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The Information Efficiency of the Corporate Bond Market

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The Information Efficiency of the Corporate Bond Market

Abstract

The link between asset prices and information fundamentals as embodied in news announcement effects is an extremely, if not the most, important area amongst current research in market microstructure. The lack of adequate transaction data posts an obstacle in this research. In this thesis, based on a valuable intraday transaction-by-transaction dataset for U.S. corporate bonds, we first examine the impact of public information contained in the macro-economic news and firm-specific information contained in corporate earnings annoucements on the prices of both corporate bonds and stocks. We find that both bonds and stocks react significantly to public news and firm-specific information, and this information is quickly incorporated into both bond and stock prices. More importantly, our results show that stocks do not lead bonds in reflecting firm-specific information, contrary to the conceived intuition that the bond market is less informationally efficient compared with the stock market.

Next we examine the frequency of information arrivals of corporate bonds and its impacts on price duration at the intraday level. We find that there are differences in price durations between corporate bonds and stocks, and for a given company, the persistence of the impact on adjusted price duration is normally higher for stocks than bonds. Our results also show that the parameter estimates are more stable and statistically significant for stocks than for bonds in most cases, which indicate that the ACD model characterized the stock return behavior better than the bond data.

Chapter 1

Objectives of This Study

The main objective of this thesis is to study the information efficiency of the corporate bond market by using a unique dataset consisting of intraday transaction-by-transaction data for U.S. corporate bonds. In this study, we try to address the following questions: Do scheduled macroeconomic news announcements have significant effects on the corporate bond market and which kind of economic announcement has the dominant effect? Do corporate stocks lead bonds in reflecting firm-specific information, or is the speed of price adjustment to firm-specific information (earnings announcements) different for bonds and stocks? Furthermore, are the trading responses to information different for corporate bonds and stocks at the intraday level?

The significance of the study lies in its pioneering contribution to the field of intraday corporate bond returns behavior study. My research is among the first studies to describe the evolution of bond prices relative to the underlying stock prices. Investigation of the corporate bond transactions data allows for a more extensive analysis of its price behavior thereby leading to an enhanced understanding of the price discovery process in this market.

Public Information and Corporate Bond Prices

A vast literature has been devoted to the study of asset prices and information fundamentals as embodied in macroeconomic announcements effects, for both stock and government bond markets. However, the literature on the corporate bond market is quite limited due to the lack of adequate data, despite its size of around $5 trillion and the significant role it plays in financial markets. The corporate bond market provides a venue for more dynamic capital exchanges and portfolio diversification. Similar to stocks and government bonds, corporate bonds react to macroeconomic announcements as firms' performance may directly or indirectly be affected by such public information. Hence, understanding the corporate bond price discovery process allows an investor to predict the impact of macroeconomic news.

In this study, using a unique dataset on intraday corporate bond transactions data, we find that both bond and stock markets react significantly to macroeconomic announcements, and the surprises in public news explains a fraction of price volatility in the aftermath of announcements.

Firm-Specific Information and Corporate Bond Prices

Besides the effect of public information, since both bonds and stocks are claims on the value of the firms' assets, firm-specific information that affects the value of those assets, will also impact prices of both the firm's bond and stock. Although bonds, being liabilities of a firm, enjoy priority over stockholders in case of liquidation, its prices are still strongly dependent on firm-specific information that conveys a firm's ability to meet interest rate payments. Thus, we investigate the effect of earnings announcements and economic news on bond prices at daily and hourly horizons by around news releases. We find that both bonds and stocks react significantly to public economic news and firm-specific information, and this information is quickly incorporated into both bond and stock prices, even at short return horizons. More importantly, our results show that stocks do not lead bonds in reflecting firm-specific information. This result may suggest that despite the preference enjoyed, bondholders immediately react either by entering into a trade or hold strategy shortly after firm-specific news.

Information Content in Trades of Corporate Bonds

Previous studies show that bond prices indeed react to macroeconomic news and firm-specific news. We enrich the analysis for further understanding of the dynamics of bond prices by examining the intensity of information flow. In this study, we employ the autoregressive conditional duration (ACD) model by Engel and Russell (1998) to estimate and compare the intensity of information arrivals and information content of bonds and stocks trades. After removing the intraday time-of-the-day effect in the transaction data, our results show that there are differences in price durations between corporate bonds and stocks, as well as between frequently traded and relatively thinly traded bonds. We also find that the parameter estimates are more stable and statistically significant for stocks than bonds in most cases, which means that the ACD model characterizes the stock data better than the bond data.

This thesis is organized as follows. Chapter 2 is the literature review, where we go through the development of study on the related areas. Chapter 3 examines the effects of macroeconomic announcements on corporate bond prices. Chapter 4 investigates the effect of corporate earnings announcements on corporate bond prices relative to stock prices. Chapter 5 examines the frequency of information arrivals of corporate bonds and its impacts on price duration at the intraday level. Chapter 6 contains our conclusions and points out the limitations of our study and directions for future research.

Chapter 2

Literature Review

To date there has been relatively little research on the behavior of the corporate bond prices, largely because reliable transactions data are rarely available (see Saring and Warga, 1989; Goodhart and O'Hara, 1997). Past studies that have sought to assess the accuracy and efficiency of the corporate bond market have relied on weekly or even monthly quotes from a single market. A high-frequency dataset based on intraday corporate bonds transactions data, however, will facilitate the understanding of the efficiency and price evolution process for corporate bond market at the intraday level.

2.1 Government Bond Prices and Economic News Effects

Many studies have sought to link the effects of macroeconomic announcements to movements in bond returns. While earlier studies relied on daily, or even weekly or monthly data (see Grossman, 1981; Urich and Wachtel, 1981; Roley and Walsh, 1985), recent work has moved toward the use of more finely-sampled intraday data.

These include Fleming and Remolona (1997, 1999), Balduzzi, Elton and Green (2001), Bollerslev, Cai and Song (2000), Green (2004), Hautsch and Hess (2002), Kuttner (2001) who study government bond markets.

Bollerslev, Cai and Song (2000) find that public information in the form of regularly scheduled macroeconomic announcements is an important source of volatility at the intraday level. Among the various announcements, the employment report, the producer price index (PPI), the employment cost, retail sales and the NAPM survey have the greatest impact on the U.S. Treasury bond market.

Fleming and Remolona (1999) study price volatility and trading behavior using data from the secondary market for U.S. Treasury securities. They find that prices adjust sharply to a just-released announcement while trading volume declines, demonstrating empirically that price responses to public information do not require trading. However, they only investigate overall volatility effects and have not distinguished between different types of announcement and different components of the announcements. By relating bond price changes to the surprise component of the announcement, Balduzzi, Elton and Green (2001) find that both positive real shocks and positive inflation shocks affect government bond prices negatively, which confirm the theoretical predications that there is an unambiguous link between macroeconomic fundamentals and the bond market, with unexpected increases in real activity and inflation raising bond yields (lowering bond prices). Moreover, they find that the absolute size of news effects generally increases with the maturity of the instrument.

However, previous research has been limited to the government bond market. The literature of the effects of macroeconomic announcements on corporate bond prices is rarely available due to the lack of adequate data, despite the size which is around $5 trillion and importance of these markets.

2.2 Bond and Stock Prices and Firm-specific Information Effects

Both bonds and stocks are claims on the value of the firm's assets. As such, the information that affects the value of those assets will impact prices of both the firm's bonds and stocks. To the extent that both markets are informationally efficient, we expect to observe a contemporaneous relationship between bond and stock returns. On the other hand, if the bond market is less efficient, stocks will reflect information about the value of underlying assets more quickly, and we should observe that stock returns have predictive power for future bond returns.

An extensive empirical literature has explored the relationship between stock and bond returns, but little consensus has emerged. Several studies find a strong contemporaneous relationship between corporate bond returns and government bond or stock returns using monthly or weekly quote data (see Cornell and Green, 1991; Kwan, 1996). In particular, Kwan (1996) finds that lagged stock returns have explanatory power for current bond yield changes.

Using a unique dataset based on daily and hourly transaction prices for 55 high-yield corporate bonds, Hotchkiss and Ronen (2002) examine the informational efficiency of the corporate bond market relative to the market for the underlying stock. They find that although positive and significant correlations between bond and stock returns persist on the daily and intradaily level, these are no causal relationships. Granger causality tests indicate that lagged stock returns are not significant in explaining bond returns. Any contemporaneous relationship we observe is best described as a joint reaction to common factors.

Since both corporate bonds and stocks react to common information events, Hotchkiss and Ronen (2002) further investigate the reaction of corporate bond and stock returns to firm-specific (earnings) information, as well as their relative speeds of adjustment to this information. They find that both daily and hourly high-yield bond returns are significantly related to unanticipated earnings. Furthermore, this firm-specific information is quickly incorporated into bond prices as into stock prices.

Less work has been done on the information efficiency and price discovery process for corporate bond market at the intraday level due to the lack of transactions data. Set against this backdrop, our study utilize a unique dataset based on intraday transactions data for U.S. corporate bonds, to examine the information efficiency and price discovery of the corporate bond market at the intraday level. In particular, our study extends Hotchkiss and Ronen (2002) by investigating the effect of public information contained in the macroeconomic announcements and firm-specific information contained in the earnings announcements on corporate bond and stock prices and how quickly this information is impounded into both prices.

2.3 Information Content of Time between Trades

In market microstructure studies, besides the linkages between asset prices and information fundamentals as embodied in news announcement effects, another important issue is the information role of time between trades.

The theoretical motivations for the empirical investigation on the role of time between trades can be found in the models of Diamond and Verrecchia (1987) and Easley and O'Hara (1992). In Diamond and Verrecchia (1987), at the beginning of the trading day, one of two possible events happens, either good news or bad news. Thus, informed traders will always trade unless they do not own the stock and short-sale constraints exist. Accordingly, long durations are likely to be associated with bad news. In Easley and O'Hara (1992), informed traders trade on either side of their signal, but only when there is a signal ("news") and therefore long durations are likely to be associated with no news. These two contributions suggest that time actually conveys information. By definition, an uninformed trader's decision to trade is independent of the existence of any information. However, informed traders only trade when they have information, hence variances in trading rates in Easley and O'Hara (1992) are associated with changing numbers of informed traders. More generally, informed traders would presumably choose to trade as quickly as possible and as much as possible once they have received their information. However, as analyzed by Easley and O'Hara (1987), informed traders may be quickly distinguished by their large volume trading and hence their profit would be lessened. Therefore the incentives to trade quickly are reduced. On the other hand, informed traders may choose to break up large volume trades, thereby generating a larger number of informationally based trades. Thus, it is reasonable to assume that variations in the trading intensity are positively related to the behavior of informed traders. Therefore trading intensity, which results in short and long durations between trades, may provide information to market participants.

The theoretical models formulate a plausible role for time, but “the importance of time is ultimately an empirical question…” (see O’Hara, 1995). In order to address this issue, an autoregressive conditional duration (ACD) model is first established by Engle & Russell (1998) to analyze the high frequently traded stocks market. Later some scholars follow their methodology and use the ACD model to analyze the price discovery in the U.S Treasury market (see Chen et al., 2006).

Based on an available large intraday dataset of U.S. corporate bond transactions data, this paper attempts to utilize ACD model to estimate and compare the price duration of corporate bonds and stocks to assess the differential information content of bonds and stocks trade frequency.

Chapter 3

Public Information and Corporate Bond Prices

Earlier public information research has been limited to the stock and government bond market. The study of the effects of economic announcements on corporate bond prices is meager mainly due to the lack of adequate transactions data, despite the huge size (around $5 trillion) and importance of this market.

Based on a valuable intraday corporate bond transaction dataset, we attempt to investigate the effects of scheduled macroeconomic announcements on corporate bond prices. We are particularly interested in if the economic announcements have significant effects on the corporate bond market and which kinds of announcements have the dominant effect. The answers for these questions have relevant implications for our understanding of the microstructure of corporate bond markets.

3.1 The Data

Firstly, this section describes the data set used in the empirical analysis: the intraday

U.S. corporate bond and stock prices data and U.S. monthly macroeconomic announcements and expectations data.

3.1.1 Transactions Data for U.S. Corporate Bonds and Stocks

Unlike stock transaction data, corporate bond transaction data historically has not been publicly reported. Over time there has been increasing concern over the lack of transparency in the corporate bond market. Beginning on July 1, 2002, the National Association of Securities Dealers (DASD) requires all bond dealers to report their transactions through its Trade Reporting and Compliance Engine (TRACE) system. Here we employ the corporate bond transaction data obtained from the TRACE system in our study. Our primary data set contains price, trading time and size of transactions for all publicly traded over-the-counter (OTC) corporate bonds. Additional information on the characteristics of each bond is collected from Bloomberg, which includes the ratings of a bond when it was issued, and the information of whether the bond contains certain provisions. Furthermore, corresponding corporate stock intraday transaction-by-transaction data for the same firms are obtained from WRDS TAQ database.

Our sample includes bond transaction records from July 1, 2002 to April 21, 2005. Among the whole sample, first we filter out those data that appears to be recorded with errors. We also exclude those bonds which we cannot identify their ratings from Bloomberg. In order to get sufficient number of transactions for each corporate bond, we exclude the bonds with the AAA rating and with a rating lower than B. To avoid the confounding effects of embedded options, we eliminate bonds with provisions, such as, callable, puttable, convertible, and sinking fund bonds. In addition, we exclude bond with floating rates, odd frequency of coupon payments and maturity less than one year. We also require that each selected firm has unbroken stock transaction records in the WRDS TAQ database over the same sample period. Finally, to mitigate the problem of nonsynchronous trading, we choose 30 most frequently traded corporate bonds from each rating class (AA, A, BBB, BB and B). Feasibility of intraday analysis of corporate bond market is the main consideration in determining the size of our final sample. Among the 150 corporate bonds chosen for the five rating classes, later some firms are dropped due to the merger and acquisition. Finally 134 of them are kept. Table 3.1 provides the list of company names together with their credit ratings.

<u>Table 3.1 about here</u>

Like most securities traded in the dealer market, the corporate bond market is illiquid, compared with the stock market. The trading activity declines rapidly for bonds that are not among most frequently traded. In order to test the effects of macroeconomic announcements at the intraday 5-minute interval level, in this chapter we choose the transactions data for those 30 most frequently traded corporate bonds (based on the trade size which is measured in millions of U.S. dollars), together with their intraday stocks data, out of 134 firms in the sample to construct our panel data set. * in Table 3.1 indicate the narrow sample of 30 firms used in this chapter.

3.1.2 Macroeconomic Announcements and Expectations

The data on monthly macroeconomic annoucements and expectations are from Bloomberg. Among all the announcements, the 21 economic annoucements which are considered to have important influences on the markets are chosen. This is a relatively more comprehensive set of economic announcements compared with the other existing studies (see Hakkio and Pearce, 1985; Ito and Roley, 1987; McQueen and Roley, 1993; Green, 2004). The 21 macroeconomic news announcements that we consider are shown in Table 3.2.

<u>Table 3.2 about here</u>

As Table 3.2 shows, twelve of the announcements occur at 8:30 AM, two at 9:15 AM, six at 10:00 AM, and one at 2:00 PM. Most of the announcements are made monthly, although Initial Jobless Claims are announced weekly. Table 3.2 shows that the number of times an announcement coincided with another announcement. For example, Change in Nonfarm Payrolls and Unemployment Rate are always released together at 8:30 AM. Table 3.2 also reports the units used to measure the announced figures. Levels are reported as units, dollars, or percentages. Changes are reported as either absolute in units or dollars, or as a percentage change from the previous observation.

3.2 Methodology

This section explains the methodology used to evaluate the effects of the different macroeconomic announcements on corporate bond and stock prices. Let F_i denote the expectation and A_i the released value for announcement i. Following Balduzzi, Elton and Green (2001), we measure the surprise contained in announcement i as

$$E_i = A_i - F_i \tag{3.1}$$

Since units of measurement differ across different economic announcements, we divide the surprises by their standard deviation across all observations to facilitate interpretation later. The “standardized” surprise measure is

$$S_i = \frac{E_i}{\sigma_i} \tag{3.2}$$

Thus, when regressing bond or stock returns on surprises, the regression coefficient is the change in return for one standard deviation change in the surprise. Since the standard deviation σ_i is constant across all the observations for a given announcement i, this adjustment does not affect either the significance of the estimate results or the fit of the overall regressions. The only reason for the standardization procedure is that it allows us to compare the size of regression coefficients associated with surprises across various announcements.

To analyze the effect of macroeconomic announcements on bond or stock prices, we regress price changes on the surprise in the economic announcements being studied and the surprises in announcements released simultaneously. Before we run the regression equation for bond price changes, we run identical regressions using price changes from five minutes before to five, 10, 15, 20, 25, 30, 35, 40, 45, 50 minutes after the announcement. The results show that price changes are relatively slow in this market compared with that of the corporate stock market. We find no additional bond price change after 50 minutes. Therefore, our choice of 50 minutes should capture all the relevant price changes. The regression equation for bond price changes is defined as

$$(P_{50it} - P_{-5it}) / P_{-5it} = \alpha_i + \beta_{0i} S_{it} + \sum_{k=1}^{K} \beta_{ki} S_{i_k,t} + \varepsilon_{it} \tag{3.3}$$

For each announcement i as numbered in Table 3.2 (i = 1, 2, …, 21) that we want to analyze,

P_{50it} is the bond price 50 minutes after announcement i at time t;

P_{-5it} is the bond price five minutes before announcement i at time t;

β_{0i} is the sensitivity of the bond price to the announcement i;

S_{it} is the standardized surprise contained in the announcement i at time t;

k denotes the kth announcement concurrent with announcement i, and K is the total number of concurrent announcements;

β_{ki} is the sensitivity of the bond price to the kth announcement concurrent with announcement i;

i_k denotes the announcement number as indicated in Table 3.2 (from 1 to 21) of the kth announcement concurrent with announcement i; and

$S_{i_k,t}$ is the standardized surprise contained in the kth announcement concurrent with announcement i at time t.

For the corresponding stock price changes in the narrow sample, we run the following regression. Before we run the regression equation for stock price changes, we also run identical regressions using price changes from five minutes before to one, two, three, four, five, 10 minutes after the announcement. The price changes are extremely rapid in this market, with most of the impact in the first minute after the release. Here, our choice of 5 minutes should capture all the relevant price changes. The regression equation for stock price changes is defined as

$$(P_{5it} - P_{-5it}) / P_{-5it} = \alpha_i + \beta_{0i} S_{it} + \sum_{k=1}^{K} \beta_{ki} S_{i_k,t} + \varepsilon_{it} \tag{3.4}$$

where

P_{5it} is the stock price five minutes after announcement i at time t;

P_{-5it} is the bond price five minutes before announcement i at time t;

For example, from Table 3.2, we know that the Change in Nonfarm Payrolls and the Unemployment Rate are always released at the same time. Moreover, the two announcements concur three times with the Personal Income and Personal Spending, and once with the Initial Jobless Claims. We include a concurrent announcement in the regression if it occurs at least 10% of the times the announcement under analysis is released. Therefore, for the Change in Norfarm Payrolls, we include one concurrent announcement, K =1, and we run the regression,

$$(P_{502t} - P_{-52t}) / P_{-52t} = \alpha_2 + \beta_{02} S_{2t} + \beta_{12} S_{12t} + \varepsilon_{2t} \tag{3.5}$$

The subscripts 2, and 12, correspond to the announcements as numbered in Table 3.2; that is, 2 represent the Change in Nonfarm Payrolls, and 12 represent the Unemployment Rate. By using our panel data set of 30 most frequently traded corporate bonds, this regression has 34*30 = 1020 observations. To estimate the surprise coefficients, here we use GLS instead of OLS to correct heteroskedasticity with cross-sectional correlation.

3.3 Empirical Test Results

In this section, we identify the type of announcements that have a significant effect on corporate bond prices, and measure the intensity of the each announcement's impact based on the empirical test results obtained.

3.3.1 Which Economic Announcements Affect Corporate Bond Prices?

Table 3.3 presents the estimation results for the corporate bonds and stocks. The table shows standard deviations and slope coefficients for each announcement, * and ** indicate that the coefficients are significant at the 5% and 1% levels, respectively.

<u>Table 3.3 about here</u>

At the same time, the estimates of slope coefficients for other contemporaneous announcements included in each individual regression for bond returns are reported in Table 3.4. * and ** indicate that the coefficients are significant at the 5% and 1% levels, respectively.

<u>Table 3.4 about here</u>

The main results follow.

First, the prices of corporate stocks and bonds react significantly to nine announcements. These nine announcements are: Change in Nonfarm Payrolls, Durable Goods Orders, Personal Income, Producer Price Index, Capacity Utilization, Industrial Production, Consumer Confidence, New Home Sales, and National Association of Purchasing Managers (NAPM). In addition, six announcements affect the prices of corporate stocks, GDP Annualized, Housing Starts, Unemployment Rate, Construction Spending, Factory Orders, and Leading Indicators; four announcements affect the prices of corporate bonds, Advanced Retail Sales, Personal Spending, Trade Balance, and Monthly Budget Statement.

In summary, among 21 macroeconomic announcements, nine announcements significantly affect the prices of both stocks and bonds, 15 announcements significantly affect the prices of stocks, while 13 announcements affect the prices of corporate bonds. These differential effects on stocks and bonds could be the result of chance, or it could be that different announcements affect in different ways stock and bond prices.

It is also important to note how we have been able to separate the effects of different announcements released concurrently by using the standardized surprises data, and how the availability of the Bloomberg forecast data allows us to calculate surprises. This is to be contrasted with Fleming and Remolona (1999), who pool the Consumer Price Index, Producer Price Index, and employment announcements together, and Ederington and Lee (1993), who identify an announcement with a dummy variable and are not able to distinguish the different components of an announcement, or to separate between concurring announcements. For example, the Change in Nonfarm Payrolls and the Unemployment Rate are always released together at 8:30 AM. Therefore, without knowing the surprise components of the two announcements, there is no way to separate their influence. However, Table 3.3 shows that the surprises in the Unemployment Rate affect corporate bond prices much less than surprises in the Change in Nonfarm Payrolls. The results show that the Change in Nonfarm Payrolls affect bond prices, while the Unemployment Rate affect is much less important. Also, consider the case of NAPM and Construction Spending. Once again, Table 3.2 shows that 30 out of 34 times they are announced at the same time. Using the surprises data, we are able to show that it is the NAPM instead of the Construction Spending that affects bond prices.

3.3.2 Sign and Size of Announcements Response

A significant dimension of this study is on the sign and size of announcement response corporate bond prices. Most theories predict an unambiguous link between macroeconomic fundamentals and the bond market, with unexpected increases in real activity and inflation lowering prices. Our results are consistent with this interpretation and the finding of previous studies (see Balduzzi, Elton, and Green, 2001). Positive real shocks and positive inflation shocks, such as, the surprises in the Advanced Retail Sales, Change in Nonfarm Payrolls, Durable Goods Orders, Personal Income, Personal Spending, Producer Price Index, Trade Balance, Consumer Confidence, NAPM, and Monthly Budget Statement, affect corporate bond price negatively.

Table 3.3 also shows that the 13 economic announcements which significantly affect the bond prices have different impacts in terms of the magnitude of price changes. Per unit of standard deviation of surprise, the most important is Change in

Nonfarm Payrolls. To gain some idea of the importance of this announcement, note that the standard deviation of the daily percentage price change for the corporate bonds is 1.38%. Thus, a one standard deviation surprise in Change in Nonfarm Payrolls, corresponding to an increasing in Change in Nonfarm Payrolls of 100,430, lead to a price change of about 16% of the normal daily volatility of price changes. Next in importance are NAPM and Consumer Confidence. A one standard deviation surprise in NAPM and Consumer Confidence leads to a price change of about 12% and 7% of the normal daily volatility, respectively. Advanced Retail Sales, Personal Spending, Capital Utilization, Industrial Production, and Monthly Budget Statement are of roughly equal importance. They induce price changes that range from 5% to 7%. Durable Goods Orders, Personal Income, Producer Price Index and Trade Balance have effects between 3% and 5% of daily volatility. Finally, New Home Sales has the smallest effect on corporate bond prices, with effect of 1% percent of daily volatility.

Chapter 4

Firm-Specific Information and Corporate Bond Prices

The previous chapter indicates both bond and stock markets react significantly to macroeconomic announcements. Since both bonds and stocks are claims on the value of the firms' assets, we can expect that firm-specific information, for example, earnings information, that affects the value of those assets, will impact prices of both the firm's bond and stock. This chapter focuses on the effect of the firm-specific information contained in earnings announcements on bond prices at daily and hourly horizons. Our tests allow us to examine how quickly the information is incorporated into bond relative to stock prices. In particular, our study extends Hotchkiss and Ronen (2002), by including public information contained in the macroeconomic announcements at the same time, to investigate the effect of public information and firm-specific information (earnings) on corporate bond prices.

4.1 The Data

Firstly, this section describes the data set used in the empirical analysis: the daily and hourly U.S. corporate bond and stock transactions data and U.S. quarterly corporate earnings announcements and analyst's forecasts.

4.1.1 Calculation of Daily and Hourly Corporate Bond and Stock Returns

Daily corporate bond and stock returns are calculated as follows. Daily bond returns, $RB_{i,t}$, are calculated using the last transaction price for the last hour of trade in bond i on day t. For the few cases in which a bond does not have a reported price for a given day, we assume that the price is equal to the last recorded price. To calculate stock returns, $RS_{i,t}$, we use the last transaction price reported on the WRDS TAQ database for the hour corresponding to the last hour of trade for corporate bond i on day t.

In addition to the daily return characteristics, in this chapter we take advantage of our unique intraday corporate bonds dataset, and calculate intradaily (hourly) bond returns. Hourly bond and stock returns are calculated similarly to daily returns. Hourly bond returns are calculated using the last transaction price for the each hour of trade in bond i on day t. To calculate stock returns, we use the last stock transaction price reported on WRDS TAQ database for each of the nine hourly trade intervals. When a bond or stock does not have a reported price for a given hour, we assume that the price remains unchanged from the most recent hour with a trade. Since the exact releasing time data for U.S. quarterly corporate earnings announcements is only available from the beginning of 2005, and our bond transactions dataset is available from July 1, 2002 to April 21, 2005, tests involving hourly corporate bond and stock returns are therefore restricted to this time period.

Following the methodology used by Hotchkiss and Ronen (2002), we also measure daily and hourly stock returns, RM_t, using the S&P 500 stock index to account for market-wide information.

4.1.2 Earnings Announcements and Analyst's Forecasts

Data on U.S. quarterly corporate earnings announcements and analyst's earnings forecasts are obtained from IBES. We report results for the entire sample of corporate bonds, including the subset of 30 most frequently traded bonds examined in the previous chapter; although some bonds are not actively traded over the entire sample time period, they may become more active in response to earnings surprises. For each firm we obtain the releasing time of the quarterly corporate earnings announcement from Dow Jones Newswires; almost all announcements for our sample occur early on the announcement day. We include only events where there is no additional significant news reported in the Dow Jones Newswires between IBES forecast date and the announcement release date. For all these events, we have underlying stock return data.

4.2 Methodology

Our dataset make it possible to examine the effect of firm-specific information contained in the earnings announcements, and at the same time public information contained in the macroeconomic announcements, on corporate bond and stock prices at short horizons and how quickly these information are impounded into both bond and stock prices.

This section explains the methodology used to evaluate the effects of firm-specific information (earnings annoucements) and public information (macro-economic announcements) on daily and hourly corporate bond and stock prices.

We compare reported earnings to the median of analyst's forecasts reported on IBES just prior to the announcement and calculate the log forecast errors,

$$FE_i = \ln(A_i / F_i) \quad (4.1)$$

where

FE_i is the log forecast error for firm i;

A_i is the announced earnings per share; and

F_i is the forecast earnings per share.

Here we exclude from the analysis the observations where A_i or F_i is negative. Our results are insensitive to alternative definitions of the forecast error $FE_i = (A_i - F_i)/F_i$. This leaves us with a sample of 110 events, which covers 110 bonds from 107 companies. Stock and bond returns are calculated for different intervals around the announcement time.

To examine whether earnings information is reflected in daily bond or stock returns and how quickly this information is completely incorporated into prices, following the methodology used in Hotchkiss and Ronen (2002), we first run the following cross-sectional regressions:

$$RB_{[t,t+1]} = \alpha_0 + \alpha_1 \cdot FE + \alpha_2 \cdot RM_{[t,t+1]} + \varepsilon \quad (4.2)$$

$$RS_{[t,t+1]} = \alpha_0 + \alpha_1 \cdot FE + \alpha_2 \cdot RM_{[t,t+1]} + \varepsilon \tag{4.3}$$

where RB and RS are the daily bond and stock returns, respectively. We examine one-day windows starting at the date prior to the announcement. For the daily data, the dependent variables for the regressions are $RB_{[t,t+1]}$ and $RS_{[t,t+1]}$, where t ranges from -1 to +3. For example, $RB_{[-1,0]}$ and $RS_{[-1,0]}$ indicate the bond and stock returns for the period starting at date -1 prior to the announcement to the announcement date, respectively. RM, the returns on the S&P 500 index, is included to control for market movements over these return intervals.

In this chapter, then we extend Hotchkiss and Ronen (2002)'s methodology, by including public information contained in the macroeconomic announcements at the same time, to investigate the effects of public information and firm-specific information (earnings) on daily and hourly corporate bond and stock prices. We run the following cross-sectional regressions:

$$RB_{[t,t+1]} = \alpha_0 + \alpha_1 \cdot FE + \alpha_2 \cdot RM_{[t,t+1]} + \alpha_3 \cdot NS_{[t,t+1]} + \varepsilon \tag{4.4}$$

$$RS_{[t,t+1]} = \alpha_0 + \alpha_1 \cdot FE + \alpha_2 \cdot RM_{[t,t+1]} + \alpha_3 \cdot NS_{[t,t+1]} + \varepsilon \tag{4.5}$$

where RB and RS are the daily or hourly bond and stock returns, respectively. We examine one-day (one-hour) windows starting at the date (hour) prior to the announcement. For the daily data, the dependent variables for the regressions are $RB_{[t,t+1]}$ and $RS_{[t,t+1]}$, where t ranges from -1 to +3. For the hourly data, t ranges from -1 to +8. In the regression equations (4.4) and (4.5), we include the public news surprise, NS, as an additional explanatory variable. $NS_{[t,t+1]}$ indicates the public news surprise contained in the macroeconomic announcements for the [t, t+1] interval. If there is no macroeconomic announcement released during the [*t*, *t*+1] interval, the public news surprise, $NS_{[t,t+1]}$, is equal to 0. To get the public news surprise for each one-day (one-hour) time interval, here we exclude from our analysis the observations where there is more than one monthly macroeconomic announcement released for each one-day (one-hour) interval. This leaves us with a sample of 78 events, which covers 78 corporate bonds from 75 companies. RM, the returns on the S&P 500 index, is still included to control for market movements over these return intervals.

4.3 Empirical Results and Analysis

In this section, we investigate the effects of public information contained in the macroeconomic announcements and firm-specific information contained in the corporate earnings annoucements on daily and hourly corporate bond and stock prices based on the empirical results we get.

Table 4.1 reports regression results for equation (4.2) and (4.3) using daily data. Test statistics are computed using heteroscedastic-consistent variance estimates (see White, 1980).

<u>Table 4.1 about here</u>

The daily regression results in each panel indicate that all information is quickly impounded into both bond and stock prices. For the bond returns, panel A shows that the forecast error is positive and significant for the one-day interval ending on the announcements date, [-1, 0]. Returns for any subsequent time interval are not significantly related to the forecast error. These results suggest that the firm-specific information related to the earnings news is completely reflected in corporate bond prices by the end of the announcement day. For the stock returns, panel B shows that the forecast error has the similar effect pattern. The forecast error is positive and significant for the one-day interval ending on the announcements date, [-1, 0], and not significant for any subsequent time interval, which means that the firm-specific information contained in the earnings announcements is also fully incorporated into the stock prices by the end of the announcement day. Market-wide information is reflected in the coefficients for the S&P 500 returns. Table 4.1 indicates that the returns on the S&P 500 index have significant explanatory power for the daily stock returns over all the intervals reported, while they are not significant for the daily bond returns over any time interval. These results suggest that the returns on the corporate stocks appear to be subject to the same type of systematic risk that affects other stocks.

Table 4.2 reports regression results for equation (4.4) and (4.5) using daily data.

Table 4.2 about here

From Table 4.2, we can find that results for the earning forecast error and the returns on S&P 500 index are nearly identical when we include the public news surprise as an additional explanatory variable. For both bond and stock returns, the forecast error is only positive and significant for the one-day interval ending on the announcements date, [-1, 0], which indicates that all information is quickly impounded into both bond and stock prices. The R^2s for the stock return regressions are consistent with those reported in Table 4.1, while the R^2s for the bond return regressions are slightly higher than those reported in Table 4.1. Our results show that for both bond and stock returns, the public news surprise contained in the macroeconomic announcements is positive and significant for the one-day interval starting at the announcement day, [0, 1]. During this one-day interval starting at the annoucement day, [0, 1], 39 macroeconomic announcements are released. Among the 39 annoucements, there includes: once Producer Price Index, three times Capacity Utilization, seven times Consumer Confidence, and 10 times Durable Goods Orders, which are shown to have significant effects on the prices of both corporate bonds and stocks based on the empirical results we get in the previous chapter.

As with the daily returns, here we also examine the speed with which information is fully incorporated into prices of both corporate bonds and stocks. Table 4.3 reports these regressions for the hourly data.

<u>Table 4.3 about here</u>

For the bond return regressions in panel A, the earnings forecast error variable is significant for the [2, 3] and [3, 4] intervals, which means the earnings information is fully incorporated into the bond prices by the end of the fourth hour following the earnings announcement. For the stock return regressions in panel B, the earnings forecast error variable is significant for the [-1, 0], [2, 3], and [4, 8] intervals, which indicates that the earnings information is fully incorporated into the stock prices by the eighth hour following the earnings announcement, with the highest significance level in the hour of the announcement. Although earnings information is incorporated into stock prices over a slightly longer time interval, the greatest impact appears in the first hour. Since most earnings announcements are released early on the announcement date, these results show that earnings information is rapidly incorporated into both bond and stock prices within the announcement day. Most importantly, however, the evidence is a contrast to the intuition that the bond market is less informationally efficient compared with the stock market, and information is only incorporated into bond prices slowly over time.

Chapter 5

Information Content in Trades of Corporate Bonds

The results of previous two chapters show that both corporate bonds and stocks react significantly to public information contained in the macroeconomic announcements and firm-specific information contained in the corporate earnings annoucements, and these information are impounded into the prices of both bonds and stocks at short horizons. We also find that stocks do not lead bonds in reflecting firm-specific information.

In the market microstructure studies, besides the linkages between asset prices and information fundamentals as embodied in news announcement effects, another important issue is the information role of time between trades. In order to address this issue, an autoregressive conditional duration (ACD) model established by Engle & Russell (1998) is used to analyze the high frequently traded stocks market and the U.S. Treasury market (see Chen et al., 2006). Now based on an available large intraday dataset of U.S. corporate bond transactions data, this chapter utilizes ACD model to estimate and compare the price duration of corporate bonds and stocks to assess the differential information content of bonds and stocks trade frequency.

5.1 The Model

Firstly, this section describes the methodology and empirical model for estimating the intensity of trade arrivals and the effects of microstructure variables on the time duration of trade and price changes: the autoregressive conditional duration (ACD) model.

5.1.1 Autoregressive Conditional Duration (ACD) Model

Information arrivals induce trades and price changes (see Admati and Pfleiderer, 1988; Easley and O'Hara, 1992). To analyze information flow at irregular arrival times, Engle and Russell (1998) suggest the autoregressive conditional duration (ACD) model for characterizing the stochastic process of time duration. Denote the interval between two consecutive arrival times, $x_t = t_t - t_{t-1}$, as duration. Specifically, the expectation of the tth duration conditional on past duration can be formulated as

$$\Psi_t = E(x_t \mid x_{t-1}, x_{t-2}, ..., x_1) = \Psi_t(x_{t-1}, x_{t-2}, ..., x_1; \Phi) \tag{5.1}$$

where Φ is the vector of the parameters of the time duration process. Assuming that the stochastic process of the tth duration, or the interval between the arrival time of the tth and (t-1)th trade, is

$$x_t = \Psi_t \varepsilon_t \tag{5.2}$$

where ε_t is an *i.i.d.* error term whose distribution is to be specified. Following the paper by Engle and Russell (1998), the conditional time duration can be specified by a general model:

$$\Psi_t = \omega + \sum_{j=1}^{m} \alpha_j x_{t-j} + \sum_{k=1}^{q} \beta_k \Psi_{t-k} \qquad (5.3)$$

which follows an ACD(m, q) process with m and q referring to lag orders, and $\Phi = (\omega, \alpha_j, \beta_k)$, j = 1, 2, …, m and k = 1, 2, …, q, are parameters to be estimated. This model has a close connection with GARCH models and shares many similar properties. The model is convenient because it can be estimated using a standard GARCH program by employing the square root of x_t as the dependent variable and setting the mean to zero (see Engle and Russell, 1998).

In general, if durations are conditionally exponential, the conditional intensity is

$$\lambda\left(t \middle| x_{N(t)}, \ldots, x_1\right) = \Psi_{N(t)+1}^{-1} \qquad (5.4)$$

It helps to reveal that the higher the conditional intensity, the higher the volatility of returns.

There are several ways to estimate the system of equation (2)-(3). The simplest way is to assume that the error term follows an exponential distribution and the lagged orders equal to one. This model is called the EACD(1,1) where E stands for the exponential distribution. Another way is to assume that the conditional distribution follow a Weibull distribution, which is equivalent to assuming that x^{θ} is exponential where θ is the Weibull parameter. Several papers (Engle and Russell, 1998; Dufour and Engle, 2000) already adopt the Weibull distribution to estimate the

ACD model. If the Weibull ACD model is estimated with the lagged orders equal to one, that is, WACD(1,1). Therefore, the conditional duration is expressed as

$$\Psi_t = \omega + \alpha_1 x_{t-1} + \beta_1 \Psi_{t-1} \tag{5.5}$$

The Weibull distribution function can be written as

$$F(x_t) = \left(\theta / \Psi_t^{\theta}\right) x_t^{\theta-1} \exp[-\left(x_t / \Psi_t\right)^{\theta}] \tag{5.6}$$

where $\theta, \Psi_t > 0$. When $\theta = 1$, x_t / Ψ_t follows an exponential distribution. The Weibull distribution is preferred if the data show an over-dispersion with extreme values (very short or long durations) more likely than the exponential distribution would predict (see Dufour and Engle, 2000). Given the conditional density function, the parameters of the ACD model can be estimated by maximizing the following log-likelihood function (see Engle and Russell, 1998):

$$L(\eta) = \sum_{t=1}^{T} \ln\left(\theta / x_t\right) + \theta \ln\left[\Gamma(1+1/\theta) x_t / \Psi_t\right] - \left[\Gamma(1+1/\theta) x_t / \Psi_t\right]^{\theta} \tag{5.7}$$

where θ and $\Psi_t > 0$, $\Gamma(\cdot)$ is the gamma function and η is a column vector containing the parameters to be estimated. Engle and Russell (1998) commend the clever optimization that eliminates the need for repeated evaluation of the gamma function. This tactic is useful when the sample size is very large.

The ACD model is essentially a model for intertemporally correlated transaction (event) arrival times. The arrival times are treated as random variables following a point process. In the context of security trading, associated with each arrival time are random variables such as volume, price or bid-ask spread. These variables are defined as "marks". Finance researchers are often interested in modeling these marks associated with the arrival times. For example, not all transactions occur because of the arrival of new information. Instead, some are triggered by pure liquidity or portfolio adjustment reasons, which may not cause any change in the expected security value. On the other hand, there are times when transactions occur as a result of new information arrival that is not publicly observable. Market microstructure theory suggests that traders possessing private information will trade as long as their information has value. This results in clustering of transactions following an information event. To examine this hypothesis, the events can be defined as a subset of the transaction arrival times with specific “marks”. For example, to examine the effect of information events, we can select data points for which price has moved beyond the bid-ask bound. This process is called “dependent thinning”.

To distinguish informed from uninformed trades, transaction arrival times are modified into price arrival times. The basic idea is to leave out those transactions that do not significantly alter price. The price movements can be classified either as transitory or permanent movements. Define the midpoint of the bid-ask spread or mid-quote to be the current price. Following Engle and Russell (1998), we define a permanent price movement as any change in current price greater than or equal to 2 ticks (Each tick is 1/8 dollar). The purpose of excluding quotes whose average prices have moved within 2 ticks is to exclude possible noisy quotes and to include only those quotes that have significant information embedded in them. The new price process is referred to as the thinned price process. Then ACD model can be applied to these new event arrival times. In this case, the intensity function is so called price intensity, which measures the instantaneous probability of a permanent price movement.

It is widely known that intraday return volatility exhibits significant deterministic (periodic) patterns. Since price duration is the inverse of volatility, the duration measure is expected to contain a deterministic component. In order to successfully implement the ACD model, this deterministic component needs to be separated from the stochastic component in empirical estimation. The strategy followed here to eliminate the intraday pattern is a simple seasonal adjustment approach. For stock, the time span within a trading day is divided into non-overlapping time intervals of 15 minutes each. The mean of price durations within each interval is computed over the entire sample period. The adjusted price duration is then computed as the price duration divided by the average price duration within that interval. The adjusted price duration series now has a mean approximately equal to one. If the adjusted duration is greater (less) than one, the duration is greater (less) than the average duration in that time interval. The ACD model can be estimated by using these adjusted price durations, as well as the raw (unadjusted) durations.

5.2 The Data

As mentioned in chapter three, our primary data set contains intraday transaction-by-transaction data on price, trading volume and trading time for 134 U.S. corporate bonds, and stocks. The study in this chapter is based on this intraday dataset.

Previous studies (see Easley et al., 1996; Wu and Xu, 2000) have used trading volume as a measure for defining the activeness of stocks. Trading volume is a preferred measure for this classification because it contains the information of frequency and size of trades, both of which are important indicators of the activeness or depth of securities. To insure enough trading activities for purposes of empirical estimation, we rank all corporate bonds by their total number of transactions, and then among all 134 corporate bonds, a sample of 60 most frequently traded bonds is chosen based on the bond transactions. Stock intraday transactions data on price, trading volume, and trading time for the same firms is obtained from TAQ database. Instead of the full sample period which covers July 1, 2002 to April 21, 2005, a narrow sample period from January 1, 2004 to December 31, 2004 is used in this chapter.

5.2.1 Adjusted Price Duration Data

To calculate the adjusted price duration, firstly, we eliminate the first quotes on any given day to remove any extra information that has accumulated since the last market close. Then by definition, transaction duration can be easily computed as the time difference between consecutive trades. Consecutive trades with same time stamp and price are aggregated and treated as one trade. Later the transaction data can be "thinned" by constructing price duration with price changes greater than or equal to two ticks. Volume is expressed in terms of the number of shares traded at each time interval. This procedure aims to eliminate possibly noisy quotes, and to include only those quotes that have significant information embedded in them.

Table 5.1 shows the summary statistics after dependent thinning where any current price movement less than two ticks are ignored. From Table 5.1, we can find that more heavily traded bonds have more transactions, shorter durations and higher volume. After the data are "thinned" by price, the price duration still tends to be lower for those actively traded bonds.

Table 5.1 about here

Since price duration is the inverse of volatility, the intraday duration is expected to contain a periodic component (time-of-the-day effect). Before implementing the ACD model, we need to separate this deterministic component from the stochastic component in empirical estimation. Here we follow the simple seasonal adjustment approach. For stocks, the time span within a trading day is divided into non-overlapping time intervals of 15 minutes each. For bonds, the intraday time span is divided into non-overlapping intervals of one hour each. The mean of price durations within each interval is computed over the entire sample period. The adjusted price duration is then computed as the price duration divided by the average price duration within that interval.

Price duration is negatively related to trading frequency or number of transactions. Here we rank all 60 bonds by the number of price duration over the sample period, and then divide the sample into price duration deciles. The first price duration decile includes the highest-frequently traded bonds and the tenth includes the lowest-frequently traded bonds. For a more concise presentation of results, later in this chapter we only report the estimates for three deciles, 1st, 4th and 9th deciles, which represent the most highly traded bonds, medium frequently traded bond and relatively thinly traded bonds, respectively.

5.3 Empirical Results and Analysis

Based on the data and methodology mentioned above, we estimate the baseline ACD model with no microstructure variables by using the adjusted duration. The adjusted duration is the price duration adjusted for the intraday deterministic pattern.

Table 5.2 reports the parameter estimates of the WACD(1,1) model for corporate bonds using adjusted price duration.

Table 5.2 about here

As shown in Table 5.2, most parameter estimates are statistically significant. The ARCH and GARCH parameters, α and β, are positive in all cases, and the estimates of β are significant in most cases, consistent with the prediction and their values fall in the theoretical range. These results indicate that there is a significant presence of duration clustering in the data, where one short price duration is more likely to be followed by another short price duration. Or equivalently, high price volatility in the current trading interval is likely to bring high price volatility at the next trading interval. As mentioned in Engle and Russell (1998), the possibility that clustering of trading may be occurring at different times for different reasons. Perhaps transaction clustering may be due to information-based trading and liquidity-based trading. The ACD estimate results shed light on this issue. The prices tend to move quickly following high transaction rates when informed traders are likely to be active, while the prices tend to move less quickly or are perhaps unaffected following higher transaction rates when liquidity traders are inferred to be dominant. The sum of α and

β represents the persistence of price duration. In our results, most of the persistence is lower than one. And the results also show that the persistence tends to be higher for frequently traded bonds than for relatively thinly traded bonds.

At the same time, the estimates for Weibull parameter θ for all bonds are statistically significant and lower than one. And the values of θ tend to be smaller for relatively thinly traded bonds compared with frequently traded bonds. This indicates that for those relatively infrequently traded bonds, long price durations are more likely than short durations.

Next we turn to the estimation of the ACD model for corporate stocks.

Table 5.3 about here

Table 5.3 reports the estimation results. Compared with the results of bonds, we find that for the same company, the persistence of the impact on adjusted price duration for corporate stocks is slightly higher than that for bonds. At the same time, our results show that the estimates for Weibull parameter θ for stocks are more stable and statistically significant than for bonds in most cases. These imply that the ACD model and the Weibull distribution assumption are more suitable for the stocks data compared with the bonds data.

Chapter 6

Conclusions

6.1 Summary

In this thesis, we first examine the effect of economic announcements on the prices of corporate bonds, which is rarely available mainly due to the lack of adequate and accessible transactions data. Our study is based on a valuable intraday transaction-by-transaction dataset on price, trading volume and trading time for U.S. corporate bonds. The dataset provides a continuous posting of prices, and the trading around announcement times is sufficiently intense for our analysis. This allows us to measure impact on price at very short intervals. Many announcements are released concurrently. By using a database on forecasts, we are able to measure the surprise component of announcement. This allows us to separate out the impact of concurrent announcements and to measure the role of public information in explaining volatility.

We find that among all 21 macroeconomic announcements we used in the analysis, 13 significantly affect the prices of corporate bonds, 15 significantly affect the prices of stocks, and seven affect the prices of both bonds and stocks, and public news can explain a fraction of price volatility in the aftermath of announcements.

Since both bonds and stocks are claims on the value of the firms' assets, we can expect that firm-specific information, that affects the value of those assets, will impact prices of both the firm's bond and stock. Thus, we investigate the effect of the firm-specific information contained in earnings announcements on bond prices at daily and hourly horizons by examining price behavior around earnings releases. What sets this study apart from prior study is that we include the public news surprise contained in the macroeconomic annoucements as an additional explanatory variable. We find that both bonds and stocks react significantly to public news and firm-specific information, and this information is quickly incorporated into both bond and stock prices, even at short return horizons. Most importantly, our results show that stocks do not lead bonds in reflecting firm-specific information, which is a contrast to the intuition that the bond market is less informationally efficient compared with the stock market, and information is only incorporated into bond prices slowly over time.

Finally, we examine the frequency of information arrivals of corporate bonds and its impacts on price duration at the intraday level. We employ the autoregressive conditional duration (ACD) model to estimate and compare the intensity of information arrivals and information content of bonds and stocks trade frequency. After removing the intraday time-of-the-day effect in the transaction data, our results show that there are differences in price durations between corporate bonds and stocks, as well as between frequently traded and relatively thinly traded bonds. For a given company, the persistence of the impact on adjusted price duration is normally higher for corporate stocks than bonds, and among all the bonds, the persistence is higher for the frequently traded bonds than the relatively thinly traded bonds. Our results also show that the parameter estimates are more stable and statistically significant for corporate stocks than for bonds in most cases, which means that the ACD model and the Weibull distribution assumption are more suitable for the stocks data than for bonds data.

6.2 Limitations

Given the work done in this thesis, there are some limitations in our study. First is the limited time horizon of the bond transactions data sample which covers the period from July 1, 2002 to April 21, 2005. Compared with previous studies on asset prices and information fundamentals as embodied in news announcement effects, for example, Balduzzi, Elton and Green (2001) use five-year intraday data for U.S. Treasuries, and Anderson et al. (2005) use 10-year high-frequency futures data, our corporate bond transactions data sample is relatively shorter, and provides relatively fewer observations for testing the effects of monthly macroeconomic annoucements and quarterly earnings announcements. Secondly, the lack of some important variables in our transactions dataset, such as, the bid-ask spread and order flow, prevents us from further testing some market microstructural hypothesis and better understanding of price behavior in corporate bond market. For example, by including the bids and asks, we can examine the effects of different announcements on the bid-ask spread, or investigate the different causes of transaction clustering, information-based or liquidity-based trading.

6.3 Future Directions of Research

Our research is one of the pioneer works in the field of empirical study of the intradaily behavior of corporate bond returns and the evolution of bond prices relative to the underlying stock prices. Analysis of the corporate bond transactions data provides an important first step toward understanding price behavior in this dealer market. Based on the availability of high-frequency bond transactions data, much work can be done following this path. We can examine the effects of public information contained in economic announcements as well as firm-specific information contained in different corporate announcements on the trading volume, bid-ask spread, and price volatility of corporate bonds. We can also study the time variation in the effects of macroeconomic announcements on corporate bond returns, since time-varying responses by the market can make security returns appear insensitive to macroeconomic announcements, even if the underlying economic news importantly affects prices (see Flannery and Protopapadakis, 2002). Furthermore, we can extend the baseline ACD model to include other outside influences as explanatory variable to understand better the information content of time between corporate bond trades. For example, it will be interesting to include the number of transactions of stocks for the same company as determinant of bond duration to see if stock trades contain information that affects corporate bond price movements.

Table 3.1 Company Names and Credit Rating

* indicates the sample of 30 firms used for panel test in chapter 3.

	Company names	**Rating**
1	CITIGROUP INC	AA
2	WAL MART STORES INC *	AA
3	GOLDMAN SACHS GROUP INC *	AA
4	MORGAN STANLEY DEAN WITTER & CO *	AA
5	MERRILL LYNCH & CO INC *	AA
6	BANK AMER CORP *	AA
7	WELLS FARGO & CO NEW *	AA
8	J P MORGAN CHASE & CO	AA
9	PROCTER & GAMBLE CO *	AA
10	DU PONT E I DE NEMOURS & CO	AA
11	MERCK & CO INC	AA
12	AMERICAN EXPRESS CR CORP	AA
13	FLEETBOSTON FINL CORP	AA
14	WACHOVIA CORP NEW	AA
15	FIRST UN CORP	AA
16	COCA COLA CO	AA
17	PEPSICO INC	AA
18	KIMBERLY CLARK CORP	AA
19	ILLINOIS TOOL WKS INC	AA
20	PITNEY BOWES INC	AA
21	LILLY ELI & CO	AA
22	HOME DEPOT INC	AA
23	WASHINGTON MUT FIN CORP	AA
24	GILLETTE CO	AA
25	BANK NEW YORK CO INC	AA
26	FIFTH THIRD BANCORP	AA
27	BARCLAYS BK PLC	AA
28	FORD MTR CR CO *	A
29	BRISTOL MYERS SQUIBB CO *	A
30	INTERNATIONAL BUSINESS MACHS CORP *	A
31	ALCOA INC *	A
32	KRAFT FOODS INC *	A
33	J P MORGAN CHASE & CO *	A
34	BELLSOUTH CORP *	A
35	LEHMAN BROS HLDGS INC	A
36	CIT GROUP INC *	A
37	CONOCOPHILLIPS	A
38	ABBOTT LABS *	A
39	TARGET CORP	A
40	GENERAL DYNAMICS CORP	A
41	BEAR STEARNS COS INC *	A
42	ANHEUSER BUSCH COS INC	A
43	AMERICAN EXPRESS CO	A
44	ALLSTATE CORP	A

Table 3.1 (*Continued*)

	Company names	Rating
45	UNITED TECHNOLOGIES CORP	A
46	HEWLETT PACKARD CO *	A
47	TELEFONOS DE MEXICO S A *	A
48	DOW CHEM CO	A
49	VIACOM INC	A
50	WASHINGTON MUT INC	A
51	DIAGEO PLC	A
52	PRUDENTIAL FINL INC	A
53	COCA COLA ENTERPRISES INC	A
54	VODAFONE GROUP PLC	A
55	BOEING CO	A
56	GENERAL MTRS CORP	BBB
57	FORD MTR CO DEL *	BBB
58	MOTOROLA INC *	BBB
59	DISNEY WALT CO *	BBB
60	AMERICAN ELEC PWR CO INC *	BBB
61	LOEWS CORP *	BBB
62	LIBERTY MEDIA CORP	BBB
63	ALTRIA GROUP INC	BBB
64	INTERNATIONAL PAPER CO	BBB
65	WEYERHAEUSER CO	BBB
66	TIME WARNER INC *	BBB
67	DUKE ENERGY CORP	BBB
68	WYETH	BBB
69	GENERAL MLS INC	BBB
70	KELLOGG CO	BBB
71	FIRSTENERGY CORP	BBB
72	EASTMAN KODAK CO	BBB
73	LOCKHEED MARTIN CORP	BBB
74	CENDANT CORP	BBB
75	COMCAST CORP NEW	BBB
76	TYSON FOODS INC	BBB
77	PROGRESS ENERGY INC	BBB
78	MASCO CORP	BBB
79	MARSH & MCLENNAN COS INC	BBB
80	ALBERTSONS INC	BBB
81	DEVON ENERGY CORP	BBB
82	MEADWESTVACO CORP	BBB
83	ELECTRONIC DATA SYS CORP	BB
84	CITIZENS COMMUNICATIONS CO *	BB
85	GAP INC	BB
86	FAIRFAX FINL HLDGS LTD	BB
87	VISTEON CORP	BB
88	AGILENT TECHNOLOGIES INC	BB
89	CHESAPEAKE ENERGY CORP	BB

Table 3.1 (*Continued*)

	Company names	Rating
90	GEORGIA PAC CORP	BB
91	AMERADA HESS CORP	BB
92	REYNOLDS R J TOB HLDGS INC	BB
93	WATSON PHARMACEUTICALS INC	BB
94	DANA CORP	BB
95	UNITED STATES STL CORP	BB
96	FISHER SCIENTIFIC INTL INC	BB
97	AVNET INC	BB
98	STARWOOD HOTELS & RESORTS WORLDWIDE INC	BB
99	XEROX CORP	BB
100	PENNEY J C INC	BB
101	UNUMPROVIDENT CORP	BB
102	ABITIBI-CONSOLIDATED INC	BB
103	UNISYS CORP	BB
104	BEST BUY CO INC	BB
105	ROYAL CARIBBEAN CRUISES LTD	BB
106	ARVINMERITOR INC	BB
107	SANMINA - SCI CORP	BB
108	LYONDELL CHEMICAL CO *	B
109	GOODYEAR TIRE & RUBR CO *	B
110	LUCENT TECHNOLOGIES INC *	B
111	TENET HEALTHCARE CORP *	B
112	AMERICAN TOWER CORP	B
113	NORTEL NETWORKS LTD	B
114	AMKOR TECHNOLOGY INC	B
115	AMAZON COM INC	B
116	MOTHERS WORK INC	B
117	FRIENDLY ICE CREAM CORP	B
118	SOLECTRON CORP	B
119	TIME WARNER TELECOM LLC	B
120	CIENA CORP	B
121	CINCINNATI BELL INC	B
122	CURATIVE HEALTH SVCS INC	B
123	VISHAY INTERTECHNOLOGY INC	B
124	INTERNATIONAL RECTIFIER CORP	B
125	AVAYA INC	B
126	OREGON STEEL MILLS INC	B
127	CROWN CASTLE INTL CORP	B
128	BALLY TOTAL FITNESS HLDG CORP	B
129	SEA CONTAINERS LTD	B
130	CENVEO CORP	B
131	ALLIANCE IMAGING INC	B
132	HANGER ORTHOPEDIC GROUP INC	B
133	ADVANCED MICRO DEVICES INC	B
134	LAMAR ADVERTISING CO	B

Table 3.2 Contemporaneous Announcements Releases

This table contains the time each announcement is released, the reported units for that announcement, and the number of times each announcement is released concurrently with that announcement under analysis for the 21 economic announcements considered in the study. In the table below, the 21 announcements are divided into four groups: 8:30am Announcements, 9:15am Announcements, 10:00am Announcements and 2:00pm Announcements. Each group contains twelve, two, six and one announcements, respectively. That means that twelve of the announcements occur at 8:30am, two at 9:15am, six at 10:00am, and one at 2:00pm. For each announcement *i* (*i* = 1, 2, …, 21) which is indicated in the first column, the corresponding row shows that the number of times each announcement in the same group is released concurrently with the announcement *i* under analysis. For example, for announcement 2, the Change in Nonfarm Payrolls, the corresponding row shows that this announcement concurs once with the Initial Jobless Claims, three times with the Personal Income and Personal Spending, and 34 times with the Unemployment Rate at 8:30am. The second column in the table also reports the units used to measure the announced figures. Levels are reported as units, dollars, or percentages. Changes are reported as either absolute in units or dollars, or as a percentage change from the previous observation. The sample period covers July 1, 2002 to April 21, 2005.

		Macroeconomic News Types											
8:30am Announcements		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	Advance Retail Sales (% change)	34	0	1	0	0	0	12	0	0	7	1	0
2	Change in Nonfarm Payrolls (change in thousands)	0	34	0	0	0	0	1	3	3	0	0	34
3	Consumer Price Index (% change)	1	0	34	0	0	10	5	0	0	0	5	0
4	Durable Goods Orders (% change)	0	0	0	33	0	0	14	2	2	0	0	0
5	GDP Annualized (% change)	0	0	0	0	33	0	12	1	1	0	0	0
6	Housing Starts (thousands)	0	0	10	0	0	34	5	0	0	1	0	0
7	Initial Jobless Claims - weekly (thousands)	12	1	5	14	12	5	147	5	5	11	8	1
8	Personal Income (% change)	0	3	0	2	1	0	5	33	33	0	0	3
9	Personal Spending (% change)	0	3	0	2	1	0	5	33	33	0	0	3
10	Producer Price Index (% change)	7	0	0	0	0	1	11	0	0	34	9	0
11	Trade Balance (change in billions)	1	0	5	0	0	0	8	0	0	9	34	0
12	Unemployment Rate (% change)	0	34	0	0	0	0	1	3	3	0	0	34

Table 3.2 (*Continued*)

	9:15am Announcements	13	14				
13	Capacity Utilization (% level)	33	33				
14	Industrial Production (% change)	33	34				
	10:00am Announcements	**15**	**16**	**17**	**18**	**19**	**20**
15	Construction Spending (% change)	34	0	0	0	0	30
16	Consumer Confidence (% level)	0	33	0	0	5	0
17	Factory Orders (% change)	0	0	34	0	0	0
18	Leading Indicators (% change)	0	0	0	34	0	0
19	New Home Sales (thousands)	0	5	0	0	32	0
20	NAPM (index value)	30	0	0	0	0	34
	2:00pm Announcements	**21**					
21	Monthly Budget Statement (change in billions)	34					

Table 3.3 Effects of Announcement Surprises on Corporate Bonds and Stocks

For corporate bonds and for each announcement i, we run the following regression,

$$(P_{50it} - P_{-5it}) / P_{-5it} = \alpha_i + \beta_{0i} S_{it} + \sum_{k=1}^{K} \beta_{ki} S_{i_k,t} + \varepsilon_{it}$$

where P_{50it} and P_{-5it} are the bond prices 50 minutes after and five minutes before the releasing time of announcement i, respectively. S_{it} is the standardized surprise for announcement i. The subscript k denotes other announcements released at the same time as announcement i.

For corporate stocks and for each announcement i, we run the following regression,

$$(P_{5it} - P_{-5it}) / P_{-5it} = \alpha_i + \beta_{0i} S_{it} + \sum_{k=1}^{K} \beta_{ki} S_{i_k,t} + \varepsilon_{it}$$

where P_{5it} and P_{-5it} are the stock prices five minutes after and five minutes before the releasing time of announcement i, respectively. Table 3.3 reports standard deviations of the surprises σ_i and slope coefficients β_{0i}. The sample covers July 1, 2002 to April 21, 2005. * and ** here indicate that the coefficients are significant at the 5% and 1% levels, respectively.

Announcements	Time	S.E.	Surprise coeff. for corporate stocks		Surprise coeff. for corporate bonds	
1. Advance Retail Sales	8:30 AM	0.004942	0.000198		-0.000855	**
2. Change in Nonfarm Payrolls	8:30 AM	100.426155	0.003850	**	-0.002251	**
3. Consumer Price Index	8:30 AM	0.001240	0.000216		-0.000103	
4. Durable Goods Orders	8:30 AM	0.023872	0.002502	**	-0.000461	**
5. GDP Annualized	8:30 AM	0.005138	0.000499	**	-0.000184	
6. Housing Starts	8:30 AM	116.948398	0.001297	**	0.000227	
7. Initial Jobless Claims - weekly	8:30 AM	16.648132	-0.000146		0.000103	
8. Personal Income	8:30 AM	0.001531	0.002296	**	-0.000416	*
9. Personal Spending	8:30 AM	0.001804	0.000302		-0.000967	**
10. Producer Price Index	8:30 AM	0.005014	-0.000512	*	-0.000409	*

Table 3.3 (*Continued*)

Announcements	Time	S.E.	Surprise coeff. for corporate stocks		Surprise coeff. for corporate bonds	
11. Trade Balance	8:30 AM	2.821109	0.000285		-0.000643	**
12. Unemployment Rate	8:30 AM	0.001285	-0.001935	**	0.000004	
13. Capacity Utilization	9:15 AM	0.002451	-0.000922	**	0.000727	*
14. Industrial Production	9:15 AM	0.002904	0.000757	**	-0.000822	*
15. Construction Spending	10:00 AM	0.008057	0.000975	**	-0.000095	
16. Consumer Confidence	10:00 AM	5.168844	0.018752	**	-0.001011	**
17. Factory Orders	10:00 AM	0.006064	0.000506	**	-0.000007	
18. Leading Indicators	10:00 AM	0.001179	0.000470	**	0.000177	
19. New Home Sales	10:00 AM	79.503677	0.000147	*	0.000171	*
20. NAPM	10:00 AM	2.000305	0.001563	**	-0.001590	**
21. Monthly Budget Statement	2:00 PM	3.435398	0.000024		-0.000743	**

Table 3.4 Effects of Contemporaneous Announcement Surprises on Corporate Bonds

For corporate bonds and for each announcement i, we run the following regression,

$$(P_{50it} - P_{-5it}) / P_{-5it} = \alpha_i + \beta_{0i} S_{it} + \sum_{k=1}^{K} \beta_{ki} S_{i_k,t} + \varepsilon_{it}$$

where P_{50it} and P_{-5it} are the bond prices 50 minutes after and five minutes before the releasing time of announcement i, respectively. S_{it} is the standardized surprise for announcement i. The subscript k denotes other contemporaneous announcements released at the same time as announcement i.

Table 3.4 reports the estimation results of slope coefficients $\beta_{ki}(k = 1,..., K)$ for other contemporaneous announcements included in each individual regression for bond returns. The sample covers July 1, 2002 to April 21, 2005. * and ** indicate that the coefficients are significant at the 5% and 1% levels, respectively.

Announ-cement i	Surprise coeff. for contemporaneus announcements											
8:30am	1	2	3	4	5	6	7	8	9	10	11	12
1	-0.000855 **						0.000374			0.000350		
2		-0.002251 **										0.000004
3			-0.000103			0.001287	-0.000378					
4				-0.000461 **			-0.000137					
5					-0.000184		0.001230 **					
6			-0.000222			0.000227	-0.000344					
7							0.000103					
8							0.000472	-0.000416 *	0.000967 **			
9							0.000472	-0.000416 *	0.000967 **			
10	-0.000967						0.001093			-0.000409 *	-0.001383 **	
11			-0.002379 **				0.000065			-0.001560 **	-0.000643 **	
12		-0.002251 **										0.000004

Table 3.4 (*Continued*)

Announcement i	Surprise coeff. for contemporaneus announcements					
9:15am	**13**	**14**				
13	0.000727 *	-0.000822 *				
14	0.000727 *	-0.000822 *				
10:00am	**15**	**16**	**17**	**18**	**19**	**20**
15	-0.000095					-0.001339 **
16		-0.001011 **			0.000428	
17			-0.000007			
18				0.000177		
19		0.000048			0.000171 *	
20	-0.000020					-0.001590 **
2:00pm	**21**					
21	-0.000743 **					

Table 4.1 Effects of Corporate Earnings Announcements on Daily Returns of Corporate Bond and Stocks

This table reports results of OLS regressions where the dependent variable is the daily corporate bond or stock return over the interval specified. Sample includes 110 observations for 110 bonds out of 134 where analyst forecasts and releasing time of quarterly earnings are available from IBES and Dow Jones Newswires, respectively. Date 0 is the date of the earnings announcement obtained from Dow Jones Newswires. Earnings forecast errors are calculated as the log of the difference between the announced and forecast earnings. T-statistics are shown in parentheses. * and ** here indicate that the coefficients are significant at the 5% and 1% levels, respectively.

Daily return interval	Earnings forecast error			S&P 500 return			R^2
Panel A: Bond returns							
[-1:0]	0.000365	(1.945841)	*	0.023647	(0.101530)		0.039740
[0:1]	0.000002	(0.006169)		0.004991	(0.029154)		0.026648
[1:2]	-0.000083	(-0.279835)		-0.112156	(-0.531101)		0.022947
[2:3]	0.000119	(0.280399)		0.217413	(0.805988)		0.014989
Panel B: Stock returns							
[-1:0]	0.001926	(1.771534)	*	1.536035	(3.072499)	**	0.154107
[0:1]	0.000817	(1.313444)		1.080704	(2.254570)	*	0.077796
[1:2]	0.000708	(1.019998)		0.869658	(2.866891)	**	0.116580
[2:3]	-0.000348	(-0.418418)		1.238502	(3.769122)	**	0.135639

Table 4.2 Effects of Corporate Earnings Announcements and Macroeconomic Announcements on Daily Returns of Corporate Bond and Stocks

This table reports results of OLS regressions where the dependent variable is the daily corporate bond or stock return over the interval specified. Sample includes 78 observations for 78 bonds out of 134 where analyst forecasts and releasing time of quarterly earnings are available from IBES and Dow Jones Newswires, respectively, and at the same time there is only one monthly macroeconomic announcement released for each one-day interval. Date 0 is the date of the earnings announcement obtained from Dow Jones Newswires. Earnings forecast errors are calculated as the log of the difference between the announced and forecast earnings. T-statistics are shown in parentheses. * and ** here indicate that the coefficients are significant at the 5% and 1% levels, respectively.

Daily return interval	Earnings forecast error			S&P 500 return			Public news surprise			R^2
Panel A: Bond returns										
[-1:0]	0.000389	(1.996267)	*	0.030999	(0.130252)		-0.001437	(-0.444613)		0.050332
[0:1]	0.000038	(0.118403)		0.025166	(0.148775)		-0.002855	(-1.812421)	*	0.029808
[1:2]	-0.000103	(-0.334365)		-0.121290	(-0.556791)		0.000165	(0.099242)		0.036659
[2:3]	0.000132	(0.307868)		0.303943	(1.013062)		-0.001600	(-1.419179)		0.025941
Panel B: Stock returns										
[-1:0]	0.002046	(1.852787)	*	1.603483	(3.172359)	**	-0.009545	(-1.405369)		0.176943
[0:1]	0.000672	(0.962018)		0.831722	(2.661894)	**	-0.003337	(-1.830921)	*	0.125614
[1:2]	0.000796	(0.562619)		1.075634	(2.246770)	*	-0.001069	(-0.190325)		0.075641
[2:3]	-0.000462	(-0.542234)		1.147735	(3.220506)	**	0.002079	(1.389304)		0.147436

Table 4.3 Effects of Corporate Earnings Announcements and Macroeconomic Announcements on Hourly Returns of Corporate Bond and Stocks

This table reports results of OLS regressions where the dependent variable is the hourly corporate bond or stock return over the interval specified. Sample includes 78 observations for 78 bonds out of 134 where analyst forecasts and releasing time of quarterly earnings are available from IBES and Dow Jones Newswires, respectively, and at the same time there is only one monthly macroeconomic announcement released for each one-hour interval. Date 0 is the hour of the earnings announcement obtained from Dow Jones Newswires. Earnings forecast errors are calculated as the log of the difference between the announced and forecast earnings. T-statistics are shown in parentheses. * and ** here indicate that the coefficients are significant at the 5% and 1% levels, respectively.

Hourly return intervel	Earnings forecast error			Public news surprise			S&P 500 return			R^2
	Coeff.	T-stat.		Coeff.	T-stat.		Coeff.	T-stat.		
Panel A: Bond returns										
[-1:0]	0.000994	(0.347881)					-0.216626	(-0.884118)		0.001123
[0:1]	0.000031	(0.003253)		-0.001158	(-0.728903)		-0.007296	(-0.015550)		0.015533
[1:2]	-0.002484	(-0.284312)		0.003015	(2.502406)	**	0.741447	(2.410687)	**	0.200433
[2:3]	0.010198	(1.868917)	*	0.000407	(0.140918)		0.029849	(0.123087)		0.112178
[3:4]	-0.030369	(-2.036866)	*	0.001363	(0.165839)		-0.374008	(-0.627638)		0.131741
[4:5]	0.025923	(1.110396)					-0.758921	(-0.932973)		0.100854
[5:6]	0.003362	(0.277317)					0.191128	(0.383720)		0.006934
[6:7]	-0.000710	(-0.099552)		0.000371	(0.042879)		0.168382	(0.415560)		0.007619
[7:8]	0.006831	(0.809825)					-0.447594	(-1.415306)		0.051362
Panel A: Stock returns										
[-1:0]	0.093000	(3.120997)	**				-0.177860	(-0.219834)		0.323332
[0:1]	0.024065	(1.044913)		0.003933	(0.899485)		1.738311	(2.187556)	*	0.169668

Table 4.3 (*Continued*)

Hourly return intervel	Earnings forecast error			Public news surprise			S&P 500 return			R^2
	Coeff.	T-stat.		Coeff.	T-stat.		Coeff.	T-stat.		
[1:2]	0.018954	(0.976779)		-0.003253	(-2.290789)	*	0.202275	(0.296069)		0.095062
[2:3]	0.023389	(1.398896)		0.015340	(1.215417)		0.108354	(0.106402)		0.077300
[3:4]	0.006675	(0.438919)		-0.005511	(-0.657190)		0.062301	(0.102494)		0.019000
[4:5]	0.054295	(3.035398)	**				-0.010574	(-0.020879)		0.246430
[5:6]	0.028392	(3.009181)	**				0.394646	(1.017973)		0.240122
[6:7]	-0.012714	(-1.717216)	*	-0.015438	(-1.717214)	*	0.682034	(1.620385)		0.331655
[7:8]	0.014064	(1.966584)	*				0.615146	(1.969927)	*	0.171428

Table 5.1 Summary Statistics

This table provides summary statistics for the sample of 60 U.S. corporate bonds used in chapter 5. The sample covers the trading period from January 1, 2004 to December 31, 2004. The data are thinned by ignoring price movements less than two ticks ($0.25). Duration is the time interval between two consecutive trades. The duration calculated after thinning is called price duration. Price duration is measured in seconds. Trading size is measured in amount of dollars. The number of observations is number of observations for the duration variables. Average price is expressed in dollars. Average daily #Trans is the mean transaction number per day.

	CUSIP	Issuer Name	NO. of Observations	Ave. Price	Ave. Price Duration	Ave. Daily # Trans	Ave. Daily Trading Size
1	345370CA	FORD MTR CO DEL	18731	98.0407	515.98	112.304	82068696
2	370442BT	GENERAL MTRS CORP	12121	107.0871	945.47	89.188	131866268
3	345397TR	FORD MTR CR CO	6944	105.5038	2939.29	62.064	34456604
4	285661AD	ELECTRONIC DATA SYS CORP	4498	96.6163	5648.25	28.484	10725984
5	02209SAA	ALTRIA GROUP INC	3912	105.1195	6093.97	25.604	17405516
6	931142BE	WAL MART STORES INC	3318	113.7523	6977.04	32.408	13330280
7	172967BS	CITIGROUP INC	3045	100.3192	8244.3	42.752	12933976
8	382550AH	GOODYEAR TIRE & RUBR CO	2957	98.0643	14696	61.119	6020300
9	38141GBU	GOLDMAN SACHS GROUP INC	2831	111.4491	9255.6	33.88	8863380
10	46625HAT	J P MORGAN CHASE & CO	2235	105.1302	12565	19.012	6186696
11	620076AR	MOTOROLA INC	2221	115.1383	11955	13.856	6191124
12	552078AM	LYONDELL CHEMICAL CO	1945	104.0295	15512	12.408	2389684
13	17453BAB	CITIZENS COMMUNICATIONS CO	1892	109.895	14834	12.772	12814272
14	590188JP	MERRILL LYNCH & CO INC	1848	108.3363	15167	17.488	5131824
15	060505AG	BANK AMER CORP	1702	116.1462	16650	16.98	5789896
16	939322AL	WASHINGTON MUT INC	1526	99.6944	18612	14.896	8471104
17	983024AA	WYETH	1522	101.0234	18633	11.836	7788840
18	87612EAJ	TARGET CORP	1505	106.1969	19395	16.928	3471820
19	949746CH	WELLS FARGO & CO NEW	1470	105.6237	19191	18.468	4978108

Table 5.1 (*Continued*)

	CUSIP	Issuer Name	NO. of Durations	Ave. Price	Ave. Price Duration	Ave. Daily # Trans	Ave. Daily Volume
20	530718AC	LIBERTY MEDIA CORP	1411	100.067	18651	13.528	24290120
21	74432QAC	PRUDENTIAL FINL INC	1375	95.7187	17994	9.492	2447948
22	460146BQ	INTERNATIONAL PAPER CO	1323	105.0755	21544	15.496	15447984
23	88033GAT	TENET HEALTHCARE CORP	1314	89.5205	21627	9.516	4413508
24	264399DK	DUKE ENERGY CORP	1295	97.0045	18747	10.244	582432
25	260543BR	DOW CHEM CO	1225	107.1226	23873	7.984	7122268
26	571748AD	MARSH & MCLENNAN COS INC	1157	101.5633	24562	9.364	6167544
27	303901AN	FAIRFAX FINL HLDGS LTD	1152	96.3483	5536.6	29.736	3556400
28	035229CT	ANHEUSER BUSCH COS INC	1150	97.4209	22499	6.528	131356
29	025818EM	AMERICAN EXPRESS CR CORP	1141	98.0825	25056	10.284	4208560
30	656569AA	NORTEL NETWORKS LTD	1134	102.9091	26446	8.5	3201976
31	46625HAP	J P MORGAN CHASE & CO	1038	105.6598	27433	16.992	7426788
32	27746QAC	EASTMAN KODAK CO	1020	105.5503	28671	6.692	1084612
33	020002AM	ALLSTATE CORP	1017	105.718	29292	11.724	1558116
34	097023AT	BOEING CO	992	101.6288	29799	7.356	3962104
35	125581AB	CIT GROUP INC	929	118.0838	28275	8.68	5740852
36	929903AD	WACHOVIA CORP NEW	919	99.19	29242	12.454	10020000
37	191219BH	COCA COLA ENTERPRISES INC	894	105.5655	33546	8.848	1066544
38	925524AQ	VIACOM INC	894	111.2991	31805	7.908	6221488
39	073902BZ	BEAR STEARNS COS INC	740	106.5674	40167	11.196	3871276
40	25243QAB	DIAGEO PLC	730	99.8795	38842	8.716	5742400
41	76182KAN	REYNOLDS R J TOB HLDGS INC	716	101.53	10076	18.224	1888416
42	370334AS	GENERAL MLS INC	716	107.2582	39816	8.2	10209860
43	539830AK	LOCKHEED MARTIN CORP	709	131.0366	41131	5.652	4876240
44	025537AA	AMERICAN ELEC PWR CO INC	703	106.0767	42579	9.784	3077192

Table 5.1 (*Continued*)

	CUSIP	Issuer Name	NO. of Durations	Ave. Price	Ave. Price Duration	Ave. Daily # Trans	Ave. Daily Volume
45	71345LEJ	PEPSICO INC	671	99.7706	28391	12.684	4056810
46	619903AC	MOTHERS WORK INC	660	97.3909	11350	18.976	2143376
47	962166BP	WEYERHAEUSER CO	658	110.9383	41075	10.08	18913824
48	151313AP	CENDANT CORP	641	114.7856	45737	5.636	7157184
49	235811AU	DANA CORP	599	118.9867	46512	4.276	3006648
50	92857TAG	VODAFONE GROUP PLC	587	117.3252	49317	5.804	5582500
51	902494AM	TYSON FOODS INC	585	117.2147	44157	7.216	16643456
52	92839UAB	VISTEON CORP	584	105.496	48407	4.846	3712500
53	887321AA	TIME WARNER TELECOM LLC	581	100.4455	12426	14.112	2011952
54	023135AF	AMAZON COM INC	518	101.0214	59521	4.992	1732064
55	339030AD	FLEETBOSTON FINL CORP	498	104.4408	60307	5.44	2612608
56	811371AH	SEA CONTAINERS LTD	473	98.9136	26526	13.225	891180
57	023551AM	AMERADA HESS CORP	466	104.0934	54749	4.5	5069112
58	029912AH	AMERICAN TOWER CORP	448	106.4706	65421	4.52	1573540
59	171779AA	CIENA CORP	381	85.3696	20560	17.116	3458600
60	574599AW	MASCO CORP	352	46.56	88218	4.36	10736056

Table 5.2 WACD Estimation for Corporate Bonds

We estimate the Weibull ACD model on the adjusted price durations which aims at removing the time-of-the-day effect. The estimated WACD(1,1) model is:

$$\Psi_t = \omega + \alpha_1 x_{t-1} + \beta_1 \Psi_{t-1}$$

where Ψ_t is conditional duration, x_t is the adjusted price duration for bonds. The estimation is obtained by maximizing the following log-likelihood function:

$$L(\eta) = \sum_{t=1}^{T} \ln(\theta / x_t) + \theta \ln[\Gamma(1+1/\theta) x_t / \Psi_t] - [\Gamma(1+1/\theta) x_t / \Psi_t]^{\theta}$$

for $\theta, \Psi_t > 0$. $\Gamma(\cdot)$ is the gamma function, θ is the Weibull parameter and η is a column vector containing the parameters to be estimated. Reported below are parameter estimates and t-statistics. Bold format denotes significance at the 5% level.

	CUSIP	Num of observations	Log-likelihood value	ω		α		β		θ	
				Estimates	T-stat.	Estimates	T-stat.	Estimates	T-stat.	Estimates	T-stat.
Panel A: 1st decile											
1	345370CA	18731	-17710	**0.00225**	**3.675**	**0.02338**	**9.239**	**0.97461**	**345.547**	**0.81944**	**184.295**
2	370442BT	12121	-9209	**0.00322**	**4.168**	**0.06324**	**10.726**	**0.93568**	**162.600**	**0.75579**	**150.196**
3	345397TR	6944	6944	**0.00155**	**4.188**	**0.00365**	**6.834**	**0.99431**	**1193.785**	**0.63316**	**115.323**
4	285661AD	4498	-538	**0.00154**	**3.420**	**0.01635**	**4.440**	**0.98001**	**240.269**	**0.55591**	**91.577**
5	02209SAA	3912	-1681	**0.00544**	**2.944**	**0.07015**	**5.070**	**0.92536**	**68.919**	**0.60759**	**83.452**
6	931142BE	3318	-2726	**0.00261**	**2.123**	**0.00485**	**3.858**	**0.99227**	**479.511**	**0.65747**	**77.909**
	Average			**0.00277**		**0.03027**		**0.96704**		**0.67156**	
Panel B: 4th decile											
19	949746CH	1470	-662	0.01246	1.516	**0.01706**	**3.153**	**0.96750**	**72.939**	**0.53083**	**51.939**
20	530718AC	1411	-587	**0.03067**	**2.282**	**0.06885**	**3.016**	**0.89472**	**28.464**	**0.53506**	**50.558**
21	74432QAC	1375	-790	0.00813	1.035	**0.02415**	**2.519**	**0.96743**	**58.567**	**0.56350**	**48.834**

Table 5.2 (*Continued*)

	CUSIP	Num of observations	Log-likelihood value	ω		α		β		θ	
				Estimates	T-stat.	Estimates	T-stat.	Estimates	T-stat.	Estimates	T-stat.
22	460146BQ	1323	-679	0.00275	1.337	**0.01663**	**4.186**	**0.97973**	**184.323**	**0.57072**	**48.908**
23	88033GAT	1314	-367	**0.11566**	**2.332**	**0.23269**	**3.303**	**0.66520**	**7.166**	**0.49919**	**48.938**
24	264399DK	1295	-336	**0.01527**	**2.947**	**0.09625**	**4.739**	**0.88801**	**46.162**	**0.53793**	**48.327**
	Average			**0.04456**		**0.11519**		**0.84431**		**0.53595**	
Panel C: 9th decile											
49	235811AU	599	-81	**0.04596**	**2.089**	**0.28949**	**5.101**	**0.71051**	**12.520**	**0.46212**	**33.063**
50	92857TAG	587	-327	0.01174	1.012	**0.02777**	**2.657**	**0.96004**	**55.165**	**0.54922**	**31.541**
51	902494AM	585	-661	**0.01950**	**2.375**	**0.20336**	**5.516**	**0.79664**	**21.609**	**0.48564**	**32.817**
52	92839UAB	584	-71	0.00733	1.467	**0.12039**	**4.365**	**0.87961**	**31.894**	**0.47476**	**32.550**
53	887321AA	581	-455	**0.74377**	**4.375**	**0.19969**	**2.192**	0.07478	0.466	**0.63446**	**31.996**
54	023135AF	518	-155	**0.06567**	**1.883**	**0.04233**	**2.081**	**0.88877**	**22.316**	**0.46858**	**30.376**
	Average			**0.14900**		**0.14717**		**0.71839**		**0.51246**	

Table 5.3 WACD Estimation for Stocks

We estimate the Weibull ACD model on the adjusted price durations which aims at removing the time-of-the-day effect. The estimated WACD(1,1) model is:

$$\Psi_t = \omega + \alpha_1 x_{t-1} + \beta_1 \Psi_{t-1}$$

where Ψ_t is conditional duration, x_t is the adjusted price duration for stocks. The estimation is obtained by maximizing the following log-likelihood function:

$$L(\eta) = \sum_{t=1}^{T} \ln(\theta / x_t) + \theta \ln[\Gamma(1+1/\theta) x_t / \Psi_t] - [\Gamma(1+1/\theta) x_t / \Psi_t]^{\theta}$$

for $\theta, \Psi_t > 0$. $\Gamma(\cdot)$ is the gamma function, θ is the Weibull parameter and η is a column vector containing the parameters to be estimated. Reported below are parameter estimates and t-statistics. Bold format denotes significance at the 5% level.

	CUSIP	Num of observations	Log-likelihood value	ω Estimates	ω T-stat.	α Estimates	α T-stat.	β Estimates	β T-stat.	θ Estimates	θ T-stat.
Panel A: 1st decile											
1	345370CA	1404	-1051	**0.063244**	**2.547790**	**0.247050**	**4.484295**	**0.725912**	**12.602832**	**0.645235**	**45.873777**
2	370442BT	8166	-5710	**0.004222**	**5.278936**	**0.195807**	**21.675273**	**0.804193**	**89.021696**	**0.723298**	**121.638350**
3	345397TR	1404	-1051	**0.063244**	**2.547790**	**0.247050**	**4.484295**	**0.725912**	**12.602832**	**0.645235**	**45.873777**
4	285661AD	2658	-1714	**0.019247**	**3.678500**	**0.305012**	**12.373783**	**0.694988**	**28.194454**	**0.651278**	**68.705312**
5	02209SAA	11464	-4048	**0.001949**	**8.653235**	**0.240403**	**31.714612**	**0.759597**	**100.207950**	**0.705402**	**146.867350**
6	931142BE	10739	-9288	**0.055473**	**7.278802**	**0.204417**	**14.461431**	**0.758427**	**45.433163**	**0.733473**	**130.816700**
	Average			**0.034563**		**0.239957**		**0.744838**		**0.683987**	
Panel B: 4th decile											
19	949746CH	6826	-6025	**0.103729**	**6.158471**	**0.241318**	**10.918936**	**0.675223**	**21.768437**	**0.763423**	**105.551990**
20	530718AC	501	-338	0.009113	1.264511	**0.061216**	**2.246287**	**0.938784**	**34.448025**	**0.584356**	**26.684961**
21	74432QAC	7463	-6881	**0.010596**	**3.177900**	**0.096171**	**10.275701**	**0.896974**	**85.641015**	**0.862868**	**113.088500**

Table 5.3 (*Continued*)

	CUSIP	Num of observations	Log-likelihood value	ω		α		β		θ	
				Estimates	T-stat.	Estimates	T-stat.	Estimates	T-stat.	Estimates	T-stat.
22	460146BQ	5572	-5126	**0.031349**	**4.146120**	**0.095858**	**7.235241**	**0.875380**	**47.944887**	**0.829559**	**97.190620**
23	88033GAT	1756	-328	**0.003335**	**3.722029**	**0.309006**	**14.427890**	**0.690994**	**32.263353**	**0.610309**	**58.000173**
24	264399DK	1583	-1266	**0.094736**	**2.780367**	**0.226538**	**4.180450**	**0.707882**	**10.596781**	**0.663867**	**49.498873**
	Average			**0.043140**		**0.210467**		**0.758085**		**0.701245**	
Panel C: 9th decile											
49	235811AU	2757	-2525	**0.014443**	**2.609917**	**0.078885**	**5.449816**	**0.908687**	**53.654678**	**0.837537**	**68.251662**
50	92857TAG	1657	-1591	0.011149	1.205055	**0.039337**	**2.346477**	**0.950233**	**39.836550**	**0.867025**	**50.126512**
51	902494AM	1941	-1478	**0.094010**	**5.195419**	**0.514462**	**10.207119**	**0.485538**	**9.633269**	**0.702398**	**58.511417**
52	92839UAB	1039	-976	**0.154305**	**2.291923**	**0.150579**	**3.256489**	**0.703648**	**7.212462**	**0.801629**	**40.820949**
53	887321AA	1409	-135	**0.014084**	**3.112435**	**0.349457**	**9.403201**	**0.650543**	**17.504850**	**0.552426**	**51.598677**
54	023135AF	1196	-950	**0.088871**	**2.386978**	**0.286101**	**4.010746**	**0.665507**	**8.299543**	**0.677853**	**44.845535**
	Average			**0.062810**		**0.236470**		**0.727360**		**0.739811**	

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