Relative Informational Efficiency and Predictability in the Corporate Bond Market

Konstantinos Tolikas*
Cardiff Business School
Cardiff University
Aberconway Building
Column Drive, CF10 3EU
Cardiff, UK

Abstract

I examine the relative informational efficiency of corporate bonds and the underlying stocks through the lead-lag relation between their daily returns. I find that the daily stock returns lead the daily bond returns for all credit rating categories but the safest (Aaa) and least safe (Ca-D) bond portfolios. These findings indicate that the stock market is more efficient than the bond market when incorporating new information. The bond market's relative informational inefficiency implies that there are trading opportunities for the bonds that are highly sensitive to the release of common information. I also find that the stock market detects impending defaults earlier than the bond market, which implies that bond holders have enough time to protect their capital.

Key words: Informational efficiency; Corporate bonds; Lead-lag relation

JEL Classification: G12, G14

* Corresponding author: Konstantinos Tolikas, Cardiff Business School, Aberconway Building, Column Drive, CF10 3EU, Cardiff, UK. Email: tolikask@cardiff.ac.uk, Tel: +44 2920 876652.

1. Introduction

The lead-lag relation between the returns of corporate bonds and those of the issuing firms' stocks reflects how information is incorporated into security prices and therefore the relative informational efficiency of bonds and stocks. Because bonds and stocks represent claims on the same corporate assets, financial theory suggests that, in a frictionless market, information that is relevant to their market value should contemporaneously affect their returns. However, if the stock market is more efficient than the bond market, stocks incorporate this information faster than bonds. Therefore, stock returns should have predictive power for future bond returns, and the activities of informed traders should lead to a lead-lag relation between the returns of the two securities.

Differences in the level of informational efficiency of the two markets may be due to the different types of investors that prevail in the two markets and the different informational environments. For example, the bond market is typically dominated by sophisticated institutional investors who have faster access to relevant information than individual investors who tend to prefer the stock market. Thus, institutional investors incorporate relevant information faster than individual investors which implies that the bond market should be more informational efficient than the stock market. On the other hand, there are significantly more financial analysts that follow the stock rather than the bonds of a firm. Thus, more stock related research is produced and disseminated to the buy-side investors, compared to bond related research which is mainly limited to firms rated by credit rating agencies. Stock analysts tend to revise their recommendations about a firm more frequent compared to the rating agencies that follow the same firm. Hence, stock prices should incorporate relevant information faster than bond prices and the stock market should be more informational efficient compared to the bond market. Under both scenarios, a lead-lag relation between the returns of the two securities should be observed. Further, a growing body of literature finds that stock markets may not integrate all available information instantly. Instead information diffusion varies significantly across industries (e.g., Hong et al., 2007; Hou, 2007). Under this scenario, the lagging market has limited ability to fully incorporate the information reflected in the leading market.

This study is motivated by the different findings of prior research on the relative informational efficiency of the debt and equity markets. As noted by Downing et al., (2009), despite its size[2] the corporate bond market is quite opaque, and as a result the studies on the relative informational efficiency of the two markets are rather inconclusive. For example, Kwan (1996) uses the quotes of bond dealers from Merrill Lynch to examine how information is incorporated into securities prices. Kwan investigates the correlation between the weekly returns of stocks and the yield changes in bonds issued by the same firm. He finds that stock returns lead bond yield changes when incorporating firm-specific information. He also finds that stocks and bonds are driven by information that is mainly related to the mean rather than the variance of the value of the firm's assets [similar results are reported by Blume et al., (1991) and Cornell and Green (1991)]. Downing et al., (2009) use intraday transaction data provided by the National Association of Securities Dealers (NASD) to examine the relation between stock and bond high frequency returns. They find that the US corporate bond market is less informationally efficient than the stock market, despite recent changes aimed at improving transparency and reducing transaction fees in the bond market. They also find that the daily stock returns lead the daily bond returns in all of the rating classes and that the hourly stock returns lead the bond returns for

[2] The Securities Industry and Financial Markets Association (SIFMA) reports that at the end of 2012 the size of the US corporate debt market was $9.1 trillion and that the 2012 average daily trading volume was $16.7 billion. In addition, during 2012, $1.37 trillion of new US corporate debt was issued.

non-convertible junk and BBB rated bonds. Hong et al., (2012) use transaction based bond index data and report strong evidence that stock returns have predictive power for both investment grade and high yield bond returns. They also find that the lead-lag relation between stock and bond returns is stronger for the high yield bonds, but they find little evidence that bond returns have predictive power for stock returns. Gebhardt et al., (2005) find that bond prices adjust slower than stock prices to information about changing default risk which implies that stock returns have predictive power for bond returns.

However, Hotchkiss and Ronen (2002) examine 55 high yield US corporate bonds and find no evidence that the stock returns systematically lead the bond returns. Instead, they argue that any contemporaneous relation between the stocks and the bonds is because of their joint reaction to common factors. Recently, Ronen and Zhou (2013), use data from the Trade Reporting and Compliance Engine (TRACE) for the US OTC corporate bond market to examine the relative efficiency of stocks and bonds by taking into account liquidity patterns and institutional features. They find that when the dynamic patterns of liquidity as well as trade size and timing effects are accounted for, stock leads disappear and therefore the lack of agreement regarding the relative efficiency of the corporate bond market can be reconciled. More recently, Bittlingmayer and Moser (2014) examine whether corporate bonds anticipate stock price changes at monthly intervals. For the case of negative news, they find that the high yield bonds are more informational efficient compared to stocks. The evidence is stronger for firms with volatile stock returns, high coupon and short maturity bonds, and stocks with high prior abnormal return. In contrast, they find that investment grade bonds have limited predictive ability for stock returns. Alexander et al., (2000), Hotchkiss and Ronen (2002), and Downing et al., (2009) attribute these conflicting findings to the opaque nature of the corporate bond market, the lack of comprehensive data, different trading mechanisms, and to the complex relation between the returns of a firm's stock and its publicly traded debt.

In this paper, I use the daily returns of the Barclays bond indices (ex-Lehman Brothers bond indices) of a wide spectrum of credit ratings and the underlying stock portfolios to examine the informational efficiency of corporate bonds relative to stocks. My investigation differs from the literature because I use data from widely used benchmarks in the corporate debt market that are made up of large samples of bonds. I use bivariate vector autoregressions (VAR) to examine the lead-lag relation between the daily returns of the bonds and those of their underlying stocks. Further, I examine the economic significance of my results for industry practitioners. Specifically, I address the following two questions: Do daily stock returns lead daily bond returns in reflecting common information? And do the empirical results have any economic significance for the market participants?

The results about the relative informational efficiency of the bond and stock markets are likely to have an impact on the decisions of rational investors. If, for example, stocks lead bonds then investors might choose to buy (sell) a firm's bonds after observing an increase (decrease) in the firm's stock price. Investors are also likely to face additional transactions costs in the less efficient market because of the greater variance in the pricing error (i.e., deviations of the market price from the efficient price)[3]. Thus, traders might not be willing to trade frequently and/or at large volumes because of the high implicit costs. The findings of this study are also of interest to the debt issuing firms because in an informationally efficient market, they are likely to raise financing more easily and less expensively. This is especially important for small- and medium-sized firms because corporate bonds typically have a maturity of between seven and ten years.

[3] Edwards et al., (2007) examine the US Over-the-Counter (OTC) corporate bond market and find that increased transparency is likely to lead to greater informational efficiency and lower transaction costs.

This time frame represents a longer term financing compared to bank loans and therefore provides these firms with enough time to grow. On the other hand, if the bond market is less informationally efficient relative to the stock market, then it will be unappealing to investors. Thus, firms might have to sell their bonds at a significant discount to tempt potential buyers.

My findings indicate that the daily stock returns lead the daily bond returns for Investment Grade, Aa, A, Baa, High Yield, Ba, B, and Caa rated bond portfolios. But, the daily stock returns do not lead the daily bond returns for the safest (Aaa) and least safe (Ca-D) bond portfolios. This finding indicates that the stock market is relatively more efficient in incorporating common information. However, although the bond market is less informationally efficient relative to the stock market, the high level of transaction costs in the bond market likely means that only speculative trades on bonds that are highly sensitive to the release of common information make economic sense (i.e., low rated bonds). I also find that the market's lead time for impending bond defaults is shorter for the low rated bonds (i.e., High Yield, Ba, B, and Caa) than for the underlying stocks. This finding implies that bond holders might have enough time to protect the value of their investments by working out of a long position in high yield bonds that are approaching default.

The remainder of this paper is organized as follows. In Section 2, I describe the data set and the methods used in this study. Section 3 presents the empirical results. In Section 4, I investigate the economic significance of the empirical results; and in Section 5, I summarize and conclude the paper.

2. Data and summary statistics

2.1. Bond portfolios

My sample is based on the daily returns of a number of Barclays corporate bond indices. These are value-weighted indices that cover a wide spectrum of credit ratings defined as the middle of the S&P, Moody's, and Fitch ratings; if a bond is rated only by two agencies then the lowest rating applies. They were formerly known as the Lehman Brothers' bond indices until Lehman's collapse in 2008, after which Barclays acquired their North American businesses.

The use of the Barclays bond indices has a number of advantages. First, the Barclays indices are commonly used benchmarks in the fixed income market that offer both great breadth of coverage and length of historical data. Second, the use of bond indices helps to mitigate problems related to non-synchronous data, stale quotes, and extreme differences in liquidity in the bonds in my sample, which could affect the interpretation of the observed lead-lag relations. Third, as noted by Ronen and Zhou (2013), in order to examine the informational efficiency of the bond market it is important to differentiate between institutional and retail sized bond trading. The use of the Barclays bond indices eliminates this problem because Barclays use bond quotes only from institutional sized transactions. Forth, Barclays price the majority of bonds that make up the indices using a combination of model prices and traders' prices, which could be actual transaction prices or actual bid prices, instead of the less reliable matrix prices[4]. In order to price the bonds, Barclays makes the conservative assumption of no reinvestment of the interim cash flows. Fifth, using portfolios of bonds is likely to diversify away most of the unsystematic risk of the bonds that make up the indices. Lastly, the bonds included in the Barclays indices need to satisfy certain criteria. In particular, the indices contain taxable corporate bonds with at

[4] Matrix pricing is an approach used to price bonds for which continuous posting of bid-ask prices is not available and therefore, actual prices do not exist. In this case, traders need to guess the price at which an active market will clear, and banks usually price a bond with an interpolation approach that uses liquid bonds with similar characteristics to the illiquid bond to be priced. Hong and Warga (2000) report that the bid prices of the Lehman Brothers bonds have fewer price discrepancies from transaction data compared to the bid prices of bonds traded on the NYSE's Automated Bond System

least one year left before maturity and a minimum of par value amount outstanding. Further, the bonds in the indices need to have a minimum issue of $250 million and to state a coupon of fixed rate. Finally, there is no maximum number of constituents and the indices are rebalanced at the end of each month.

My sample includes the Barclays bond indices rated as Aaa, Aa, A, Baa, Ba, B, Caa, and Ca-D. I also add two broad bond portfolios called Investment Grade (IG), which comprises all of the bonds with at least Baa credit rating, and High Yield (HY), which comprises all of the bonds with a credit rating below Baa. Table 1 contains the descriptive statistics of the bond indices across the spectrum of credit ratings used in my analysis.

Insert Table 1 about Here

The table shows that the sum of the bonds rated Baa and higher (3,237) and the sum of the bonds rated below Baa (1,566) are lower than the number of bonds contained in the IG and HY bond indices respectively. This difference is because of the credit rating migrations during the time periods in which the daily returns for these indices are available. The table also shows that 67.4% of the 4,803 bonds are rated Baa and higher and 32.6% are below Baa. The Baa rated bonds have the longest average time to maturity with 11.18 years, and the Ca-D rated bonds the shortest with 6.22 years. The yields of the bonds with higher credit ratings tend to be considerably lower than those of the bonds with lower credit ratings. For example, the average yield of the Ca-D rated bonds is 27.73% while the average yield of the Aaa rated bonds is 4.46%. However, the coupon increases as the credit rating decreases, with the Ca-D rated bonds offering the highest (8.53%) and the Aa rated bonds the lowest (5.14%) average coupon rates. Table 1 also shows that the amount outstanding of the bonds with lower credit ratings is smaller than that of the bonds with higher credit ratings. Further, bonds with a lower credit rating are issued by smaller firms with the average market capitalization of an IG issuer being about 4.5 times larger than that of an HY issuer. Table 1 also indicates that the starting date for each index varies from January 1989 to January 2004. Thus, the number of daily returns available for the analysis of each index varies significantly.

2.2. Stock portfolios

I use the firm's name and ISIN code from Thomson Reuters to match the constituents of the Barclays' bond indices to the stocks of the issuing firms and I then construct the associated value-weighted stock portfolios. Table 2 contains the descriptive statistics of the associated stock portfolios. The matching process results in a total of 1,431 firms that have issued 4,803 bonds. The number of matched firms indicates that many of them issued more than one bond.

Insert Table 2 about Here

The ratio of total liabilities over total assets discloses that the firms that issue bonds with low credit ratings tend to be more leveraged compared to the firms that issue bonds with higher credit ratings. In addition, the Altman's *z*-score [Altman (1968)], a measure of financial distress, indicates that lower leveraged firms of larger size tend to have a lower probability of bankruptcy. These results are consistent with the credit rating of the firms contained in the Barclays bond indices.

2.3. Returns for the bond and stock portfolios

The daily returns for bond indices and the associated stock portfolios are calculated as the percentage daily price changes over the time periods in which the daily data are available. Table 3 presents the descriptive statistics for the daily returns of the bond and the stock portfolios. As expected the mean daily returns for both the bond and stock portfolios are close to zero with the exception of the mean daily return for the Ca-D rated bond index, which has a daily return of 0.06%. However, this is also associated with a considerably higher standard deviation; indeed, the risk increases as the credit rating of the bond indices decreases. Noticeable is that the correlation coefficients between the returns of the high rated bond indices and the stock portfolios are negative, while that correlation coefficients between the returns of the low credit rated bond indices and the stock portfolios are positive. Further, for the Aaa and Ca-D credit ratings the coefficients are statistically indistinguishable from zero. For the HY rating category, the correlation between the bond and stock portfolio returns is positive and significantly higher (0.386) than the correlation for the IG rating category (-0.117). These findings are expected because the low credit rated bonds are closer to default, and their future cash flows, similar to the equity's future cash flows, are very sensitive to information related to the value of the firm and less sensitive to the movements in interest rates. Thus, as Merton (1974) notes, the low credit rated bonds behave more similarly to equity relative to the higher rated bonds. On the other hand, the higher rated bonds have relatively stable future cash flows and therefore a low correlation with stocks. Therefore, those bonds are affected more by the movements in interest rates compared to the lower rated bonds. This argument is empirically supported by the correlation coefficients between the bond indices and the returns of the three-month Treasury notes reported in Table 3. For example, the estimated correlation coefficients for the Aaa, Aa, A, and Baa rated bond indices are negative and very high (-0.650, -0.781, -0.748, and -0.743 respectively). But for the Ba, B, Caa, and Ca-D rated bond indices, the correlation coefficients are very low and statistically indistinguishable from zero (-0.016, -0.012, 0.028, and 0.019 respectively). These results are qualitatively similar to the results reported by Kwan (1996) and Downing et al., (2009).

Insert Table 3 about Here

3. Methodology and empirical results

The general belief is that information can be classified as public and private. Public information is known to all market participants while private information is known only to informed traders. If the bond and stock markets are equally efficient informationally, then public information is instantly and simultaneously incorporated into prices. Hence, individual bonds and stocks should tend to be contemporaneously correlated, and the direction of this relation is determined by the type of information released over time. The information on an increase in the firm's future cash flows should lead to an increase in the stock's price. In addition, the firm's bonds should also increase in value because they are claims on the firm's cash flows and their default risk is less. Thus, a positive (negative) correlation is expected between the firm's stock and bond prices (returns). However, the arrival of information about a risky project with a potentially high return increases the variance in the assets of the firm but not the risk-adjusted value of the firm (i.e., the higher expected cash flows are now discounted more heavily). The default risk of the firm's bonds now increases and leads to a lower debt value. But, the value of the stock increases because of the potential to reap a high return. Thus, a positive relation is expected between the firm's stock and bond returns. However, as noted by Downing et al., (2009), these two possible influences on the stock and the bond returns are not mutually exclusive. It should also be noted that it is possible that bonds may lead in incorporating a particular type of information, such as a change in the probability of default, and lag in incorporating another type of information, such as an increase in sales revenue. Hence, the signs of the estimated coefficients of the lagged stock returns in my models represent the net effect of these possibilities. Further, in the presence of information asymmetries, informed traders tend to systematically trade in either the bond or the stock market because of differences in trading fees, mechanisms, liquidity, institutional constraints, marginal tax brackets, and insider related legislation (i.e., disclosure requirements). Thus if private information is not simultaneously embedded into the prices of the bond and its underlying stock, then a lead-lag relation should exist between the bond and the stock returns.

Following Downing et al., (2009), Hotchkiss and Ronen (2002), and Kwan (1996), I examine the lead-lag relation between the bond and the issuing firm's stock returns. In particular, I assume that the following bivariate vector autoregressive (VAR) system describes the relation between the returns of the bond and the stock portfolios:

$$y_t = c + \sum_{i=1}^{L} \beta_i R_{B,t-i} + \sum_{i=1}^{L} s_i R_{S,t-i} + \varepsilon_t \tag{1}$$

where y_t is the variable set $[R_{B,t}, R_{S,t}]'$, $R_{B,t}$ is the daily return on a bond portfolio at time *t*, $R_{S,t}$ is the daily return on the underlying stock portfolio at time *t,* and *L* is the lag length. The lag length is set equal to five and is determined by the Akaike Information Criterion (AIC) and the empirical results in the literature[5] The *c*, β_i, and s_i are the intercept term and the coefficients matrices to be estimated respectively, and ε_t is the error term.

[5] The AIC assesses the overall quality of a statistical model by taking into account the number of parameters to be estimated as well as the goodness of fit of the model to the empirical data. Thus, starting from a number of candidate models for the data, the AIC can be used to determine the 'true' model. Based on the AIC criterion Downing et al., (2009) use a lag length equal to five for daily data and report that their conclusions are not sensitive to changes in lag lengths. Similar findings are reported by Hotchkiss and Ronen (2002).

The dynamics of how common information is embedded into the bond and stock markets is examined by including the lagging terms in the model. The null hypothesis is that the bond market and the associated stock market have equal informational efficiency. Therefore, if the bonds and the stocks instantly and simultaneously incorporate information, then I expect the coefficients of all of the lagged terms to be statistically equal to zero. I test this hypothesis by examining the Granger (1969) causality test statistic. This statistic is the F-statistic of the null hypothesis that all lagged stock market coefficients are statistically equal to zero, $H_0 = [\beta_i] = [S_i] = 0$, for all i. The Granger causality test can help to determine whether the stock (bond) returns are important in explaining the bond (stock) returns. In the case of small samples and to enhance the conclusions made on the basis of the Granger causality test, Downing et al., (2009) propose the use of an additional test that tests whether the sum of the lagged coefficients is statistically equal to zero[6]. This 'Sum' test is useful because if the Granger causality is rejected, then a simultaneous rejection gives further support to the hypothesis that a lead-lag relation exists between the bond and the stock returns.

The VAR system is estimated with ordinary least squares (OLS), and the summary results for the daily returns stratified by credit rating are presented in Table 4. Similarly to Downing et al., (2009) and Hotchkiss and Ronen (2002), the results are also insensitive to the number of lags used. With the exception of the Aaa and Ca-D rated bond portfolios, the returns of the bond portfolios exhibit predictability with the lagged returns of the associated stock portfolios. For example, for the IG, Aa, A, Baa, HY, Ba, B, and Caa rating categories there are many statistically significant coefficients for the stock returns that help to explain the bond returns. However, the Granger test fails to reject the null hypothesis that each of the estimated

[6] This test is known as the Wald's test and is typically used to test the joint significance of a number of estimated coefficients.

coefficients is equal to zero; and the Sum test provides further support for the IG rating category. The results also indicate that the returns of the less safe bond portfolios (e.g., HY, Ba, B, and Caa categories) tend to be more sensitive to the lagged returns of the underlying stock portfolios. This observation is expected because the low rated bonds resemble equity more closely than high rated bonds [for an in-depth discussion of the equity component of low rated bonds see, among others, Fridson (1994) and Cornell and Green (1991)]. Further, with the exemption of the weak evidence for the Aaa and Ca-D bond portfolios, there is no evidence that the daily bond returns lead the daily stock returns.

Insert Table 4 about Here

Overall, I find that the daily stock returns lead the bond returns for the IG, Aa, A, Baa, HY, Ba, B, and Caa rated bond portfolios but not for the safer (Aaa) and the least safe (Ca-D) bond portfolios. The results imply that the stock market is more efficient when incorporating common information that includes information that might lead to big corporate losses. However, whether the detected lead-lag relation is a causal one is not clear, and therefore it can be regarded as a joint reaction to common risk factors. Moreover, the more predictable bond portfolios are issued by firms that tend to have a lower Altman's *z*-score; a measure of financial distress with low values indicating higher probabilities of firm bankruptcy (see Table 2 for the Altman's *z*-score values of the Barclays' bond indices' associated stock portfolios). A likely explanation for the lack of equal informational efficiency is that the arrival of information for the issuing firms in financial distress induces trading in both bonds and stocks and leads to the observed lead-lag relation between the bond and the stock returns. My results complement Downing et al., (2009) and Kwan (1996) who also find that the significance of the lead-lag relation between the bond and the stock returns varies with respect to the credit rating of the bond. However, my results differ from the results of Hotchkiss and Ronen (2002) who find that the informational efficiency of high yield corporate bonds is similar to that of the underlying stocks. As Downing et al., (2009) note, this similarity might be because the costs of the bond transactions were higher during the time period covered by Hotchkiss and Ronen (2002); and as a result, the information that induces the trading in the stocks might not have been of a sufficient magnitude to trigger trading in the firms' bonds. Other possible reasons include the differences in the time periods examined, number of bonds, and the types of data used (i.e., bond portfolios versus individual bonds, daily versus intraday).

4. Economic significance of results

In this section, I assess whether the relative informational inefficiency of the bond and stock markets has any economic significance for the market participants. For that reason, I examine whether a profitable strategy can be devised on the basis of the lead-lag relation between the returns of the stocks and the bonds. I also examine whether the relative informational inefficiency of the bonds allows the impending default of the bonds to be perceived ahead of time.

4.1. Predictability and profitability

The economic significance of the findings can be assessed by examining the performance of the bond portfolios that are formed on the basis of the behavior of the past returns of the individual stocks (i.e., the Barclays bond indices constituents). In particular, following Downing et al., (2009) and Lo and MacKinlay (1990) I track, for each credit category, the performance of the bond portfolios that are formed by investing the fraction $w_{bi,t}$ in bond b_i:

$$w_{b_i,t} = \frac{1}{N}\left(R_{s_i,t-1} - R_{m,t-1}\right) \quad (2)$$

where N is the number of stocks in the stock portfolio that corresponds to a bond portfolio of a particular credit rating category, $R_{s_i,t-1}$ is the daily return on the stock of firm s_i at time t-1, and $R_{m,t-1}$ is the daily return on the stock portfolio at time t-1 for all of the firms with a bond in a particular credit rating class.

This trading strategy implies that I go long (short) on the bond whose underlying stock has achieved above (below) average returns in the previous period. In order to assess the economic significance of the lead-lag relation between the daily stock and bond returns in different credit categories, I track the performance of the resulting bond portfolios over one day, one week (i.e., five trading days), and one month (i.e., 22 trading days). I also calculate the cumulative return over the time period of January 1, 2004, to December 31, 2012; a period in which the daily returns are available for all of the bond portfolios. Assuming no trading costs, if the lead-lag relation between stocks and bonds is economically significant, then the formed bond portfolios should lead to an excess return.

Insert Table 5 about Here

The results are summarized in Table 5. For all of the holding periods, the average return is close to zero for all of the credit categories. Consistent with the previous finding that the lower rated bonds tend to be more sensitive to movements in their underlying stocks, the most profitability exists in the lower rated portfolios. For example, when the formed bond portfolio is held for one day, the average return is zero in the Aaa rating category but the return is 0.005% in the Ca-D rating category. Further, the longer the holding period of the bond portfolio is, the larger the total return is. For example, for a holding period of one day, the total profit is 0.191% in the Aaa rating category and 3.798% in the Ca-D rating category; but for one month, the total profit is 0.709% in the Aaa rating category and 9.918% in the Ca-D rating category. However, for most credit categories, a trader is unlikely to exploit the lead-lag relation between the bonds and stocks. This is because the transaction costs in the bond market tend to be considerable. For example, Edwards et al., (2007) report round-trip transaction costs of about 124 basis points for a transaction of $20,000 and 48 basis points for a transaction of $200,000 in the US OTC corporate bond market; however, their estimates vary considerably from 150 basis points for the smallest trade sizes to about 8 basis points for the largest trade sizes [similar results are reported by Goldstein et al., (2006), Hong and Warga (2000), Harris and Piwowar (2006), Schultz (2001), and Chakravarty and Sarkar (2003)]. These costs mean that any potential trading profit is likely be eliminated in the long run. These results are qualitatively similar with the results reported by Downing et al., (2009).

4.2. Predictability and the market perception of default

I examine whether the relative informational inefficiency of bonds compared to stocks is useful in predicting the impending default of the bonds. Hillmer and Yu (1979) propose a statistical technique that is based on the measurement of the amount of time that the market's mean and variance of returns takes to reflect the arrival of new information. By examining the structural changes in these two market attributes, I can determine at what time the stock and bond markets perceive the impending default of a firm. The market perception time is defined as the earliest point in time at which the market perceives an impending firm default, and the market lead interval is the time between the perception time and the actual bankruptcy. If the market lead interval for stocks is significantly longer than that of bonds, then the investors might have enough time to protect their capital by selling the risky bonds off well before they default or fall significantly in value.

In order to construct my data set of US corporate defaults, I use the definition of default in Standard and Poor's *Annual U.S. Corporate Default Study and Rating Transitions* report in which default is the firm's failure to make a required payment (interest or principal) on its debt obligation, or the filing for bankruptcy, or the initiation of a distressed exchange offer. I exclude a failure to pay interest on the date it is due but which is made within the grace period. I also do not consider preferred stock dividends as financial obligations, and therefore do not consider the failure of the firm to pay a preferred stock dividend as equivalent to firm default. My definition includes firms that have selectively defaulted (SD) and firms that are under regulatory supervision because of severe worries about their financial condition (R). The actual time of default is defined as the earliest of (i) the date the firm filed for bankruptcy, (ii) the date the firm failed to make a required interest or principal payment, (iii) the date the bond was downgraded to D, SD, or R by S&P, or (iv) the date that the distresses exchange offer was initiated. I also supplement and double-check my data by searching in the Lexis/Nexis database for all bankruptcies, corporate defaults, and distressed exchange offering. I use the daily returns of the Barclays High Yield index that excludes defaults (HYED) for a period of two years before and two years after the default date.[7] For the bonds that defaulted, I calculate the time series of the excess return over the four-year period as the difference between the return on the bond and the return on the HYED index. Unsurprisingly, the number of defaults increases as the credit ratings

[7] I use the Barclays High Yield index that excludes defaults because I want to use a proxy for the high yield debt market returns that does not include the impact of bonds that defaulted; otherwise I could double count the defaults. This approach is similar to Hradsky and Long (1989) and Ramaswami (1991) who use the monthly returns of the Blume-Keim index of lower grade bonds.

of the issuing firms decrease. For example, the number of defaults for the Aaa rated firms is zero but the number of defaults for the Ca-D rated firms is 173 (Table 6).

Insert Table 6 about Here

The market's perception time is determined on the basis of the structural changes in the mean and variance of the return, which are detected using the cumulative sum tests.[8] Let X_t be a market behavior variable, return or variance, of a stock or bond at time period *t*. I assume that the market behavior variable is a function of an information set that might contain various pieces of information like earnings reports, merger announcements, credit rating downgrades,…etc. The parameter X_t responds to different pieces of information that arrive at fixed or random time points. I assume that the information about the default is disclosed at time t_2 and that the market perceives the impending default at time t_1. The realization $\{X_t | t = t_s, t_s + 1, \cdots, t_1, t_1 + 1, \cdots, t_m\}$ is the observed sequence of the market behavior variable (i.e., return or variance) in which t_s is some starting time before t_1, and t_m is a time after t_1 and before t_2. Following Hillmer and Yu (1979), I assume that (i) $\{X_t | t_1 < t \leq t_m\}$ are *iid* with a known mean of ϑ_c and a known variance τ_c^2, (ii) $\{X_t | t_s \leq t \leq t_1\}$ are *iid* with a known mean of ϑ and a known variance τ^2, and (iii) $\{X_t | t_1 < t \leq t_m\}$ and $\{X_t | t_s \leq t \leq t_1\}$ are mutually independent. I also assume that the main effect of the release of the default information is a structural change in the parameter (i.e., return or variance).

The cumulative sum of the deviations, S_k, over a period *k* of the random process X from its mean *μ* can be written as:

$$S_k = \sum_{t=t_s}^{k} (X_t - \vartheta) = \sum_{t=t_s}^{k} Y_t \tag{3}$$

[8] This part draws mainly from Ramaswami (1991, 1987) and Hillmer and Yu (1979).

where $Y_t = X_t - \vartheta$ is the cumulative sum of the deviations from ϑ. Billingsley (1968) uses Donsker's theorem to show that if Y_t is *iid* with a mean μ (equal to zero in this case) and a finite variance τ^2, then S_k is asymptotically a Weiner process with a drift μ. Every time the cumulative sum of the deviations changes from zero, then the parameter experiences a change from ϑ to ϑ_c. Hillmer and Yu (1979) construct a critical value δ_k by defining:

$$Prob\left(S_j \leq \delta_j\,, for\; j \leq k \middle| No\; parameter\; change\right) = \alpha \tag{4}$$

where a structural change in the parameter for time $j \leq k$ occurs every time $S_j \leq \delta_j$, and the probability of a type II error is α. In addition, $\delta_k = -\sqrt{k}\tau Z_{\alpha/2}$ where $N(Z_{\alpha/2}) = 1 - \alpha/2$, $N(X)$ is the standard normal cumulative distribution function, and α is the confidence level. The time of the market's perception of default t_1 can then be:

$$t_1 = T - \frac{\delta_T}{\vartheta_c - \vartheta} \tag{5}$$

where T is the time that a structural change in the parameter occurs, δ_T is the critical value at a certain confidence level, ϑ is the value of the parameter before the structural change, and ϑ_c is the value of the parameter after the structural change.

The market lead time for both the return and the variance can then be calculated as the difference between the market's perception time and the time at which the default takes place, that is, $t_2 - t_1$. The reasoning is that as the market perceives an impending default, the returns of the high risk bonds should decrease and the variance should increase.

Table 6 displays the results. In general, an impending firm default is perceived by the stock and bond markets well in advance because the default is reflected in the market's lead times associated with the mean and the variance of returns. Further, the average market lead times associated with the return and the variance for both the stocks and the bonds become longer as the credit rating of the firm deteriorates. For example, an impending default of the really risky firms, Ca-D rated, is perceived as early as 14 months before the actual default while the market lead time drops to about four months for safer bonds, Aa rated. The average market lead times associated with the return and the variance of both the stocks and the bonds are similar for the firms that are rated IG, Aa, A, and Baa. This finding indicates that the structural changes in the return and the variance of the stocks and bonds of the potentially defaulting firms occur at about the same time. For example, a decrease in the expected return of the stocks and bonds of firms rated Aa is perceived by the stock market 3.8 months and by the bond market 3.3 months before the actual default. In addition, an increase in the riskiness of the Aa rated firms is perceived by both the stock and bond markets 2.2 months in advance of the default event. However, when I examine riskier bonds (i.e., HY, Ba, B, Caa, and Ca-D rated) the average market lead times are longer for stocks than bonds. For example, the stock market appears to perceive a decrease in the returns of the stocks of firms that are likely to default about two months earlier than the bond market perceives a decrease in the returns of the bonds of these firms. Furthermore, the stock market perceives an increase in the riskiness of the stocks of the firms likely to default about 1.5 months earlier than the bond market perceives an increase in the riskiness of the bonds of these firms. For example, the average market lead time for the return of the stocks of the firms that have issued Caa rated bonds is 16.2 months and the variance is 8.5 months. These numbers compare to 14.1 for the return and 6.9 months for the variance in the bonds.

The existence of significant market lead times for the impending defaults of highly rated firms as well as the longer market lead times for stocks compared to the market lead times of riskier bonds indicate that bond holders have enough time to work out of their long positions on bonds or to devise a hedging strategy in order to protect the value of their investment in the debt market. My results complement Ramaswami (1991, 1987) who finds that the market lead times of high yield bonds are about ten months for the mean and five months for the variance of returns.[9] He also argues that these lead times occur because the high yield bond market is less informationally efficient relative to the stock market and/or because bond holders are more optimistic than stock holders.

5. Conclusion

This study contributes to the literature by providing further evidence on how the arrival of common information in the market place is incorporated into the prices of bonds and the issuing firms' stocks. In particular, I use the Barclays bond indices data with a wide spectrum of credit ratings to examine the relative informational efficiency of bonds and stocks issued by the same firms. I use a bivariate VAR to investigate the lead-lag relation between the returns of the bonds and those of the issuing firms' stocks. My findings indicate that the daily stock returns lead the daily bond returns for the Investment Grade, Aa, A, Baa, High Yield, Ba, B, and Caa rated bond portfolios but not for the safest and the least safe bond portfolios that are rated Aaa and Ca-D. This finding indicates that the stock market is more efficient relative to the bond market in incorporating common information. In general, my results are consistent with the results of Downing et al., (2009), Hong et al. (2012), and Gebhardt et al. (2005). However, I also find that the relative efficiency of the bond and stock markets varies with the creditworthiness of the bond portfolio examined. Furthermore, my results and inferences are based on data from bond indices, which means that they should be interpreted with caution. For example, Downing et al., (2009)

[9] Although not the focus of this paper, it worth adding that the variation of market lead times raises concerns with respect to the assumption of a uniform event period in event studies.

examine individual corporate bonds and find substantial cross-sectional variation, which indicates that there are both predictable and unpredictable bonds in each credit rating category. In addition, the detected lead-lag relation is not clearly a causal one, and therefore it might be regarded as a joint reaction to common risk factors. The differences between my results and Hotchkiss and Ronen (2002), Ronen and Zhou (2013), and Bittlingmayer and Moser (2014) might be because of differences in the data used (e.g., bonds indices versus individual bonds, sample size, time period covered, size of transaction costs).

Overall, the results support the view that the bond market is relatively less informationally efficient compared to the stock market. In terms of the economic significance of my results, although it is possible to devise economically significant trading strategies based on the lead-lag relation between stocks and bonds, the high transaction costs likely only make sensible the transactions on bonds that are highly sensitive to the release of common information (i.e., low rated bonds). For the lower rated firms, I also find that the average market lead times for their impending defaults associated with the mean and variance of their stocks are longer compared to the average market lead times for the bonds in the same rating category. The existence of a longer lead time implies that bond holders have plenty of time to get out of their long positions in potentially defaulting bonds or to devise hedging strategies to protect the value of their investment in the debt market.

References

Alexander, G., Edwards, A., Ferrin, M., 2000. What does the Nasdaq's high-Yield bond market reveal about bondholder-stockholder conflict?. Financial Management 29, 23-39.

Altman, E., 1968. Financial rations, discriminant analysis, and the prediction of corporate bankruptchy. Journal of Finance 23, 589-609.

Bessembinder, H., Maxwell, W., Venkataraman, K., 2006. Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. Journal of Financial Economics 82, 251-288.

Blume, M. E., Keim, D., Patel, S., 1991. Returns and volatility of low-grade bonds: 1977-1989. Journal of Finance 46, 49-74.

Billingsley, P., 1968. Convergence of Probability Measures, Wiley, New York.

Bittlingmayer, G. and Moser, S. M., 2014. What does the corporate bond market knows?, Financial Review 49, 1-19.

Chakravarty, S., Sarkar, A., 2003. Trading costs in three U.S. bond markets. Journal of Fixed Income 13, 39-48.

Cornell, B., Green, K., 1991. The investment performance of low-grade bond funds. Journal of Finance 46, 29-48.

Downing, C., Underwood, S., Xing, Y., 2009. The relative informational efficiency of stocks and bonds: An intraday analysis. Journal of Financial and Quantitative Analysis 44, 1081-1102.

Edwards, A. K., Harris, L. E., Piwowar, M. S., 2007. Corporate bond market transaction costs and transparency. Journal of Finance 62, 1421-1451.

Fridson, S. M., 1994. Do high-yield bonds have an equity component?. Financial Management 23, 82-84.

Gebhardt, W. R., Hvidkjaer, S., and Swaminathan, B., 2005. Stock and bond market interaction: Does momentum spill over? Journal of Financial Economics 75, 651-690.

Goldstein, M. A., Hotchkiss, E. S., Sirri, E. R, 2007. Transparency and liquidity: A controlled experiment on corporate bonds. Review of Financial Studies 20, 235-273.

Granger, C. W. J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37, 424–438.

Hansen, L., 1982. Large sample properties of generalized method of moment estimation. Econometrica 50, 1029-1054.

Hardsky, G. T., Long, R. D., 1989. High-yield default losses and the return performance of bankrupt debt. Financial Analysts Journal 45, 38-49.

Harris, L., Piwowar, M., 2006. Secondary trading costs in the municipal bond market. Journal of Finance 61, 1361-1397.

Hillmer, S. C., Yu, P. L., 1979. The market speed of adjustment of new information. Journal of Financial Economics 7, 321-345.

Hong, G., Warga, A., 2000. An empirical study of bond market transactions. Financial Analysts Journal 56, 32-46.

Hong, Y., Lin, H. and Wu, C., 2012. Are corporate bond market returns predictable? Journal of Banking and Finance 36, 2216-2232.

Hong, H, Torous, W. and Valkanov, R., 2007. Do industries lead stock markets? Journal of Financial Economics 83, 367-396.

Hotchkiss, E. S., Ronen, T., 2002. The information efficiency of the corporate bond market: An intraday analysis. Review of Financial Studies 15, 1325-1354.

Hou, K., 2007. Industry information diffusion and the lead-lag effect in stock returns. Review of Financial Studies 20, 1113-1138.

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

Lo, A. W., MacKinlay, A. C., 1990. When are contrarian profits due to stock market overreaction?. Review of Financial Studies 3, 175-205.

Merton, R., 1974. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 29, 449-470.

Ramaswami, M., 1991. Hedging the equity risk of high-yield bonds. Financial Analysts Journal 47, 41-50.

Ramaswami, M., 1987. Stock market perception of industrial firm bankruptcy. Financial Review 22, 267-278.

Ronen, T. and Zhou, X., 2013. Trade and information in the corporate bond market. Journal of Financial Markets 16, 61-103.

Scholes, M., Williams, J., 1977. Estimating betas from nonsynchronous data. Journal of Financial Economics 5, 309-327.

Schultz, P., 2001. Corporate bond trading costs: A peek behind the curtain. Journal of Finance 56, 677-698.

Securities Industry and Financial Markets Association (SIFMA), www.sifma.org.

Standard and Poor's, various years. Annual U.S. Corporate Default Study and Rating Transitions, New York.

Table 1: Characteristics of Bond Portfolios

Table 1 displays the daily average values for the characteristics of the Barclays bond indices. The 'Start Date' gives the date when the daily data for a particular index became available. The 'Number of Bonds' gives the average number of bonds in an index. The 'Yield' gives the average yield, 'Years to Maturity' gives the average time remaining to maturity, and the 'Duration' gives the average duration. The 'Coupon' gives the average coupon, 'Amount Outstanding' gives the average market value of the bonds that remain outstanding, and the 'Market Capitalization' gives the average market capitalization of the bonds.

Credit Rating	**Start Date**	**Number of Bonds**	**Yield (%)**	**Years to Maturity (Yrs)**	**Duration (Yrs)**	**Coupon (%)**	**Amount Outstanding ($mil.)**
Investment Grade (IG)	01/02/1989	3560	6.45	11.33	5.93	7.14	711,712
Aaa	06/01/2000	67	4.46	10.13	6.25	5.26	632,897
Aa	01/01/2004	319	4.26	7.93	5.46	5.14	984,581
A	06/01/2000	1382	5.14	10.16	6.21	6.07	831,501
Baa	06/01/2000	1469	5.92	11.18	6.55	6.69	580,860
High Yield (HY)	08/03/1998	1587	10.00	7.61	4.58	8.14	548,034
Ba	08/03/1998	551	7.94	8.27	4.91	7.69	600,551
B	08/03/1998	697	9.75	7.28	4.43	8.40	541,706
Caa	08/03/1998	268	14.69	6.91	4.22	8.49	470,177
Ca-D	08/03/1998	50	27.73	6.22	3.35	8.53	573,967

Table 2: Characteristics of Stock Portfolios

Table 2 displays the daily average values for the characteristics of the associated stock portfolios. The 'Number of Firms' gives the number of firms that have issued the bonds in the associated bond indices. The 'Market Capitalization' gives the average market capitalization of the issuers in each credit rating category. The 'Altman's *z*-score' gives the Altman's (1968) average measure of financial distress (z >2.6 indicates that a firm is in the *safety* zone, 1.1 <z< 2.6 indicates that a firm is in the *gray* zone, and z <1.1 indicates that a firm is in the *bankruptcy* zone). The 'Total Liabilities/Total Assets' gives the average ratio of the total liabilities and the total assets of the firm.

Credit Rating	**Number of Firms**	**Market Capitalization ($bil.)**	**Altman's *z*-score**	**Total Liabilities/ Total Assets**
Investment Grade (IG)	669	110,415	2.951	0.614
Aaa	3	262,821	4.533	0.459
Aa	31	820,442	3.320	0.576
A	226	85,997	3.156	0.597
Baa	472	222,466	2.681	0.632
High Yield (HY)	626	24,905	1.896	0.720
Ba	228	52,869	1.901	0.674
B	324	4,792	1.871	0.750
Caa	141	7,055	1.944	0.812
Ca-D	6	14,154	1.033	0.863

Table 3: Descriptive Statistics of the Daily Returns of the Bond Indices and the Stock Portfolios

Table 3 contains the descriptive statistics for the Barclays bond indices and the associated stock portfolios. For both the bond indices and the stock portfolios, 'Mean' and 'St.Dev.' are the average daily return and the standard deviation of the daily returns, respectively. The $\rho_{B,S}$ is the contemporaneous correlation between the bond and the stock daily returns, and $\rho_{B,T}$ is the contemporaneous correlation between the bond and the three-month Treasury note daily returns (the *p*-value of the null hypothesis that the estimated correlation is statistically equal to zero is given in parenthesis).

Credit Rating	**Mean (%)**	**St.Dev. (%)**	**Mean (%)**	**St.Dev. (%)**	$\rho_{B,S}$	$\rho_{B,T}$
	Bonds (*B*)		**Stocks (*S*)**			
Investment Grade (IG)	0.00	0.33	0.02	0.97	-0.117 (0.000)	-0.673 (0.000)
Aaa	0.01	0.48	0.01	0.02	-0.003 (0.874)	-0.650 (0.000)
Aa	0.00	0.33	0.02	0.93	-0.255 (0.000)	-0.781 (0.000)
A	0.01	0.36	0.01	1.11	-0.245 (0.000)	-0.748 (0.000)
Baa	0.01	0.37	0.01	1.33	-0.174 (0.000)	-0.743 (0.000)
High Yield (HY)	0.00	0.36	0.01	0.95	0.386 (0.000)	-0.003 (0.869)
Ba	0.00	0.34	0.01	1.40	0.189 (0.000)	-0.016 (0.323)
B	0.00	0.44	0.01	1.38	0.256 (0.000)	-0.012 (0.467)
Caa	0.01	0.75	0.00	1.22	0.194 (0.000)	0.028 (0.091)
Ca-D	0.06	3.22	0.00	1.79	0.020 (0.225)	0.019 (0.254)

Table 4: The Daily Returns of the Bond Indices and the Underlying Stock Portfolios

Table 4 presents the estimates of the following bivariate vector autoregressive model:

$$y_t = a + \sum_{i=1}^{L} \beta_i R_{B,t-i} + \sum_{i=1}^{L} s_i R_{S,t-i} + \varepsilon_t$$

where y_t is the variable set $[R_{B,t}, R_{S,t}]'$,$R_{B,t}$ is the daily return of the Barclays bond index with a particular credit rating at time *t*,$R_{S,t}$ is the daily return on the underlying stock portfolio at time *t*, and *L*(= 5) is the lag length. The α is the intercept term, β_i and s_i are the coefficients matrices to be estimated respectively, and ε_t is the error term. The *t*-statistics of the coefficient estimates are given in parentheses below the estimates. The '*N*' is the number of data points, and 'Sum' is the *F*-statistics (*p*-value in parenthesis) of the null hypothesis that the sum of the estimated coefficients is statistically equal to zero. The 'Granger' is the *F*-statistics (*p*-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero.

	Lagged Bond returns					Lagged Stock returns							
Credit Rating	β_1	β_2	β_3	β_4	β_5	s_1	s_2	s_3	s_4	s_5	***N***	**Sum**	**Granger**
Investment grade (IG)											6256		
Stock	0.033	-0.016	0.065	-0.041	0.029	0.129	-0.048	0.007	0.001	-0.051		1.554	22.476
	(0.883)	(-0.417)	(1.749)	(-1.117)	(0.789)	(10.095)	(-3.711)	(0.566)	(0.103)	(-3.971)		(0.213)	(0.000)
Bond	0.005	-0.015	-0.022	-0.007	0.001	0.034	0.014	0.016	0.015	0.009		2.640	1.150
	(0.357)	(-1.170)	(-1.723)	(-0.570)	(0.064)	(7.705)	(3.104)	(3.686)	(3.268)	(1.986)		(0.104)	(0.331)
Aaa											3278		
Stock	0.001	0.000	0.001	0.000	-0.001	1.809	-2.069	1.292	1.237	-1.373		1990.38	0.978
	(1.858)	(-0.438)	(2.566)	(-0.381)	(-2.053)	(27.704)	(-22.026)	(12.897)	(12.023)	(-19.689)		(0.000)	(0.430)
Bond	-0.014	-0.005	0.071	-0.014	-0.016	-0.345	-2.353	4.042	-2.853	2.508		2.190	2.970
	(-0.783)	(-0.295)	(4.029)	(-0.807)	(-0.922)	(-0.154)	(-0.730)	(1.176)	(-0.808)	(1.048)		(0.139)	(0.011)
Aa											2343		
Stock	-0.088	-0.102	-0.073	-0.120	-0.090	0.039	-0.094	-0.002	0.008	-0.052		13.555	20.643
	(-1.406)	(-1.642)	(-1.171)	(-1.929)	(-1.477)	(1.815)	(-4.327)	(-0.086)	(0.368)	(-2.361)		(0.000)	(0.000)
Bond	-0.019	-0.039	0.009	0.031	0.008	0.061	0.026	0.021	0.021	0.008		5.800	2.211
	(-0.882)	(-1.799)	(0.424)	(1.438)	(0.394)	(8.335)	(3.443)	(2.829)	(2.855)	(1.128)		(0.016)	(0.051)
A											3278		
Stock	-0.074	-0.085	0.032	-0.063	0.068	-0.020	-0.045	0.012	0.002	-0.045		2.549	22.134
	(-1.317)	(-1.527)	(0.575)	(-1.143)	(1.240)	(-1.092)	(-2.466)	(0.651)	(0.097)	(-2.461)		(0.111)	(0.000)
Bond	-0.019	-0.027	0.007	0.034	0.031	0.045	0.025	0.029	0.018	0.002		10.844	1.404

	(-1.029)	(-1.487)	(0.364)	(1.920)	(1.757)	(7.753)	(4.202)	(4.840)	(3.124)	(0.290)		(0.001)	(0.220)
Baa											3278		
Stock	0.088	-0.009	0.078	-0.049	0.065	0.091	-0.045	-0.001	-0.009	-0.061		1.036	18.059
	(1.374)	(-0.141)	(1.226)	(-0.767)	(1.020)	(5.098)	(-2.487)	(-0.055)	(-0.525)	(-3.389)		(0.309)	(0.000)
Bond	0.007	-0.025	0.004	0.028	0.033	0.031	0.014	0.021	0.013	0.016		12.244	0.983
	(0.415)	(-1.430)	(0.198)	(1.588)	(1.856)	(6.275)	(2.723)	(4.150)	(2.673)	(3.250)		(0.001)	(0.426)
High Yield (HY)											3756		
Stock	0.028	0.039	0.057	0.088	0.022	0.428	-0.123	0.035	-0.017	-0.045		64.874	100.43
	(0.601)	(0.822)	(1.209)	(1.848)	(0.494)	(25.160)	(-6.520)	(1.848)	(-0.900)	(-2.519)		(0.000)	(0.000)
Bond	0.165	0.039	0.030	0.087	0.079	0.131	-0.009	0.023	0.005	0.012		612.24	2.080
	(9.728)	(2.305)	(1.781)	(5.137)	(4.942)	(21.466)	(-1.288)	(3.465)	(0.774)	(1.909)		(0.000)	(0.065)
Ba											3756		
Stock	-0.122	-0.022	-0.054	0.075	0.015	0.078	0.016	0.009	0.016	-0.037		0.042	63.75
	(-1.645)	(-0.295)	(-0.728)	(1.017)	(0.218)	(4.703)	(0.908)	(0.551)	(0.956)	(-2.140)		(0.839)	(0.000)
Bond	0.128	0.039	0.044	0.053	0.042	0.060	0.019	0.014	0.014	0.007		248.71	0.879
	(7.716)	(2.323)	(2.655)	(3.175)	(2.630)	(16.095)	(4.960)	(3.747)	(3.684)	(1.805)		(0.000)	(0.494)
B											3756		
Stock	0.037	-0.065	0.037	0.084	0.041	0.057	0.050	0.011	0.016	-0.033		6.742	77.872
	(0.658)	(-1.138)	(0.659)	(1.511)	(0.762)	(3.357)	(2.846)	(0.635)	(0.893)	(-1.892)		(0.010)	(0.000)
Bond	0.018	0.084	0.082	-0.004	0.104	0.088	0.043	0.008	0.011	0.012		278.58	1.060
	(1.075)	(5.048)	(4.917)	(-0.227)	(6.568)	(17.713)	(8.216)	(1.512)	(2.139)	(2.403)		(0.000)	(0.381)
Caa											3756		
Stock	0.039	0.052	0.066	0.039	0.052	0.071	0.035	-0.008	0.008	-0.055		35.228	37.511
	(1.412)	(1.849)	(2.358)	(1.386)	(1.905)	(4.262)	(2.100)	(-0.459)	(0.465)	(-3.240)		(0.000)	(0.000)
Bond	0.077	0.036	0.016	0.069	0.036	0.117	0.048	0.034	-0.002	0.018		226.12	4.226
	(4.620)	(2.192)	(0.954)	(4.159)	(2.203)	(11.930)	(4.801)	(3.414)	(-0.186)	(1.813)		(0.000)	(0.001)
Ca-D											3756		
Stock	0.022	0.009	-0.002	0.016	0.029	-0.044	0.000	-0.016	0.022	-0.009		0.422	2.220
	(2.447)	(1.025)	(-0.227)	(1.728)	(3.154)	(-2.700)	(0.014)	(-0.964)	(1.348)	(-0.554)		(0.516)	(0.050)
Bond	-0.095	0.001	-0.034	-0.010	-0.013	-0.005	0.030	0.024	-0.052	0.070		1.202	3.657
	(-5.796)	(0.061)	(-2.079)	(-0.598)	(-0.790)	(-0.169)	(1.027)	(0.830)	(-1.792)	(2.399)		(0.273)	(0.002)

Table 5: Predictability and Profitability

Table 5 reports the performance (i.e., profit or loss) of the trading strategies based on the bond portfolios that are formed by assigning a positive (negative) weight to the bonds whose associated stock achieved an above (below) average return over the previous period. The 'Mean' gives the average return for the holding period, and the 'Total' gives the cumulative return for the period January 1, 2004, to December 31, 2012.

	Holding period					
	Day		Week		Month	
Credit Rating	Mean (%)	Total (%)	Mean (%)	Total (%)	Mean (%)	Total (%)
Investment Grade (IG)	0.000	0.191	0.000	0.419	0.002	0.709
Aaa	0.000	0.279	-0.001	-0.022	0.002	0.521
Aa	-0.000	0.244	-0.001	-0.016	-0.001	-0.019
A	0.000	0.160	0.002	0.489	0.003	1.523
Baa	0.000	0.422	0.003	0.681	0.002	1.629
High Yield (HY)	0.003	1.111	0.002	2.481	0.003	4.467
Ba	0.001	1.681	0.003	3.991	0.005	6.201
B	0.003	2.341	0.004	4.763	0.004	7.115
Caa	0.002	2.759	0.002	5.505	0.005	8.625
Ca-D	0.005	3.798	0.003	6.698	0.007	9.918

Table 6: The Average Market Lead Times of Impending Defaults

Table 6 displays the average market lead times of the impending defaults for the whole spectrum of credit ratings. The 'Market Lead Time' is defined as the duration in months between the market perception time and the date of the actual default. The 'Time Period' is the time period over which the information about corporate defaults was collected. For each credit category, this Time Period is defined as the time period that starts two years after the date's daily data is available and ends two years before the last date's daily data is available in my data set. The 'Defaults' is the total number of firm defaults during the associated time period. The number of defaults, the names of the firms that defaulted, and the actual dates of the defaults are collected from the Standard and Poor's (S&P) *Annual U.S. Corporate Default Study and Rating Transitions* reports for various years and the S&P's CreditPro database. I also supplement and double-check my data set by conducting a search for bankruptcies, defaults, and distressed exchange offers in the Lexis/Nexis database. The default date is defined as the date the firm failed to make a required payment (interest or principal), the date the firm filed for bankruptcy, or the date the firm initiated a distressed exchange offer. The 'St.Dev' is the standard deviation of the average market lead time for the bonds that belong to a particular credit category. Although the analysis is conducted using daily data, the market lead time results are expressed in months; for that reason, I make the assumption that each month has 22 trading days.

				Average Market Lead Time (months)			
				Stocks		**Bonds**	
Credit Rating	**Time Period**	**Defaults**		**Return**	**Variance**	**Return**	**Variance**
Investment Grade (IG)	01/02/1991-12/31/2010	50	Mean	5.7	3.7	5.0	3.1
			Min	1.7	1.3	1.8	2.2
			Max	8.8	7.4	7.7	8.8
			St.Dev	3.9	3.5	3.3	4.1
Aaa	06/01/2002-12/31/2010	0	Mean	-	-	-	-
			Min	-	-	-	-
			Max	-	-	-	-
			St.Dev	-	-	-	-
Aa	01/01/2006-31/12/2010	7	Mean	3.8	2.7	3.3	2.2
			Min	0.8	0.9	1.5	1.3
			Max	5.5	4.0	5.2	5.3
			St.Dev	2.2	1.7	2.1	2.7
A	01/06/2002-12/31/2010	43	Mean	4.3	1.9	4.0	2.0
			Min	1.2	0.5	0.9	0.6
			Max	8.6	5.1	7.5	4.7
			St.Dev	4.4	3.2	3.3	1.9
Baa	06/01/2002-12/31/2010	63	Mean	7.0	4.4	6.6	4.7

			Min	2.7	1.3	3.1	2.0
			Max	11.2	9.1	10.1	9.9
			St.Dev	5.2	4.6	3.9	4.5
High Yield (HY)	08/01/2000-12/31/2010	738	Mean	10.5	6.6	8.4	5.2
			Min	2.9	1.9	1.8	1.7
			Max	18.2	14.4	23.1	15.3
			St.Dev	6.9	6.4	9.2	7.7
Ba	08/01/2000-12/31/2010	74	Mean	14.0	8.1	12.2	6.8
			Min	5.6	2.7	5.8	2.0
			Max	26.3	18.8	21.9	16.1
			St.Dev	8.4	7.5	8.9	6.4
B	08/01/2000-12/31/2010	172	Mean	13.2	10.4	10.8	8.8
			Min	5.6	2.4	4.4	1.9
			Max	27.2	22.2	25.5	27.1
			St.Dev	8.1	8.0	7.3	7.2
Caa	08/01/2000-12/31/2010	561	Mean	16.2	8.5	14.1	6.9
			Min	6.7	3.3	5.3	1.6
			Max	35.1	21.0	26.3	19.7
			St.Dev	10.3	7.4	11.1	8.3
Ca-D	08/01/2000-12/31/2010	173	Mean	14.1	9.3	14.6	9.7
			Min	6.7	3.3	3.2	1.8
			Max	34.4	22.2	26.1	17.7
			St.Dev	11.2	10.7	10.2	8.1