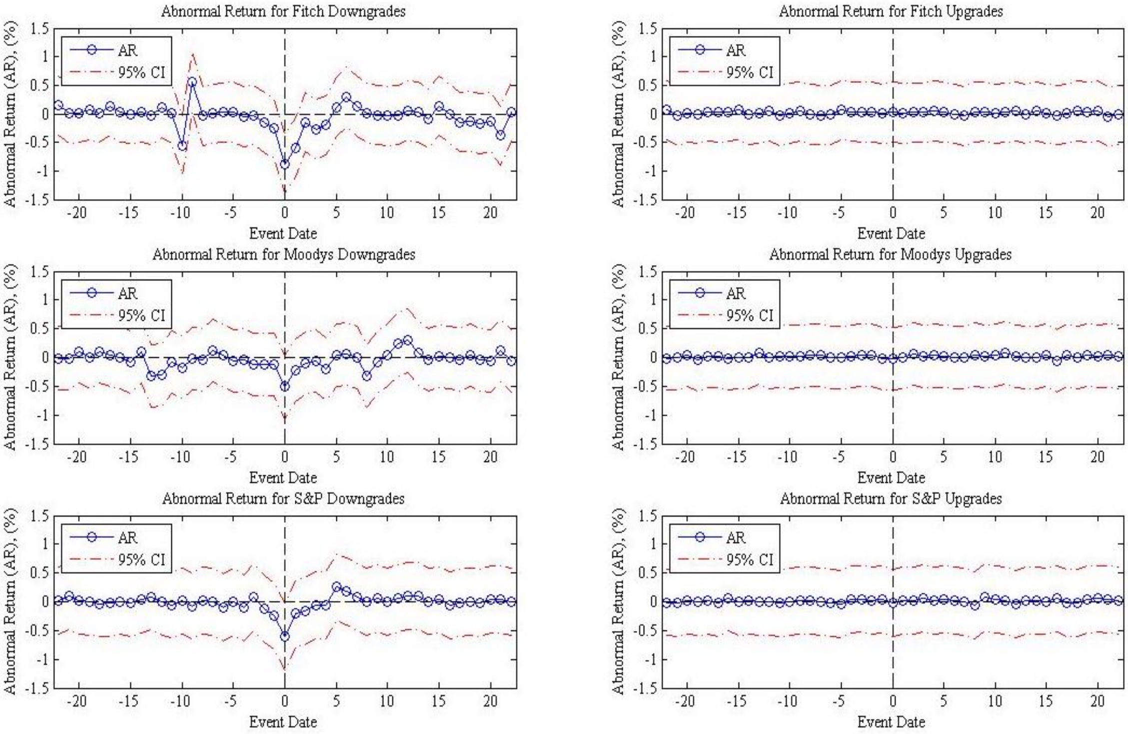

Figure 4 Average Abnormal Returns for Rating Changes within Investment Grade

The evolution of average abnormal returns, AR, for rating changes within investment grade in the event window of 45 days. The left hand side panel contains the figures for downgraded bonds; the first figure is for Fitch, the second for Moody's and the third for S&P. The right hand side panel presents the results for upgraded bonds for the same order of rating agencies, Fitch, Moody's and S&P. The 95% confidence intervals are computed using the variance estimator robust for cross-correlation given in equation (16), and a 5% significance level.

The results for the sample of upgraded bonds are in stark contrast to those for rating downgrades: as can be seen from Figure 4 the mean abnormal return for upgrades hovers consistently around zero, with no change to this performance even on or immediately around the credit event. The largest impact is for bonds rated by Fitch; on the day of the upgrade the mean abnormal return amounts to 0.027% (with a t-statistic of 0.1 this is far from significant). Further, the direction of the abnormal return on the event day is not conclusively positive, as both Moody's and S&P report slight negative abnormal returns for the event day. However, the proportion of event days with positive albeit small average abnormal returns ranges between 67% and 76% for the three rating agencies.

If the corporate bond market investors are perceived to be segmented into categories formed on the basis of their demand, that is, if there exist separate clienteles driven partly by regulatory restrictions on particular grades of credit ratings, then the results for bond rating changes that occur within investment grade may be supportive of the clientele effect hypothesis discussed in section 1.3. As regulations require some market participants to hold only investment grade securities; when bonds are downgraded, these investors may be forced to sell their investments. Hence, a strong price reaction especially when a bond crosses the boundary between investment and speculative grade boundary can be expected (this category of rating changes is discussed in more detail in section 6.3 below). Further, it can be argued that since a given investor knows he is restricted to holding investment grade securities only in his portfolio, a downgrade even within investment grade could drive a fund manager to sell, in order to avoid the risk of being a forced seller later, on potentially worse terms, when the bond is further downgraded into speculative grade.

This price pressure caused by institutional and regulatory frictions is closely related to the theoretical model of "predatory trading", developed by Brunnermeier and Pedersen (2005), where sophisticated traders prey on distressed investors who are publicly known to be in the position of forced liquidation with respect to their investments. Market participants, such as hedge funds and broker-dealers, are well aware of regulatory guidelines that govern the investments of many mutual funds, and are hence privy to the information that a rating downgrade may induce forced selling. According to this theory, if a distressed investor is forced to sell, instead of providing liquidity, other market participants drive prices further down by trading in the same direction. This causes prices to overshoot and liquidity to dry up, compared to "normal" market conditions. The presence of a regulated clientele for investment grade securities coupled with the possibility of "preying" by non-regulated market participants, could explain the significance of the results for investment grade downgrades.

6.3 Credit Rating Changes Crossing the Boundary

For the sample of bonds whose ratings cross the boundary between investment and speculative grades, only the results for bonds downgraded by S&P may support the clientele effect hypothesis. The mean abnormal returns for both the event day and day +1 are significantly negative at -0.85% and -1.58% (t-statistics -2.86 and -5.32) respectively. Further, day +1 is the largest negative event related mean abnormal return recorded in the sample. Interestingly, according to anecdotal evidence from the fund management industry, many US dollar denominated bond funds both in the United States and internationally are regulated precisely by S&P, lending incremental support to the idea of (forced) selling by regulated investors in the event of a downgrade to speculative grade. Although none of the mean abnormal returns for Fitch are small enough to be significant, 90% of those returns are negative in the 21 day event window, conveying a clear negative trend in the returns for bonds crossing into speculative grade.

Tables 15-17

Represent the results for rating changes that cross the boundary between investment and speculative grades for each credit rating agency, divided into two panels according to the event type. The first row gives the number of events, N, for both downgrades and upgrades. The first column is the event day, the second the average abnormal return (AR), the third the cumulative abnormal return (CAR) and the last column gives the t-statistic according to equation (17). Event day zero is highlighted in bold.

Table 15 Crossover results for bonds rated by Fitch

	Downgrades, N = 1633			**Upgrades, N = 119**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	-0.0321	-2.4138	-0.1209	0.0218	0.3370	0.0822
-9	-0.1569	-2.5707	-0.5911	0.0332	0.3702	0.1249
-8	-0.1117	-2.6824	-0.4209	-0.0139	0.3563	-0.0522
-7	0.1353	-2.5471	0.5097	0.0078	0.3641	0.0296
-6	0.1861	-2.3610	0.7013	-0.1432	0.2209	-0.5396
-5	-0.1144	-2.4754	-0.4312	-0.0053	0.2156	-0.0200
-4	-0.1256	-2.6010	-0.4731	0.0199	0.2355	0.0750
-3	-0.3866	-2.9876	-1.4568	-0.1230	0.1126	-0.4633
-2	-0.2042	-3.1918	-0.7694	0.1625	0.2751	0.6125
-1	0.0333	-3.1585	0.1254	0.0276	0.3027	0.1040
0	**-0.1074**	**-3.2659**	**-0.4045**	**0.0827**	**0.3855**	**0.3118**
1	-0.1560	-3.4219	-0.5879	-0.0078	0.3777	-0.0295
2	-0.1311	-3.5531	-0.4942	-0.0887	0.2889	-0.3343
3	-0.1044	-3.6575	-0.3934	-0.0481	0.2409	-0.1811
4	-0.0659	-3.7234	-0.2483	0.0673	0.3081	0.2535
5	-0.1298	-3.8531	-0.4889	0.2092	0.5173	0.7881
6	-0.1694	-4.0225	-0.6383	-0.1169	0.4004	-0.4405
7	-0.2423	-4.2648	-0.9128	0.0749	0.4753	0.2823
8	-0.2593	-4.5241	-0.9772	0.1321	0.6074	0.4977
9	-0.1493	-4.6734	-0.5626	-0.1500	0.4574	-0.5651
10	-0.0059	-4.6793	-0.0221	0.0837	0.5411	0.3153

Table 16 Crossover results for bonds rated by Moody's

	Downgrades, N = 1416			**Upgrades, N = 135**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	-0.0066	1.1595	-0.0236	0.0412	0.7457	0.1483
-9	-0.0931	1.0664	-0.3351	-0.1706	0.5751	-0.6140
-8	-0.2092	0.8571	-0.7529	0.1729	0.7480	0.6221
-7	0.0625	0.9196	0.2248	0.0757	0.8236	0.2723
-6	-0.0173	0.9023	-0.0623	0.0301	0.8538	0.1084
-5	0.0490	0.9513	0.1764	-0.1681	0.6857	-0.6048
-4	-0.0219	0.9294	-0.0789	-0.0089	0.6768	-0.0321
-3	0.1186	1.0480	0.4268	0.0307	0.7075	0.1106
-2	0.1231	1.1711	0.4428	0.0632	0.7707	0.2273
-1	0.1235	1.2945	0.4443	0.0115	0.7822	0.0413
0	**0.0526**	**1.3471**	**0.1893**	**0.2809**	**1.0631**	**1.0109**
1	-0.1308	1.2164	-0.4706	0.0238	1.0869	0.0858
2	0.0764	1.2927	0.2748	0.5029	1.5898	1.8098
3	-0.1295	1.1633	-0.4660	0.8319	2.4217	2.9937
4	-0.0941	1.0692	-0.3385	-0.1232	2.2985	-0.4435
5	-0.3855	0.6837	-1.3872	-0.1650	2.1335	-0.5936
6	-0.2381	0.4456	-0.8567	0.2007	2.3342	0.7222
7	0.0882	0.5339	0.3175	0.0237	2.3580	0.0854
8	0.0550	0.5889	0.1978	-0.0677	2.2903	-0.2435
9	-0.1292	0.4597	-0.4648	-0.0214	2.2689	-0.0770
10	0.0040	0.4637	0.0145	-0.0328	2.2362	-0.1180

Table 17 Crossover results for bonds rated by S&P

	Downgrades, N = 1040			**Upgrades, N = 126**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	1.4082	-3.0148	4.7421	-0.1043	-0.1536	-0.3512
-9	0.3245	-2.6903	1.0926	0.0383	-0.1153	0.1291
-8	0.0262	-2.6641	0.0881	-0.0910	-0.2063	-0.3065
-7	0.0183	-2.6458	0.0616	0.0704	-0.1358	0.2371
-6	0.0473	-2.5985	0.1594	0.0565	-0.0793	0.1904
-5	0.0865	-2.5120	0.2912	0.1058	0.0265	0.3563
-4	0.1266	-2.3854	0.4263	0.1407	0.1672	0.4739
-3	-0.1089	-2.4943	-0.3669	-0.0921	0.0751	-0.3102
-2	0.1138	-2.3806	0.3831	-0.0706	0.0045	-0.2377
-1	0.4756	-1.9050	1.6017	0.0698	0.0743	0.2351
0	**-0.8494**	**-2.7544**	**-2.8604**	**0.1796**	**0.2539**	**0.6047**
1	-1.5790	-4.3334	-5.3172	0.0201	0.2740	0.0679
2	0.0265	-4.3068	0.0894	-0.0199	0.2541	-0.0670
3	-0.3313	-4.6382	-1.1158	0.2204	0.4745	0.7422
4	-0.0740	-4.7122	-0.2492	-0.1080	0.3665	-0.3637
5	-0.1847	-4.8968	-0.6219	0.1165	0.4830	0.3923
6	-0.2760	-5.1729	-0.9295	-0.0636	0.4194	-0.2143
7	-0.0096	-5.1824	-0.0322	0.0445	0.4639	0.1499
8	0.1306	-5.0518	0.4399	-0.0640	0.4000	-0.2154
9	0.0348	-5.0169	0.1173	0.1522	0.5522	0.5126
10	0.5166	-4.5004	1.7395	-0.1273	0.4249	-0.4287

The mean abnormal returns for upgrades from speculative grade to investment grade on and surrounding day zero are not significant. However, regardless of the lack of significance, the event day for bonds upgraded by Moody's and S&P report the two largest positive average abnormal returns in the sample, +0.28 and +0.18 (t-statistics of 1.0 and 0.6) respectively. Perhaps partial anticipation of these events, as discussed in section 6.1 dampens these results. Further, whereas the clientele hypothesis for downgraded bonds is based on the notion that regulatory restrictions induce selling on bond downgrades, there is no equivalent pressure for bond upgrades: the improved performance of a company as signalled by an upgrade may not be incentive enough for a fiduciary to invest.

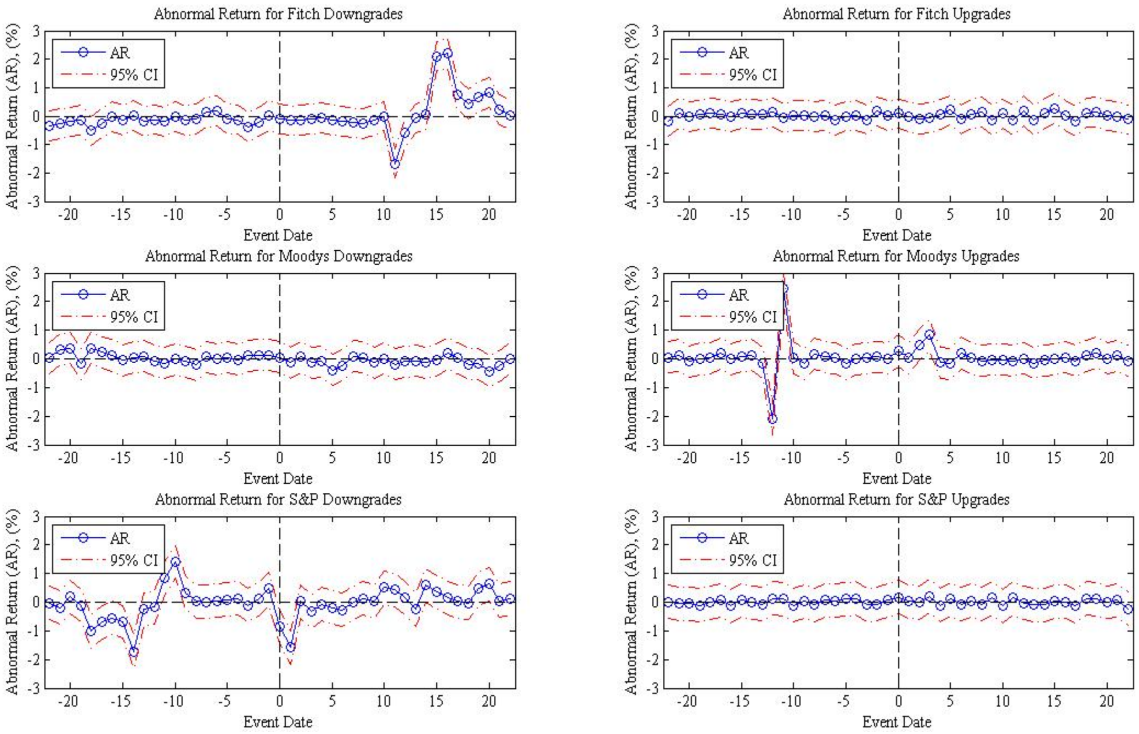

Figure 5 Average Abnormal Returns for Rating Changes Crossing the Boundary
The evolution of average abnormal returns, AR, for rating changes that cross the boundary between investment grade and speculative grade in the event window of 45 days. The left hand side panel contains the figures for downgraded bonds; the first figure is for Fitch, the second for Moody's and the third for S&P. The right hand side panel presents the results for upgraded bonds for the same order of rating agencies, Fitch, Moody's and S&P. The 95% confidence intervals are computed using the variance estimator robust for cross-correlation, given in equation (16), and a 5% significance level.

6.4 Credit Rating Changes within Speculative Grade

Hand et al. (1992) and Hite and Warga (1997) report that the magnitude of the negative average abnormal return increases for bonds downgraded within speculative grade. The results from this study provide contrary evidence, as no single day average abnormal return is statistically significant for bonds downgraded (or upgraded) by the three agencies. The joint significance test for days 0 and +1 for bonds downgraded by S&P yields a significant result at -0.86% (t-statistic -2.06). The reasons behind the conflicting evidence of speculative grade downgrades could be due to the difference in sample periods and databases used. The sample used in this study contains the peak of credit markets in 2007, which indicates low credit risks and perhaps stable performance for speculative grade bonds. The absence of a significant reaction may also be considered as support for the clientele effect hypothesis. Regulated investment funds are not likely to have invested in this credit grade, and for other market participants such as hedge funds, the level of the credit rating may not be a concern.

Tables 18-20

Represent the results for rating changes within speculative grade for each credit rating agency, divided into two panels according to the event type. The first row gives the number of events, N, for both downgrades and upgrades. The first column is the event day, the second the average abnormal return (AR), the third the cumulative abnormal return (CAR) and the last column gives the t-statistic according to equation (17). Event day zero is highlighted in bold.

Table 18 Speculative grade results for bonds rated by Fitch

	Downgrades, N = 3,355			**Upgrades, N = 1,130**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	-0.0110	-0.7456	-0.0415	0.2672	0.9519	1.0067
-9	-0.0526	-0.7981	-0.1981	0.2758	1.2277	1.0392
-8	-0.0360	-0.8341	-0.1357	-0.0662	1.1616	-0.2493
-7	0.0526	-0.7815	0.1983	0.0956	1.2572	0.3602
-6	0.0441	-0.7374	0.1661	-0.1201	1.1370	-0.4525
-5	-0.0055	-0.7429	-0.0208	0.0398	1.1768	0.1498
-4	-0.0261	-0.7690	-0.0982	-0.0234	1.1535	-0.0880
-3	-0.3258	-1.0948	-1.2276	-0.0222	1.1313	-0.0835
-2	-0.1390	-1.2338	-0.5236	0.0742	1.2055	0.2795
-1	-0.1172	-1.3509	-0.4415	0.0253	1.2308	0.0955
0	**-0.0709**	**-1.4218**	**-0.2670**	**0.0300**	**1.2608**	**0.1129**
1	-0.1448	-1.5666	-0.5457	-0.0639	1.1968	-0.2409
2	-0.1194	-1.6860	-0.4499	0.0462	1.2430	0.1741
3	-0.1710	-1.8570	-0.6442	0.2606	1.5037	0.9821
4	-0.1867	-2.0437	-0.7034	0.1616	1.6653	0.6089
5	-0.2623	-2.3059	-0.9882	0.0661	1.7313	0.2490
6	-0.1249	-2.4308	-0.4705	0.1071	1.8385	0.4037
7	-0.3416	-2.7724	-1.2873	-0.0112	1.8273	-0.0422
8	-0.2967	-3.0691	-1.1178	-0.0447	1.7826	-0.1684
9	-0.2585	-3.3276	-0.9739	0.2165	1.9991	0.8157
10	-0.1308	-3.4584	-0.4928	0.0928	2.0919	0.3498

Table 19 Speculative grade results for bonds rated by Moody's

	Downgrades, N = 3,072			**Upgrades, N = 560**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	0.0045	1.3874	0.0163	0.0711	0.2753	0.2557
-9	-0.0752	1.3122	-0.2706	0.0099	0.2851	0.0355
-8	-0.1201	1.1922	-0.4321	-0.0480	0.2372	-0.1726
-7	0.0462	1.2383	0.1662	0.0665	0.3037	0.2394
-6	-0.0205	1.2178	-0.0738	-0.0375	0.2662	-0.1350
-5	0.0400	1.2578	0.1438	-0.0564	0.2097	-0.2031
-4	0.0334	1.2912	0.1202	0.0110	0.2207	0.0396
-3	0.1407	1.4319	0.5062	-0.0606	0.1601	-0.2181
-2	0.0532	1.4851	0.1916	-0.0380	0.1222	-0.1366
-1	0.1546	1.6398	0.5565	-0.0274	0.0948	-0.0985
0	**-0.1627**	**1.4771**	**-0.5855**	**0.1132**	**0.2081**	**0.4075**
1	0.0763	1.5534	0.2746	0.0504	0.2585	0.1813
2	-0.0210	1.5324	-0.0756	0.1614	0.4199	0.5808
3	0.0249	1.5573	0.0896	0.0938	0.5136	0.3375
4	-0.0839	1.4734	-0.3019	-0.0135	0.5001	-0.0487
5	-0.1091	1.3643	-0.3926	-0.0062	0.4939	-0.0223
6	0.0282	1.3924	0.1013	0.1066	0.6005	0.3837
7	0.3125	1.7050	1.1247	-0.0149	0.5857	-0.0534
8	-0.0263	1.6786	-0.0947	-0.0170	0.5687	-0.0611
9	-0.0444	1.6342	-0.1598	-0.0074	0.5613	-0.0265
10	-0.2321	1.4022	-0.8351	0.0769	0.6382	0.2768

Table 20 Speculative grade results for bonds rated by S&P

	Downgrades, N = 3,564			**Upgrades, N = 1,286**		
Event Day	AR, %	CAR, %	t-stat	AR, %	CAR, %	t-stat
-10	0.5035	0.1188	1.6954	0.0751	0.4094	0.2530
-9	0.1172	0.2360	0.3948	0.0528	0.4621	0.1776
-8	0.0029	0.2389	0.0097	-0.0604	0.4017	-0.2035
-7	0.0017	0.2406	0.0057	0.2262	0.6279	0.7618
-6	0.0206	0.2613	0.0695	0.3063	0.9342	1.0313
-5	0.0134	0.2746	0.0450	-0.0793	0.8549	-0.2671
-4	-0.0278	0.2468	-0.0937	0.0985	0.9534	0.3318
-3	-0.0039	0.2429	-0.0131	-0.1095	0.8439	-0.3687
-2	-0.0495	0.1934	-0.1666	-0.0631	0.7808	-0.2126
-1	-0.0585	0.1349	-0.1971	0.0833	0.8641	0.2804
0	**-0.4482**	**-0.3133**	**-1.5093**	**-0.0342**	**0.8298**	**-0.1153**
1	-0.4165	-0.7298	-1.4024	0.0008	0.8306	0.0027
2	0.0245	-0.7053	0.0826	0.1255	0.9561	0.4225
3	-0.1488	-0.8541	-0.5012	0.0352	0.9913	0.1186
4	0.0162	-0.8379	0.0547	0.0045	0.9958	0.0153
5	-0.0839	-0.9217	-0.2824	0.0664	1.0622	0.2235
6	-0.1398	-1.0616	-0.4709	0.1643	1.2265	0.5532
7	-0.0889	-1.1505	-0.2994	0.1314	1.3579	0.4425
8	0.0811	-1.0693	0.2733	0.1133	1.4712	0.3816
9	0.0207	-1.0486	0.0697	0.1765	1.6477	0.5944
10	-0.0323	-1.0809	-0.1086	-0.0302	1.6175	-0.1018

In Figure 6 below, the average abnormal return for both downgrades and upgrades is very volatile throughout the event window, and whilst there are some scattered large negative and positive spikes in the return series, these do not coincide with days near event day. Speculative grade bonds are inherently a riskier investment than investment grade bonds and some degree of higher volatility is to be expected, however, the large return reversal observed are likely to be driven by macroeconomic or industry specific events.

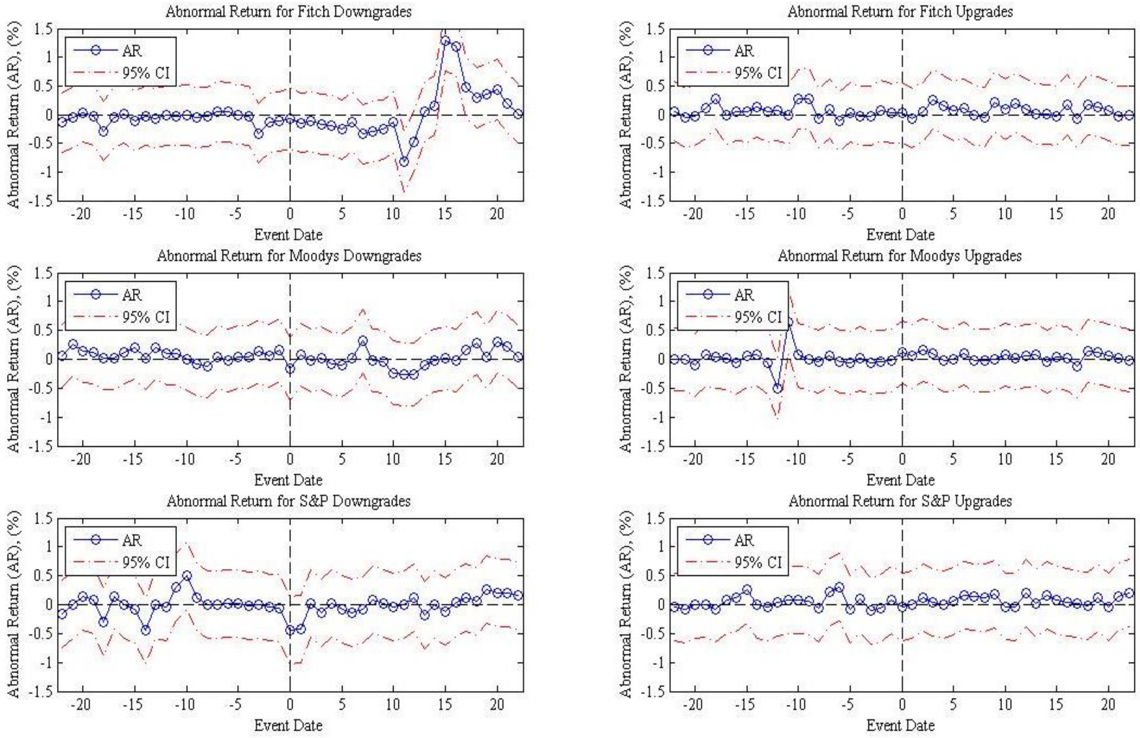

Figure 6 Average Abnormal Returns for Rating Changes within Speculative Grade
The evolution of average abnormal returns, AR, for rating changes within speculative grade in the event window of 45 days. The left hand side panel contains the figures for downgraded bonds; the first figure is for Fitch, the second for Moody's and the third for S&P. The right hand side panel presents the results for upgraded bonds for the same order of rating agencies, Fitch, Moody's and S&P. The 95% confidence intervals are computed using the variance estimator robust for cross-correlation, given in equation (16), and a 5% significance level.

The asymmetry in response of bond abnormal returns to downgrades and upgrades has been observable for all four categories of credit rating events examined in this paper. This result has also been reported in most previous studies of the impact of credit rating changes on security returns, such as Holthausen and Leftwich (1986), Hand et al. (1992), Hite and Warga (1997), Steiner et al. (2000).

Aside from the clientele effect hypothesis, where regulatory constraints cause selling and hence price pressure for downgrades, the asymmetry has also been explained by reputational concerns of rating agencies. Holthausen and Leftwich (1986) conjecture that rating agencies face an asymmetric loss function, where the reputational risk for an incorrect assessment of credit risk in a downgrade scenario is higher than that of an upgrade, as downgrades impose real costs to issuers in the form of increased funding costs. This may prompt the agencies to dedicate more resources into revealing negative information to the market.

6.5 Results from Wilcoxon Signed Rank Test

As discussed in section 5.3, the Wilcoxon signed rank test is a widely used non-parametric test for detecting abnormal returns. The results using the Wilcoxon signed rank test in this study are reported over tables 21-23 below.

As can be seen from the tables below the rejection frequency of the null hypothesis of a symmetric distribution of average abnormal returns is overwhelming; the p-values from the Wilcoxon signed rank test are very small or equal to zero. Across all three credit agencies, this test rejects the null hypothesis on all days in the event window and in all categories of rating changes, with the exception of rating changes that cross the boundary between investment and speculative grades. Further, the null is not rejected on some days in the event window for bonds upgraded by Moody's within speculative grade. These high rejection rates are clearly inconsistent with the results found using the t-test presented in equation (17).

The reason behind what seem like artificially high rejection rates is the violation of the maintained assumption of symmetry in distribution of the average abnormal returns underlying the Wilcoxon signed rank test. To support this explanation, Figures 7 and 8 below illustrate two examples of a non-parametric distribution fitted on the average abnormal return data of rating downgrades and upgrades.[17]

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[17] Figures 7 and 8 use the entire sample of upgrades and downgrades for Fitch. The distributional results for other rating categories and agencies used are comparable to those presented.

Tables 21-23

Represent the results from the Wilcoxon signed rank test for rating changes, separately for each rating agency, starting with Fitch (table 21), then Moody's (table 22) and lastly S&P (table 23). Each table is divided into two panels according to the event type. The first column is the event day, the second the reports the p-value from the Wilcoxon signed rank test for the full sample of rating changes, the third for rating changes within investment grade, the fourth for rating changes crossing from investment grade to speculative grade or vice versa and the last column reports the p-value for rating changes within speculative grade. The event day zero is highlighted in bold.

Table 21 Wilcoxon signed rank p-value for rating changes by Fitch for the four rating categories examined

	Downgrades for				**Upgrades for**			
Event Day	Full Sample	Investment Grade	Crossing	Speculative Grade	Full Sample	Investment Grade	Crossing	Speculative Grade
-10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1202	0.0000
-9	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.2900	0.0000
-8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6521	0.0002
-7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2235	0.0000
-6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0458	0.0404
-5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0958	0.0000
-4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0391	0.0000
-3	0.0000	0.0000	0.0844	0.0000	0.0000	0.0000	0.4658	0.0000
-2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0417	0.0000
-1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0058	0.0000
0	**0.0000**	**0.0001**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.1404**	**0.0000**
1	0.0000	0.0000	0.0006	0.0000	0.0000	0.0000	0.0510	0.0000
2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1729	0.0000
3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3370	0.0000
4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2433	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0037	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6665	0.0000
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0104	0.0001
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6606	0.0000
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0212	0.0000

Table 22 Wilcoxon signed rank p-value for rating changes by Moody's for the four rating categories examined

	Downgrades for				**Upgrades for**			
Event Day	Full Sample	Investment Grade	Crossing	Speculative Grade	Full Sample	Investment Grade	Crossing	Speculative Grade
-10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0785	0.0021
-9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6415	0.0019
-8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1861	0.0905
-7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0044	0.0002
-6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3821	0.0752
-5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4566	0.0004
-4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1638	0.0268
-3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8159	0.2141
-2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0511
-1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0037	0.0810
0	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0002**	**0.0000**
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3481	0.0146
2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.7118	0.0326
3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0379	0.1585
4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5204	0.0063
5	0.0000	0.0000	0.9059	0.0000	0.0000	0.0000	0.5457	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1939	0.0003
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0148	0.0294
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4045	0.0354
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5548	0.0055
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1694	0.0000

Table 23 Wilcoxon signed rank p-value for rating changes by S&P for the four rating categories examined

	Downgrades for				**Upgrades for**			
Event Day	Full Sample	Investment Grade	Crossing	Speculative Grade	Full Sample	Investment Grade	Crossing	Speculative Grade
-10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9137	0.0000
-9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2946	0.0000
-8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2175	0.0000
-7	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000	0.0194	0.0000
-6	0.0000	0.0000	0.0019	0.0000	0.0000	0.0000	0.0300	0.0000
-5	0.0000	0.0000	0.0041	0.0000	0.0000	0.0000	0.0078	0.0000
-4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0085	0.0000
-3	0.0000	0.0000	0.1273	0.0000	0.0000	0.0000	0.6656	0.0003
-2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4614	0.0000
-1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0167	0.0000
0	**0.0000**	**0.0000**	**0.0764**	**0.0000**	**0.0000**	**0.0000**	**0.0011**	**0.0000**
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0175	0.0000
2	0.0000	0.0000	0.0009	0.0000	0.0000	0.0000	0.0309	0.0000
3	0.0000	0.0000	0.1242	0.0000	0.0000	0.0000	0.0029	0.0000
4	0.0000	0.0000	0.0604	0.0000	0.0000	0.0000	0.8428	0.0000
5	0.0000	0.0000	0.7438	0.0000	0.0000	0.0000	0.0013	0.0000
6	0.0000	0.0000	0.7444	0.0000	0.0000	0.0000	0.6654	0.0000
7	0.0000	0.0000	0.0030	0.0000	0.0000	0.0000	0.2134	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1880	0.0000
9	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.5232	0.0000
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8205	0.0000

Perhaps unsurprisingly, the distributions for the average abnormal return for both type of rating changes are strongly skewed. For downgraded bonds in Figure 7, the distribution has a heavy negative skewness recorded at -7.4. The distribution for upgrades is skewed to the right with a skew of 0.7. This analysis calls into question the applicability of the Wilcoxon signed rank test for the data in this paper, and casts some doubt on the results of previous studies, where the null hypothesis of no abnormal performance is rejected without any discussion of symmetry in the distribution of average abnormal returns.

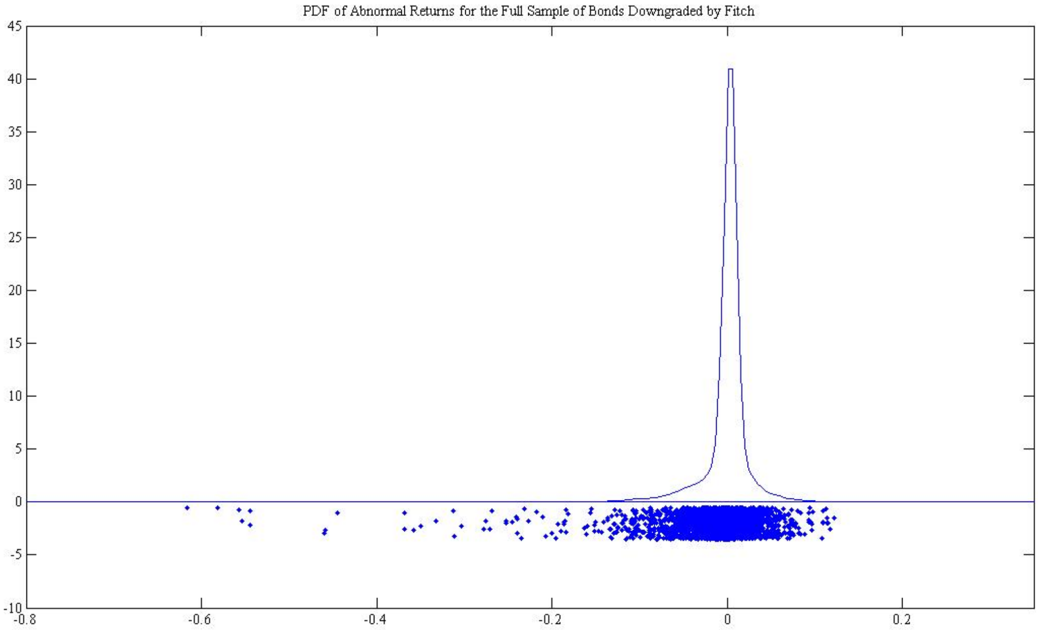

Figure 7 PDF of abnormal returns for the full sample of bonds downgraded byFitch
Illustrates a negatively skewed distribution of the average abnormal return for bonds downgraded by Fitch for the full sample.

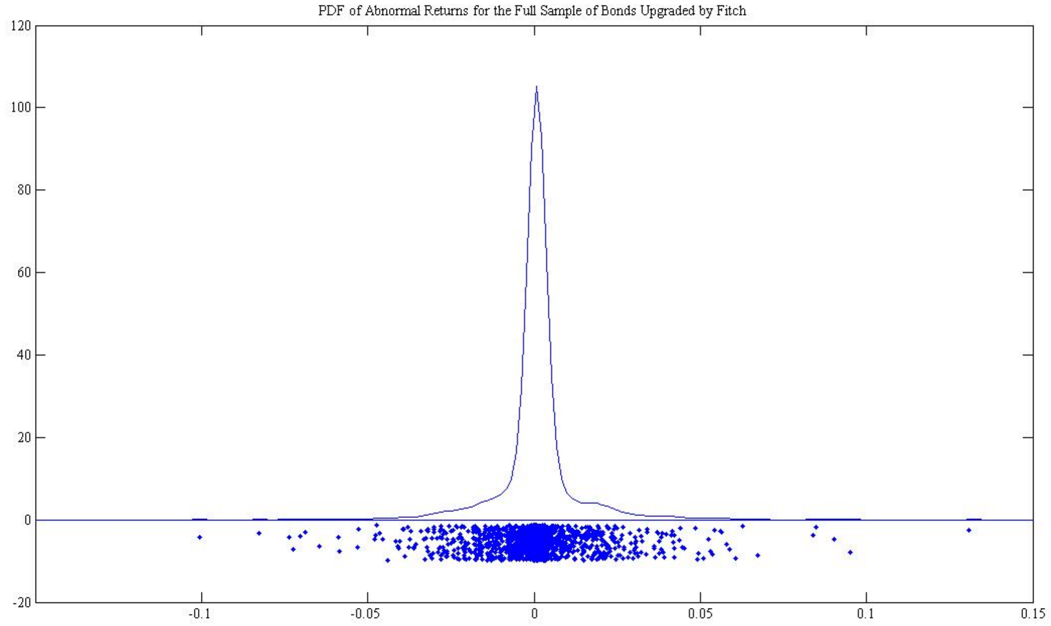

Figure 8 PDF of abnormal returns for the full sample of bonds upgraded byFitch
Illustrates a positively skewed distribution of the average abnormal return for bonds upgraded by Fitch for the full sample.

6. Conclusion

This paper investigates the impact of credit rating events on corporate bond returns, using a very recent and very large dataset for the secondary over-the-counter US corporate bond market. This comprehensive sample captures a unique period of time in financial markets, yielding interesting conclusions on the behaviour of bond returns around rating changes.

The results for the entire sample of downgrades and upgrades across all credit grades are consistent with market efficiency, implying that the information content of bond ratings is limited; the information summarised in bond ratings regarding credit risks, profitability and issuers' operating prospects is already incorporated in market prices. However, partial market anticipation of the credit rating change may be subduing the market response, as the rating agencies may have indicated a potential future rating change by placing the bond on a credit watch list, or as documented by Ederington and Yawitz (1987) and Hull et al. (2004), rating changes may be predictable from publicly available information.

The results from analysing rating changes within particular categories of credit grades provide some evidence of market inefficiency of the semi strong-form, particularly for downgrades within investment grade and for bonds downgraded into speculative grade by S&P. The main hypothesis discussed to explain this result is the clientele effect hypothesis, where regulated investors constrained to holding investment grade bonds are forced to sell their investments when bonds are downgraded, producing significant negative abnormal bond returns on and surrounding the event day 0. Further, consistent with the findings of the existing literature investigating the effect of rating changes on bond and stock returns, this paper documents a striking asymmetry in the response of bond returns to downgrades versus upgrades. For the entire sample, and for the four classes of rating grades analysed, the US corporate bond market is informationally efficient with respect to rating upgrades.

An interesting extension to the analysis of this paper would be to take advantage of the intraday price information contained in TRACE and to construct a high-frequency dataset of bond transaction prices and credit rating changes. This would require the precise time of the rating change announcement to be available, a feature currently not included in the data contained in FISD. A high-frequency analysis of the impact of credit rating changes on bond returns would provide more precise information on the efficiency of the corporate bond market.

7. References

Becker, Bo and Todd Milbourn, 2008, Reputation and competition: evidence from the credit rating industry, Harvard Business School working paper 09-051

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring Abnormal Bond Performance, *Review of Financial Studies* 22, 4219-4258

Bessembinder, Hendrik, William F. Maxwell, and Kumar Venkataraman, 2006, Optimal market transparency: Evidence from the initiation of trade reporting in corporate bonds, *Journal of Financial Economics* 82, 251-288

Blume, Marshall E., Felix Lim and A. Craig MacKinley, 1998, The declining credit quality of U.S. corporate debt: myth or reality?, *Journal of Finance* 53, 1389-1413

Brown, Stephen J. and Jerold B. Warner, 1980, Measuring Security Price Performance, *Journal of Financial Economics* 8, 205-258

Brunnermeier, Markus K., Lasse Heje Pedersen, 2005, Predatory Trading, *Journal of Finance* 60, 1825-1862

Campbell, John Y., Andrew W. Lo and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets*, Princeton University Press

Ederington, Louis, Jess B. Yawitz and Brian E. Roberts, 1984, The Informational Content of Bond Ratings, Working Paper No. 1323, NBER Working Paper Series

Ederington, Louis and Jess B. Yawitz, 1987, The bond rating process, in *Handbook of Financial Markets and Institutions*, ed. by E. Altman, John Wiley and Sons, New York

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

Fabozzi, Frank J., 2002, *The Handbook of Fixed Income Securities*, McGraw-Hill

Fama, Eugene F., 1991, Efficient Capital Markets: II, *Journal of Finance* 46, 1575-1617

Fama, Eugene F., Lawrence Fisher, Michael Jensen and Richard Roll, 1969, The Adjustment of Stock Prices to New Information, *International Economic Review* 10, 1-21

Fitch Ratings, 2009, *Definitions of Ratings and Other Scales*, Fitch Ratings, New York, NY

Hand, John R. M., Robert W. Holthausen, Richard W. Leftwich, 1992, The effect of Bond Rating Agency Announcements on Bond and Stock Prices, *Journal of Finance* 47, 733-752

Handjinicolaou, George, and Avner Kalay, 1984, Wealth redistributions or changes in firm value: An analysis of returns to bondholders and stockholders around dividend announcements, *Journal of Financial Economics* 14, 35-63

Hite, Gailen and Arthur Warga, 1997, The effect of Bond-Rating Changes on Bond Price Performance, *Financial Analysts Journal* 53, 35-51

Holthausen, Robert W. and Richard W. Leftwich, 1986, The effect of Bond Rating Changes on Common Stock Prices, *Journal of Financial Economics* 17, 57-89

Hull, John, Mirela Predescu and Alan White, 2004, The relationship between credit default swap spreads, bond yields, and credit rating announcements, *Journal of Banking and Finance* 28, 2789-2811

Jorion, Philippe, Zhu Liu and Charles Shi, 2005, Informational effects of regulation FD: evidence from rating agencies, *Journal of Financial Economics* 76, 309-330

Katz, Steven, 1974, The Price Adjustment Process of Bonds to Rating Reclassifications: A Test of Bond Market Efficiency, *Journal of Finance* 29, 551-559

Kliger, Doron and Oded Sarig, 2002, The information value of bond ratings, *Journal of Finance* 55, 2879-2901

Kothari, S. P. and Jerold B. Warner, 2006, Econometrics of Event Studies, in *Handbook of Corporate Finance: Empirical Corporate Finance*, ed. by B. Espen Eckbo, Elsevier/North Holland

Lehmann, E. L., 1975, *Nonparametrics: Statistical Methods Based on Ranks*, McGraw-Hill International Book Company

Malkiel, Burton, 1992, Efficient Market Hypothesis, in *New Palgrave Dictionary of Money and Finance*, ed. by P. Newman, M. Milgate and J. Eatwell, Macmillan, London

Maxwell, William F. and Clifford P. Stephens, 2003, The Wealth Effects of Repurchases on Bondholders, *Journal of Finance* 58, 895-919

Miller, Merton and Franco Modigliani, 1961, Dividend Policy, Growth and the Valuation of Shares, *Journal of Business* 34, 411-433.

Moody's Investors Service, 2008, *Moody's Rating Symbols & Definitions*, New York, NY

Roberts, H., 1967, Statistical versus Clinical Prediction of the Stock Market, unpublished manuscript, Center for Research in Security Prices, University of Chicago

Roll, Richard, 1977, A Critique of the Asset Pricing Theory's Tests: Part I, *Journal of Financial Economics* 4, 129-176

Securities and Exchange Commission, 2003, Report on the Role and Function of Credit Rating Agencies in the Operation of the Securities Markets, As Required by Section 702(b) of the Sarbanes-Oxley Act of 2002

Standard & Poor's, 2008, *Standard & Poor's Rating Definitions*, McGraw-Hill Companies

Steiner, Manfred and Volker G. Heinke, 2001, Event Study Concerning International Bond Price Effects of Credit Rating Actions, *International Journal of Finance and Economics* 6, 139-157

Financial Industry Regulatory Authority (FINRA), *TRACE Fact Book*, 2008, Washington DC

Wakeman, L. Macdonald, 1990, The Real Function of Bond Rating Agencies, in *The Modern Theory of Corporate Finance*, ed. by Clifford W. Smith, Jr., McGraw-Hill

Weinstein, M., 1977, The Effect of a Rating Change Announcement on Bond Price, *Journal of Financial Economics* 5, 329-350

Chapter 2

Price Discovery in the Corporate Bonds Markets: An Intraday Analysis of the Price Impact of Order Flow

Abstract

This paper analyses how order flow, captured by investor “buy” and “sell” trades, impacts corporate bond prices. Order flow is considered to have an important informational role, as it acts as a conduit through which private information about the fundamental value of a security is aggregated into prices. The relationship between returns and order flow is modelled using a bivariate vector autoregression (VAR) model. The information content of a trade is measured by the long-run price impact of a shock to order flow. Using a novel and rich dataset of the US corporate bond market, I analyse intraday transaction prices and trades for 1,148 of the most liquid corporate bonds from November 2008 to June 2011, a total of 9.5 million trades. I investigate the long-run price impact of order flow through sorts on credit ratings, proxies for liquidity, liquidity risk and bond specific characteristics. I also consider the origin of the order flow, large trade size being indicative of trading from institutional investors. The long-run price impact is particularly strong and significant for institutional order flow and for bonds with higher default risk, higher volatility and lower liquidity.

1. Introduction

The role played by information in price discovery is at the heart of market microstructure models. An important conduit for information revelation is order flow, or signed transaction volume. In a market with asymmetrically informed traders, order flow conveys private information that is impounded into asset prices. Importantly, only information can cause a persistent, long-run impact on prices and the presence of market frictions only gives rise to contemporaneous, transient price impacts. Therefore, the process of price adjustment need not be instantaneous and prices will adjust until they reflect all available information. The existing literature has documented the importance of order flow as a key component of price formation; see for example, Hasbrouck (1991) for equity markets, Evans and Lyons (2002) for the foreign exchange market, Brandt and Kavajecz (2004), Green (2004) and Pasquariello and Vega (2007) for Treasury markets. This paper examines the role of order flow in price discovery in the corporate bond markets.

The US corporate bond market has attracted renewed interest in recent years from academics, regulators and market practitioners spurred on by both the improved transparency of the market via the introduction of TRACE (Trade Reporting and Compliance Engine) in 2002, resulting in better availability of corporate bond market data and, importantly, the scale and longevity of the financial crisis of 2008, where the credit markets took centre stage. Moreover, due to its sheer size, the corporate bond market warrants careful attention; at the end of 2012 the outstanding principle of corporate bonds stood at $9.1 trillion, forming nearly 24% of all outstanding fixed income obligations in the US and second only to the Treasury market.[18] The advances in transparency, making the

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[18] Outstanding principal refers to the loan amount payable at maturity. The data on outstanding principal is from Securities Industry and Financial Market Association (www.sifma.org)

sequence of past prices and trades in the corporate bond markets only newly observable, provide an opportunity for furthering our understanding of price formation in this segment of the fixed income market. How does the order flow of individual investors and institutions impact corporate bond prices? Are long-run price impacts from trading more pronounced for bonds that share certain characteristics?

The main objective of this paper is to systematically estimate the price impact of order flow on corporate bond prices. Price impacts are estimated using the seminal approach of Hasbrouck (1991) and a novel, augmented dataset of TRACE corporate bond data containing signed trades, obviating the need to use noisy algorithms, such as Lee and Ready (1991), to determine the direction of the trade. Furthermore, the price impacts are estimated individually for each bond at an intraday level. The empirical findings of this paper have two main contributions to the existing literature. Firstly, to the best of my knowledge, this paper is the first to directly estimate the price impact of order flow in the corporate bond market. Secondly, this paper links the occurrence and magnitude of long-run price impacts and, therefore, the pervasiveness of asymmetric information to bond characteristics, as well as to two broad segments of clientele, institutional and retail investors.

The trading behaviour of institutional investors has long been of interest (see for example Chan and Lakonishok (1995)) and it is of particular relevance for the corporate bond markets, as institutional investors have been shown to be dominant market participants (see for example, Bessembinder and Maxwell (2008)). Further, Ronen and Zhou (2013) show that when only institutional trades in corporate bonds are considered, the stock market no longer leads the corporate bond market in informational efficiency and when equity market liquidity is low, bond markets are shown to adjust faster to firm-specific news. As discussed in Bessembinder and Maxwell (2008) and Ellul et al. (2011), institutional investors can be separated by the credit rating class they primarily invest in.[19] The clientele in investment grade bonds, which consists of bonds with low or moderate credit risk, is likely to be formed by insurance companies, pension and mutual funds that face regulatory constraints that restrict them into this lower credit risk category. Additionally, the preponderance of retail investors is likely higher in investment grade bonds. Speculative grade bonds, also known as high yield bonds, are subject to significantly higher risk of default, and are likely to attract more sophisticated institutional investors, such as hedge funds and distressed debt funds. Hence, due to the relative importance of institutional investors and consistent with the existing literature, I separate the primary analysis of long-run price impacts on two axes: credit rating (investment or speculative grade) and trade type (trades placed by institutional investors or all investors in the market).

Subsequently, I investigate whether there exists a systematic link between the long-run price impacts and bond characteristics through sorting the price impacts by observable variables within each rating class and trade category. This conditional sorting methodology allows for a better assessment of the relation between the long-run price impact, or more precisely, the presence of informational asymmetry, and external characteristics of corporate bonds and the prevalent market structure. For example, sorting price impacts by liquidity proxies allows for the examination of whether bonds with higher perceived illiquidity have higher price impacts from a shock to order flow. It is important to note that this conditional sorting methodology is a non-parametric approach to investigate the

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[19] Ellul et al. (2011) document that solely insurance companies hold more than one third of all investment grade debt.

relationship between the price impact and the sorting variables; it makes no assumptions on the functional form of the relationship and thus allows for the possibility of non-linearity and non-monotonicity. This is of particular advantage in the present example, as the relationship between price impacts and the observable sorting variables is unknown and the use of linear regression to evaluate the relationship could be subject to misspecification bias (Patton and Timmermann (2010)).

The sort variables used in this analysis include two different proxies for liquidity, namely, a bond’s daily dollar volume and number of trades, two different proxies for liquidity risk (the volatility of the liquidity proxies) and two bond specific characteristic, original issue size and maturity. These variables were selected as they have been demonstrated to play central roles as determinants of asset returns. Most recently, Bao et al. (2011) and Dick-Nielsen et al. (2012) show that illiquidity can explain a large component of yield spreads (the difference between the yield on a corporate bond and a Treasury bond yield of the same maturity). Chordia et al. (2001) investigate the importance of liquidity and liquidity risk on expected returns on equities and show that variability of liquidity is negatively related to stock returns and Bao and Pan (2013) show that price volatility is an important component of yields spreads. External bond characteristics such as original issue size and maturity are widely known to contribute to the price behaviour of corporate bonds (see, for example, Elton et al. (2004)).

The results of this paper show that unanticipated order flow in the corporate bond market conveys novel information to the market causing persistent impacts on prices. For all trade types, 16% of bonds have a significant long-run price impact from order flow and across these bonds, the average impact is 6 basis points (bps, 1 bps is 0.01%). For institutional sized trades, approximately 34% of bonds have significant long run price impacts from trading and across these bonds the average impact is 13bps. The long-run price impact is highest for institutional order flow in speculative grade bonds. Approximately 52% of speculative grade bonds in the sample experience statistically significant long-run price impacts from a shock to institutional order flow compared with 33% of investment grade bonds. The magnitude of the price impact is economically and statistically significant and ranges between 17.5 to 12.5 bps for a one standard deviation shock to order flow. Persistent price impacts resulting from order flow including both institutional and retail sized trades (henceforth "all trades") are determinedly lower both in significance and magnitude.[20] The higher persistent price impacts for institutional order flow are interpreted to result from institutional investors' private information being partially revealed to the market. Also, the incidence of asymmetric information and hence, adverse selection costs are higher for speculative grade bonds.

The results of conditionally sorting long-run price impacts by external bond characteristics reveal that persistent price impacts are increasing in illiquidity, return volatility and maturity for both credit ratings, whilst liquidity risk and long-run price impacts are negatively correlated. These directional relationships are statistically significant. The occurrence and magnitude of the price impacts are most prominent in the "institutional" trade category. The relationship between persistent price impacts and issue size is inconclusive.

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[20] In order to facilitate comparisons between the trade categories the size of the shock is standardized to the size of a one standard deviation shock to order flow from all trade types. See the results section for more details on this standardization.

This paper draws most methodological influence from the vector autoregression (VAR) model of Hasbrouck (1991). The underlying premise of the model is that the information content of a trade is captured by the long-run price impact and must be inferred from the unanticipated component of order flow (as measured by the regression residual). The remaining variables in the model are predictable and contain no new information (Hasbrouck (1991)). The long-run information effect of a trade is measured by the cumulative impulse response function derived from a shock to order flow. Only a persistent impact captures the information effect of a trade on prices, net of any transient influences, such as inventory control, order fragmentation and portfolio rebalancing. The impact of these latter influences is captured by the contemporaneous price impact, which I also estimate in this paper.

This paper is related to two recent studies of information in the corporate bond market; Ronen and Zhou (2013) investigate the relative informational efficiency of the corporate bond and equity markets with respect to firm-specific news releases finding that accounting for institutional dominance and bond specific characteristics, equity markets do not lead corporate bond markets in informational efficiency. This is particularly true when equity market liquidity is low. Han and Zhou (2013) examine the role asymmetric information plays in the corporate bond market, by computing two theoretical measures of information asymmetry and assessing their impact on yield spreads. While these studies enhance our understanding of the corporate bond markets neither tackles the importance of order flow as a channel for information revelation in price discovery. This paper documents that institutional order flow has a statistically significant, persistent impact on prices, particularly for bonds with higher credit risk, return volatility, longer maturity and lower liquidity.

Better availability of corporate bond data since the launch of TRACE has increased academic interest in this segment of the fixed income market. The key strands of interest have focused on improvements in market transparency, investigations into liquidity and relative information efficiency with respect to the equity markets. The main studies of transparency, Bessembinder et al. (2006), Edwards et al. (2007) and Goldstein et al. (2007) have focused on transaction costs and therefore evaluating the "tightness" of the market (Bessembinder and Maxwell (2008)). The concept of liquidity in this paper, in turn, is best described as "resiliency", as large and persistent price impacts from the trading process are an indication of a lack of resilience in the market. Dick-Nielsen et al. (2012) provide a summary of the recent papers aiming to explain the "credit spread puzzle", referring to the inadequacy of pricing models in explaining yield spreads by default risk. Ronen and Zhou (2013) and Downing et al. (2009) study the relative informational efficiency of corporate bond and equity markets to varying conclusions. The former finds that stock markets do not lead corporate bond markets, whilst the latter concludes that corporate bond markets are less informationally efficient.

The remainder of the paper is organized as follows. Section 2 outlines the VAR model used and explains estimation and inference. Section 3 details the data used in this study; it explains how databases were merged and provides descriptive statistics. Section 4 reports and discusses the empirical results. Concluding remarks are provided in section 5.

2. Methodology

2.1 A VAR Model for Returns and Order Flow

I use the linear, bivariate vector autoregression (VAR) model of Hasbrouck (1991) to estimate contemporaneous and long-run price impacts.

$$B_0 y_t = k + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t$$

$$u_t \sim WN(0, V_u)$$

(1)

Where y_t is the vector $[r_t, x_t]'$, r_t is the return on the bond between trade t-1 and trade t, and x_t is the associated signed volume of trade t, which is positive for buy trades and negative for sell trades. The coefficients to be estimated are the intercept k, the slope coefficient matrices B_j on lagged bond returns and signed volume and B_0, which has just one parameter (b_0). The model is set in "transaction time", which means that the observations are not equally spaced; the time between observations is random as it depends on the arrival of trades.

Note that equation (1) can be written as:

$$r_t = k_1 + b_0 x_t + \sum_{i=1}^{P_1} a_i r_{t-i} + \sum_{i=1}^{P_2} b_i x_{t-i} + e_t$$

(2a)

$$x_t = k_2 + \sum_{i=1}^{P_3} c_i r_{t-i} + \sum_{i=1}^{P_4} d_i x_{t-i} + v_t$$

(2b)

where the lag length, P_i, is allowed to vary differently for both variables, returns and signed volume, in both equations (2a) and (2b). Henceforth this model is denoted as a VAR(P_1,P_2,P_3,P_4).

It should be emphasized that the model detailed in equations (1) and (2a), (2b) is a structural VAR, where transaction level returns and signed volume are not determined simultaneously, but signed volume is allowed to contemporaneously impact returns, whilst not opposite is not the case. This ordering of variables stems from the timing of the actual trading process; the trader determines his buy or sell trade volume at time t based on all the information available, including the prevailing quote levels. The prevailing bid (ask) quote is the price at which a customer sell (buy) trade is executed in period t. The signed trade volume then updates the information set at time t to reflect (with noise) the trader's private information and the dealer adjusts his quotes based on this information revelation at time t. The inclusion of the contemporaneous signed volume in the return equation allows for the examination of both contemporaneous and lagged impacts of order flow on returns.

The choice of lag length, P_i, is guided by two distinct methods for model selection; firstly optimizing using the Bayesian, Hannan-Quinn and Akaike information criteria (henceforth BIC, HQIC and AIC, respectively) and secondly by selecting the smallest model while ensuring that the null hypothesis of zero residual autocorrelation cannot be rejected. The test used for this purpose is a robust Ljung-Box test with White (1980) HAC standard errors. The search for an optimal model is conducted over twelve models, where the lag length P_i can take values of 3, 5, 10, 15 and 20. The model chosen by both HQ and BIC and the robust Ljung-Box test is a VAR(3,3,3,15). This model is then estimated individually for each bond, and separately for "all trades" and "institutional trades" categories.

In contrast with Hasbrouck (1991), instead of using an indicator variable for buy and sell trades, where trades have been signed using the Lee & Ready algorithm (Lee and Ready, (1991)), I use the *actual* signed volume as specified in TRACE as the trade variable.[21] Rather than using the mid-quote as the primary price variable as in Hasbrouck (1991) I use the transaction price as the price variable, as quote data is not publicly available for corporate bonds. [22]

Finally, the VAR model has standard underlying assumptions. Firstly, both the bond return and signed volume series are assumed covariance stationary, which allows for the MA(∞) representation of the VAR model used to obtain impulse response functions, see Hamilton (1994, Ch. 11). Secondly, the innovations are assumed to be "white noise" processes; they are mean zero $E[e_t] = E[v_t] = 0$ and serially uncorrelated; $E[e_t e_s] = E[v_t v_s] = E[e_t v_s] = 0 \; for \; all \; t \neq s,$ a reasonable assumption if enough lags are included.

2.2 Impulse Response Functions

Given a structural VAR of the form specified in equation (1) above, the impulse response function is defined as the change in the dependent variables with respect to a shock (or

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[21] In Hasbrouck (1991) the model is deemed "better-behaved" with an indicator; unreported results using volume are "positive, but highly variable".

[22] Some indicative quote data may be available, but these quotes for informational purposes rather firm quotes for trading.

"impulse") to the innovations. It is a known, but complicated nonlinear function of the VAR parameters:

$$\frac{\partial E[y_{t+h}]}{\partial u_t'} = \begin{bmatrix} \frac{\partial E[r_{t+h}]}{\partial e_t} & \frac{\partial E[r_{t+h}]}{\partial v_t} \\ \frac{\partial E[x_{t+h}]}{\partial e_t} & \frac{\partial E[x_{t+h}]}{\partial v_t} \end{bmatrix} = f(k, B_0, \dots, B_p, V_u, h)$$

(3)

The upper-right element of this matrix is of particular interest: $\frac{\partial E[r_{t+h}]}{\partial v_t}$, which is the price impact of a trade. The *persistent* price impact of a trade is captured by the cumulative impulse response function. The cumulative impulse response, α_m, is defined as the summation of the expected return given the trade volume innovation:

$$\alpha_m = \sum_{j=0}^{m} \frac{\partial E[r_{t+j}]}{\partial v_t}$$

(4)

The process α_m is stationary; $\alpha_\infty \equiv lim\ \alpha_\infty\ as\ m \to \infty$. As discussed above, the long run impact (α_m) is interpretable as a measure of asymmetric information embedded in the trades (Hasbrouck (1991) and Pasquariello and Vega (2007)).

2.3 Estimation and Inference

The VAR model is estimated by OLS, which provides consistent estimates of the parameters even when the residuals do not follow a Normal distribution (using Quasi-Maximum Likelihood theory), see Hamilton (1994). However, the standard errors used to compute the significance of the parameters must be "robust" to non-Normality. Hence, inference is conducted using a bootstrap procedure, which captures potential non-

Normality and heteroskedasticity, see Efron and Tibshirani (1998) and Luktepohl (2000). The use of bootstrap methodology also makes it easier to obtain confidence intervals on the long-run impact, which is a complicated non-linear function of the estimated parameters, and obtaining standard errors via the Delta method would be a tedious exercise.

As such, I use a "block bootstrap", which re-samples the data directly (in blocks), see Politis and Romano (1994). The bootstrap procedure is outlined as follows. First, the VAR model is estimated on the original data and the long-run impact, $\hat{\alpha}_m$, is computed. Second, a bootstrap sample of the data is generated (using the "stationary bootstrap" of Politis and Romano, (1994)): a date is randomly selected to start the bootstrap block. Then, the length of the block is selected randomly using the Geometric distribution with an average length k* = 20 observations, selected such that it is long enough to cover all non-zero autocorrelations of the residuals. Using the start date and the block length, a "block" of the original data is extracted. This process is continued until a time series of length T, one bootstrap sample, is formed. The VAR model is estimated on the *bootstrapped* data, and the long-run impact, ${\hat{\alpha}_m}^{(b)}$is computed. The bootstrap sample is formed and the VAR model estimated 1000 times to obtain an estimated distribution of the long-run impact. Finally, a 95% confidence interval for $\hat{\alpha}_m$ is obtained using the 2.5% and 97.5% percentiles of the bootstrap estimates, ${\hat{\alpha}_m}^{(b)}$.

3. Data

3.1 Evolution of TRACE

The primary data source I use for bond transaction information is the Trade Reporting and Compliance Engine (TRACE) extracted through Wharton Research Data Services

(WRDS).[23] The TRACE system is a new database for the secondary over-the-counter US corporate bond market providing real-time transaction information for market participants: retail and institutional investors, broker-dealers and regulators. TRACE is supplied and operated by the Financial Industry Regulatory Authority (FINRA).[24] The bond transaction data includes customer and inter-dealer transactions in "TRACE-eligible securities", which are depository-eligible, SEC registered, US dollar denominated securities across all credit grades.

TRACE was initiated in July 2002 in an effort to improve the transparency and efficiency of the over-the-counter bond market. The public reporting (by FINRA member firms, such as broker-dealers) of bond transactions was implemented in three phases, each of which increased the number of securities information was disseminated on and reduced the delay allowed when reporting trades. The final phase was fully effective in February 2005 and since then TRACE captures 99% of all public transactions, representing 95% of the total dollar value traded.[25] Since January 2006 the TRACE system has provided real-time reporting of all transactions. The few trades that fall outside the scope of TRACE are those that occur on exchanges. Edwards et al. (2007) report that less than 5% of bonds are listed on the New York Stock Exchange (NYSE), and for these bonds, less than 40% of trades occur on the NYSE.

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[23] Parts of the following description of the evolution of the TRACE database also appears in the first chapter of the thesis “The Impact of Credit Rating Events on Corporate Bond Returns”.

[24] FINRA was created in July 2007 through the merger of the National Association of Securities Dealers (NASD) and the member regulation, enforcement and arbitration functions of the New York Stock Exchange. It is a self-regulatory organization for all securities firms in US that interact with the public.

[25] See TRACE Fact Book 2008.

TRACE reports the time and date of bond transactions, making intra-day price information available, although many bonds trade infrequently and may only have a few trades per month or even per year. In addition to the reported price and yield of a bond, TRACE disseminates information on trading volume as transaction par value, however only through an indicator for large transactions. For trades in investment grade bonds with a par value of more than $5 million, TRACE contains an indicator of "5MM+". Similarly, for speculative grade debt, transactions greater than $1 million are reported as "1MM+". Since November 2008, TRACE has publicly disseminated the direction of the trade; an indicator detailing whether the trade is buyer or seller initiated or an interdealer trade. This trade direction indicator is a key variable for the present study.

The impact of this real-time database of secondary market transaction information available to investors has been remarkable. In contrast to equities, which are mostly traded on organized exchanges, bond trades commonly amount to transactions between a dealer and a client carried out over the phone or on electronic trading platforms. As a result, the details of the transaction, bond price and traded volume are private information to the transacting parties. Two recent papers by Edwards et al. (2007) and Bessembinder et al. (2006) examine the impact of the introduction of TRACE on transaction costs associated with bond trades in the secondary market. Edwards et al. (2007) find that secondary transactions costs drop by up to 2% when bond prices are disseminated by TRACE. Their estimated round-trip transaction costs range from 150 to 3 bps, depending on trade size, issue size, the credit quality and time to maturity of the bond.

In addition to latest reported transaction prices being available on FINRA's website, TRACE pricing is also available through Bloomberg, a real-time news and financial information service used extensively by both professional investors and dealers in the corporate bond market. The wide availability of TRACE transaction prices increases information flow into the market - last transaction prices can be verified along with other relevant bond characteristics prior to trading. This level public price information enhances the quality of trade execution. Investors now have a better gauge on pricing, as TRACE provides an alternative pricing source to prices posted by broker-dealers, whose incentives are generally not aligned with those of their customers.

3.2 Data Filtering

The sample period for the analysis runs from 3 November 2008 to 30 June 2011. The start of the sample is dictated by the availability of the indicator detailing the direction of the trade. This sample period contains over 29 million unique bond trades by 44,514 unique bond issues. Following filtering processes set forth by Edwards et al. (2007), Bessembinder et al. (2008), Downing et al. (2009) and Bao et al. (2011) before, nonstandard and erroneous transactions, such as trades flagged as cancelled, corrected, traded or reported outside market hours from the TRACE dataset are eliminated. Trades with a commission included in the price and trades with unconventional settlements are also deleted. This process reduces the bond transaction sample to roughly 26 million transactions and 37,083 unique bonds issues.

Given that TRACE only contains information pertaining to bond transactions, in order to obtain a complete record of the bonds trading, the TRACE transaction data needs to be matched with information on bond characteristic such as coupon, maturity and bond rating.

Mergent's Fixed Income Securities Database (FISD) is used to obtain information on bond characteristics. Following Bessembinder et al. (2006) bond characteristic information is used to select a sample of straight corporate debt, that is, bonds with no conversion privileges or other special features, and with a set maturity and coupon date. The filter based on FISD data eliminates 13 characteristic types.[26] Approximately 85% of the bonds in the TRACE sample were matched with characteristics in FISD, after which the number of bonds decreases to 15,511 and the number of trades to approximately 16.5 million. Additionally, Bloomberg is used to obtain data on Standard & Poor's (S&P) bond ratings. In the case where an S&P rating is missing (only one such case) the Moody's rating for the issue was used. The rating used in the study is the rating the bond received at issuance.

In order to analyse price impact from order flow, the bond needs to be relatively liquid and have a reasonable number of transactions during the sample period. A trading frequency based filter following Bao et al. (2011) is implemented to retain a sample of liquid securities. In particular, to be included in the analysis each bond must trade on at least 75% of the 645 trading days in the sample. Additionally, for a bond to be included in the analysis, it must be in issuance for at least 252 days in the sample. Further, any remaining holiday dates are removed from the sample based on Securities Industry and Financial Markets Association (SIFMA) recommendations for the Treasury market.[27] These dates also encompass NYSE market closures. After the use of these additional filters, the final sample contains 1,148 bonds and roughly 9 million trades.

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[26] The filter removes bonds that are asset backed, convertible, exchangeable or putable, bonds that have non-standard coupons (variable and zero coupon), bonds that have defaulted or are in bankruptcy, bonds with enhancement, bonds that are issued in foreign currency or are placed privately, perpetual bonds, preferred securities and bonds with a tender exchange offer.

[27] Only the current calendar year of holiday dates for TRACE is available. In order to remove historic holiday dates I used Treasury market closure dates.

The decrease in both the number of bonds and transactions from the raw data to the retained sample is considerable. While it would be desirable to estimate price impacts for all the bonds in the TRACE database, the paucity of trades for many corporate bonds combined with the VAR methodology and its requirement for a sufficient number of observations, render the exercise practically infeasible. Table 1 illustrates the evolution of the sample using number of bonds and total number of transactions at each filtering stage.

Table 1 Data Filtering
This table contains a summary of the impact of the different filters used to arrive to the final sample, both in terms of number of individual bonds and total number of trades.

	No. of Bonds	**Decrease, %**	**Total No. of trades (MM)**	**Decrease, %**
Totals in sample period	**44,514**		**29.18**	
Observations subtotals:				
TRACE filter	37,083	16.69	26.03	10.79
FISD match	31,568	14.87	-	-
FISD filter	15,511	50.86	16.48	36.68
Frequency & Holiday filter	1,148	92.60	9.49	42.44
Final Sample:	**1,148**	**92.60**	**9.49**	**42.44**

Following previous studies of the corporate bond market, I further divide this base sample of 1,148 bonds into two categories based on investor type. Crabbe and Turner (1995), Alexander et al. (2000) and Edwards et al. (2007) classify trades with 100 or more bonds (or \$100,000 or more of par value) as institutional, that is, trades of this size have likely been executed by institutional investors as opposed to individual retail investors. Hence, the "institutional trades" sample in this study only includes bond trades of more than 100 bonds. The deletion of small trades to create the institutional sample means that some bonds with many retail-sized trades, but only a few institutional sized trades, may not have enough observations for the estimation of the VAR(3,3,3,15) model, and so I exclude bonds with fewer than 500 institutional observations from the "institutional trades" sample. The samples retained for analysis are as follows. The “all trades”-category has 1,148 bonds of which 1,079 bonds (94%) and 69 bonds (6%) are rated as investment and speculative grade, respectively. Similarly, the “institutional trades” –category has 945 bonds of which 876 bond (93%) and 69 (7%) are rated as investment and speculative grade, respectively.

As reported in Table 2 below, the S&P credit ratings for the investment grade bonds for both trade types lie within the full investment grade scale from AAA to BBB-.[28] The rating distribution is positively skewed with an average rating of AA- and a median of A-. For speculative grade bonds, the sample is identical for both trade types, with the lowest rating of CCC+, four grades above default. The rating distribution for bonds below investment grade is negatively skewed. Given the high proportion of investment grade bonds for both trade type samples, the rating characteristics for the total sample map closely the credit ratings of the investment grade bond.

On average, nearly 1,900 trades (29% of all trades) for the average bond are institutional, consisting of more than 100 bonds. For speculative grade bonds the prevalence of institutional trades is higher at 2,000 (34% of all trades). The distribution of trade size in this sample is consistent with previous studies of the corporate bond market, as Ronen and Zhou (2013) report that 65% of all trades are retail size transactions.

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[28] S&P assigns ratings using an alphabetical scale ranging from investment grade (AAA, AA, A and BBB) to speculative grade (BB, B, CCC, CC, C and D). These ratings are further segmented by adding a plus or a minus sign after the alphabetical rating.

Table 2 Summary Statistics for Trade Categories

The table contains summary statistics on the composition of the "all trades" (left-hand side panel) and "institutional trades" (right-hand side panel) – samples. The number of trades per bond and the average bond rating are reported separately by credit grade, Panel A for investment grade and Panel B for speculative grade bonds, and finally, Panel C for all bonds in the sample.

	All Trades					Institutional Trades				
	mean	median	max	min	stdev	mean	median	max	min	stdev
Panel A: Investment Grade Bonds										
Num. obs per bond	6,615	4,366	63,596	1,261	6,618	1,867	1,370	11,727	500	1,518
Rating	AA-	A-	AAA	BBB-		AA-	A-	AAA	BBB-	
Panel B: Speculative Grade Bonds										
Num. obs per bond	5,915	4,247	22,526	1,291	4,852	2,023	1,771	7,921	508	1,293
Rating	BB	BB+	BB+	CCC+		BB	BB+	BB+	CCC+	
Panel C: All Bonds										
Num. obs per bond	6,573	4,356	63,596	1,261	6,526	1,878	1,385	11,727	500	1,503
Rating	AA-	A-	AAA	CCC+		AA-	A-	AAA	CCC+	

The 1,148 bonds in the sample were issued by 302 unique firms. The distribution of the number of bonds issued by the same firm is right skewed, with an average of 3.80 bonds outstanding for each firm, which exceeds the median of 2 bonds per firm. The firms with most bonds in the sample are mainly financial, such as Bank of America, Citigroup, Goldman Sachs, JP Morgan and Morgan Stanley, financing arms of corporations such as General Electric and General Motors although the top ten issuers ranked by number of bonds also includes non-financial companies, such as Verizon Communications and Wal-Mart.

3.3 Summary Statistics for Sort Variables

I explore the relationship between the bond characteristic-based sort variables using cross sectional sample correlations between the time series averages of each sorting variable for each bond.[29] These correlations are used to give ex ante guidance on what the relationship between price impacts, liquidity proxies and liquidity risk and other characteristics might be.

The correlations between the liquidity proxies and their second moments are all quite high, ranging from 0.476 (between standard deviation of volume and standard deviation of number of trades) to 0.956 (between volume and its standard deviation), indicating that liquidity risk is increasing in the level of liquidity. Bond issue size is also highly positively correlated with the liquidity proxies and their volatilities. Volatility of returns and maturity show lowest negative correlations, and the lowest correlation occurs between return volatility and standard deviation of volume. Maturity is negatively correlated with all but one sort variable, return volatility. This positive correlation between maturity and return volatility is likely to be driven by the higher sensitivity of long duration bonds to interest rate fluctuations.

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[29] Bond characteristics (issue size and maturity) are constant through time, so the correlation is computed at the level of the variable, instead of an average.

Table 3 Simple Correlations

The table contains the cross sectional sample correlations between the time series averages of each sorting variable for each bond. The liquidity proxies are volume, defined as the total dollar volume, num trades, the total number of trades, and std volume and std num trades are the standard deviations of their respective liquidity proxies. Std returns is the daily return volatility, issue size is the original principal amount issued, and maturity is the time to maturity at issuance.

	Num Trades	Std Volume	Std Num Trades	Std Returns	Issue Size	Maturity
Volume	0.567	0.956	0.500	-0.298	0.744	-0.139
Num Trades		0.478	0.863	-0.126	0.577	-0.192
Std Volume			0.476	-0.371	0.675	-0.177
Std Num Trades				-0.169	0.432	-0.235
Std Returns					-0.304	0.342
Issue Size						-0.105

Table 4 below reports the average values of the liquidity proxies between “all trades” and “institutional trades”. The differences between the two trade categories are as expected given that for a trade to be qualified as an “institutional trade”, the number of bonds traded must be greater than or equal to 100. Hence, the average volume must be higher for institutional trades as only trades with more than 100 bonds are included. Further, the institutional sample is characterized by a lower number of trades per day (compared with the “all trades”-sample) as trades with less than 100 bonds are eliminated from each trading day to create the institutional sample.

Comparing the quartiles of dollar volume across credit grades, the lowest two volume quartiles, for both retail and institutional sized trades, are higher for speculative grade bonds. With an equal average number of trades per day for the two credit grades, this implies that the trade size for speculative grade bonds is larger than for investment grade bonds, potentially driven by the presence of individual retail investors trading in small size in the investment grade market bringing down the average daily volume. The ranking reverses for highest two volume quartiles; investment grade bonds are both traded in higher volume and number compared to speculative grade bonds. The higher dollar volume in the top two quartiles of investment grade bonds is likely to be caused by large trades by institutional investors. Consistent with this hypothesis, the average daily dollar volume for institutional trades is higher for every quartile for investment grade bonds compared with that of speculative grade bonds. The average number of trades per day is stable between the two credit grades; implying that on average, trades in investment grade bonds are larger than those for speculative grade bonds when traders are assumed to be institutional. However, it should be noted here that we do not have accurate knowledge of the actual transaction sizes in the highest quartiles implying that the average volumes are likely to be understated due to the truncation of trade volume in TRACE.

Table 4 Liquidity Proxy Summary Statistics

The table contains summary statistics for the two liquidity proxies used in this paper. Panel A details the average values of daily dollar volume and number of trades per day for investment grade bonds, separately for each trade type, "all trades" and "institutional trades". Panel B reports the same for speculative grade bonds.

	All Trades		**Institutional Trades**	
Quartile	Volume ($000)	Nr. of Trades	Volume ($000)	Nr. of Trades
Panel A: Investment Grade Bonds				
1	486	4	1,498	2
2	1,387	6	2,416	3
3	2,603	10	3,647	4
4	7,145	24	8,024	7
Panel B: Speculative Grade Bonds				
1	991	4	1,401	2
2	1,605	6	1,856	3
3	2,417	9	2,592	4
4	5,398	21	5,656	7

It is also worth noting that the interquartile range for the liquidity measures is narrower for speculative than investment grade bonds. This higher variability in the level of liquidity proxies for investment grade bonds carries over to measures of their second moments, detailed in Table 5 below. The second moments of the liquidity proxies are captured by the standard deviation of dollar volume and number of trades. The average value of the standard deviation of volume is higher for investment grade bonds, compared with speculative grade bonds for both “all trades” and “institutional trades”, with the single exception first quartile “all trades” in speculative grade bonds. The converse is true for standard deviation of number of trades in the “institutional trades” category, although the ranking reverses for the “all trades” category. Higher dispersion among the measures of liquidity risk for investment grade bonds is also demonstrated by wider interquartile ranges for both measures, with the exception of the number of trade- measure for “institutional trades”.

The higher volatility of trading activity in the investment grade bond market may be driven by the clientele effect (see Merton (1987) and Chordia et al. (2001)), where more volatile trading activity is an indication of a more heterogeneous clientele. As discussed above, investment grade bonds are more likely to be held by “buy-to-hold” pension and mutual funds and insurance companies as they face regulatory constraints that curtail their investment in speculative grade bonds (Bessembinder and Maxwell (2008)) and Ellul et al. (2011)). Further, investment grade bonds are a more approachable lower risk investment for individual retail investors, whilst speculative grade bonds tend to fall into the portfolios of hedge funds and other sophisticated opportunistic investors.

The higher variability in the volatility of number of trades for speculative grade bonds is likely to be driven by the presence of clustering of trading activity, which gives rise to higher trade volatility. Speculative grades are more sensitive to firm-specific information whilst investment grade bonds are more substitutable (Ronen and Zhou (2013)). Hence, speculative grade bonds are subject to more event-driven trading around, for example, earnings announcements, giving rise to clustering of trades.

Table 5 Summary Statistics on the Variability of Liquidity Proxies
The table contains summary statistics for the two measures of variability of liquidity used in this paper. Panel A details the average values of the standard deviation of daily dollar volume and the standard deviation of number of trades per day for investment grade bonds, separately for each trade type, "all trades" and "institutional trades". Panel B reports the same for speculative grade bonds.

	All Trades		**Institutional Trades**	
Quartile	Volume Volatility	Volatility Nr. Trades	Volume Volatility	Volatility Nr. Trades
Panel A: Investment Grade Bonds				
1	1,092	3	2,445	2
2	2,814	5	3,896	2
3	4,406	9	5,381	3
4	9,296	22	10,240	6
Panel B: Speculative Grade Bonds				
1	1,373	3	1,464	2
2	2,023	5	2,058	3
3	2,919	9	2,936	4
4	6,762	19	6,908	7

In addition to the liquidity proxies and their standard deviations, I investigate the relationship between long run price impacts and three additional characteristics; return volatility and two bond specific characteristics determined and fixed at issuance; original issue size and maturity. The summary statistics for these characteristics are reported in Table 6 below.

In comparing the quartile averages across the two credit grades, the differences in the three characteristics are consistent with what is expected for riskier, lower credit quality securities: speculative grade bonds have, on average, higher return volatility, smaller issue size and shorter maturities. On average, maturities are shorter for speculative grade bonds in each quartile, with the exception of the first quartile, where speculative grade bonds have slightly longer maturities. Hence, on average, investors in speculative grade debt are not willing to commit capital for as long a time period as for investment grade bonds. Issue sizes can be expected to be smaller for speculative grade bonds, as a large fraction of the potential investors in the corporate bond market have regulatory restrictions on their ability to invest in this riskier debt category (Ellul et al. (2011)). It is likely that these restrictions would, to some extent, reduce the demand for riskier debt in the market place, resulting in smaller issue sizes. The occurrence of higher return volatility for speculative grade bonds is consistent with earlier findings; see for example Bao and Pan (2013) who document that bonds with lower credit ratings are more volatile.

Within each rating category, there is more variability in the bond specific characteristics for investment grade bonds, as measured by the interquartile range. Hence, investment grade bonds constitute a more heterogeneous sample measured by this set of three bond characteristics.[30] In comparing the variability of the characteristics within the two trade types, higher dispersion in the "all trades" category is an expected result of the exclusion of trades with less than 100 bonds for the "institutional trades" category; this truncates trade observations in the left tail of the distribution and reduces more extreme values for the "institutional trades" category.

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[30] Speculative grade bonds may also have more variability in characteristics not measured here, such as in option features.

For investment grade bonds, there is approximately 80% of overlap in the number bonds in the “all trades” and “institutional trades” samples, which introduces some variability in the characteristics across the two trade categories. As discussed above, some bonds are dropped from the “institutional trades” sample as they do not have enough institutional sized observations for the estimation of the VAR model. All of the bond characteristics, except for the average principal are higher in the “all trades” categories, implying that some bonds with relatively small original issue sizes have been eliminated due to the lack of institutional trading in the issues. Conversely, the sample of speculative grade bonds is identical across the two trade categories implying that the bond specific characteristics are identical, given that these attributes are fixed at issuance, but the daily return volatility is higher for “all trades”. This is a natural result from the construction of “institutional trades” sample; whilst the sample of bonds is identical between the two trade categories, the time series of trades and hence returns can be different, as for “institutional trades” only trades with more than 100 bonds are retained in the sample.

Table 6 Summary Statistics of Bond Characteristics

The table contains summary statistics for the bond specific characteristics analysed in this paper. Panel A details the average values of return volatility, issue size and maturity for investment grade bonds, separately for each trade type, "all trades" and "institutional trades". Panel B reports the same for speculative grade bonds.

	All Trades			**Institutional Trades**		
Quartile	Return Volatility	Issue size ($m)	Maturity	Return Volatility	Issue size ($m)	Maturity
Panel A: Investment Grade Bonds						
1	1.005	254	5.676	0.757	416	5.182
2	1.567	608	10.000	1.168	682	9.921
3	2.379	964	13.452	1.689	1,028	-
4	4.976	2,018	28.145	3.699	2,224	25.063
Panel B: Speculative Grade Bonds						
1	1.374	346	6.208	1.087	346	6.208
2	1.967	530	8.700	1.593	530	8.700
3	2.568	865	10.000	2.189	865	10.000
4	3.936	1,523	15.333	3.167	1,523	15.333

4. Results

In what follows, the magnitude and significance of the contemporaneous and long-run price impacts estimated using equations 2 and 4, respectively, are examined. The results are stratified by credit rating; following previous literature (see for example, Bessembinder et al. (2008), Edwards et al. (2007) and Bao et al. (2011)) the price impacts are analysed separately for investment grade and speculative grade bonds. The results are further segmented by clientele by analysing the price impacts in two trade types: "all trades" and "institutional trades". The comparability of the price impacts in these categories is ensured by only considering shocks based on one standard deviation of the "all trades" order flow equation residuals. On average, the size of this shock is $700,000, which is approximately 50% of the size of a one standard deviation shock to institutional order flow.

4.1 The Contemporaneous Price Impact of Order Flow

As detailed in Table 7 below, the proportion of bonds with a significant (at the 5% level) contemporaneous price impact from a shock to signed volume is high, regardless of whether "all trades" or only "institutional trades" are considered, and it ranges from 83% and 91% across credit grades. The highest proportion occurs for speculative grade bonds (97.1%), when all trades of the bonds are analysed. It is also worth noting that within the "all trades" category, the size of the impact is strikingly similar across credit grades and across all bonds and significant bonds; it ranges between 11.2 and 12.4 bps for a one standard deviation shock to order flow. Hence, there seems to be little heterogeneity in terms of contemporaneous price impacts across credit grades. An interesting contrast is provided by the comparison of "all trades" and "institutional trades" for both credit grades. When only institutional trades are considered, the magnitude of the contemporaneous price impact is nearly halved for investment grade bonds, whilst for speculative grade bonds, the size of the impact is largely unchanged with a reduction of less than 2 bps. A reason behind the decrease in the price impact for investment grade bonds and the relative stability in the price impact for speculative grade bonds may be found in the prevalence of retail trades in the former rating category.

Table 7 Contemporaneous Price Impact

The table contains results for the average contemporaneous price impacts separately for investment and speculative grade bonds. The table is divided into two according to trade type, "all trades" and "institutional trades" and within each the results are reported separately for both credit grades; Panel A for investment grade bonds and Panel B for speculative grade bonds, and finally Panel C for all bonds in the sample. The contemporaneous price impact is captured by the coefficient on the contemporaneous trade term in the estimation of a VAR(3,3,3,15) of bond returns and signed volume and from a one standard deviation shock of signed buy volume. The model is estimated separately for individual bonds, and separately for the trade categories, "all trades" and "institutional trades".

All Trades					Institutional Trades				
			Average Contemporaneous Impact					Average Contemporaneous Impact	
Nr. Bonds	Nr. Significant	Significant bonds, %	All bonds	Significant bonds	Nr. Bonds	Nr. Significant	Significant bonds, %	All bonds	Significant bonds
Panel A: Investment Grade Bonds									
1,079	974	90.269	0.112	0.117	876	718	81.963	0.064	0.071
Panel B: Speculative Grade Bonds									
69	67	97.101	0.121	0.124	69	65	94.203	0.103	0.108
Panel C: All Bonds									
1148	1,041	90.679	0.112	0.118	945	783	82.857	0.067	0.074

Ronen and Zhou (2013), in testing the relative efficiency of corporate bond and equity markets, argue that the pooling of retail and institutional sized trades in the analysis of information efficiency confounds inference. When retail trades are included the authors find that equity markets appear to lead corporate bond markets in information revelation around earnings announcements. When retail trades are excluded, the lead disappears and in some cases, the corporate bond market is found to be the premier venue of information revelation. Whilst the research question in this study is different from that of Ronen and Zhou (2013), similar conclusions can be drawn here. In comparing the contemporaneous price impacts across "all trades" and "institutional trades" for investment grade bonds, the inclusion of noisy retail trades leads to higher price impacts. These higher price impacts point to the conclusion that the investment grade bond market is less liquid for retail traders than it is for institutional traders, where the contemporaneous price impacts are considerably lower. This dichotomy of liquidity is consistent with the extant literature on transactions cost for the two segments of the corporate bond market. Bessembinder et al. (2006) and Edwards et al. (2007) document that transaction costs are decreasing in trade size; smaller sized retail trades face higher trade execution costs than institutional trades. This implies that the corporate bond market for retail investors is less liquid than for institutional investors. The lower transaction costs for institutional investors could stem from dealers' search for repeat business by giving better terms of trade to professional investors; inventory management considerations and higher sophistication regarding the opaque corporate bond market on the part of the institutional investors (see Bessembinder et al. (2006) and Edwards et al. (2007)). Extending this rationale to speculative grade bonds; the relative stability of the price impact between the two trade categories can be explained through the relative paucity of retail sized trades in this segment of the corporate bond market.

Another potential driving force behind the lower contemporaneous price impact of institutional trades in investment grade bonds is informational asymmetry and the delayed dissemination of information. If institutional investors are trading the bonds for informational reasons, that is, they possess novel information about the bond or the issuing company, the information embedded in the signed trading volume may not be revealed to the market at once, it may take time for other market participants to recognize and act upon the informational content in the trade. Consequently, in this case, we would expect to see lower contemporaneous price impacts and higher long run price impacts as other market participants learn from trading, therefore aiding information revelation over time.

4.2 The Long-run Price Impact of Order Flow

As described by Hasbrouck (1991), long-run price impacts from trading are driven by information. If a trade reveals new information to the market place, it should have a permanent impact on asset prices. Hence, the long run price impact is an economically interesting quantity to measure, more so than the transient contemporaneous price impact, as only information has the ability to permanently change asset prices.

The price impact of a shock to order flow can be illustrated diagrammatically using the cumulative impulse response function. Figure 1 below illustrates some common shapes of the cumulative impulse response function among the 1,148 bond studied in this paper. The long-run price impact is calculated over 40 trades; however, as Figure 1 illustrates, the permanent level of the impact is typically reached several trades prior. For example, for the bond in the top panel, the initial, contemporaneous impact is high at approximately 18 bps, the convergence to the level of the permanent price impact is rather rapid; the bond reaches the long-run price impact of approximately 10 bps after five trades.

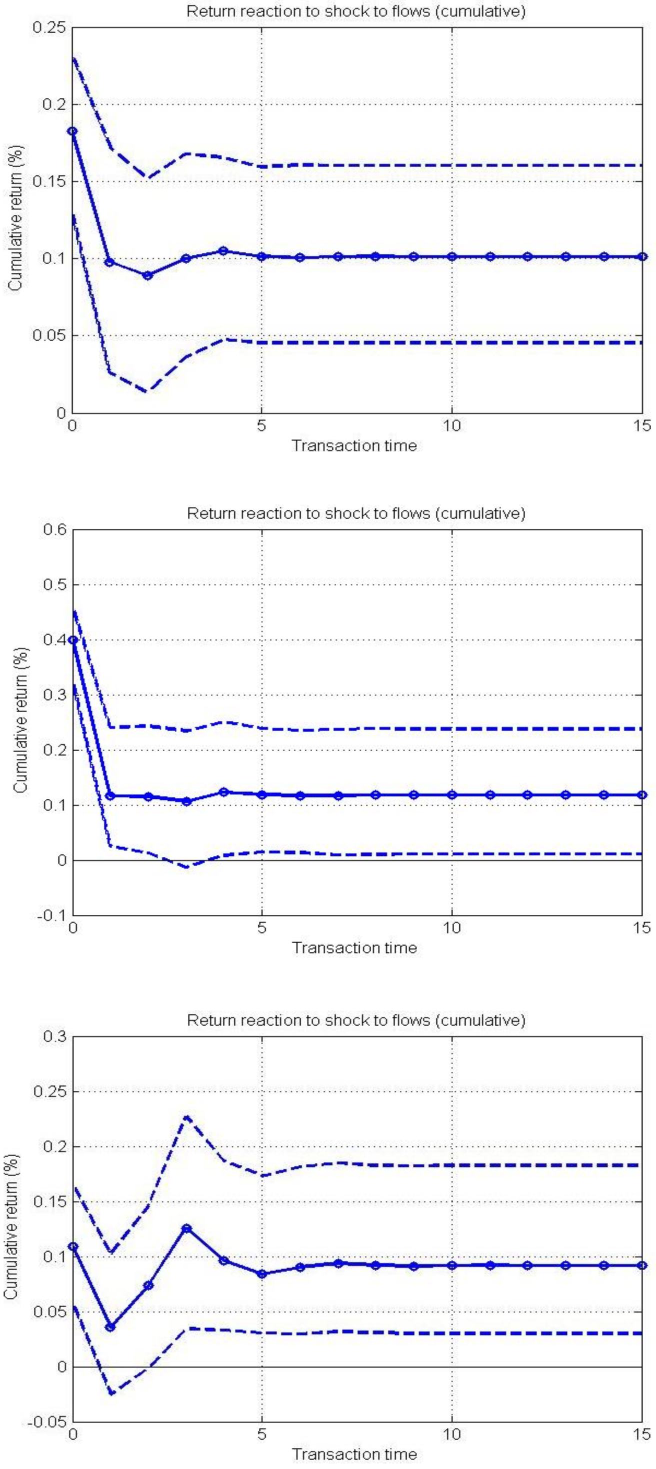

Figure 1 The Cumulative Impulse Response Function, the process of price adjustment
The figure depicts the process of cumulative price adjustment for three representative bonds for a one standard deviation shock to order flow. The return adjustment is in percentage points, and it is illustrated for 15 transactions. A 95% confidence interval for the cumulative impulse response function is also presented.

Table 8 below details the significance and magnitude of the long run price impact from a shock to order flow for both investment and speculative grade bonds. The highest proportion of significant, permanent price impacts from trading occur when only institutional trades are analysed; 32.5% and 52.2% of investment and speculative grade bonds, respectively. For “all trades” the percentages are lower at 15% and 34.8% respectively. Even though these proportions are lower than those for the transient contemporaneous impact, they are economically meaningful and above the significance level for the test (5%).

Further insights can be gleaned from comparisons of price impacts across credit grades. Regardless of trade type, speculative grade bonds have a higher proportion of bonds with significant permanent price impacts and these impacts are higher in magnitude in comparison to investment grade bonds. It can be argued that high yield bond prices are more sensitive to the presence of asymmetric information, as trading in lower grade bonds is likely to be driven by individual issuer characteristics and firm fundamentals than trading in investment grade securities, which are more substitutable and traded more on bond characteristics such as duration (Ronen and Zhou (2013)). Hence, trades in speculative grade bonds are perhaps more likely to reveal new information to the market place. Further, superior information regarding future cash flows is particularly valuable in a deteriorating financial situation; in a market with asymmetric information, trades in securities with higher risks of a credit rating downgrade or default are more likely to cause a price impact as market participants aim to glean more information from the order flow. The result that bonds with lower credit ratings are likely to be subject to more informed trading is consistent with Han and Zhou (2013) who find that measures of information asymmetry are higher for lower rated bonds.

The separation of "all trades" and "institutional trades" was designed to segment the market so as to better capture the price impact of the trading activity of institutional investors. Institutional investors can be described as more sophisticated; they have the economies of scale to access multitudes of company information, including meetings with CEOs, CFOs and company board members, the manpower to analyse and forecast cash flow information to assess the future profitability and financial stability of the company. According to market microstructure theory (Easley and O'Hara (1987)) informed traders are likely to trade in large positions to take advantage of their superior information. This conclusion seems to hold for the corporate bond markets; the estimated long-run price impacts for institutional trades are strikingly high compared to "all trades" for both credit grades. For investment grade bonds the size of the significant price impact increases from 5.5 to 12.5 bps (approximately 2.3 times) moving across the trade categories. For speculative grade bonds the increase is smaller, from 9.4 to 17.5 bps (nearly 1.9 times). The size of these long-run price impacts is compatible with what has been documented for other asset a markets. For a representative stock, Ames Department Store, Hasbrouck (1991) reports the permanent long-run price impact of approximately 18 bps. In Pasquariello and Vega (2007), the price impact of a shock ranges between 2.86 and 10.4 bps on Treasuries of varying maturity. However, it should be noted that these price impacts are not explicitly comparable as the sizes of the shocks have not been standardized.[31]

Han and Zhou (2013) argue that the breaking of up of large block trades into smaller trades in order to minimize price impact, common practice in equity markets, may not be as prevalent in the corporate bond markets. This is also evidenced by lower transaction costs

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[31] For example, in Hasbrouck (1991) the size of the shock is equal to one buy trade. The size of the shock in Pasquariello and Vega (2007) is not explicitly reported.

for larger trades; Bessembinder et al. (2006) document that one-way transaction costs are between 5 to 8 bps for institutional sized trades after the introduction of TRACE. Edwards et al. (2007), find that small trades experience the highest transactions costs at 92 bps, medium sized trades have execution costs of 18bps and large trades of 8bps. However, the size of the price impacts estimated in this paper, in particular for speculative grade bonds, may provide a rational for order splitting in the corporate bond market.

The difference in magnitude between the price impacts of investment and speculative grade bonds in both trade categories could be driven by the proportion of informed traders within each rating class. According to Hasbrouck (1991), the magnitude of the price impact is a positive function of the proportion of informed traders in the market. As discussed above, the speculative grade market likely consists of more sophisticated institutional investors than the market for investment grade bonds, and therefore the magnitude of the long run price impact for speculative bonds is expected to be higher.

Table 8 Long-run Price Impact
The table contains results for the average long-run price impacts separately for investment and speculative grade bonds. The table is divided into two according to trade type, "all trades" and "institutional trades" and within each the results are reported separately for both credit grades; Panel A for investment grade bonds and Panel B for speculative grade bonds, and finally Panel C for all bonds in the sample. The long run price impacts are the cumulative impulse response functions from the estimation of a VAR(3,3,3,15) of bond returns and signed volume and are obtained from one standard deviation shock of signed buy volume. The model is estimated separately for individual bonds, and separately for the trade categories, "all trades" and "institutional trades".

All Trades					Institutional Trades				
Nr. Bonds	Nr. Significant	Significant bonds, %	Average Contemporaneous Impact		Nr. Bonds	Nr. Significant	Significant bonds, %	Average Contemporaneous Impact	
			All bonds	Significant bonds				All bonds	Significant bonds
Panel A: Investment Grade Bonds									
1,079	162	15.014	0.011	0.055	876	285	32.534	0.063	0.125
Panel B: Speculative Grade Bonds									
69	24	34.783	0.049	0.094	69	36	52.174	0.120	0.175
Panel C: All Bonds									
1,148	186	16.202	0.014	0.060	945	321	33.968	0.067	0.130

4.3 Long-run Price Impact and Liquidity

Large and persistent price impacts from the trading process are an indication of a lack of resilience, a component of liquidity, in the market (Hasbrouck (2007)). Given that the presence of significant long run price impacts implies a lack of liquidity, I investigate the relationship between the long run price impacts and two proxies of liquidity. Sorting the long run price impacts by two liquidity proxies, daily dollar trading volume and daily number of trades, I am able to answer the question: are significant long run price impacts correlated with measures of liquidity? The hypothesis for this relationship is an expectation of negative correlation between long-run price impacts and liquidity proxies; higher price impacts are expected to coincide with low trading volume and few trades per day.

The hypothesis of negative correlation between liquidity proxies and long run price impacts can also be approached via the asymmetric information rationale, where more frequently traded stocks face a lower probability of informed trading and hence, lower long run price impact. Easley et al. (2002) demonstrate that the presence of asymmetric information is negatively correlated with average daily trading volume and turnover. The measure of asymmetric information that the authors develop is the probability of information based trading (PIN), which is essentially a ratio of the arrival rate of information-based orders to the arrival rate of all orders. Easley et al. (2002) use observable data on number of trades and volume to estimate unobserved information events and the division of trade between informed and uninformed traders. Abnormal buy or sell volume is interpreted as information based trades. The negative correlation between PIN and the two liquidity proxies in the equity market reinforce the hypothesis that daily trading volume should be negatively correlated with long run price impact, an alternative measure of asymmetric information, in the corporate bond market.

The negative relation between daily dollar volume and the long run price impact is also consistent with the results of Alexander et al. (2000), who argue that bonds with lower liquidity are also bonds with higher adverse selection costs of making markets, again, reinforcing the results that trades in lower liquidity bonds are more informative. Han and Zhou (2013) demonstrate that information asymmetry is higher for bonds with higher credit risk and larger size trades. The results of the current paper are consistent with Han and Zhou (2013); the magnitude of the long-run price impacts is consistently higher for institutional trades and speculative grade bonds in comparison to “all trades” and investment grade bonds, respectively.

The results for the conditional sorts by credit grade and then separately by the two liquidity proxies, presented in Tables 9 and 10 below, are consistent with the hypothesis of negative correlation outlined above; bonds with the highest significant long-run price impacts have also the lowest liquidity. The price impact is generally increasing in illiquidity and significant at the 5% level in particular for the institutional trade category.

It should be noted that the focus of the discussion of the results is mostly on the magnitude and direction of the average long-run price impacts for bonds with a *significant* price impact. The goal of this paper is to examine bonds where trading activity causes a significant long-run price impact. Given that the VAR model is estimated for a large number of bonds in the sample (rather than using a representative security like in Hasbrouck (1991) or three Treasury securities as in Pasquariello and Vega (2007)) heterogeneity among the bonds and their price reactions to trading is likely. Averaging across all bonds, this heterogeneity will mute the average size of the price impact. To that effect, rather than using sorting variables to understand cross-sectional variation when the long-run impact is not different from zero, I focus on the bonds that have significant long-run price impacts; do commonalities arise within this group of bonds that might better help explain what kind of bonds are more likely to have a persistent impact from trading activity?

In Table 9 below, for institutional bond trades, the significant long-run price impact is monotonically increasing as daily trading volume decreases. The highest significant long-run price impact occurs for the lowest quartile of dollar volume; for investment grade bonds the impact peaks at 18.1 bps and for speculative grade bonds at 24.7 bps, an increase of 83 and 113% respectively. For all bond trades, the significant long-run price impacts are also negatively correlated with trading volume, but the relation is only monotonic for speculative grade bonds. This increase in the price impact in illiquidity is found to be significant, at the 5% level, for both investment and speculative grades bonds, with the exception of the increase in the average impact across all bonds in the speculative grade category. For the “all trades”-category, the significance of the trend is less prominent; the magnitude of the price impacts is lower across the board, and whilst the impacts are still increasing in illiquidity only the difference between the fourth and the first quartiles for investment grade bonds is significant. Hence, illiquidity as proxied by low daily trading volume coincides with high long-run price impacts particularly for institutional sized trades.

Table 9 Long-run Price Impact and Volume

The table contains results for long run price impacts of corporate bonds sorted by credit grade and then by quartiles of average daily trading volume. The table is divided into two panels by credit grade, Panel A for investment grade bonds and Panel B for speculative grade bond. Within both credit grades the price impacts are estimated separately for each bond and sorted independently for each trade type, "all trades" and "institutional trades". The second and the fifth columns of both panels report the proportion of significant bonds (in percent), the third and sixth columns detail the size (in basis points) of the long-run price impact averaged across all bonds within the credit grade and trade type and the fourth and the seventh columns report the average size of the long-run price impact for the bonds where the impact is significantly different from zero at the 5% level. The final two rows of each panel report the difference between the fourth quartile and the first quartile values and its t-statistic.

	All Trades			**Institutional Trades**		
Quartile	Significant bonds	Average Long-run Parameter		Significant bonds	Average Long-run Parameter	
		All bonds	Significant bonds		All bonds	Significant bonds
Panel A: Investment Grade Bonds						
1	11.852	0.003	0.069	26.941	0.083	0.181
2	10.741	0.016	0.068	31.963	0.066	0.126
3	13.755	0.011	0.042	34.247	0.048	0.108
4	24.815	0.016	0.046	38.813	0.054	0.100
Q4-Q1	12.963	0.013	-0.022	11.872	-0.030	-0.081
t-stat	3.948	3.113	-3.170	2.666	-3.701	-5.398
Panel B: Speculative Grade Bonds						
1	29.412	0.058	0.106	35.294	0.148	0.247
2	33.333	0.049	0.111	61.111	0.137	0.207
3	29.412	0.036	0.069	41.176	0.097	0.174
4	47.059	0.054	0.085	76.471	0.098	0.118
Q4-Q1	17.647	-0.004	-0.021	41.176	-0.050	-0.129
t-stat	1.077	-0.293	-0.800	2.657	-1.811	-2.544

The results of the conditional sort of price impacts by the average number of bonds per day as an alternative liquidity proxy are consistent with the analysis for daily trading volume; bonds with fewer trades per day have larger long run price impacts. The similarity is to be expected given the high correlation (0.567) between the two sorting variables, as detailed in Table 3 above. The magnitude of the long run price impacts for both liquidity variables are strikingly similar; however, the significance of the differences between the fourth and first quartiles of average daily number of trades is somewhat diminished compared to the test for volume.

Table 10 Long-run Price Impact and Number of Trades
The table contains results for long run price impacts of corporate bonds sorted by credit grade and then by quartiles of average number of trades per day. The table is divided into two panels by credit grade, Panel A for investment grade bonds and Panel B for speculative grade bond. Within both credit grades the price impacts are estimated separately for each bond and sorted independently for each trade type, "all trades" and "institutional trades". The second and the fifth columns of both panels report the proportion of significant bonds (in percent), the third and sixth columns detail the size (in basis points) of the long-run price impact averaged across all bonds within the credit grade and trade type and the fourth and the seventh columns report the average size of the long-run price impact for the bonds where the impact is significantly different from zero at the 5% level. The final two rows of each panel report the difference between the fourth quartile and the first quartile values and its t-statistic.

	All Trades			**Institutional Trades**		
Quartile	Significant bonds	Average Long-run Parameter		Significant bonds	Average Long-run Parameter	
		All bonds	Significant bonds		All bonds	Significant bonds
Panel A: Investment Grade Bonds						
1	11.111	0.007	0.068	17.352	0.067	0.188
2	12.222	0.014	0.062	29.680	0.074	0.169
3	10.037	0.009	0.058	37.443	0.054	0.100
4	27.778	0.015	0.043	47.489	0.056	0.093
Q4-Q1	16.667	0.009	-0.025	30.137	-0.010	-0.095
t-stat	5.005	2.106	-3.436	7.116	-0.098	-5.638
Panel B: Speculative Grade Bonds						
1	29.412	0.059	0.113	29.412	0.138	0.264
2	16.667	0.041	0.094	33.333	0.090	0.223
3	41.176	0.043	0.087	64.706	0.136	0.179
4	52.941	0.055	0.085	88.235	0.118	0.126
Q4-Q1	23.529	-0.003	-0.028	58.824	-0.019	-0.138
t-stat	1.436	-0.223	-1.017	4.346	-0.662	-2.483

For both liquidity proxy sorts, it should be noted that the proportion of significant bonds does not necessarily increase in the direction of increasing magnitude of the price impact. In fact, the proportion of significant bonds is volatile or negatively correlated with the magnitude of the price impact. This inconsistency is likely driven by the difficulty of estimating the VAR model with fewer observations. A decrease in the precision in estimating the VAR model for bonds with few observations, that is, for bonds that fall into the first or second quartile of daily volume and number of trades makes the estimates noisier and significance harder to detect. For example, the standard error of the estimate maybe much higher than the average estimate of the long run impact; it could be the case that in moving down the volume quartiles, we increase the price impact, but we might even further increase the variance, making the significance of the impact harder to detect and causing the proportion of significant bonds to remain low.

4.4 Long-run Price Impact and Liquidity Risk

The relationship between liquidity risk and the long-run price impact is expected to be negative; given that the correlation between the liquidity proxies and their standard deviations is high (0.956 for volume and 0.863 for number of trades) it is to be anticipated that the sort results of long-run price impacts by the variability of liquidity model that of proxies of liquidity. This expectation is further supported by Chordia et al. (2001), who argue that both levels of liquidity measures and their volatility should affect price behaviour.[32] The authors investigate the impact of these second moments of liquidity on expected equity returns and find the relation to be negative and significant; increased variability in trading activity decreases expected returns. This result is perhaps counterintuitive since if agents are assumed to be risk averse in variability in liquidity, higher volatility of liquidity should command higher expected returns. Easley et al. (2002) in explaining expected returns using PIN and other explanatory variables find the variability of trading activity to be negatively related to expected returns. Hence, to the

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[32] Chordia et al. (2001) measure the variability in trading activity using coefficient of variation (CV) of volume and of turnover. In unreported results the authors also use standard deviation of volume and obtain similar results. In unreported results to this paper, using CV of volume and CV of number of trades also produces qualitatively similar results.

extent that permanent, long-run price impacts are factored into expected bond returns, there is an expectation that the relationship between liquidity volatility and long-run price impacts is negative.

The notion that low volatility of liquidity markets see higher long-run price impacts from trading also harks back to the seminal Kyle (1985) model, where the demand (order flow) of informed traders is a function of the variance of the demand of noise trades. Informed traders, acting strategically, use the variability in order flow to hide their own trades, so as not to reveal information that leads to adverse price movements against them. The noisier the market, the better the informed trades can hide their trades and the greater the opportunity for them to make profits. Hence, the presence of traders with superior information acting strategically also gives rise to the suggested hypothesis; long-run price impacts are higher when the volatility of liquidity is low.

The results from the conditional sorts of long-run price impacts by the standard deviation of volume and number of trades are consistent with the hypothesis of negative correlation discussed above and analogous to the results with volume and number of trades as the conditional sort variables. In particular, the magnitude and direction of the long-run price impacts for institutional trades provide compelling support, a result consistent with notion that institutional investors harbour superior information and that their trades are more likely to reveal novel information. The average long run impacts for “all bonds” and for “significant bonds” are both significantly increasing when standard deviation of volume decreases. The significant price impact approximately doubles for both credit grades as we move from the highest standard deviation quartile to the lowest, from 11.2 bps to 24.7 bps for speculative grade bonds and from 9.7 bps to 18.9 bps for investment grade bonds. The difference in the high-low quartile sort for the standard deviation of number of trades is similar both in magnitude and significance.

However, the sort results for “all trades” are somewhat inconclusive. The difference in the price impact is significantly different from zero only for investment grade bonds, for both standard deviation of volume and number of trades. Further, the direction of the price impact is reversed for “all bonds” in the standard deviation of volume sort, with high standard deviation of volume recording the highest price impact. However, the actual magnitude of the impact across quartiles is very low, approximately 1-2bps, and is as such less economically meaningful.

Table 11 Long-run Price Impact and Standard Deviation of Volume

The table contains results for long run price impacts of corporate bonds sorted by credit grade and then by quartiles of the standard deviation of volume. The table is divided into two panels by credit grade, Panel A for investment grade bonds and Panel B for speculative grade bond. Within both credit grades the price impacts are estimated separately for each bond and sorted independently for each trade type, "all trades" and "institutional trades". The second and the fifth columns of both panels report the proportion of significant bonds (in percent), the third and sixth columns detail the size (in basis points) of the long-run price impact averaged across all bonds within the credit grade and trade type and the fourth and the seventh columns report the average size of the long-run price impact for the bonds where the impact is significantly different from zero at the 5% level. The final two rows of each panel report the difference between the fourth quartile and the first quartile values and its t-statistic.

	All Trades			**Institutional Trades**		
Quartile	Significant bonds	Average Long-run Parameter		Significant bonds	Average Long-run Parameter	
		All bonds	Significant bonds		All bonds	Significant bonds
Panel A: Investment Grade Bonds						
1	14.074	0.007	0.074	29.224	0.091	0.189
2	10.000	0.013	0.057	31.507	0.064	0.125
3	12.639	0.011	0.045	34.247	0.046	0.099
4	24.444	0.015	0.045	36.986	0.049	0.097
Q4-Q1	10.370	0.009	-0.030	7.763	-0.042	-0.092
t-stat	3.082	2.008	-4.222	1.732	-4.307	-6.225
Panel B: Speculative Grade Bonds						
1	29.412	0.061	0.106	35.294	0.148	0.247
2	38.889	0.043	0.089	61.111	0.138	0.200
3	35.294	0.038	0.081	47.059	0.106	0.185
4	35.294	0.055	0.096	70.588	0.088	0.112
Q4-Q1	5.882	-0.006	-0.011	35.294	-0.060	-0.135
t-stat	0.367	-0.369	-0.365	2.204	-2.158	-2.665

Table 12 Long-run Price Impact and Standard Deviation of Number of Trades

The table contains results for long run price impacts of corporate bonds sorted by credit grade and then by quartiles of the standard deviation of number of trades per day. The table is divided into two panels by credit grade, Panel A for investment grade bonds and Panel B for speculative grade bond. Within both credit grades the price impacts are estimated separately for each bond and sorted independently for each trade type, "all trades" and "institutional trades". The second and the fifth columns of both panels report the proportion of significant bonds (in percent), the third and sixth columns detail the size (in basis points) of the long-run price impact averaged across all bonds within the credit grade and trade type and the fourth and the seventh columns report the average size of the long-run price impact for the bonds where the impact is significantly different from zero at the 5% level. The final two rows of each panel report the difference between the fourth quartile and the first quartile values and its t-statistic.

	All Trades			**Institutional Trades**		
Quartile	Significant bonds	Average Long-run Parameter		Significant bonds	Average Long-run Parameter	
		All bonds	Significant bonds		All bonds	Significant bonds
Panel A: Investment Grade Bonds						
1	12.963	0.006	0.066	18.265	0.067	0.186
2	10.370	0.014	0.073	32.877	0.076	0.152
3	13.011	0.011	0.050	34.703	0.057	0.122
4	24.815	0.014	0.041	46.119	0.051	0.083
Q4-Q1	11.852	0.008	-0.025	27.854	-0.016	-0.102
t-stat	3.559	1.817	-3.852	6.536	-0.153	-6.294
Panel B: Speculative Grade Bonds						
1	29.412	0.058	0.113	35.294	0.148	0.259
2	16.667	0.034	0.080	33.333	0.065	0.141
3	41.176	0.048	0.093	64.706	0.147	0.194
4	52.941	0.059	0.085	82.353	0.125	0.141
Q4-Q1	23.529	0.001	-0.028	47.059	-0.023	-0.118
t-stat	1.436	0.060	-0.994	3.174	-0.780	-2.276

4.5 Long-run Price Impact and Return Volatility

As discussed above, liquidity and long-run price impacts are negatively related; price impacts increase as bonds have lower liquidity, as measured by daily dollar volume and number of trades. Given that the sample correlation between return standard deviation and the liquidity proxies is negative (-0.298 with volume and -0.126 with number of trades), therefore the relationship between return volatility and long-run price impacts is expected to be positive – an increase in return volatility should result in higher price impacts. The presence of asymmetrically informed traders and the likelihood of information based trading is also expected to increase in return volatility, as Easley et al. (2002) demonstrate that in equity markets, PIN is positively correlated with the volatility of asset returns. This hypothesis is also consistent with results from Hasbrouck (1991) for the equity markets.

The results are particularly compelling for the “institutional trades” category. For both credit grades, the increase in the price impact from the first to the fourth return volatility quartile is significant. This is the case for both “all bonds” and “significant bonds”. Whilst the magnitude of the impact is larger for speculative grade bonds, the long-run price impact is monotonically increasing in return volatility for investment grade bonds. Hence, the results are consistent with the above hypothesis. For the “all trades” the lack of significance is again notable, only significant investment grade bonds register a significant increase in the long-run price impact as return volatility increases.

Table 13 Long-run Price Impact and Return Volatility

The table contains results for long run price impacts of corporate bonds sorted by credit grade and then by quartiles of return volatility. The table is divided into two panels by credit grade, Panel A for investment grade bonds and Panel B for speculative grade bond. Within both credit grades the price impacts are estimated separately for each bond and sorted independently for each trade type, "all trades" and "institutional trades". The second and the fifth columns of both panels report the proportion of significant bonds (in percent), the third and sixth columns detail the size (in basis points) of the long-run price impact averaged across all bonds within the credit grade and trade type and the fourth and the seventh columns report the average size of the long-run price impact for the bonds where the impact is significantly different from zero at the 5% level. The final two rows of each panel report the difference between the fourth quartile and the first quartile values and its t-statistic.

	All Trades			**Institutional Trades**		
Quartile	Significant bonds	Average Long-run Parameter		Significant bonds	Average Long-run Parameter	
		All bonds	Significant bonds		All bonds	Significant bonds
			Panel A: Investment Grade Bonds			
1	12.963	0.006	0.033	32.877	0.027	0.053
2	15.185	0.010	0.045	35.160	0.047	0.091
3	18.587	0.020	0.055	31.963	0.064	0.131
4	14.444	0.010	0.080	31.963	0.111	0.229
Q4-Q1	1.482	0.004	0.047	-0.913	0.084	0.175
t-stat	0.501	0.865	6.197	-0.204	7.161	12.187
			Panel B: Speculative Grade Bonds			
1	11.765	0.030	0.100	41.176	0.061	0.095
2	38.889	0.045	0.081	55.556	0.126	0.173
3	64.706	0.069	0.084	70.588	0.183	0.233
4	23.529	0.054	0.132	47.059	0.110	0.165
Q4-Q1	11.765	0.024	0.032	5.882	0.049	0.070
t-stat	0.911	1.561	0.707	0.346	2.077	2.122

4.6 Long-run Price Impact and Bond Characteristics

The two bond specific characteristics that form the basis of further conditional sorts of the long-run impact are issue size and time to maturity both measured at the time of issuance. Bonds with smaller issue sizes are expected to have lower trading volume and a less trades per day; as there is simply less principal to trade. Hence, ceteris paribus, bonds with smaller issues trade less frequently and are more illiquid. The time to maturity of a bond and its liquidity have been found to be inversely related in the existing literature; as a bond becomes more seasoned, it tends to settle into buy & hold investors' portfolios (e.g. pension funds). With time, less of the issue is available to trade and the bond becomes more illiquid, see for example Sarig and Warga (1989), Alexander et al. (2000) and Hotchkiss and Jostova (2007). Smaller issue size and a longer time to maturity indicate lower liquidity. Bonds with higher price impacts are also bonds with lower liquidity.

To analyse the effect of maturity on the long-run price impact, I use time to maturity measured at issuance to sort the price impacts within each credit grade. In the extant literature, bond maturity is often linked to liquidity; as a bond gets more seasoned it settles into buy-and-hold investor portfolios reducing the issue's liquidity as there is less of the original issue size left in circulation (Sarig and Warga (1989) and Alexander et al. (2000)). Given that at issuance, a bond's age and time-to-maturity are correlated, time to maturity at issuance is an appropriate measure to capture this pricing behaviour related to a bond becoming more seasoned, implying that long maturity bonds should also be more illiquid (Sarig and Warga (1989)).

The sample correlations detailed in Table 3 above point to similar conclusions; maturity has low negative correlation with liquidity proxies and their second moments (from -0.139 with volume and to -0.235 with standard deviation of number of trades) implying that illiquidity increases with maturity. As the primary goal of the conditional sorting methodology is to systematically link bond specific characteristics within the two rating grades to long-run price impacts, the negative sample correlation between the sort variables of maturity and liquidity proxies gives guidance on the relation between maturity and long-run price impacts; the conjectured directionality is positive, the longer the maturity, the higher the price impact.

The positive relationship between bond maturity and long-run price impact also garners support from the relationship between bond return volatility and maturity, which in the sample correlations in Table 3 is positive at 0.342. Further, Bao and Pan (2013) document that bond volatility is higher for longer maturity bonds. For the equity market, Easley et al. (2002) link PIN with equity return volatility and find a positive correlation, implying that asymmetric information based trading is more prevalent for higher volatility equities. Ronen and Zhou (2013), in investigating what types of bonds attract the most trading from institutions after earnings announcements find that 80% of these bonds are long maturity bonds. Further, given the results for long-run price impacts sorted by return volatility within each credit grade, discussed above for this paper, it is likely that price impacts are indeed increasing in maturity.

Table 14 below shows that the increasing relationship between maturity and long-run price impact is strong and statistically significant for both credit grades in the institutional trade size category. The mean impact for significant bonds recorded for the fourth quartile of speculative grade bonds is the highest for all sort variables; the average significant long-run price impact for speculative grade bonds, with an average maturity of 15 years is approximately 35 bps. There is no significant directionality in the long-run price impact for speculative grade bonds in the "all trades" category; for all bonds the impact is flat at approximately 5 bps and for significant bonds it is roughly unchanged at 10 bps. For investment grade bonds, the increasing relationship between maturity and long-run price impact from the first to the fourth quartile is significant for both trade types[33]. The absolute magnitudes are lower than for speculative grade bonds, ranging from 4.5 to 7.4 bps in the "all trades" category and approximately from 9 bps to 22 bps for institutional trades. Hence, long-run price impacts are highest for long maturity bonds, low credit rating bonds when the trades are most likely by institutions.

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[33] The third quartile of investment grade bonds when only institutional trades are counted is empty as no investment grade bonds fall into that specific maturity quartile. The bonds that form the third quartile for "all trades", by implication, have only retail sized trades.

Table 14 Long-run Price Impact and Maturity

The table contains results for long run price impacts of corporate bonds sorted by credit grade and then by quartiles of maturity at issuance. The table is divided into two panels by credit grade, Panel A for investment grade bonds and Panel B for speculative grade bond. Within both credit grades the price impacts are estimated separately for each bond and sorted independently for each trade type, "all trades" and "institutional trades". The second and the fifth columns of both panels report the proportion of significant bonds (in percent), the third and sixth columns detail the size (in basis points) of the long-run price impact averaged across all bonds within the credit grade and trade type and the fourth and the seventh columns report the average size of the long-run price impact for the bonds where the impact is significantly different from zero at the 5% level. The final two rows of each panel report the difference between the fourth quartile and the first quartile values and its t-statistic.

	All Trades			**Institutional Trades**		
Quartile	Significant bonds	Average Long-run Parameter		Significant bonds	Average Long-run Parameter	
		All bonds	Significant bonds		All bonds	Significant bonds
			Panel A: Investment Grade Bonds			
1	12.000	0.009	0.045	31.169	0.041	0.093
2	15.778	0.011	0.042	32.527	0.052	0.097
3	8.219	-0.017	0.069	-	-	-
4	19.847	0.022	0.074	36.316	0.115	0.217
Q4-Q1	7.847	0.014	0.029	5.147	0.074	0.124
t-stat	2.493	3.191	4.055	1.111	6.070	8.235
			Panel B: Speculative Grade Bonds			
1	20.833	0.051	0.101	58.333	0.095	0.149
2	35.000	0.040	0.078	55.000	0.126	0.161
3	47.368	0.056	0.096	47.368	0.117	0.181
4	50.000	0.054	0.099	50.000	0.214	0.346
Q4-Q1	29.167	0.003	-0.002	-8.333	0.119	0.197
t-stat	1.324	0.156	-0.063	-0.366	2.911	2.901

Although discussed as a bond specific characteristic in this paper, a bond’s issue size has a meaningful relationship with liquidity. Several studies documenting the relationship between issue size and liquidity find evidence of positive correlation; as the issue size increases liquidity improves, see for example Alexander et al. (2000), Hong and Warga (1998) and Hotchkiss and Jostova (2007). Hotchkiss and Jostova (2007) find that increasing issue size improves liquidity of both credit grades, but this is particularly true for investment grade bonds. The result can be linked to the “inventory paradigm” of Demsetz (1968), Ho and Stoll (1981) and Stoll (1989), according to which liquidity depends on the cost of financing inventories as dealers need to fund the assets (their inventory) on their balance sheets. The longer the bond spends in the inventory, the higher the inventory cost (Crabbe and Turner (1995)) and hence, larger issues that trade more frequently and ease the dealers’ inventory management are expected to have higher liquidity. However, the extant empirical literature does not provide conclusive results on the relationship between issue size and liquidity. Warga (1992), Fridson and Garman (1998) and Crabbe and Turner (1995) do not find evidence in support of the positive correlation between issue size and liquidity. In particular, according to Crabbe and Turner (1995), smaller offering amounts do not command a liquidity premium, implying that investors view large and small issues with similar characteristics as close substitutes. Given the positive correlation between liquidity proxies and the long run price impact documented above, and considering the extent to which small issue sizes imply increased illiquidity, there is indeed a strong supposition that long run price impacts should be decreasing in issue size.

Support for this hypothesis also stems from the asymmetric information literature from the equity markets. In Hasbrouck (1991), the long price impact and size (as measured by the market value of the firm’s equity) are negatively correlated. Further, Easley et al. (2002)

find a higher presence of asymmetric information, as measured by PIN, for smaller issue sizes. However, it should be noted that the measure of size used in this study is not identical to that used for equity markets; size is measured by the market value of the firm's equity whereas here the issue size is the maturity, or par value of the bond issue. The market value of the bond issue can be equal to the par value of the bond or vary far from it, depending on market conditions and level of interest rates. However, in additional support to the relation between issue size and asymmetric information, Lu et al. (2010) find that correlations between three different measures of asymmetric information from the equity markets are negatively correlated with bond issue size. Hence, the ex-ante belief that bonds with smaller issue sizes are exposed to more informed trading and as a result, have higher price impacts emerges again.

The results from the conditional sort of long-run price impacts by issue size within each credit grade are somewhat inconclusive. The only clear, significant negative correlation between long-run price impacts and issue size occur for investment grade bonds in both trade categories. The trend is particularly clear for the "institutional trades" category, where the long-run price impact is monotonically increasing, as issue size decreases. For speculative grade bonds long-run the difference between the highest and lowest issue size quartiles is not significant. Hence, for speculative grade bonds, issue size is not a particularly informative variable to sort on.

Table 15 Long-run Price Impact and Issue size

The table contains results for long run price impacts of corporate bonds sorted by credit grade and then by quartiles of issue size. The table is divided into two panels by credit grade, Panel A for investment grade bonds and Panel B for speculative grade bond. Within both credit grades the price impacts are estimated separately for each bond and sorted independently for each trade type, "all trades" and "institutional trades". The second and the fifth columns of both panels report the proportion of significant bonds (in percent), the third and sixth columns detail the size (in basis points) of the long-run price impact averaged across all bonds within the credit grade and trade type and the fourth and the seventh columns report the average size of the long-run price impact for the bonds where the impact is significantly different from zero at the 5% level. The final two rows of each panel report the difference between the fourth quartile and the first quartile values and its t-statistic.

	All Trades			**Institutional Trades**		
Quartile	Significant bonds	Average Long-run Parameter		Significant bonds	Average Long-run Parameter	
		All bonds	Significant bonds		All bonds	Significant bonds
			Panel A: Investment Grade Bonds			
1	12.177	0.009	0.069	21.429	0.075	0.176
2	12.121	0.009	0.049	30.846	0.057	0.134
3	10.286	0.013	0.062	35.398	0.062	0.124
4	25.926	0.016	0.047	45.498	0.056	0.092
Q4-Q1	13.749	0.007	-0.021	24.069	-0.019	-0.084
t-stat	4.134	1.582	-3.074	5.547	-0.200	-5.321
			Panel B: Speculative Grade Bonds			
1	33.333	0.051	0.099	44.444	0.107	0.175
2	31.818	0.047	0.087	45.455	0.128	0.200
3	25.000	0.048	0.121	50.000	0.117	0.192
4	47.059	0.051	0.082	76.471	0.127	0.151
Q4-Q1	13.725	0.001	-0.018	32.026	0.020	-0.024
t-stat	0.835	0.064	-0.797	2.054	0.906	-0.870

5. Conclusion

Order flow is an important conduit for information overlooked by traditional asset pricing models. In a market with asymmetrically informed traders, order flow conveys private information that is impounded into asset prices producing a permanent price impact. The importance of order flow has been demonstrated previously for several asset markets, however, this paper marks the first investigating its importance for corporate bonds.

I estimate both the contemporaneous and long-run price impacts of order flow for corporate bonds, segmenting the market by credit grade and investor type. For all trade types, 16% of bonds have a significant long-run price impact from order flow and across these bonds the average impact is 6 bps. For institutional sized trades, approximately 34% of bonds have significant long run price impacts from trading and across these bonds the average impact is 13bps. The higher persistent price impacts for institutional order flow can be interpreted as the result of institutional investors' private information being partially revealed to the market.

These results are particularly useful to market practitioners who are looking to minimize costs of trading. In trading large positions, if the price impact of the trade exceeds transaction costs, order splitting may be optimal. In particular, bonds with lower credit quality, lower liquidity, higher return volatility and longer maturity are shown to consistently have higher price impacts from a shock to order flow and should be traded with care.

6. References

Alexander, Gordon J., Amy K. Edwards and Michael G. Ferri, 2000, The Determinants of Trading Volume of High-Yield Corporate Bonds, *Journal of Financial Markets* 3, 177-204

Bao, Jack, Jun Pan and Jiang Wang, 2011, The Illiquidity of Corporate Bonds, *Journal of Finance* 66, 911-946.

Bao, Jack and Jun Pan, 2013, Bond Illiquidity and Excess Volatility, *Review of Financial Studies* 26, 3068-3103

Bessembinder, Hendrik and William Maxwell, 2008, Transparency and the Corporate Bond Market, *Journal of Economic Perspectives* 22, 217-234

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

Brandt, Michael W. and Kenneth A. Kavajecz, 2004, Price Discovery in the U.S. Treasury Market: The Impact of Order Flow and Liquidity on the Yield Curve, *Journal of Finance* 59, 2623-2654

Chan and Lakonishok, 1995, The Behaviour of Stock Prices Around Institutional Trades, *Journal of Finance* 50, 1147-1174

Chordia, Tarun, Avanidhar Subrahmanyam and V. Ravi Anshuman, 2001, Trading Activity and Expected Stock Returns, *Journal of Financial Economics* 59, 3-32

Crabbe, Leland E. and Christopher M. Turner, 1995, Does the Liquidity of a Debt Issue

Increase with its Size? Evidence from the Corporate Bond and Medium-Term Note Markets, *Journal of Finance* 50, 1719-1734

Demsetz, Harold, 1968, The Cost of Transacting, *Quarterly Journal of Economics* 82, 33-35

Dick-Nielsen, Jens, Peter Feldhütter and David Landon, 2012, Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis, *Journal of Financial Economics* 103, 471-492

Downing, Chris, Shane Underwood and Yuhang Xing, 2009, The Relative Informational Efficiency of Stocks and Bonds: An Intraday Analysis, *Journal of Financial and Quantitative Analysis* 44, 1081-1102

Easley, David, Soeren Hvidkjaer and Maureen O'Hara, 2002, Is Information Risk a Determinant of Asset Returns?, *Journal of Finance* 57, 2185-2221

Easley, David and Maureen O'Hara, 1987, Price, Trade Size and Information in Securities Markets, *Journal of Financial Economics* 19, 69-90

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate Bond Market Transaction Costs and Transparency, *Journal of Finance* 62, 1421-1451

Efron, Bradley and Robert J. Tibshirani, 1998, An Introduction to the Bootstrap, *Monographs on Statistics and Applied Probability 57*, Chapman & Hall/CRC

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad, 2011, Regulatory Pressure and Fire Sales in the Corporate Bond Market, *Journal of Financial Economics* 101, 596-620

Elton, Edwin, Marting J. Gruber, Deepak Agrawal and Christopher Mann, 2004, Factors Affecting the Valuation of Corporate Bonds, *Journal of Banking and Finance* 28, 2747-2767

Evans, Martin D. D. and Richard K. Lyons, 2002, Order Flow and Exchange Rate Dynamics, *Journal of Political Economy* 110, 170-180

Fridson, Martin and Christopher Garman, 1998, Determinants of Spreads on New High Yield Bonds, *Financial Analyst Journal* 52, 28-39

Goldstein, Michael A., Edith S. Hotchkiss and Erik R. Sirri, 2007, Transparency and Liquidity: A Controlled Experiment on Corporate Bonds, *Review of Financial Studies* 20, 235-273

Green, Clifton T., 2004, Economics News and the Impact of Trading on Bond Prices, *Journal of Finance* 59, 1201-1233

Hamilton, James, D., 1994, Time Series Analysis, Princeton University Press

Han, Song and Xing Zhou, 2014, Informed Bond Trading, Corporate Yield Spreads, and Corporate Default Prediction, *Management Science* 60, 675-694.

Hasbrouck, Joel, 1991, Measuring the Information Content of Stock Trades, *Journal of Finance* 46, 179-207

Hasbrouck, Joel, 2007, Empirical Market Microstructure: The Institutions, Economics and Econometrics of Securities Trading, Oxford University Press

Ho, Thomas and Hans Stoll, 1981, Optimal Dealer Pricing under Transactions and Return Uncertainty, *Journal of Financial Economics* 9, 47-73

Hong, Gwangheon and Arthur Warga, 1998, An Empirical Study of Bond Market Transactions, *Financial Analyst Journal* 56, 32-46

Hotchkiss, Edith and Gergana Jostova, 2007, Determinants of Corporate Bond Trading: A Comprehensive Analysis, *working paper*, Boston College

Kyle, Albert, 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-1335

Lee, Charles M. C. and Mark J. Ready, 1991, Inferring Trade Direction from Intraday Data, *Journal of Finance* 46, 733-746

Lu, Chia-Wu, Tsung-Kang Chen and Hsien-Hsing Liao, 2010, Information Uncertainty, Information Asymmetry and Corporate Bond Yield Spreads, *Journal of Banking &Finance* 34, 2265-2279

Luktepohl, Helmut, 2000, Bootstrapping Impulse Responses in VAR Analyses, working paper, Humboldt-Universität

Merton, Robert, C., 1987, A Simple Model of Capital Market Equilibrium with Incomplete Information, *Journal of Finance* 42, 483-510

Patton, Andrew J. and Allan Timmermann, 2010, Monotonicity in Asset Returns: New Tests with Applications to the Term Structure, the CAPM and Portfolio sorts, *Journal of Financial Economics* 98, 605-625.

Pasquariello, Paolo and Clara Vega, 2007, Informed and Strategic Order Flow in the Bond Markets, *Review of Financial Studies* 20, 1975-2019.

Politis, Dimitris N. and Joseph. P. Romano, 1994, The Stationary Bootstrap, *Journal of the American Statistical Association* 89, 1303-1313

Ronen, Tavy and Xing Zhou, 2013, Trade and Information in the Corporate Bond Market, *Journal of Financial Markets* 16, 61-103

Sarig, Oded and Arthur Warga, 1989, Bond Price Data and Bond Market Liquidity, *Journal of Financial and Quantitative Analysis* 24, 367-378

Stoll, Hans, 1989, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *Journal of Finance* 44, 115-134

Warga, Arthur, 1992, Bond Returns, Liquidity and Missing Data, *Journal of Financial and Quantitative Analysis* 27, 605-617

White, Halbert, 1980, A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica* 48, 817-838

Chapter 3

High Frequency Data and Stock-Bond Correlations[34]

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[34] Joint work with Dr Andrew Patton at Duke University

Abstract

Realized measures of volatility have been shown to be important in modelling and forecasting equity, exchange rate, and Treasury bill return volatility. We provide novel evidence on the importance of high frequency measures of volatility and correlation for the corporate bond market. We merge the NYSE's TAQ database on high frequency equity prices with the TRACE database for corporate bonds, and show that the information contained in high frequency data is valuable in modelling the dynamics of the firm-level covariance matrix of bond and stock returns, for over 100 U.S. firms.

1. Introduction

Accurate estimates and forecasts of future correlation are instrumental to optimal portfolio choice as they are critical in the quantification of portfolio risk. Further, examining the correlation between debt and equity is important for our understanding of price formation and the information revelation between corporate bond and equity markets. This paper assesses the value of high frequency estimates of corporate bond volatility and firm-level stock-bond correlations for forecasting future volatility and correlation. Our empirical findings contribute to the large literature on “realized measures” of volatility, which have been shown to be important in modelling and forecasting equity returns, exchange rates, and Treasury bond volatility,[35] by providing new evidence on their importance for the corporate bond market.

We show, using intraday transaction data from the TRACE (Trade Reporting and Compliance Engine) database for the US corporate bond market that the inclusion of high frequency measures improves corporate bond volatility and correlation estimates beyond the dynamics of standard GARCH (generalized autoregressive conditional heteroskedasticity) and DCC (dynamic conditional correlation) models, due to Bollerslev (1986) and Engle (2002). The results presented in this paper demonstrate that at the weekly frequency, including realized corporate bond volatility in the model for conditional variance leads to significant improvements in fit for 72% of the bonds in our sample. The inclusion of realized correlation improves correlation estimates for approximately 20% of

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[35] For example, for equities, see Shephard and Sheppard (2010), and Hansen et al. (2011), for exchange rates see Andersen et al. (2003) and Shephard and Sheppard (2010), and for Treasury bonds see Andersen and Benzoni (2010) and Cieslak and Povala (2016). See Fleming et al. (2003) for an application showing the value of high frequency data for a portfolio decision involving the S&P 500 index, gold, and a Treasury bond.

stock-bond pairs. A joint test of all three realized measures, realized corporate bond and stock volatility and realized correlation, shows that these measures are significantly different from zero for 89% of firms in the sample. The gains at the daily and monthly frequencies are smaller though still substantial; with 83% and 70% of firms indicating that including realized volatilities and correlations significantly improves estimates of the conditional covariance matrix.

We compile the realized volatility and correlation measures and estimate our time series models over three different holding periods, daily, weekly and monthly; these frequencies trade off the improved accuracy of realized measures over longer frequencies against loss of observations for the estimation of time series models. Further, we account for the effects of asynchronous trading and microstructure noise present at the highest frequency by using refresh time sampling (following Barndorff-Nielsen et al. 2011) to synchronize stock and bond data. Our results are robust to variations in the treatment of the trend in volatility and mean for corporate bonds, to differences in accounting for abnormal trading around newly issued and maturing bonds, to the specific refresh time sampling scheme used, and to the use of all versus only “large” trades in model estimation. The addition of a liquidity measure (log transaction volume or Amihud (2002) measure) as an explanatory variable increases the importance of realized correlation.

Our paper is related more generally to research that investigates the relationship between debt and equity with respect to informational efficiency across the two markets. These studies estimate contemporaneous correlations between the two asset classes but do not model the time series dynamics of correlation. With theoretical underpinnings in structural models of credit risk (Merton 1974), and as noted by Kwan (1996), contemporaneous correlation between corporate bonds and stocks can reveal the driver of firm-specific news: information about a firm's expected asset value drives stock and bond prices in the same direction, resulting in positive correlation, whereas information about the variance of a firm's asset value will move stock and bond prices in opposite directions leading to negatively correlated returns.[36]

Kwan (1996) provides insight to firm level correlations between a company's debt and equity; he finds that contemporaneous stock return – bond yield correlation is negative (which implies positive correlation between bond *returns* and equities) indicating that the firm-specific information driving both stocks and bonds is related to the mean of the firm's asset value as opposed to its variance. [37] Stratifying the sample by credit rating, the correlation between AAA rated bonds and the firm's equity is effectively zero, whilst high yield bonds and the firm's equity are significantly correlated.

More recently, Downing et al. (2009) examine a comprehensive TRACE sample of hourly and daily bond return for both investment grade and high yield bonds and find that for bonds rated BBB or lower, contemporaneous correlation between equity is positive and significantly different from zero unlike for higher rated investment grade bonds (A to AAA) which the authors find to be contemporaneously uncorrelated. The results are consistent with predictions from theoretical models such as Merton (1974): bond holders of lower

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[36] In the Merton (1974) model, the value of debt is determined by the difference between the value of a riskless bond and a put option, and equity is viewed as a call option on the firm's assets. Consequently, both debt and equity increase with asset value, whilst an increase in volatility, which increases the value of both the call and the put options, increases equity value but decreases the value of the debt (Lando (2004)).

[37] Kwan (1996) also estimates cross-serial correlations and finds that the stock market is more informationally efficient, leading the bond market in the discovery of firm specific information.

rated bonds are more likely to take control of the firm in the event of bankruptcy, making high yield bonds more equity-like. Further, they find that for high yield bonds, equity returns lead bond returns whilst for investment grade bonds no lead-lag relationship with equity returns exists. Bao and Hou (2013) examine the comovement of stocks and corporate bonds using hedge ratios, the relative returns of corporate bonds and equities, derived from the Merton (1974) model. They find that bonds with higher credit risk as well as bonds maturing relatively late in the firm's debt maturity structure have the highest levels of comovement with equities. Our analysis builds on this work to consider the *dynamic* contemporaneous correlation between bond and stock returns, and analyses the value of high frequency information for capturing changes in this correlation over time.

Better estimates of stock-bond correlations are also valuable to investors known as "dual holders"; institutional investors, company CEOs and especially large financial conglomerates, e.g. mutual fund families who hold both debt and equity of the same firm. Recent research suggests that the presence of dual ownership reported is prevalent and economically significant: Bodnaruk and Rossi (2016) estimate that for a given company, dual holders own approximately 10% of outstanding shares, and bond holdings constitute approximately 36% of their total exposure to the firm. These authors find evidence of coordination in the presence of dual holders in targets of mergers and acquisitions, which results in lower equity premia and larger bond abnormal returns both of which are more pronounced when target debt is non-investment grade and the dual holdings are large. Bodnaruk and Rossi (2016) also find that dual holders maximize overall compensation across equity and debt holdings and accept a lower equity premium for parting with their voting rights as they will gain more on their bond holdings. Whilst some coordination between these entities can be interpreted as a breach of fiduciary duty to, for example fund investors, other forms of dual holding can be thought to reduce conflicts of interest between risky asset holders (Jensen and Meckling (1976) and Jensen (1987)).

Previous research has shown a link between corporate bond volatility and illiquidity; in a recent paper Bao and Pan (2013) document that empirical volatilities are higher than the Merton (1974) model would imply. Moreover, they find that this excess volatility is closely related to proxies of illiquidity. More generally, illiquidity is a dominant feature of the corporate bond market; see for example Bessembinder and Maxwell (2008) for an overview. Prior to the implementation of TRACE, corporate bonds traded in an opaque dealer market with little pre- or post-trade transparency. Corporate bond trading is characterized by infrequent trading and high bid-ask spreads; Edwards et al. (2007) report that bonds in their sample trade on average 2.4 times per day (the median is 1.1) and the median bond trades only on 48% of all days in their sample. Corporate bonds trade infrequently also with respect to other fixed income securities; Bessembinder and Maxwell (2008) show that corporate bonds constitute about 3% of total trading activity in fixed income securities compared with 59% for Treasury bonds. The introduction of TRACE has been shown to lower transaction costs (see for example Edwards et al. (2007)), but liquidity remains low and time-varying.

The initiation of TRACE significantly improved the availability of corporate bond transaction data and enabled more accurate measurement of liquidity. Better data combined with the financial crisis of 2008 has brought illiquidity to the forefront of corporate bond market research. Recent efforts have focused on formulating new measures to capture illiquidity at the individual bond level and on assessing the impact of illiquidity on yield spreads, the difference between the yield on a corporate bond and a Treasury bond yield of the same maturity. For example, Bao et al. (2011) find that for investment grade bonds illiquidity is equally important with credit risk in explaining yield spreads in normal times and during the credit crisis illiquidity overshadows credit risk. Dick-Nielsen et al. (2012) document increased liquidity premia for corporate bonds across rating classes during the 2008 crisis whilst the contribution of illiquidity before the onset of the crisis was small. Moreover, illiquidity is one of the leading explanations for the “credit spread puzzle”; the failure of credit risk to fully explain changes yields spreads (see for example Huang and Huang (2003), Collin-Dufresne et al. (2001) and Chen et al. (2007)).

Given the previously documented relationship between illiquidity and excess volatility, we analyse illiquidity as an additional explanatory variable in explaining the time series dynamics of return volatility and stock-bond correlation. Using two liquidity measures, log transaction volume and the Amihud measure, we find that these liquidity proxies are useful in identifying information in realized correlations in particular. For example, including the lagged Amihud measure as a control variable, the proportion of firms for which realized correlation is significant rises to 38% (compared with 20% in the baseline model).

The remainder of the paper is organized as follows. Section 2 describes the corporate bond and equity market data and details how these datasets were merged. Section 3 outlines the methodology used to obtain realized variances, covariances and correlations and explains how these measures are incorporated into time series models. Section 4 reports and discusses the empirical results, Section 5 presents robustness checks and Section 6 provides concluding remarks.

2. Data description

The analysis in this paper relies on merging to two large, messy, databases: the TRACE database for corporate bond prices and the TAQ (NYSE Trades and Quotes) database for equity prices. We describe each of these databases in detail below, as well as the data cleaning rules and filters we apply. In addition to these two databases, we use Mergent's Fixed Income Securities Database (FISD) and Bloomberg to obtain bond characteristics and Standard & Poor's (S&P) credit ratings, and the CRSP database to link the ticker in the TAQ database to a CUSIP, which can be used to match with a bond in TRACE.

2.1 Corporate Bond Data

The source for corporate bond transaction data used in this paper is TRACE, a database created by FINRA (Financial Industry Regulatory Authority) in July 2002. TRACE provides real time pricing information for all market participants. FINRA members (virtually all US broker-dealers) are required to report secondary market transaction information such as price, date and time of execution and trade volume, which is then disseminated across a variety of platforms such as Bloomberg and Reuters, as well as on FINRA's website. The creation of TRACE was a response to calls to make over-the-counter corporate bond markets more transparent; prior to TRACE there was no public dissemination of prices leaving particularly retail investors in the dark with respect to historical pricing and best execution.

The transaction reporting was implemented in stages; beginning with the first phase where transaction information was disseminated for investment grade bonds with an issue size of $1bn or more as well as 50 high yield bonds, a total of 520 securities. The second phase, in place from April 2003, expanded transaction reporting to include investment grade bonds with smaller issue sizes, increasing the set of bonds to 4,650. The third phase expanded the universe to approximately 99% of all public transactions (FINRA, TRACE Fact Book (2015)). Since these initial stages, TRACE has expanded the information it disseminates publicly by including additional variables, such as a buy-sell indicator. More recently, information on primary market transactions, US Agency securities and asset- and mortgage-backed securities has been added into the dissemination requirement.

The version of TRACE used in this paper is “TRACE Enhanced Historical Data” downloadable via Wharton Research Data Services (WRDS). This version of the data provides transaction information to previously non-disseminated bonds (from the early years of the database), uncapped volume information[38], and it provides more detailed identifying information for better filtering of erroneous trades (Dick-Nielsen, (2014)).

Historical TRACE data is known to contain some errors, particularly in the early years of the database and we account for these by implementing standard cleaning filters commonly used in the corporate bond literature (see Dick-Nielsen (2009 and 2014) for details). We delete cancelled, reversed and corrected trades, we eliminate trades where the transaction price includes a commission or a flag for special trade conditions or pricing (such as

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[38] The standard historical TRACE data caps disseminated volumes for large transactions. For investment grade bonds trades larger than $5m were reported as “+5MM” and for high yield bonds trades larger than $1m were reported as “+1MM”.

delayed reporting, odd settlement periods or matrix pricing) and we account for double counting introduced by interdealer and agency trades.[39]

We merge the clean TRACE transaction data with bond characteristics and ratings data from Mergent's FISD. We require that bonds included in the sample have non-missing information on bond ratings and characteristics (such as coupon, maturity and issue date). In addition to the ratings data from FISD we also obtain bond ratings at issuance from Bloomberg. Similar to other empirical studies of corporate bonds, we limit our sample to include fixed rate bonds that are not convertible, exchangeable, putable or callable,[40] and bonds that are not in default or in bankruptcy. We also exclude asset backed and preferred securities, perpetuals, bonds issued in foreign currencies and placed privately. After imposing these conditions, we are left a sample of 14,995 bonds.

In order to be included in our subsequent analysis, we also impose that a bond must be in issuance for 1,000 days in our sample period (July 2002 to December 2013), and must trade on at least 50% of the days they are in issuance. We impose these additional restrictions as the time series models we use in our analysis, described in Section 3.3, require a reasonably long sample of time series observations. Bessembinder et al. (2009) document that in 2006 the average bond trades only on 52 days per year, and so this requirement is indeed a strong

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[39] An agency transaction arises when a broker does not own the bond a customer wants to buy and needs to purchase it from another dealer. This sequence of transactions involves an interdealer trade (reported to TRACE by both FINRA members) and a dealer-customer trade. Hence, TRACE data will contain three identical transaction reports on effectively the same trade.

[40] Following Bao and Hou (2013) we eliminate bonds with fixed-price call options and retain bonds with make-whole call provisions. Make-whole calls are a common tool to improve a firm's financial flexibility and involve redemption of the bond at the maximum of par or the present value of remaining cash flows discounted at a comparable maturity Treasury yield plus a spread, typically between 0 and 50bps. In practice, make-whole calls are rarely exercised and Powers and Tsyplakov (2008) show that the theoretical and empirical impacts of make-whole call provisions on bond prices are negligible.

one. The resulting sample includes 1,479 bonds, or around 10% of the original sample. Comparing the bond identifier, the 9-digit CUSIP, with the 6-digit firm identifier, we find that there are 547 unique firms behind these 1,479 bonds. As we only want to match a single bond to a given stock, if a firm has multiple bonds available for analysis, we choose the bond with the largest overlap with our sample period.

2.2 Equity return data

We match the firms in the TRACE sample with equities in the TAQ database. The TAQ database uses a stock's ticker as its identifier, and this is not an entry in the TRACE database. To overcome this, we match the stock's ticker to its CUSIP using the CRSP database, and then match stock and bond data using the firm-level CUSIP as the common identifier. We are able to match a total of 290 to stocks in the TAQ database. The unmatched CUSIPs belong to private companies, companies not listed on US exchanges and companies which are, typically through corporate actions, no longer in existence.

The TAQ database provides the trades for all individual securities listed on the NYSE, NASDAQ, and AMEX stock exchanges. We use the consolidated trade files in TAQ to extract second-by-second transaction prices. We adopt the cleaning methods for TAQ data used in many previous papers, see Barndorff-Nielsen et al. (2009) for a summary. In brief, we only keep observations that occurred during the hours of 9:30am to 4pm on Mondays through Fridays, that are *not* flagged with a "correction indicator," that do not indicate a negative transaction price or volume. In the event that multiple trades are listed with the same (one-second) time stamp, we use the median of the prices and the sum of the volumes at that second.

2.3 The merged stock-bond data

Finally, we impose some constraints on the number of time series observations on the merged stock-bond sample. It is common in the empirical corporate bond literature to exclude observations for newly issued bonds and bonds close to maturity, as these periods have an abnormal amount of trading (new issues trade frequently, whereas maturing bonds trade less), see for example, Ronen and Zhou (2012) and Goldstein et al. (2007). Consequently, we drop the first 90 days after the bond is issued (only if this 90 days overlaps with our sample), and the last 90 days before it matures (again only if this is in our sample period). We retain firms with at least 500 daily observations, 200 weekly observations, and 72 monthly observations. It is the latter condition that is most strongly binding, as it requires 6 years of data, however the GARCH-DCC models we employ below cannot be reliably used with much less than this number of observations. With these conditions imposed, we are left with 111 firms. It should be noted, given our criteria for sample selection above, that the bonds issued by these 111 firms are likely to be among the most liquid bonds in TRACE, and so the results in this paper are representative not for the universe of corporate bonds in the TRACE database, but for very liquid corporate bonds for which intra-daily data is consistently available.

Table 1 below presents some summary statistics on the stock and bond data for these 111 firms. We see that corporate bonds have lower mean returns than stocks, and lower standard deviations.[41] We also see that the average number of days available for use in estimation of our time series models below is 1,120, and the average number of high frequency observations available for constructing realized variances and correlations is 5.4. The lower panel reports the average correlations for three holding periods, daily, weekly and monthly. These average correlations rise from 0.03 to 0.18 as we increase the length of the holding period, which we explore further below.

Table 1 Summary statistics on the bond and stock data
This table presents summary statistics across the 111 bond-stock pairs in our sample. The top panel presents cross-firm averages of annualized average returns and annualized return standard deviations. (Note that the bond returns do not incorporate cash flows from coupons.) The second panel presents the average number of daily observations, and the average number of intra-daily observations, for each bond-stock pair. The lower panel reports the average bond-stock return correlation for three frequencies: daily, weekly, and monthly.

	Bond	**Stock**
Mean return (annualized)	6.03%	9.06%
Mean std dev (annualized)	24.66%	35.34%
Number of daily obs	1,120.30	
Median number of HF obs	5.36	
Mean daily correlation	0.028	
Mean weekly correlation	0.120	
Mean monthly correlation	0.176	

The average correlations reported in Table 1 mask the vast cross-sectional differences in average correlations. To better understand these, Figure 1 below presents average stock-

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[41] Note that the bond returns here do *not* include cash flows from coupon payments, and so the true average return on these corporate bonds is actually higher. Also note that these average returns are computed over the sample for each stock-bond pair, and each pair can have different start and end dates for their sample.

bond correlations sorted by bond credit rating. We sort the 111 bonds in our sample into five bins: “high yield” (S&P rating of BB+ or lower, a total of 16 bonds), “borderline high yield” (rating of BBB-, 7 bonds), “borderline investment grade” (ratings of BBB and BBB+, 28 bonds), “A rated” bonds (ratings of A-, A or A+, 46 bonds), and “AA or better” bonds (rating of AA- or higher, 14 bonds).

Consistent with past work, such as Kwan (1996), Downing et al. (2009) and Bao and Hou (2013), we find average correlations are monotonically decreasing in credit rating. The highest rated bonds have essentially zero correlations with equities. The lowest rated bonds have positive average correlation, around 0.1 for daily returns, 0.3 for weekly returns, and nearly 0.4 for monthly returns.

The observed higher correlation between high yield bonds and equity is to be expected; speculative grade bonds are deemed more equity-like than highly rated bonds as, intuitively, the risk of default and therefore the chance that bond holders take over the firm is higher. Across rating classes, the correlation between debt and equity is largely positive, reflecting the fact that both debt and equity are claims on the same cash flows of the firm and that the firm specific information driving stock and bond prices reflects information about the mean value of the firm’s assets (Kwan (1996)).

Figure 1 also reveals evidence of the so-called “Epps (1979) effect,” whereby measured correlations between assets with differing liquidity tend to be biased towards zero. At the daily frequency, bonds are very illiquid and daily prices are sometimes stale, leading to correlations that are shrunk towards zero. At the weekly and monthly frequencies this staleness is less of a concern, and the bias is reduced or eliminated. The clear presence of this effect in this figure is a motivation for our study of *dynamic* correlations at daily, weekly, and monthly frequencies as well.

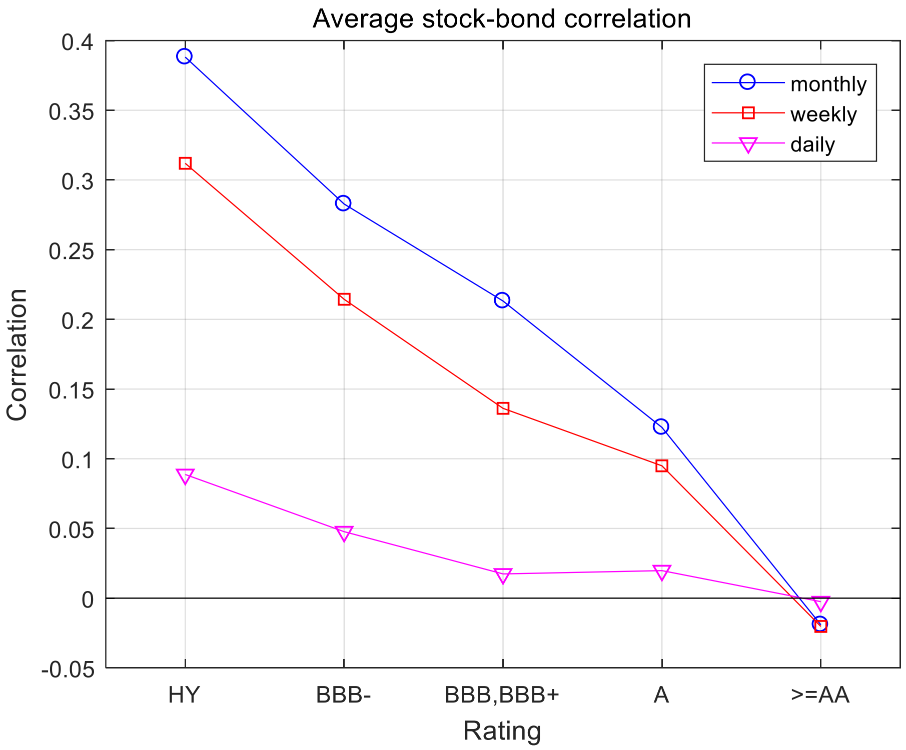

Figure 1 Average stock-bond correlations
Average stock-bond correlations for daily, weekly and monthly returns, by bond rating at time of issuance, for the 111 firms in our sample.

Figure 2 (panel A) below presents a sort of average stock-bond correlations by bond issue size; a common indirect measure of liquidity (Houweling et al. (2005)). Bonds with larger issue sizes might be expected to trade more often as there is simply more principal to trade, and this is confirmed in panel B, where we report the average number of high frequency observations[42] for each issue size quintile. Several studies mention issue size as a determinant of liquidity linking it to lower inventory costs for dealers; larger issues have

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[42] In this panel we define "high frequency" observations as those that are present within the holding period. For daily returns, these correspond to intra-daily observations, while for monthly returns these are intra-monthly.

been shown to have lower bid-ask spreads (see for example, Hong and Warga (2000) Edwards et al. (2007) and Bessembinder et al. (2006)). Further, it is easier for smaller issue sizes to get settled into buy-and-hold investors' portfolios, leaving the actual tradable amount on the market even smaller, thereby lowering liquidity (Houweling et al. (2005)). Figure 2 (panel A) shows that for our sample of firms, average stock-bond correlations decrease with issue size, implying that for more liquid bonds (as proxied by issue size) there is less comovement with equities. Panels C and D show the two time-varying liquidity measures used in this paper, log transaction volume and the Amihud (2002) measure, stratified by issue size. Both liquidity proxies convey the same message; more liquid bonds as measured by higher transaction volume and a smaller Amihud measure have large issue sizes. It follows, that the returns on these bonds are also less correlated with equity returns

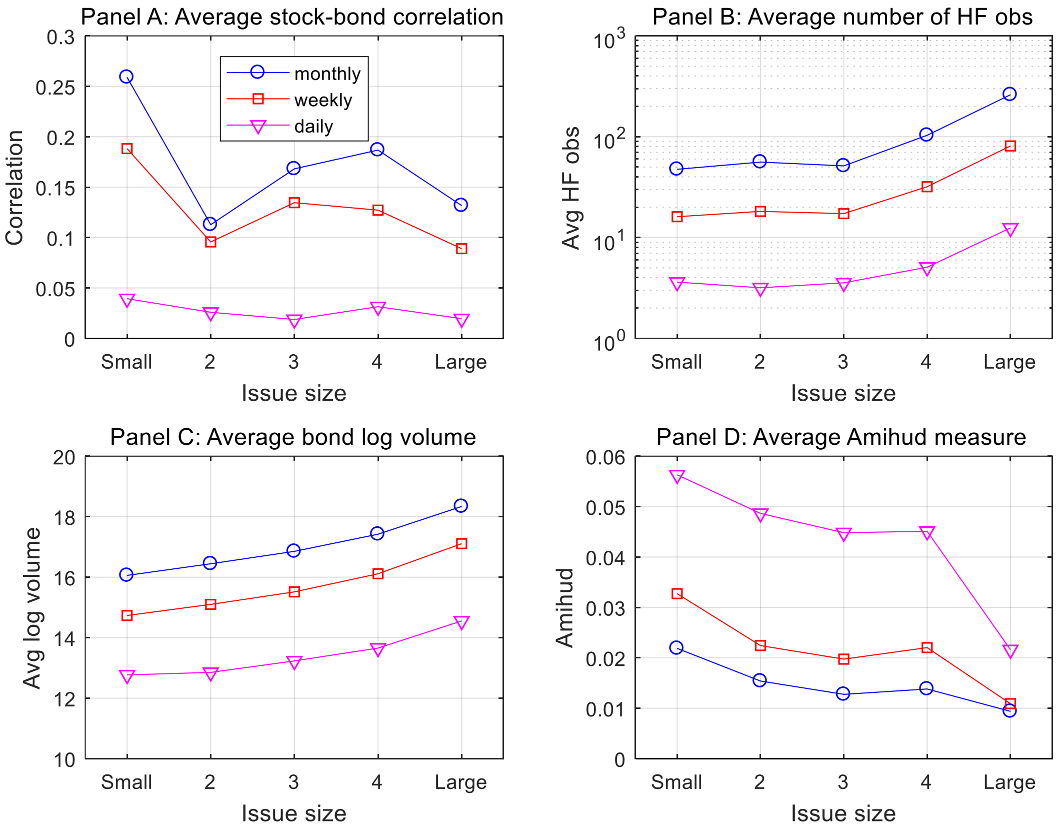

Figure 2 Average stock-bond correlations and liquidity proxies
This figure reports various measures across bond issue size quintiles, for the 111 firms in our sample, for daily, weekly and monthly returns. Panel A plots the average stock-bond correlations, panel B plots the average number of high frequency (intra-holding period) observations (in log-scale), panel C shows the average log transaction volume, and panel D plots the Amihud illiquidity measure.

2.4 An illustrative example: General Mills

With 111 pairs of stock and bond returns, displaying data is difficult. As an illustration, Figure 3 below shows stock and bond prices and returns for one representative firm, General Mills. The firm's equity trades under the ticker GIS, and we study the bond with CUSIP 370334BF0, which was issued on March 12, 2008 and matured on March 17, 2015. (Our sample ends in December 2013, however.) The issue size for this bond was $750m, with a par value of $1000 and a coupon of 5.2%. S&P rated the bond as BBB+, that is, towards the low end of investment grade.

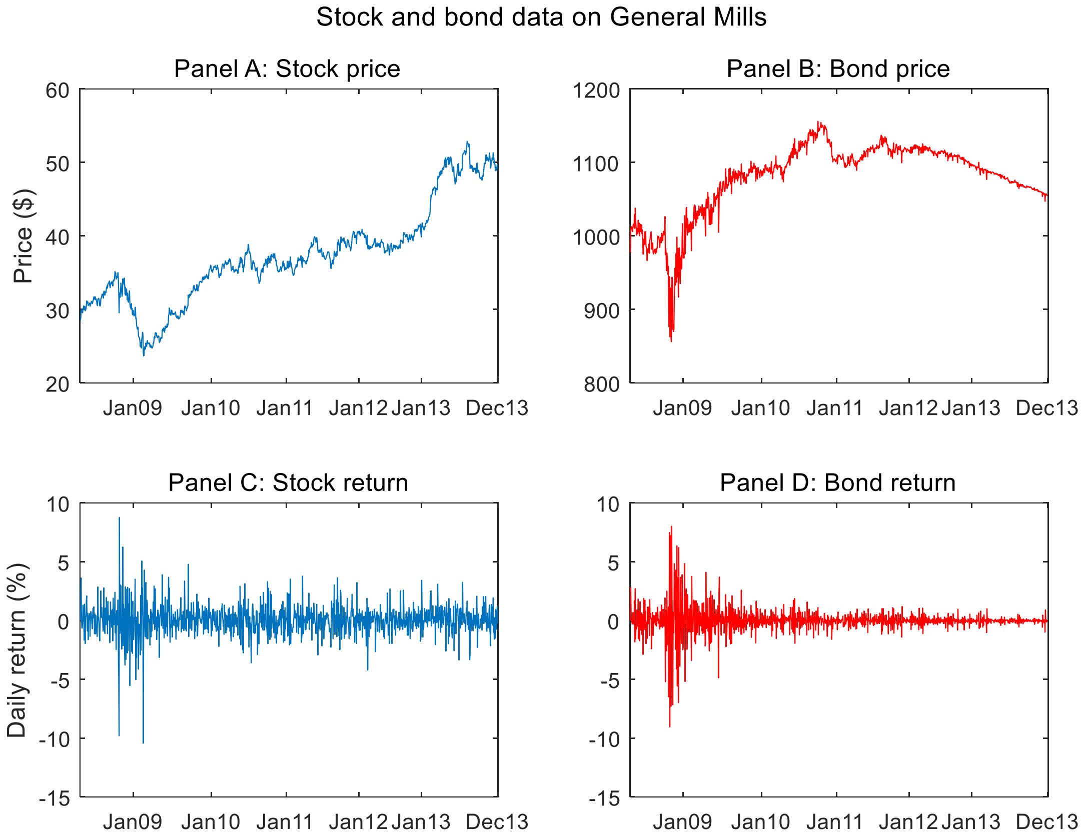

Figure 3 Stock and bond data on General Mills
Time series trends for General Mills share and bond prices in panels A and B respectively and returns in panels C and D respectively.

Figure 3 shows the time series of General Mills share and bond price[43] in panels A and B respectively as well as their returns in panels C and D. A few dynamics are noteworthy: the impact of the credit crisis is noticeable for both assets as higher volatility in mid-2008, and the bond price increase post-crisis reflects the decrease in interest rates and the consecutive low interest rate environment that followed. In the latter half of panel B we observe the decline in the bond price as it moves closer to its par value payable at maturity, a dynamic referred to as “pull to par”. The decline in price is accompanied by lower volatility for bond

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[43] General Mills had a 2:1 stock split on June 9, 2010, and we adjust the prices from before this date so that the return on the split date does not distort our analysis. We do the same for all stocks in our sample.

returns (panel D) whilst equity volatility remains relatively constant (panel C). This deterministic feature of bond volatility will be discussed in Section 3.3, and we will adjust our time series models to incorporate it.

3. Realized volatility, and models for stock and bond volatility and correlation

3.1 Realized variances, covariances, and correlations

Before introducing the time series models we employ for time-varying volatility and correlation, we first describe how we construct measures of volatility and correlation from high frequency data. Following Andersen and Bollerslev (1998) and a large subsequent literature in financial econometrics, we can obtain an estimate of the variance of an asset return over some period (e.g., one day) by summing the squared high frequency returns observed within that period. That is, using "realized variance":

$$RV_{i,t} = \sum_{j=1}^{m_t} r_{i,j,t}^2, \text{ for } i \in \{B, S\} \tag{1}$$

where m_t is the number of high frequency observations available (which can vary over time) in period *t*, and $r_{i,j,t}$ is the return on asset $i \in \{B, S\}$, over the j^{th} intra-daily window in period *t*. As mentioned above, we will consider holding periods of one day, one week and one month. Clearly, we will have more high frequency observations available for longer holding periods, which will generally improve the accuracy of realized volatility, but with the cost that we have fewer time series observations to estimate our time series models.

Realized covariances are computed as:

$$RCov_t = \sum_{j=1}^{m_t} r_{B,j,t} r_{S,j,t} \tag{2}$$

And finally, realized correlations are obtained as:

$$RC_t = RCov_t / \sqrt{RV_{B,t} RV_{S,t}} \tag{3}$$

The theory for these measures is presented in Andersen et al. (2003) and Barndorff-Nielsen and Shephard (2004); see Aït-Sahalia and Jacod (2014) for a recent survey of this literature.

We include overnight returns in all of our analyses. Unlike analyses involving very liquid assets, our use of corporate bond returns and refresh-time sampling (described in the next section) means we have an average of only 5.4 observations per day. This makes the overnight period less anomalous than in other applications, where the close-to-open return is large relative to the short intervals during the trade day. Moreover, we estimate our models over three holding periods (daily, weekly, and monthly) and including the overnight return makes the longer holding periods more economically meaningful.[44]

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[44] Omitting the overnight return would require us to define the weekly return, for example, as the sum of the five open-to-close returns over that week, which differs from most market participants' interpretation of a "weekly return."

3.2 “Refresh time” sampling for realized variances and correlations

When constructing univariate realized measures, such as realized volatility, the two main choices regarding the sampling scheme are whether to use “calendar-time” sampling (e.g., sampling every 5 minutes) or “business time” sampling (e.g., sampling every 5 transactions). Using every single transaction has been generally found to be problematic, see Hansen and Lunde (2006) for a review, due to the presence of market microstructure noise at the highest frequencies, thus most authors use a frequency lower than the highest available. When constructing multivariate realized measures, on the other hand, one also has to decide on a way to deal with the inevitable *asynchronicity* of the observed transactions, that is, the fact that transactions occur at different times. If we wish to construct a measure like covariance or correlation, then we need to find a way to synchronize the observed data.

We follow Barndorff-Nielsen et al. (2011) and use “refresh time” sampling to synchronize the stock and bond data in our sample. This is a type of “business time” sampling scheme that seeks to minimize the impact of asynchronously observed trades. This method takes the two asynchronous sequences of prices and creates a single synchronized sequence by adding an observation to the synchronized sequence only when *both* assets have traded since the previous observation. If the assets happen to always trade at the same times, then the refresh time data is identical to the original data. If one asset trades every second time the other asset trades, then the refresh time data will include every second observation of the more frequently-traded asset, and every trade of the less frequently-traded asset. When the trades times are randomly scattered through time for both assets, refresh time provides a way to obtain a sequence of prices that makes use of the most recent prices available, dropping observations on the asset that trades many times when the other asset has not traded. The benefit of refresh time sampling is that it means we can use simple realized covariance (equation 2 above) to estimate covariances. An alternative is to use a more complicated estimator, such as the Hayashi-Yoshida (2004) estimator, on the calendar-time prices, however this can lead to problems with the positive definiteness of the realized covariance matrix.

In our application, the corporate bond is substantially less liquid than the stock for all firms, and this leads the refresh time samples that we construct to almost match the original sequence of bond prices: our refresh time data contains, on average, 96.5% the number of observations in the original sequence of bond prices. Thus using refresh time in our application leads to very little loss of data.[45]

3.3 Incorporating realized variance and correlation into time series models

We study the value of high frequency data for bond and stock volatility and correlation by incorporating realized volatility and correlations into standard time series models, and testing the significance of the coefficient on these realized measures. In the univariate case, this is sometimes called a "GARCH-X" model (see Engle and Patton (2001) and Han (2015) for example), and has also been used in the context of conditional copula models in De Lira Salvatierra and Patton (2015).

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[45] When applying refresh time sampling to assets that are equally liquid but with uncorrelated trade times, the loss of data can be substantial, especially in high dimension applications, see Hautsch et al. (2010).

For each firm, we specify:

$$\begin{bmatrix} r_{B,t} \\ r_{S,t} \end{bmatrix} = \begin{bmatrix} \mu_{B,t} \\ \mu_{S,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{B,t} \\ \varepsilon_{S,t} \end{bmatrix} \tag{4}$$

where

$$V \begin{bmatrix} \varepsilon_{B,t} \\ \varepsilon_{S,t} \end{bmatrix} = \begin{bmatrix} \sigma_{B,t}^2 & \sigma_{B,t}\sigma_{S,t}\rho_{BS,t} \\ \cdot & \sigma_{S,t}^2 \end{bmatrix} \tag{5}$$

We denote the return on the bond and the stock over period t as $r_{B,t}$ and $r_{S,t}$. The period is either one day, week, or month. We estimate all of the models below separately for each holding period.

We use the BIC (Bayesian Information Criterion) to choose the optimal ARMA(p,q) model for the conditional mean of each return series, allowing p and q to vary between zero and two. We then specify the conditional variance to follow the GARCH(1,1) of Bollerslev (1986):

$$\sigma_{i,t}^2 = \omega_i + \beta_i \sigma_{i,t-1}^2 + \alpha_i \varepsilon_{i,t-1}^2, \text{ for } i \in \{B, S\} \tag{6}$$

We then augment the GARCH(1,1) model with lagged realized variance:

$$\sigma_{i,t}^2 = \omega_i + \beta_i \sigma_{i,t-1}^2 + \alpha_i \varepsilon_{i,t-1}^2 + \gamma_i RV_{i,t-1}, \text{ for } i \in \{B, S\} \tag{7}$$

Equation (7) is a GARCH-X model, where the "X" variable is (lagged) realized variance, and we will refer to it as the "GARCH-RV" model. By testing the significance of γ_i we can determine the value of realized variance for modelling stock or bond volatility, beyond the predictability captured by a standard GARCH model. This is, clearly, a tougher hurdle than simply asking whether realized variance helps explain future variance.

We then construct the standardized residuals:

$$\vartheta_{i,t} = \varepsilon_{i,t}/\sigma_{i,t} \text{ for } i \in \{B, S\} \tag{8}$$

and specify the conditional correlation to follow the DCC model of Engle (2002):

$$R_{BS,t} = Q_t^{*-1} Q_t Q_t^{*-1} \tag{9}$$

$$Q_t = W + \beta_C Q_{t-1} + \alpha_C \vartheta_{B,t-1} \vartheta_{S,t-1}$$

$$Q_t^* = \begin{bmatrix} \sqrt{Q_{11,t}} & 0 \\ 0 & \sqrt{Q_{22,t}} \end{bmatrix}$$

To study the importance of realized correlations for modelling dynamic stock-bond correlations, we also consider a "DCC-RC" model, where we augment the DCC model with lagged realized correlation:

$$Q_t = W + \beta_C Q_{t-1} + \alpha_C \vartheta_{B,t-1} \vartheta_{S,t-1} + \gamma_C RC_{t-1} \tag{10}$$

We measure the importance of high frequency information for modelling stock-bond correlations by testing the significance of the coefficient on lagged realized correlation in the DCC-RC specification (equation 10). This is a simple *t*-test on a single parameter, and since we expect the coefficient on lagged realized variance and correlation to be positive, we implement it as a one-sided test:

$$H_0\text{: } \gamma_C = 0 \quad vs \quad H_1\text{: } \gamma_C > 0 \tag{11}$$

We also consider the *joint* significance of all three realized measures (stock RV, bond RV and RC) in the joint model for the entire conditional covariance matrix. This is done to summarize the overall information of high frequency data for modelling stock-bond variances and covariances.

We noted in Section 2.4 that the price our representative bond is “pulled to par” as it moves towards the end of its life. This movement towards par value is common to all bonds as they are redeemable at maturity at par value. However, as interest rates change and news is revealed to the market, bond prices will fluctuate, and extent and timing of this movement is at least partly random, given that perfectly predictable movements in the bond price would lead to arbitrage opportunities. We also observe a decline in bond volatility as bonds move closer to maturity, which is partly driven by a decreasing sensitivity of a bond’s price to changes in interest rates: for bonds with less time to maturity, there are fewer cash flows remaining that can be impacted by changes in interest rates, reducing this source of bond return volatility.

We adjust our GARCH(1,1) model above to deal with this systematic decline in volatility by scaling the residuals from the mean equation by the square-root of the inverse time to maturity, rescaled by root-250 to "normalize" volatility to be for a bond with one year remaining to maturity:

$$\tilde{\varepsilon}_{B,t} = \sqrt{\frac{250}{T-t+1}}\,\varepsilon_{B,t} \tag{12}$$

We then estimate the GARCH(1,1) model on the normalized residuals, $\tilde{\varepsilon}_t$, and obtain the standardized residuals as $\vartheta_{B,t} = \tilde{\varepsilon}_{B,t}/\sigma_{B,t}$. The choice of 250 is arbitrary, and has no impact on our results. The assumption that the variance diminishes with the square root of the time to maturity is consistent with the log bond price following a Brownian bridge, which we observe at the random point $\log P_{B,t}$ and with known terminal value equal to the par value. Our baseline analyses include this volatility de-trending, and in our robustness checks we show results when this feature is removed from the model.

3.4 Stock and bond volatilities and correlation for General Mills

To illustrate the output of the volatility and correlation models we estimate, consider again the results for a single firm, General Mills. Figure 4 below presents the fitted conditional volatility for stock returns and bond returns, as well as the conditional correlation between these returns, at the weekly frequency. In each panel we present the estimated volatility or correlation based on a GARCH/DCC model with and without realized variance or realized correlation.

In the top panel we see that the “GARCH-RV” fitted stock return volatility differs markedly from that obtained from a model without RV. The effect is particularly pronounced in late 2008, at the height of the financial crisis. The p-value for the significance of RV in this model is 0.000, confirming that including RV does indeed improve the fit of this model. The middle panel shows the equivalent figure for bond volatility. Here, the differences are not as pronounced, and in contrast with stock return volatility, both the GARCH and GARCH-RV models captured a large increased in bond return volatility during the financial crisis. The p-value for the significance of RV in this model is 0.013, indicating that including RV also improves the fit of this model. The lower panel shows the fitted correlations from the DCC and DCC-RC models. We observe that the estimates are essentially identical, suggesting that realized correlation does not help explain correlations beyond the DCC model for this firm. The p-value for the significance of RC in this model is 0.270, meaning we fail to reject the null that the coefficient on RC is zero for this firm.

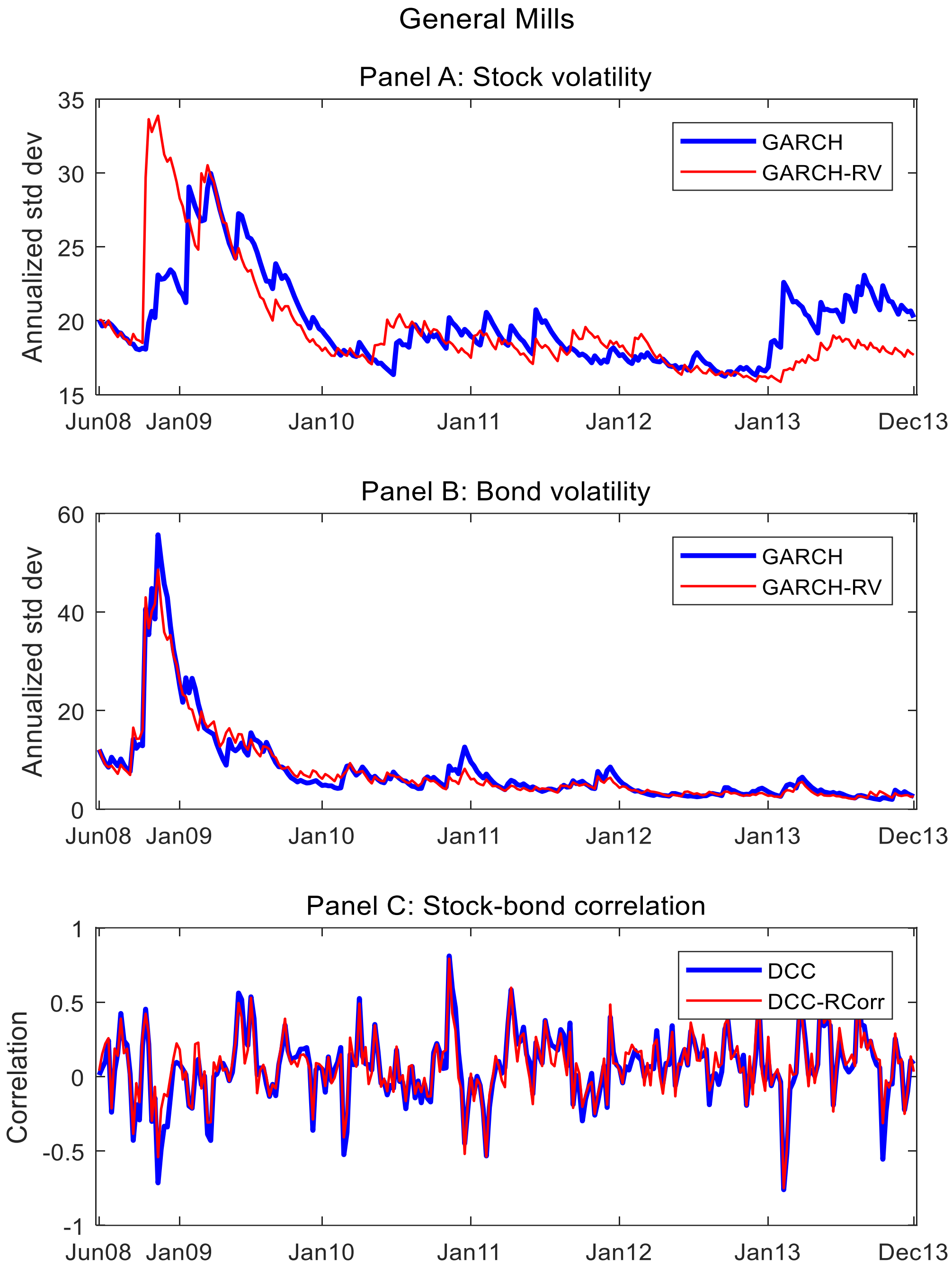

Figure 4 General Mills stock and bond volatility and correlation
Time series volatility estimated by GARCH and GARCH-RV models for the General Mills share and bond returns in panels A and B respectively and stock-bond correlation estimated by DCC and DCC-RV models in panel C.

4. The value of high frequency stock and corporate bond data for volatility modelling

We now turn to focus of this paper: the significance of stock RV, bond RV, and realized correlation in volatility and correlation models, across the entire 111 firms in our sample. Given the relative illiquidity of the corporate bond market, we consider this question for three different frequencies: daily, weekly, and monthly. Figure 1 revealed a clear "Epps effect" in average correlations, with correlations being smaller for higher-frequency data, and we might expect this lead to us finding more significant results when using realized correlations at lower (e.g., weekly or monthly) frequencies. However, it is not clear that we should expect monotonically stronger results for lower frequencies, as we are measuring the usefulness of these realized measures *beyond* the dynamics captured by the familiar GARCH and DCC models. It is well known that volatility and correlation dynamics are different at the daily and monthly frequencies, and it is possible that at lower frequencies the realized measures are more reliable, but there are less gains to be had beyond standard GARCH and DCC models from including such measures.

The results of our first analysis of the value of high frequency data for modelling stock and bond variances and correlations are presented in Table 2. This table presents the proportion of the 111 firms in our sample for which realized stock variance, realized bond variance, realized correlation, or all three measures jointly, are significant at the 5% level. Consistent with the large literature on the value of high frequency data for stock volatility, we find that realized variance is significant for 77% of firms at the daily frequency, 86% of firms at the weekly frequency, and 74% of firms at the monthly frequency. This is strong, but not surprising, evidence of the value of high frequency data for modelling stock return volatility.

The second row presents the first, to the best of our knowledge, results on the value of high frequency data for modelling corporate bond return volatility. There, despite the well-known illiquidity of the corporate bond market, we find strong evidence that realized bond variance is useful for predicting future variance, above and beyond what is captured by a GARCH model. We find significant coefficients on realized variance for 78% of bonds at the daily frequency, 72% at the weekly frequency, and 61% at the monthly frequency. Thus, we observe differences in the value of this high frequency data across holding periods, but even in the least significant case we find well over half of the bonds in our sample are better modelled by including realized volatility in the volatility model than by ignoring it.

Table 2 The proportion of firms for which realized measures are significant
This table presents the proportion of the 111 firms in our sample for which realized stock volatility, realized bond volatility, realized correlation, or all three measures jointly, are significant at the 5% level. The models are estimated at three frequencies: daily, weekly, and monthly.

Frequency	Daily	Weekly	Monthly
Stock Volatility	0.766	0.856	0.739
Bond Volatility	0.784	0.721	0.613
Correlation	0.126	0.198	0.045
All	0.829	0.892	0.703

The third row of Table 2 presents the proportions of times that realized correlation is significant when included in a DCC model. The proportions here are lower than for volatilities: we find 12% significant at the daily frequency, 20% at the weekly frequency, and just 5% at the monthly frequency. (Recall that our tests use a 5% significance level, and so the results for the monthly frequency are consistent with no value.) While these proportions are lower than for volatilities, we emphasize that for the weekly frequency we find a sizeable proportion (just under 20%) of firms have DCC models that are significantly improved by including realized correlation as an additional explanatory variable.

Finally, to measure the overall value of high frequency data for modelling the entire covariance matrix, we report the results of a joint test that all three realized measures (realized stock and bond volatility, and realized correlation) have coefficients equal to zero. The bottom row of Table 2 indicates that we can reject this null for 83% of firms at the daily frequency, 89% at the weekly frequency, and 70% at the monthly frequency. These confirm the above individual results that realized measures constructed using high frequency bond and stock return data are useful for modelling the conditional covariance matrices of these returns.

Next, we expand our analysis to take into account the time-varying liquidity of the stock and bond markets. Illiquidity is a particularly important feature of the corporate bond market, see Bao et al. (2011), Bessembinder and Maxwell (2008) and Dick-Nielsen et al. (2012), and a concern may arise that our realized measures of volatility and correlation are actually tracking time-varying liquidity instead, and if liquidity helps explain future volatility or correlation, then explanatory power attributed in Table 2 to realized volatility or correlation may actually be due to liquidity. Bao et al. (2011) and Bao and Pan (2013), for example, show that volatility and corporate bond market illiquidity are correlated.[46]

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[46] The measures of volatility in Bao et al. (2011) and Bao and Pan (2013) are each different to our approach of using a dynamic GARCH model augmented by realized volatility to directly model volatility. Bao et al. (2011) use the VIX index computed from S&P 500 index options and Bao and Pan (2013) use excess volatility, the difference between empirical volatility and a Merton (1974) model implied volatility.

Alternatively, if liquidity and realized volatility/correlation are *both* useful explanatory variables for future volatility/correlation, then including liquidity in the model may help us detect more cases where realized volatility/correlation are significant.

We consider two measures of liquidity: the log transaction volume, and Amihud's (2002) measure of price sensitivity to trade volume. The Amihud measure we use is defined as:

$$L_{i,t} = Med\left[\frac{|r_{i,j,t}|}{Vol_{i,j,t}}\right] \tag{13}$$

where $r_{i,j,t}$ is the return on asset $i \in \{B, S\}$, over the j^{th} intra-daily period on day t, $Vol_{i,j,t}$ is the trade volume over the same period, and "Med" indicates the median across all periods in that interval (day, week or month). The original Amihud measure used the sum, rather than the median, over the periods in the interval, but we follow Dick-Nielsen et al. (2012) and use the median.[47]

We include the liquidity variable (log-volume or Amihud) lagged one period in the same way as we include realized volatility or realized correlation. Denoting the liquidity measure as LQ, the extended models are:

$$\sigma_{i,t}^2 = \omega_i + \beta_i\sigma_{i,t-1}^2 + \alpha_i\varepsilon_{i,t-1}^2 + \gamma_i RV_{i,t-1} + \delta_i LQ_{i,t-1}, \text{ for } i \in \{B, S\} \tag{14}$$

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[47] In unreported results we also considered using the sum and found very similar results.

$$Q_t = W + \beta_C Q_{t-1} + \alpha_C \vartheta_{B,t-1} \vartheta_{S,t-1} + \gamma_C RC_{t-1} + \delta_C LQ_{B,t-1} \tag{15}$$

In the correlation model we include the liquidity measure for the corporate bond market, as that is likely the most important source of illiquidity in this pair of assets.

In Table 3 we present results on the proportion of the 111 firms in our sample for which realized stock volatility, realized bond volatility, realized correlation, or all three measures jointly, are significant at the 5% level, after including the liquidity measure in the model. [48] We find that including a measure of liquidity leads to no large changes in the proportion of firms for which realized volatility is significant in the stock or bond volatility models. However, we find important differences for the correlation model when including lagged bond liquidity in the model: realized correlation is identified much more strongly as a useful explanatory variable for future correlations. The proportions of firms for which realized correlation is significant rises to 18%, 38% and 21% when using lagged Amihud as a control variable, from 13%, 20% and 5% (at the daily, weekly, and monthly frequencies) in the baseline model with no liquidity variables included. The results using lagged volume are similar, with the proportions being 16%, 32% and 19%. These results indicate that simple measures of bond market liquidity (transaction volume or Amihud's measure) are helpful for predicting future correlations on their own, and they are helpful for identifying the information in realized correlations.

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[48] As the focus of this paper is on the significance of realized volatility and correlation, not liquidity, for modelling variances and correlations, we do not test the significance of the coefficients on the LQ measures. In unreported results, we find that the liquidity measures are significant for around 30% of stock volatility models, around 35% of bond volatility models, and around 21% of correlation models.

Table 3 Controlling for liquidity in the GARCH-RV and DCC-RC models
This table presents the proportion of the 111 firms in our sample for which realized stock volatility, realized bond volatility, realized correlation, or all three measures jointly, are significant at the 5% level, when including a control for (lagged) liquidity. We use either log volume (left panel) or the Amihud (2002) measure of liquidity. The models are estimated at three frequencies: daily, weekly, and monthly.

	Log volume			**Amihud measure**		
Frequency	Daily	Weekly	Monthly	Daily	Weekly	Monthly
Stock Volatility	0.802	0.856	0.631	0.721	0.766	0.613
Bond Volatility	0.802	0.739	0.586	0.748	0.631	0.487
Correlation	0.162	0.324	0.189	0.180	0.378	0.207
All	0.856	0.946	0.676	0.838	0.865	0.604

To analyse how our results vary in the cross section, Figure 5 below presents the proportion of firms for which a joint test indicated the significance of realized stock and bond volatility and realized correlation, sorted according to four variables: credit rating, the median number of high frequency observations, issue size, bond trade volume.[49] We see that the proportion of firms for which realized measures are significant is generally higher for higher-rated bonds, and for the two measures of bond liquidity (issue size and volume). We also observe, unsurprisingly, that this proportion is broadly increasing with the number of high frequency observations available to compute these measures.

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[49] For the latter two variables we simply use quintiles to disaggregate the firms, and each quintile contains 22 or 23 firms. For credit ratings we use the same grouping as Figure 1, the number of firms in the five ratings groups are 16, 7, 28, 46, 14. The median number of high frequency observations was too discrete to use quintiles and so we use the groups listed in Figure 5; the number of firms in the five groups are 30, 33, 17, 13, 18.

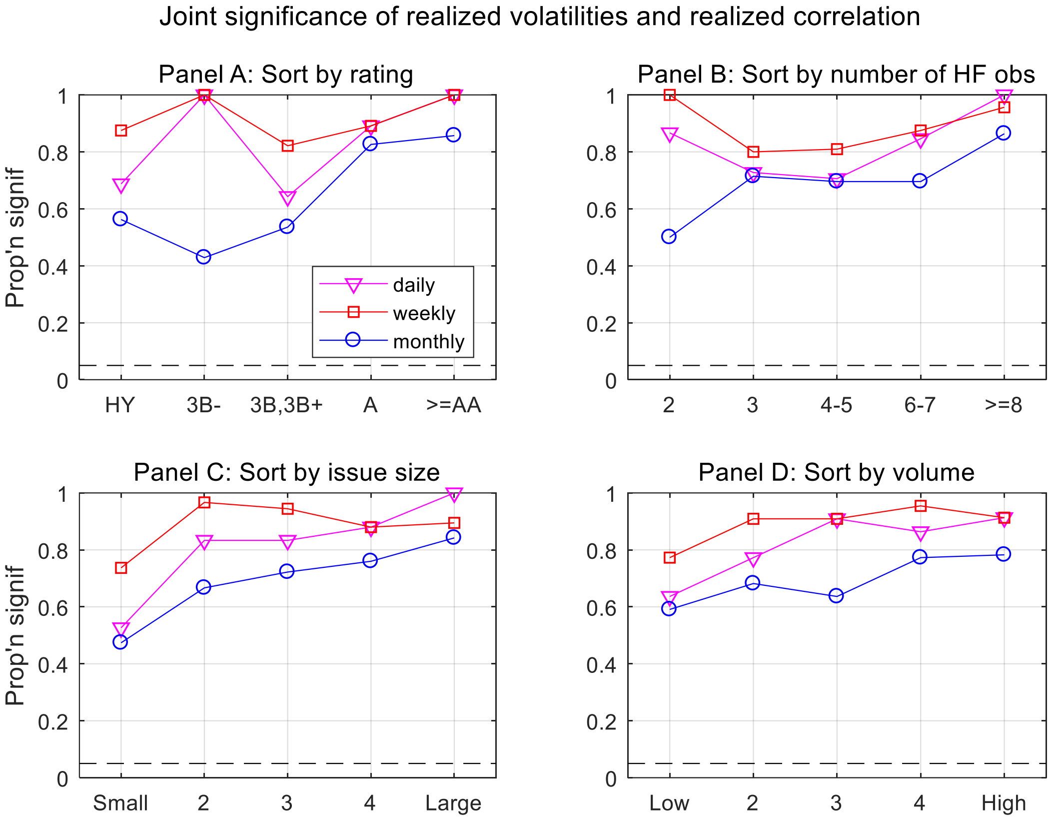

Figure 5 Joint significance of Realized volatilities and realized correlation
This figure plots the proportion of firms for which a joint test indicated the significance of realized stock and bond volatility and realized correlation, sorted according to four variables: panel A sorts by credit rating, panel B sorts by the median number of high frequency observations, panel C sorts by quintile of issue size, and Panel D sorts by quintiles of bond trade volume.

5. Robustness checks

This section presents results from alternative specifications as a check on the robustness of our main results to the specific choices made in our baseline analysis.

Firstly, we consider the impact of including a deterministic trend in the volatility model, as described in equations (6) and (7). The inclusion of this trend was motivated by the "pull to par" effect observed in bond prices, with the volatility clearly declining as the time to maturity declined. In the left panel of Table 4 below we present results when this trend is omitted from the model. For ease of comparison our main results from Table 2 are presented in the middle panel of Table 4. Note that there is no trend in the model for stock volatility, and so the results for that model are the same in all three panels of Table 4.

Next we consider also adjusting the ARMA(*p*,*q*) model for the conditional mean of bond returns. We implement this adjustment assuming a linear reversion of the log bond price to the log par value. We define:

$$\tilde{r}_{B,t} = r_t - \frac{logFV - logP_t}{T-t+1} \tag{16}$$

and then estimate the optimal ARMA(*p*,*q*) model on these “de-trended” returns. The results when a trend is included for both the conditional mean and the conditional volatility are presented in the right panel of Table 4.

Across the three panels in Table 4, we see only small variations in the proportions of firms for which a realized measure is significant. Note that this does not mean that the inclusion of the time trend is inconsequential in terms of the parameter estimates, the predictions from these models, or the model fit; only that the importance of information contained in realized bond volatility and realized correlation are relatively unaffected by whether the trend is included.

Table 4: Robustness to inclusion of a deterministic time trend

This table presents the proportion of the 111 firms in our sample for which realized stock volatility, realized bond volatility, realized correlation, or all three measures jointly, are significant at the 5% level. The models are estimated at three frequencies: daily, weekly, and monthly. The middle panel corresponds to Table 2, and is included here for ease of reference. The left panel reports the results when no deterministic trend in volatility is included. The right panel reports the results when a deterministic trend in the conditional mean and volatility are both included.

	No time trend in mean or volatility			**Base case: Trend only in volatility**			**Time trend in mean and volatility**		
Frequency	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Daily	Weekly	Monthly
Stock Volatility	0.766	0.856	0.739	0.766	0.856	0.739	0.766	0.856	0.739
Bond Volatility	0.766	0.721	0.694	0.784	0.721	0.613	0.784	0.721	0.613
Correlation	0.126	0.189	0.036	0.126	0.198	0.045	0.126	0.189	0.045
All	0.847	0.883	0.757	0.829	0.892	0.703	0.838	0.892	0.703

Next we study whether the results of our analysis change if we only include bond trades with large trading volumes. Following Edwards et al. (2007) and Bessembinder et al. (2009), we classify trades of 100 bonds or more ($100K or more in par volume) as "institutional" trades. The motivation for only including such trades is that these trades are potentially the ones with the most information and are likely executed by institutional investors, while "small" trades are done for other purposes (to address liquidity needs, for example) or are more likely to be traded by small retail investors. On the other hand, eliminating smaller trades from the sample reduces the number of high frequency observations available to construct realized measures, potentially making them (even) noisier. Across all bonds, we find that 28.4% of trades are "institutional." In panel B of Table 5 below we present results based only on these institutional trades. We find that in all three models (stock volatility, bond volatility and stock-bond correlation), limiting the sample to only institutional trades somewhat negatively impacts the value of realized measures: the proportions for firms for which realized volatility or correlation is significant drops by about 20% (averaging across the three holding periods), by about 10% for bond volatility, while stock-bond correlation remains largely unchanged from the base case. Thus it seems that dropping the smaller trades leads to slightly worse realized measures than those based on both large and small trades.

Table 5: Robustness checks

Notes: This table presents the proportion of the 111 firms in our sample for which realized stock volatility, realized bond volatility, realized correlation, or all three measures jointly, are significant at the 5% level. The models are estimated at three frequencies: daily, weekly, and monthly. Panel A presents the base case of from Table 2 for ease of comparison. Panel B shows the results when only "institutional" trades (those with volume of at least $100K) are used. Panel C excludes the first 365 days after the bond is issued (only if this overlaps with our sample period) and the last 365 days before it matures (only if this is in our sample period). Finally, panel D modifies the "refresh time" sampling scheme to only use every second observation.

	Panel A: Base case			**Panel B: Institutional trades only**		
Frequency	Daily	Weekly	Monthly	Daily	Weekly	Monthly
Stock Volatility	0.766	0.856	0.739	0.577	0.640	0.541
Bond Volatility	0.784	0.721	0.613	0.604	0.649	0.658
Correlation	0.126	0.198	0.045	0.135	0.225	0.099
All	0.829	0.892	0.703	0.667	0.829	0.631
	Panel C: Drop first and last year of bond data			**Panel D: SkipK = 2**		
Stock Volatility	0.739	0.775	0.676	0.667	0.838	0.694
Bond Volatility	0.721	0.703	0.559	0.748	0.694	0.550
Correlation	0.135	0.171	0.036	0.126	0.162	0.045
All	0.802	0.838	0.622	0.775	0.910	0.667

Next we consider excluding the first 365 days after the bond is issued (only if this overlaps with our sample period) and the last 365 days before it matures (only if this is in our sample period). Our base case analysis dropped only the first and last 90 days. If the behaviours of stock and bond volatility and correlation are markedly different in the first and last year, then dropping these from the sample could increase the proportions of firms for which realized measures are found to be useful. On the other hand, dropping around four times as many observations almost certainly reduces the accuracy of the estimated parameters and makes it harder to reject the null of a zero coefficient. Panel C of Table 5 reveals that the latter effect is dominant: we see that the proportions of firms for which realized volatility or correlation is significant drops by about 5% for stock and bond volatility, and by about 2% for correlations.

Finally, we consider a refinement of the “refresh time” sampling scheme that we used to synchronize the high frequency stock and bond prices. Refresh time sampling is designed to reduce the attenuation bias in realized correlations constructed using asynchronous prices. However, as noted above, given the stark difference in the number of high frequency observations in the stock and corporate bond markets, refresh time sampling is almost equivalent to simply using every available bond price, and matching it with the most recent stock price. This means that the resulting sequence of bond prices remains susceptible to univariate sources of noise in high frequency prices, such as bid-ask bounce. We therefore consider using “skip k” refresh time sampling where we construct the refresh time prices as above, but then only use every second observation.[50] In theory this reduces both the impact of asynchronous trading *and* univariate sources of noise like bid-ask bounce. However, like the use of only institutional trades, this also substantially reduces the number of high frequency observations available to construct realized measures, potentially making them noisier.

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[50] We also consider using only every third refresh time observation, and the results were qualitatively similar to those reported here.

Panel D of Table 5 shows the results, and reveals that the “skip k” realized stock volatility is markedly worse at the daily frequency, which is to be expected: the refresh time sampling frequency is already low enough that any univariate stock market microstructure noise would be mostly eliminated, and lowering the frequency even further does not reduce the noise but does make realized stock volatility a less precise estimator. For the weekly and monthly holding periods the impact on realized stock volatility is not as great. A similar finding applies to realized bond volatility: the performance is worse for the daily holding period, but not much affected for the weekly or monthly holding periods. For realized correlations the competing impacts of moving to “skip k” sampling appear to balance out: the proportions of firms for which realized correlation is significant is roughly unaffected.

Overall, we conclude from these robustness checks that our main finding on the proportions of firms for which realized volatility and correlation are significant additions to standard GARCH and DCC models is mostly unaffected by variations in the treatment of the trend in volatility and mean, the inclusion of observations at the start and near the end of a bond’s life, the use of small and large trades, or the specific refresh time sampling scheme we adopt.

6. Conclusion

This paper presents novel evidence on the value of high frequency corporate bond data for volatility and stock-bond correlation estimation. Using GARCH and DCC models augmented with realized corporate bond volatility, equity volatility, and firm level stock-bond correlations, we show that high frequency corporate bond data improves volatility and correlation estimates beyond the dynamics captured by standard GARCH and DCC models. Using a sample of 111 stock-bond pairs, with the bonds selected to be among the most liquid available in the TRACE database, we find that realized corporate bond volatility significantly improves upon a standard volatility model for 72% of the bonds in our sample. The inclusion of realized correlation improves correlation estimates for approximately 20% of stock-bond pairs. Jointly testing corporate bond and stock realized volatility and realized correlation we find significant gains for 89% of firms in the sample.

We find that including liquidity (as captured by transaction volume or the Amihud (2002) measure) as an additional explanatory variable in our time series models further reveals the information contained in realized measures. We show that our main findings are robust to variations in refresh time sampling, in the treatment of the trend in volatility and mean for bond returns, changes in our approach to dealing with new issues and maturing bonds as well as the inclusion of small and large trades.

Our results suggest intraday corporate bond data should not be discounted even though the frequency of corporate bond trading, even for the most liquid bonds, pales in comparison to that of the equity market. Portfolio managers and so called “dual holders” of company debt and equity can benefit from using intraday corporate bond data in their forecasts of volatility and correlation.

References

Aït-Sahalia, Yacine and Jean Jacod, 2014, *High Frequency Financial Econometrics*, Princeton University Press, Princeton.

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

Andersen, Torben G. and Luca Benzoni, 2010, Do Bonds Span Volatility Risk in the U.S. Treasury Market? A Specification Test for Affine Term Structure Models, *Journal of Finance* 65, 603-653.

Andersen, Torben G., and Tim Bollerslev, 1998. Answering the skeptics: yes, standard volatility models do provide accurate forecasts. *International Economic Review* 39, 885–905.

Andersen, Torben G., Tim Bollerslev, Peter F. Christoffersen, Francis X. Diebold, 2006. Volatility and correlation forecasting. In: Elliott, Graham, Granger, Clive W.J., and Timmermann, Allan (Eds.), *Handbook of Economic Forecasting*. North Holland Press, Amsterdam

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Paul Labys, 2003, Modeling and forecasting realized volatility, *Econometrica* 71, 579–625.

Bao, Jack and Kewei Hou, 2013, Comovement of corporate bonds and equities, working paper

Bao, Jack and Jun Pan, 2013, Bond Illiquidity and Excess Volatility, *Review of Financial Studies* 26, 3068-3103

Bao, Jack, Jun Pan and Jiang Wang, 2011, The Illiquidity of Corporate Bonds, *Journal of Finance* 66, 911-946.

Barndorff-Nielsen, Ole E., and Neil Shephard, 2004. Econometric analysis of realized covariation: high frequency based covariance, regression and correlation in financial economics. *Econometrica* 72 (3), 885–925.

Barndorff-Neilsen, Ole E., Peter R. Hansen, Asger Lunde, and Neil Shephard, 2009, Realised kernels in practice: trades and quotes, *Econometrics Journal* 12, 1-32.

Barndorff-Neilsen, Ole E., Peter R. Hansen, Asger Lunde, and Neil Shephard, 2011, Multivariate realised kernels: consistent positive semi-definite estimators of the covariation of equity prices with noise and non-synchronous trading, *Journal of Econometrics* 162, 149-169.

Bessembinder, Hendrik, Kathleen Kahle, William Maxwell and Danielle Xu, 2009, Measuring Abnormal Bond Performance, *Review of Financial Studies* 22, 4219-4258

Bessembinder, Hendrik and William Maxwell, 2008, Transparency and the Corporate Bond Market, *Journal of Economic Perspectives* 22, 217-234

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

Bodnaruk, Andriy and Marco Rossi, 2016, Dual ownership, returns and voting in mergers, *Journal of Financial Economics* 120, 58-80.

Bollerslev, Tim, 1986, Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, 31, 307-327.

Chen Long, David Lesmond and Jason Wei, 2007, Corporate yield spreads and bond liquidity, *Journal of Finance* 62, 119-149

Cieslak, Anna and Pavol Povala, 2016, Information in the Term Structure of Yield Curve Volatility, *Journal of Finance* 71, 1393-1436.

Collin-Dufresne, Pierre, Robert Goldstein and J. Spencer Martin, 2001, The determinants of credit spread changes, *Journal of Finance* 56, 2177-2207

De Lira Salvatierra, Irving and Andrew J. Patton, 2015, Dynamic Copula Models and High Frequency Data, *Journal of Empirical Finance* 30, 120-135.

Dick-Nielsen, Jens, 2009, Liquidity Biases in TRACE, *The Journal of Fixed Income* 19, 43-55

Dick-Nielsen, Jens, 2014, How to Clean Enhanced TRACE data

Dick-Nielsen, Jens, Peter Feldhütter and David Lando, 2012, Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis, *Journal of Financial Economics* 103, 471-492

Downing, Chris, Shane Underwood and Yuhang Xing, 2009, The Relative Informational Efficiency of Stocks and Bonds: An Intraday Analysis, *Journal of Financial and Quantitative Analysis* 44, 1081-1102

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate Bond Market Transaction Costs and Transparency, *Journal of Finance* 62, 1421-1451.

Engle, Robert F., 2002, Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business and Economic Statistics*, 20, 339–350.

Engle, Robert F. and Andrew J. Patton, 2001, What good is a volatility model? *Quantitative Finance* 1, 237-245.

Epps, Thomas W., 1979, Comovements in Stock Prices in the Very Short Run, *Journal of the American Statistical Association*, 74, 291–298.

FINRA, Trace Fact book, 2015.

Fleming, Jeff, Chris Kirby and Barbara Ostdiek, 2003, The economic value of volatility timing using ‘‘realized’’ volatility, *Journal of Financial Economics* 67, 473-509.

Goldstein, Michael A., Edith S. Hotchkiss and Erik R. Sirri, 2007, Transparency and Liquidity: A Controlled Experiment on Corporate Bonds, *Review of Financial Studies* 20, 235-273.

Han, Heejoon, 2015, Asymptotic Properties of GARCH-X Processes, *Journal of Financial Econometrics* 13, 188-221.

Hansen, Peter R., and Asger Lunde, 2006. Realized variance and market microstructure noise. *Journal of Business & Economic Statistics* 24 (2), 127–161

Hansen, Peter R., Zhuo Huang, Howard H. Shek, 2011, Realized GARCH: a joint model for returns and realized measures of volatility, *Journal of Applied Econometrics* 27, 877–906

Hautsch, Nikolaus, Lada M. Kyj, Roel C.A. Oomen, 2012, A blocking and regularization approach to high-dimensional realized covariance estimation, *Journal of Applied Econometrics* 27, 625-645

Hayashi, Takaki and Nakahiro Yoshida, 2005, On covariance estimation of non-synchronously observed diffusion processes, *Bernoulli* 11, 359-379.

Hong, Gwangheon and Arthur Warga, 2000, An empirical study of bond market transactions, *Financial Analysts Journal* 56, 32-46

Houweling, Patrick, Albert Mentink and Ton Vorst, 2005, Comparing possible proxies of corporate bond liquidity, *Journal of Banking & Finance* 29, 1331-1358

Huang, Jing-zhi and Ming Huang, 2003, How much of the corporate-treasury yield spread is due to credit risk? Unpublished working paper, Penn State University and Stanford University.

Jensen, Michael C., 1987, The free cash flow theory of takeovers: a financial perspective of mergers and acquisitions and the economy, Federal Reserve Bank of Boston 31, 102-148

Jensen, Michael C. and William H. Meckling, 1976, Theory of the firm: managerial behavior, agency costs and ownership structure, *Journal of Financial Economics* 3, 305-360

Kwan, Simon H., 1996, Firm-specific information and the correlation between individual stocks and bonds, *Journal of Financial Economics* 40, 63-80

Lando, David, 2004, *Credit risk modelling: theory and applications*, Princeton University Press.

Merton, Robert C., (1974), On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance* 29, 449–470

Powers, Eric and Sergey Tsyplakov, 2008, What is the cost of financial flexibility? Theory and evidence for make-whole call provisions, *Financial Management* 37, 485-512.

Ronen, Tavy and Xing Zhou, 2013, Trade and Information in the Corporate Bond Market, *Journal of Financial Markets* 16, 61-103.

Shephard, Neil and Kevin Sheppard, 2010. Realising the future: forecasting with high frequency based volatility (HEAVY) models, *Journal of Applied Econometrics* 25, 197–231.