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The Relative Informational Efficiency of Stocks and Bonds: An Intraday Analysis

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Abstract

In light of recent improvements in the transparency of the corporate bond market, we examine the relation between high frequency returns on individual stocks and bonds. In contrast to the authors of previous literature, we employ comprehensive transactions data for both classes of securities. We find that hourly stock returns lead bond returns for nonconvertible junk- and BBB-rated bonds, and that stock returns lead bond returns for convertible bonds in all rating classes. Most of the predictable nonconvertible bonds are issued by companies in financial distress, while the predictable convertible bonds are those with conversion options more deeply in-the-money. These results indicate that the corporate bond market is less informationally efficient than the stock market, notwithstanding the recent improvements in bond market transparency and associated reductions in corporate bond transaction costs.

I. Introduction

There is much to be learned about the nature of information and how information is incorporated into security prices by examining the correlations between stock and bond returns. As noted by Kwan (1996), the contemporaneous correlation between stock and bond returns reveals whether the common element of firm-specific news pertains to information about the mean value of the firm's assets or the variance of the asset return. The cross-serial correlation between stock and bond returns reflects the relative informational efficiency of the two markets: Evidence of a lead-lag relation in one direction or the other has been interpreted as indicative of the activities of informed traders in the market where returns carry predictive content.

However, the market for corporate bonds has long been relatively opaque compared to the market for corporate equity. As a result, previous studies of the

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relation between stock and bond returns have drawn conflicting conclusions from dealer quotes of uncertain quality or narrow data sets that leave the generality of the results open to question. For example, based on a sample of dealer quotes, Kwan (1996) presents evidence suggesting that stock returns predict future bond returns, while bond returns provide no explanatory power for future stock returns.[1] In contrast, Hotchkiss and Ronen (2002) examine the returns on 20 high yield bonds traded on the National Association of Securities Dealers' (NASD's) fixed income pricing system (FIPS) in 1995 and find no evidence that stock returns lead bond returns.

In recent years, the NASD has made sweeping reforms of the reporting requirements for over-the-counter corporate bond transactions in an effort to improve the transparency of the market, culminating in the public dissemination of information on most corporate bond transactions. As shown in Edwards, Harris, and Piwowar (2007), Bessembinder, Maxwell, and Venkataraman (2007), and Goldstein, Hotchkiss, and Sirri (2007), these improvements in bond market transparency have led to lower transaction costs and greater liquidity in the bond market. In light of these results, we exploit the newly available NASD data on corporate bond transactions to make the most comprehensive study to date of the relative informational efficiency of the corporate bond and equity markets.

We analyze daily and hourly bond and stock returns over the period from October 1, 2004 to December 31, 2005, for a total of 2,173 hourly observation periods over 312 business days. Our sample includes returns on 3,000 bonds and the associated equity issued by 439 firms. We begin by documenting that the contemporaneous correlations between bond and equity returns are insignificantly different from 0, on average, for firms carrying AAA, AA, and A credit ratings. For firms rated BBB or lower, we find that, on average, the contemporaneous correlations are positive, consistent with these securities being more like equity than safer bonds. Intuitively, lower rated bonds are more like equity because the bondholders are more likely to take over the firm in default. This intuitive notion is given a precise characterization in Merton (1974) and the subsequent literature on the structural modeling of defaultable bond prices. Our results here are also consistent with the empirical evidence of Kwan (1996), who analyzed the contemporaneous correlations between equity returns and changes in quoted bond yields.

We employ bivariate vector autoregressions in order to examine the lead-lag relations between bond and equity returns. In examining portfolio and individual security returns at the daily and hourly levels, we find clear evidence that the equity returns for riskier firms (junk-rated and, to a lesser extent, BBB-rated) lead their associated nonconvertible bond returns. In contrast, we find no evidence of a lead-lag relation between the equity and nonconvertible bond returns for safer firms. Regressions including Treasury note returns and S&P 500 returns indicate

[1]Blume, Keim, and Patel (1991) and Cornell and Green (1991) also find a contemporaneous relationship between corporate bond returns and both government bond and stock returns. Altman, Gande, and Saunders (2008) examine the informational efficiency of the bond market versus the loan market and conclude that the loan market is more efficient in incorporating information around events such as defaults and bankruptcies. Blanco, Brennan, and Marsh (2005) find that credit default swaps lead investment grade corporate bonds in incorporating new information.

that AAA-, AA-, and A-rated bond returns are most closely related to movements in risk-free rates, which is consistent with these bonds having stable expected cash flows and, hence, little correlation with equity returns.

Within each rating class, on average the bonds that exhibit predictability also exhibit higher probabilities of financial distress, whether distress is measured by the Altman (1968) or the Shumway (2001) distress metrics. Indeed, a firm-by-firm examination of the results reveals that the bulk of the nonconvertible bonds with predictable returns are liabilities of firms that do in fact encounter financial difficulties or outright bankruptcy over our sample period. These firms are clearly generating news of sufficient import to bond values to produce trading in the firms' bonds, even in the face of steep transaction costs, and the price movements in this trading reveal the relative informational inefficiency of the corporate bond market. For example, among the BBB-rated firms, a substantial number of bonds issued by the domestic U.S. automakers are predictable. Over the period we study, the U.S. automakers are under significant financial pressure, and their bonds are downgraded to junk. In the junk class, the predictable bonds tend to be claims on the airlines, many of which went into bankruptcy following September 11, and on other firms that moved closer to or into bankruptcy during our sample period. We also find that convertible bonds exhibit predictability in all rating classes; the predictability of a convertible bond is related to the extent to which its conversion option is in-the-money.

Taken together, these results indicate that the bond market is in general less informationally efficient than the equity market. As shown in Edwards et al. (2007), the transaction costs for corporate bonds remain relatively high compared to those for equities. Our results suggest that, given these relatively high transaction costs, only bonds with a high degree of sensitivity to firm-specific news will transact when news is released and thus reveal the lesser informational efficiency of the bond market. The apparently conflicting conclusions reached in the previous studies likely result from the fact that the previous research relied upon less comprehensive data than those we employ in this study. We are able to examine a wide range of bonds and provide the clearest picture to date of the relative efficiency of the stock and bond markets.

The results of this study also have implications for the debate on the effects of transparency on market activity. Edwards et al. (2007) examine the liquidity of corporate bonds and show that the increased transparency brought about by Trade Reporting and Compliance Engine (TRACE) lowered transactions costs for investors. Goldstein et al. (2007) find that increased transparency leads to liquidity improvements for small- and medium-sized trades in actively traded bonds. Bessembinder et al. (2007) use the National Association of Insurance Commissioners (NAIC) database of insurance company trades to show that trading costs for institutional bond trades go down when transparency increases due to TRACE. It is notable that, despite these documented improvements in liquidity as a result of heightened transparency, we still find evidence of a lead-lag relation for bond and equity returns. It would thus appear that the relative inefficiency of the bond market reflects more than a lack of transparency.

The remainder of the paper is organized as follows. Section II discusses the equity and bond data used in the study. Section III presents our methodology and discusses the results. Section IV concludes and suggests direction for further research.

II. Data

A. Bonds

Our data for corporate bond returns are from the NASD TRACE system. The TRACE system was implemented in response to growing pressure from investors to make the corporate bond market more transparent. Since July 1, 2002, the NASD has required that all over-the-counter corporate bond transactions in TRACE-eligible securities be reported through the TRACE system.[2] NASD members were initially required to report corporate bond transactions within 75 minutes of a trade's occurrence. On October 1, 2003, this reporting lag was reduced to 45 minutes. The required reporting time was further reduced to 30 minutes on October 1, 2004 and reached the final goal of 15 minutes on July 1, 2005. Transaction information for bonds on the public dissemination list is transmitted on a real-time basis to fee-paying subscribers.[3]

While NASD guidelines require all corporate bond trades to be reported, the public dissemination of these trade reports has been gradually phased in since the initiation of TRACE. For our study we focus on Phase III, in which all corporate bond trades were publicly disseminated. This allows us to examine the relation between stock and bond returns for a comprehensive sample of corporate bonds across the spectrum of credit quality, issue size, liquidity, etc. Phase III was implemented on October 1, 2004, and the sample used in our study runs through December 31, 2005.[4]

Over 22,000 bonds have at least one trade during the Phase III period that we study, but the vast majority trade very infrequently. In fact, almost 5,000 of the bonds trade 10 or fewer times over our October 2004 to December 2005 sample period. In order to carry out a meaningful analysis of the cross-market return dynamics between a firm's debt and equity, we impose the initial requirement that a bond trade at least once per day on average.[5] After matching with equity, this results in a sample of 3,000 total bonds issued by 439 firms. Our sample is

[2]TRACE-eligible securities include all U.S. dollar-denominated debt securities that are depository eligible under NASD Rule 11310(d). Specifically excluded is debt issued by government-sponsored entities, mortgage- or asset-backed securities, collateralized mortgage obligations, and money market instruments.

[3]Trade information is also freely available on the Web site (http://www.investinginbonds.com). These reporting lags do not appear to be related to our lead-lag results: We find that the lead-lag relation exists over much longer time horizons.

[4]Phase I of TRACE only provided for dissemination of trades in investment grade bonds with an issue size greater than $1 billion, and a small number of high yield bonds that were carried over from the NASD's FIPS. Phase II, implemented in March 2003, expanded the universe to all bonds rated A and above with an issue size greater than $100 million, and 120 BBB bonds with issue sizes less than $1 billion. Even under Phase II, trading in the vast majority of bonds in the BBB and junk categories was not subject to public dissemination.

[5]This cutoff also ensures that we do not include a subset of bonds that were still subject to delayed dissemination during the time period of our sample. Trades of greater than $1 million in BB (B or lower) issues which trade on average *less* than once per day were disseminated two (four) days after execution. This rule was changed in January 2006.

much larger than the sample of Hotchkiss and Ronen (2002), who studied 20 junk bonds, and Kwan (1996), who studied 702 bonds across all rating categories.[6] In addition to the trading activity requirement, we subject the data to a set of screens designed to remove erroneous trades, such as trades that are flagged as canceled or corrected, and data records with missing or invalid information. Finally, we remove any trades representing a 30% or greater price reversal relative to the surrounding trades, as manual verification of a subset of these records revealed that they contain data input errors in the price field.

For much of the analysis we stratify the bonds according to their credit ratings. Bonds are classified by first assigning a rating number based on their ratings from Standard and Poor's, Moody's, and Fitch rating services. An average of the ratings across the three agencies is calculated, and this overall rating number is used to assign each bond to a rating category that is equivalent to the S&P ratings categories AAA, AA, A, BBB, and junk.

Table 1 displays descriptive statistics for the bonds in our final sample. About two-thirds of the 3,000 bonds are rated either BBB or junk, with over 1,000 in each category. There are 439 firms represented in the sample, indicating that many of the firms have multiple bonds outstanding. It is worth noting that the overall number of firms (bonds) is less than the sum of the number of firms (bonds) over the rating categories. This occurs due to rating migrations over the course of the sample period, more often due to downgrades than upgrades. For example, some bonds are rated BBB for a portion of the sample and junk for the remainder of the sample.

TABLE 1

Summary Statistics

Summary statistics for the securities used in the empirical analysis. The column "Number of Bonds" is the number of individual bonds in each category, while "Number of Firms" displays the number of firms issuing these securities. The number of firms is less than the number of bonds, since some firms have issued multiple bonds. Credit ratings are assigned as a numeric average of the credit ratings of the major credit rating agencies. The number of bonds in the sample split by credit rating does not add up to the "All Firms" total because of rating transitions over the sample period; the same is true of the number of firms in the credit rating categories. The column "Years to Maturity" shows the average years remaining to maturity for the bonds in each category, and "Coupon" shows the average annualized coupon rate on the bonds. "Amount Outstanding" gives the average face value of the bonds, and "Market Capitalization" is the average market capitalization of the firms in each category, measured at the beginning of our sample period. Convertible bonds are excluded.

Credit Rating	Number of Bonds	Number of Firms	Years to Maturity	Coupon (%)	Amount ($mil) Outstanding	Market Capitalization ($bil)
All firms	3,000	439	8.2	6.01	431.76	56.78
AAA	172	33	10.8	5.12	497.63	288.25
AA	439	78	6.2	4.58	726.28	112.67
A	826	222	8.4	5.65	532.70	61.43
BBB	1,166	170	8.5	6.18	363.56	20.39
Junk	1,064	223	8.1	6.82	295.94	4.26

[6]Kwan (1996) uses weekly yield changes in his analysis, resulting in a larger sample size, though the accuracy of the dealer quotes is open to question, particularly for the bonds that trade relatively infrequently. Hotchkiss and Ronen (2002) use daily and hourly return observations. We also used several more stringent trading activity requirements, which resulted in far fewer bonds being included in our sample. The qualitative results are virtually unchanged when we use the more strict requirements.

On average, the bonds in our sample have 8.2 years remaining to maturity, with the AAA bonds having the longest average maturity at 10.8 years. Bonds rated A and below have average maturities ranging from 8.1 to 8.5 years. As expected, the coupon rate generally increases as the credit quality of the bond decreases.[7] The average coupon rate ranges from 5.12% for AAA bonds to 6.82% for junk bonds.[8] Lower credit quality issuers tend to be smaller firms—the average market capitalization of AAA issuers is about 70 times larger than that of junk issuers. Thus, the lower quality issuers tend to float smaller bond issues than the more highly rated issuers. The average junk bond issue in our sample is $296 million, and issue size increases monotonically with the exception of the AAA issues. Overall, the minimum trading requirement that we impose on the bonds restricts the sample to relatively large bond issues.

B. Stocks

We match the bonds in our sample to their associated equity data using the ticker symbols assigned to the bonds by the NASD, and we verify each match using company descriptive information from Bloomberg. The intraday equity price observations are drawn from the NYSE TAQ database. We initially collect the last trade in five minute intervals for all equities that have debt in the TRACE database. We filter the data using the applicable rules in Weston (2000). We then match the last trade of the hour for each bond in the database with the most recent trade for that firm's equity in our database of five-minute observations from TAQ.[9]

C. Returns

Individual hourly (daily) bond returns are calculated using the last bond trade we observe in each hour (day). We exclude bond trades that occur outside of equity market trading hours. Following Hotchkiss and Ronen (2002), we assume a zero return for trading intervals where no trades occur.[10] Individual hourly (daily) equity returns are calculated using the last equity trade price prior to the last bond trade in each hour (day).

Panels A and B of Table 2 present summary statistics for the daily and hourly returns and trading volumes for the stocks and bonds that appear in our data set. The returns average close to 0, and the median returns are exactly 0 for daily bond returns and hourly bond and stock returns, as one would expect for such

[7]Corporate bonds are typically issued at or very close to par value, with compensation for risks born being reflected in the spread of the coupon rate to the relevant risk-free rate.

[8]The average coupon rate on AAA bonds is slightly above that for AA bonds owing to the relatively long average maturity of the AAA bonds.

[9]Our results are insensitive to the matching procedure used. Using the last equity trade of the hour or the first equity trade after the bond trade both produce results nearly identical to those reported in this paper. We also account for the potential effects of reporting lags in the corporate bond market by matching bond trades with the last equity trade that occurred at least 15 minutes before the bond transaction and by restricting the sample to the period of 15-minute required reporting (post July 1, 2005). Again, the results are qualitatively nearly identical to those reported here. In practice, the NASD stated in 2005 that over 80% of transactions were actually reported in less than 5 minutes.

[10]For the portfolio returns analysis, we considered an alternative specification where no-trade intervals were discarded. The same qualitative results held.

short holding periods. As expected, the standard deviation of returns is highest for both junk bonds and their associated equity returns. The AAA-rated bonds exhibit mean returns that are higher than those of AA- and A-rated bonds, but these results should be treated with caution. While there are 172 AAA bonds in the data set, 118 of these are liabilities of General Electric or one of its subsidiaries. Hence, the statistics for AAA bonds largely reflect the fortunes of General Electric over our sample period.

TABLE 2

Stock and Bond Returns and Trade Volumes

Table 2 displays summary statistics for the returns and transaction volumes of the stocks and bonds that appear in our estimation data set. Individual daily (hourly) bond returns are calculated using the last bond trade of each day (hour), where we exclude trades falling outside of equity market trading hours. The last bond trade of each period is matched to the most recent equity trade, where the equity prices are collected in five-minute windows from the TAQ database. The equity returns are then computed from this matched sample. The returns are expressed in percentages. The columns $\rho_{S,B}$ display the average contemporaneous correlations between the returns on the bonds and equity in the indicated rating category. In Panel C, average daily trade volumes are first computed for each security. We then compute the mean, median, and standard deviation of the security-level averages of the securities in each category. The sample period is from October 1, 2004 to December 31, 2005, for a total of 2,173 hourly observation periods over 312 business days.

Panel A. Daily Returns

	Bond Returns			Stock Returns			$\rho_{S,B}$		
Credit Rating	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
AAA	0.00782	0.00000	1.38624	0.01175	–0.03793	1.08300	0.008	0.002	0.073
AA	0.00409	0.00000	0.95451	0.04152	0.02030	1.05195	0.007	0.009	0.098
A	0.00017	0.00000	1.07834	0.03445	0.00486	1.17937	0.002	0.002	0.084
BBB	–0.02460	0.00000	1.82302	–0.03938	–0.05463	1.92065	0.058	0.050	0.105
Junk	0.02963	0.00000	2.41240	–0.08843	–0.11589	2.75508	0.070	0.059	0.114

Panel B. Hourly Returns

	Bond Returns			Stock Returns			$\rho_{S,B}$		
Credit Rating	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
AAA	0.00115	0.00000	0.73678	0.00175	0.00000	0.41802	0.002	0.001	0.021
AA	0.00053	0.00000	0.53288	0.00597	0.00000	0.41274	0.001	0.002	0.031
A	0.00004	0.00000	0.56885	0.00500	0.00000	0.46274	0.004	0.002	0.048
BBB	–0.00348	0.00000	0.97088	–0.00551	0.00000	0.68394	0.007	0.006	0.029
Junk	0.00422	0.00000	1.27345	–0.01311	0.00000	1.05867	0.012	0.006	0.042

Panel C. Average Daily Trade Volumes ($mil)

	Bond Volume			Stock Volume		
Credit Rating	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
AAA	0.376	0.020	1.300	513.629	538.644	320.781
AA	0.647	0.050	1.732	300.189	244.611	255.302
A	0.570	0.025	1.638	189.331	142.105	179.842
BBB	0.612	0.015	1.952	169.572	126.235	189.410
Junk	0.405	0.025	0.840	126.930	58.808	174.706

In Panel C of Table 2 we see that, for a given firm, its debt trades far less often than its equity. Average daily trade volume in bonds totals about $376,000 to $647,000, depending on the rating category. Average equity volumes are vastly higher, ranging from $126 million to $513 million, depending on rating.[11]

[11] As noted above, many firms have multiple bond issues outstanding. However, when we consider the total trade volume for all of the bonds that a firm has outstanding, equity trade volume still dwarfs that of the firm's debt.

The statistics on bond trade volumes in Panel C of Table 2 also indicate that, on average, AA- and BBB-rated debt tend to trade in slightly higher daily volumes than other categories. It is worth noting, however, that these daily measures reflect very heavy volumes in a few bonds—perhaps due to institutional trading activity—as indicated by the fact that the median daily volumes are substantially lower than the means in each rating class. The median figures indicate that the median bond in each category sees daily trading volume of \$15,000 to \$50,000 per day.

III. Empirical Results

Following the previous literature, we assume a general structure for the lead-lag relation between bond and equity returns, as given by the following vector autoregressive system:

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

where z_t is the vector $[R_{B,t}, R_{S,t}]'$, $R_{B,t}$ is the return on the bond (portfolio or individual bond) at time t, and $R_{S,t}$ is the return on the associated stock (portfolio or individual stock). The coefficients to be estimated are the intercepts, c, and the slope coefficient matrices, b_i and s_i, on the lagged bond and equity returns. The lag-length L is set to 5 for the daily returns and 10 for the hourly returns. The lag-length choices are guided by the Akaike Information Criterion; our conclusions are not sensitive to changes in the lag-lengths.

Our null hypothesis is that the bond and stock markets are equally efficient. For each equation in the system, we test this hypothesis in two ways. First, we examine the statistic for the standard Granger causality test, which is simply the F-statistic for the null hypothesis that all of the lagged cross-market returns are equal to 0. Second, we calculate the statistic for the weaker test that the *sum* of the lagged cross-market coefficients is equal to 0. The sum test is useful for qualifying our conclusions when the Granger causality test rejects the null based on a small subset of the lag coefficients—a result that is often difficult to interpret. In this case, a simultaneous rejection under the sum test reinforces the conclusion that a robust lead-lag relationship exists, while failure to reject the sum test qualifies the Granger causality test results.

A. Portfolio Returns

In order to compare our results to those in the previous literature, we begin with a portfolio-level analysis of nonconvertible bonds. We first form equally weighted bond portfolios for each bond rating category and compute the returns on each portfolio. We then calculate stock portfolio returns for an equally weighted portfolio of all of the equities corresponding to the bonds appearing in the bond portfolio. Note that the number of securities in each portfolio will change through time if a bond is removed from the list of TRACE-eligible securities (for example, if the bond matures or is called) or if its credit rating changes. If a firm has multiple bonds in the bond portfolio, we increase the weight on the firm's equity in the equity portfolio accordingly.[12]

At a daily frequency, the junk bond portfolio returns are predictable with their associated lagged equity returns; none of the other bond portfolios exhibit conclusive evidence of predictability. Table 3 displays the estimation results and test statistics stratified by the bonds' ratings. For the AAA-, AA-, and A-rated nonconvertible bond portfolios, both the Granger causality and sum tests fail to reject the null hypothesis of equal informational efficiency. The adjusted R^2 statistics indicate that the inclusion of lagged returns provide little, if any, additional explanatory power for the AAA-, AA-, and A-rated portfolios.

For the BBB-rated portfolio, the Granger test rejects the null, but the sum test fails to reject it. The Granger causality test apparently picks up significant coefficients on the second, third, and fourth lags of stock returns, but the coefficients are relatively small in magnitude. However, the inclusion of lagged stock returns boosts the adjusted R^2 from 0.262 to 0.318 in the bond return equation. For the junk bond portfolio returns, both the sum and Granger tests reject their respective nulls at the 5% level of significance. The inclusion of lagged equity returns in the junk bond return specification boosts the adjusted R^2 statistic from 0.361 to 0.448.

In Table 4, we report the vector autoregression (VAR) results for hourly bond and equity portfolio returns. When measured at an hourly frequency, we find strong evidence of predictability in BBB- and junk-rated bond returns. Consistent with our results based on daily returns, we find no evidence of a lead-lag relation between bond returns and equity returns for the AAA-, AA-, and A-rated bond portfolios.

For the BBB-bond equation, the sum and Granger statistics both reject the null hypothesis of equal informational efficiency, and the addition of lagged equity returns boosts the adjusted R^2 statistic from 0.215 to 0.239. The results for hourly returns on junk bonds largely mimic those for daily returns. The sum test and Granger causality test reject their respective nulls. Moreover, the addition of lagged equity returns boosts the adjusted R^2 measure from 0.340 to 0.377, indicating that the lagged equity returns provide an economically significant improvement in the predictive power of the specification.[13] Comparing the magnitudes of the lagged equity return coefficient estimates across the junk and BBB return regressions, we see that junk bond returns are somewhat more sensitive to lagged stock returns, as we might expect given that junk bonds are closer to equity than are BBB-rated bonds.

B. Individual Bond and Equity Returns

We turn now to a more detailed examination of the basic predictability results established in the previous section. First, we focus on establishing the degree of cross-sectional variation in the predictability of nonconvertible bond returns. We

[12]For example, if a portfolio has 20 bonds and five are issued by the same firm, then that firm's equity receives a 25% weight in the equity portfolio.

[13]It is worth noting that adding lagged equity returns actually increases the R^2 values more for daily returns than for hourly returns. The larger sample size is likely responsible for the stronger Granger and sum test results in the hourly analysis.

TABLE 3
Daily Bond and Equity Portfolio Returns

Table 3 displays estimates of the bivariate vector-autoregressive specification:

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

where $z_t = [R_{B,t}, R_{S,t}]'$, $R_{B,t}$ is the daily return on an equally weighted portfolio of bonds with the indicated rating, and $R_{S,t}$ is the daily return on an equally weighted portfolio formed from the stock of the same firms. The lag-length L is set to five days. Robust t-statistics are shown beneath the coefficient estimates. "Sum" gives the F-statistic and p-value for the null hypothesis that the sum of the cross-market coefficients equals 0. "Granger" gives the F-statistic and p-value for the null hypothesis that all of the cross-market coefficients are equal to 0. The column labeled "Own" shows the adjusted R^2 statistic from a regression including only lagged own-market returns, and "Own+" gives the adjusted R^2 from the regressions shown. The sample period is from October 1, 2004 through December 31, 2005, for a total of 312 trading days. Convertible debt is excluded, and only bonds with at least 300 trades are included in the sample.

	Lagged Bond Returns					Lagged Stock Returns								
	b_1	b_2	b_3	b_4	b_5	s_1	s_2	s_3	s_4	s_5	Sum	Granger	Own	Own+
AAA														
Stock	0.253	0.120	–0.223	0.110	0.072	–0.043	–0.102	–0.030	0.042	–0.005	0.243	0.374	0.000	–0.010
	(0.890)	(0.416)	(–0.777)	(0.386)	(0.254)	(–0.742)	(–1.769)	(–0.523)	(0.723)	(–0.081)	(0.622)	(0.866)		
Bond	–0.115	0.010	0.038	0.027	0.028	0.000	–0.009	0.013	0.004	0.002	0.146	0.402	–0.000	–0.010
	(–1.977)	(0.174)	(0.650)	(0.462)	(0.481)	(0.024)	(–0.724)	(1.133)	(0.309)	(0.188)	(0.703)	(0.847)		
AA														
Stock	0.142	–0.179	–0.112	–0.081	0.432	–0.041	–0.048	0.009	0.008	0.071	0.086	0.447	–0.007	–0.016
	(0.418)	(–0.525)	(–0.327)	(–0.240)	(1.272)	(–0.710)	(–0.833)	(0.160)	(0.143)	(1.232)	(0.769)	(0.815)		
Bond	0.119	–0.008	0.005	0.050	–0.025	0.004	0.002	0.009	–0.005	0.003	0.259	0.255	0.000	–0.011
	(2.065)	(–0.144)	(0.093)	(0.869)	(–0.428)	(0.361)	(0.188)	(0.887)	(–0.506)	(0.274)	(0.611)	(0.937)		
A														
Stock	0.138	–0.433	–0.059	–0.012	0.528	–0.014	–0.002	0.020	0.023	0.067	0.088	1.008	–0.011	–0.010
	(0.440)	(–1.337)	(–0.181)	(–0.036)	(1.691)	(–0.236)	(–0.026)	(0.349)	(0.400)	(1.158)	(0.767)	(0.413)		
Bond	0.277	–0.038	0.030	0.079	–0.103	–0.013	0.006	–0.005	–0.005	0.012	0.041	0.724	0.069	0.064
	(4.830)	(–0.645)	(0.500)	(1.329)	(–1.809)	(–1.224)	(0.592)	(–0.466)	(–0.501)	(1.150)	(0.840)	(0.606)		
BBB														
Stock	0.302	–0.001	0.166	0.204	0.104	0.011	–0.030	0.011	–0.011	0.035	3.077	0.661	–0.011	–0.017
	(0.902)	(–0.002)	(0.434)	(0.559)	(0.335)	(0.182)	(–0.483)	(0.175)	(–0.166)	(0.538)	(0.080)	(0.653)		
Bond	0.623	–0.172	0.100	0.018	–0.094	0.011	–0.042	0.031	–0.025	0.021	0.012	5.935	0.262	0.318
	(10.043)	(–2.390)	(1.417)	(0.262)	(–1.648)	(0.984)	(–3.619)	(2.646)	(–2.061)	(1.761)	(0.914)	(0.000)		
Junk														
Stock	0.094	–0.174	–0.327	–0.364	0.585	0.082	0.029	0.074	0.135	–0.069	0.378	2.336	0.003	0.025
	(0.392)	(–0.667)	(–1.262)	(–1.387)	(2.753)	(1.334)	(0.435)	(1.126)	(2.059)	(–1.071)	(0.539)	(0.042)		
Bond	0.497	–0.019	0.096	–0.255	0.032	0.107	–0.008	–0.005	0.030	0.015	14.134	10.438	0.361	0.448
	(8.028)	(–0.283)	(1.427)	(–3.755)	(0.582)	(6.742)	(–0.466)	(–0.297)	(1.735)	(0.879)	(0.000)	(0.000)		

TABLE 4

Hourly Bond and Equity Portfolio Returns

Table 4 displays estimates of the vector-autoregressive specification:

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

where $z_t = [R_{B,t}, R_{S,t}]'$, $R_{B,t}$ is the hourly return on an equally weighted portfolio of bonds with the indicated rating, and $R_{S,t}$ is the hourly return on an equally weighted portfolio formed from the stock of the same firms. The lag-length L is set to 10 hours; we suppress the last five hourly coefficients for brevity. Robust t-statistics are shown beneath the coefficient estimates. "Sum" gives the F-statistic and p-value for the null hypothesis that the sum of the 10 cross-market coefficients equals 0. "Granger" gives the F-statistic and p-value for the null hypothesis that all 10 of the cross-market coefficients are equal to 0. The column labeled "Own" shows the adjusted R^2 statistic from a regression including only lagged own-market returns, and "Own+" gives the adjusted R^2 from the regressions shown. The sample period is from October 1, 2004 through December 31, 2005, for a total of 2,173 hourly intervals. Convertible debt is excluded, and only bonds with at least 300 trades are included in the sample.

	Lagged Bond Returns					Lagged Stock Returns								
	b_1	b_2	b_3	b_4	b_5	s_1	s_2	s_3	s_4	s_5	Sum	Granger	Own	Own+
AAA														
Stock	0.056	0.021	–0.064	0.080	0.098	0.013	–0.009	0.015	–0.023	–0.016	0.896	0.421	–0.001	–0.004
	(0.660)	(0.244)	(–0.739)	(0.921)	(1.122)	(0.597)	(–0.426)	(0.717)	(–1.057)	(–0.739)	(0.344)	(0.937)		
Bond	–0.140	–0.080	–0.060	–0.077	–0.015	–0.005	0.001	0.003	–0.005	0.000	1.298	0.412	0.024	0.022
	(–6.502)	(–3.673)	(–2.741)	(–3.492)	(–0.692)	(–0.831)	(0.101)	(0.489)	(–0.902)	(0.010)	(0.255)	(0.942)		
AA														
Stock	–0.118	–0.002	–0.024	–0.143	0.013	0.075	0.011	0.007	–0.029	0.009	0.001	0.287	0.004	0.001
	(–0.801)	(–0.011)	(–0.162)	(–0.959)	(0.090)	(3.451)	(0.502)	(0.304)	(–1.319)	(0.412)	(0.982)	(0.984)		
Bond	0.084	0.017	0.076	0.002	0.004	0.004	–0.002	–0.001	0.005	0.003	0.384	0.719	0.013	0.012
	(3.798)	(0.762)	(3.411)	(0.071)	(0.161)	(1.152)	(–0.476)	(–0.421)	(1.486)	(0.826)	(0.535)	(0.707)		
A														
Stock	0.229	0.017	–0.132	–0.266	–0.009	0.051	0.018	0.004	–0.029	0.002	0.008	0.713	–0.000	–0.001
	(1.381)	(0.098)	(–0.767)	(–1.542)	(–0.050)	(2.345)	(0.817)	(0.169)	(–1.345)	(0.107)	(0.929)	(0.713)		
Bond	0.196	0.066	0.058	0.056	0.030	–0.004	–0.001	–0.003	–0.001	–0.001	1.313	0.982	0.078	0.078
	(9.074)	(2.936)	(2.591)	(2.511)	(1.316)	(–1.488)	(–0.236)	(–0.927)	(–0.258)	(–0.275)	(0.252)	(0.457)		
BBB														
Stock	0.174	–0.118	–0.020	0.194	0.353	0.121	–0.001	–0.006	0.034	0.014	1.887	0.868	0.023	0.023
	(1.093)	(–0.715)	(–0.113)	(1.090)	(1.980)	(5.586)	(–0.049)	(–0.283)	(1.562)	(0.643)	(0.170)	(0.562)		
Bond	0.135	0.199	0.113	0.031	0.029	0.021	0.004	0.004	0.006	0.005	42.099	7.898	0.215	0.239
	(6.249)	(8.822)	(4.669)	(1.269)	(1.184)	(6.966)	(1.279)	(1.489)	(2.033)	(1.676)	(0.000)	(0.000)		
Junk														
Stock	–0.031	0.142	–0.279	0.060	0.098	0.011	0.028	0.050	0.022	0.020	0.366	1.267	0.001	0.003
	(–0.213)	(0.950)	(–1.833)	(0.396)	(0.647)	(0.516)	(1.258)	(2.251)	(0.993)	(0.903)	(0.545)	(0.243)		
Bond	0.198	0.189	0.082	–0.003	0.077	0.018	0.023	0.011	0.005	0.005	94.510	13.637	0.340	0.377
	(9.118)	(8.532)	(3.630)	(–0.135)	(3.424)	(5.692)	(7.192)	(3.353)	(1.629)	(1.383)	(0.000)	(0.000)		

then attempt to identify the determinants of predictability in the cross section. The paper closes with our analysis of convertible bonds.

1. Cross-Sectional Variation in Bond Return Predictability

We start by estimating the VAR system in equation (1) separately for each bond using daily and hourly returns.[14] We do not present summary parameter estimates for the regressions; however, the results exhibit substantial cross-sectional variation, particularly for the bonds in the BBB and junk categories. For example, in the BBB-rated category, the mean of the estimated coefficients on the first lag of equity returns, s_1, is 0.020 and the standard deviation is 0.057. In the junk category, the mean of the estimated coefficients on the first lag of equity returns in the bond-return regression is 0.024 and the standard deviation is 0.064. These results suggest that there are both predictable and unpredictable bonds in each category. A similar conclusion emerges from an examination of the results based on security-level VARs of daily returns, also omitted for brevity.

The statistical significance of these results is summarized in Table 5, where we show the proportion of the sample in the indicated rating category for which we reject the Granger and sum hypotheses at the 5% level of significance. Table 5 also summarizes the results from the daily returns regressions. As can be seen, in line with our portfolio-level results, there is scant evidence of predictability in the AAA-, AA-, and A-rated bond categories. For BBB-rated bonds, however, we find that for daily returns we reject under the sum test for 19.1% of the bonds, and for hourly returns we reject for 36.1% of the bonds. The Granger causality test rejects for 34.0% of BBB-rated bonds using daily returns and for 34.8% of the bonds using hourly returns. For junk bond returns, we reject under the sum test for 62.0% and 54.9% of the bonds at the daily and hourly frequencies, respectively. Under the Granger causality test, we reject for 56.3% and 48.7% of the bonds at the daily and hourly frequencies, respectively.

2. Determinants of Predictability

It is clear from these results that equity returns lead bond returns for BBB- and junk-rated bonds.[15] However, there is substantial cross-sectional variation in the degree to which this lead-lag relation holds at the bond level. In this subsection, we examine the bond-level results more closely in order to identify the cross-sectional determinants of predictability and potential explanations for why our portfolio-level results differ from those of Hotchkiss and Ronen (2002).

That highly rated bonds exhibit little correlation with stock returns could be indicative of the fact that these bonds have relatively stable expected cash flows.

[14]In order to be included in the hourly bond-by-bond analysis, we impose the following requirements: First, for a return observation to be included in the sample, we require that there be at least one trade in the previous 10 trading hours. We then include all bonds that have at least 700 hourly return observations meeting this criteria. This results in a final sample containing 2,682 unique bonds. The results are not sensitive to wide variation in this cutoff.

[15]It is worth noting that we have also conducted these regression tests for pooled cross-sectional time-series specifications. Our conclusions do not change, so we have omitted these results for brevity.

TABLE 5

Security-Level Hypothesis Test Results

Table 5 displays the results of hypothesis tests on the security-level coefficient estimates for the vector-autoregressive specification:

$$z_{j,t} \quad = \quad c_j + \sum_{i=1}^{L} b_{i,j} R_{B,t-i,j} + \sum_{i=1}^{L} s_{i,j} R_{S,t-i,j} + \varepsilon_{j,t},$$

where $z_{j,t} = [R_{B,t,j}, R_{S,t,j}]'$, $R_{B,t,j}$ is the return on bond j at time t and $R_{S,t,j}$ is the return on stock j. We set $L = 5$ at the daily frequency and $L = 10$ at the hourly frequency based on the Akaike Information Criterion. The statistic "Sum" gives the proportion of bonds or stocks for which the F-statistic for the null hypothesis that the sum of the cross-market coefficients equals 0 is statistically significant at the 95% level. The statistic "Granger" gives the proportion of bonds or stocks for which the F-statistic for the null hypothesis that all of the cross-market coefficients are equal to 0 is statistically significant at the 95% level. The sample period is from October 1, 2004 through December 31, 2005, for a total of 2,173 hourly observation intervals over 312 trading days. Convertible debt is excluded, and only bonds with at least 700 (100) hourly (daily) return observations are included.

	Share of Sample Rejecting H_0			
	Daily		Hourly	
	Sum	Granger	Sum	Granger
AAA				
Stock	0.037	0.080	0.013	0.094
Bond	0.055	0.043	0.038	0.050
AA				
Stock	0.063	0.058	0.057	0.103
Bond	0.118	0.099	0.106	0.103
A				
Stock	0.049	0.062	0.049	0.091
Bond	0.046	0.060	0.058	0.082
BBB				
Stock	0.092	0.113	0.077	0.148
Bond	0.191	0.340	0.361	0.348
Junk				
Stock	0.064	0.111	0.091	0.191
Bond	0.620	0.563	0.549	0.487

In this case, the returns on safe bonds would be expected to be primarily sensitive to interest rate movements. To the extent that the variance in stock returns embeds a large component related to news about future cash flows, we would expect to find low contemporaneous and lagged correlations between safe bond returns and equity returns. In contrast, lower rated bonds (BBB- and junk-rated) are closer to default, and thus their expected cash flows are relatively sensitive to news about the value of the firm—in this sense, these bonds are more "equity-like." It therefore follows that the returns on lower rated bonds would be more highly correlated with their associated equity returns than relatively safe bonds, both contemporaneously and, if the bond market is comparatively less efficient than the equity market, at a lag. If the bond returns are reacting to news about the variance of the firm—for example, if equity holders are boosting the risk of the firm as it moves toward bankruptcy—then the relation between bond returns and lagged equity returns would be negative. On the other hand, if the bond returns simply reflect news about the value of the firm, then we would expect to find a positive relation with lagged equity returns. Of course, these are not mutually exclusive possibilities, and hence the signs on the lagged equity returns represent a net effect over these two possible influences on bond returns.

These hypotheses are tested in Table 6, which presents the results of portfolio-level regressions of bond returns on lagged bond returns, contemporaneous and lagged Treasury note returns, contemporaneous and lagged returns on the S&P 500, and contemporaneous and lagged stock returns, as follows:

$$R_{b,t} = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=0}^{L} \beta_{T,i} R_{T,t-i} + \sum_{i=0}^{L} \beta_{\mathrm{SP},i} R_{\mathrm{SP},t-i} + \sum_{i=0}^{L} \beta_{S,i} R_{S,t-i} + \varepsilon_t, \qquad (2)$$

where $R_{b,t}$ is the return on an equally weighted portfolio of the bonds in the given rating category, $R_{T,t}$ is the return on the on-the-run 5-year Treasury note, $R_{\mathrm{SP},t}$ is the return on the S&P 500 index, and $R_{S,t}$ is the return on the portfolio of equities associated with the bonds in the sample. We employ the 5-year Treasury note, as it is the most actively traded Treasury security, producing the most hourly observations, though our conclusions are not sensitive to the particular choice of Treasury security. We carry out the tests at the daily and hourly frequencies where, as before, the lag length L is set to 5 for daily returns and 10 for hourly returns. Following Cornell and Green (1991) and Hotchkiss and Ronen (2002), we report the sum of the coefficients as opposed to the individual coefficients, and the standard errors are adjusted to account for potential serial correlation and heteroskedasticity using Hansen's (1982) generalized method of moments. The p-values are presented for tests of the null hypothesis that the sum of the coefficients is equal to 0.

If our above hypotheses are correct, then we should expect to find that highly rated bond returns are driven by movements in risk-free rates (Treasury note returns), while the lower rated bonds should be related to equity returns. The results for daily returns shown in Panel A of Table 6 are broadly consistent with these hypotheses. As can be seen, the AAA-, AA-, and A-rated portfolio returns are principally sensitive to Treasury rate movements, while the BBB- and junk-rated portfolios exhibit little sensitivity to Treasury rate movements. In line with our previous results, none of the daily portfolio returns exhibit much sensitivity to either the S&P 500 or their associated equity returns.

The results for hourly returns in Panel B provide support for the notion that lower rated bonds are more equity-like and hence sensitive to firm-specific news. We again find that the AAA-, AA-, and A- rated bond returns are relatively strongly related to Treasury note returns, with statistically significant sums of coefficients equal to 0.229, 0.186, and 0.120, respectively. In contrast, the BBB- and junk-rated portfolio returns are not sensitive to Treasury note returns. As we found in our earlier tests at the hourly frequency, BBB- and junk-rated portfolio returns are sensitive to the lagged returns of their associated equity, with statistically significant sums of coefficients equal to 0.070 and 0.148, respectively. The AAA-, AA-, and A-rated portfolio returns are not sensitive to their lagged equity returns. The coefficients on lagged bond returns are similar in nature to those in the portfolio VARs: For all categories except AAA, the sum of the lagged bond return coefficients is positive and usually significant. For the smaller AAA portfolio, the

TABLE 6

The Relation between Bond Returns, Equity Returns, and Treasury Rates

Table 6 reports results of the regression

$$R_{b,t} = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=0}^{L} \beta_{T,i} R_{T,t-i} + \sum_{i=0}^{L} \beta_{\mathrm{SP},i} R_{\mathrm{SP},t-i} + \sum_{i=0}^{L} \beta_{S,i} R_{S,t-i} + \varepsilon_t, \quad (2)$$

where $R_{b,t}$ is the return on an equally weighted portfolio of the bonds in the given rating category, $R_{T,t}$ is the return on the on-the-run 5-year Treasury note, $R_{\mathrm{SP},t}$ is the return on the S&P 500 index, and $R_{S,t}$ is the return on the portfolio of equities associated with the bonds in the sample. Panel A presents results for daily returns; Panel B presents results for hourly returns. The lag length L is set to 5 for daily returns and 10 for hourly returns. Standard errors are calculated using Hansen's (1982) generalized method of moments, and p-values for tests of the null hypothesis that the sum of the coefficients equals 0 are shown in parentheses. The sample period is from October 1, 2004 through May 31, 2005, resulting in 1,155 (165) hourly (daily) observations.

Credit Rating	$\sum_{i=1}^{L} \beta_{B,i}$	$\sum_{i=0}^{L} \beta_{T,i}$	$\sum_{i=0}^{L} \beta_{\mathrm{SP},i}$	$\sum_{i=0}^{L} \beta_{S,i}$	Adj. R^2
Panel A. Daily Returns					
AAA	–0.030	0.324	–0.021	0.018	0.056
	(0.878)	(0.067)	(0.768)	(0.804)	
AA	0.178	0.277	0.088	–0.037	0.112
	(0.232)	(0.049)	(0.117)	(0.435)	
A	0.280	0.261	0.092	–0.054	0.297
	(0.015)	(0.034)	(0.156)	(0.373)	
BBB	0.553	–0.138	–0.064	0.044	0.520
	(0.000)	(0.488)	(0.573)	(0.567)	
Junk	0.482	0.028	0.109	0.096	0.552
	(0.001)	(0.861)	(0.310)	(0.131)	
Panel B. Hourly Returns					
AAA	–0.353	0.229	–0.002	–0.018	0.030
	(0.013)	(0.013)	(0.968)	(0.633)	
AA	0.182	0.186	0.024	0.005	0.036
	(0.095)	(0.025)	(0.253)	(0.769)	
A	0.477	0.120	–0.003	0.002	0.116
	(0.000)	(0.048)	(0.897)	(0.922)	
BBB	0.675	0.027	–0.071	0.070	0.437
	(0.000)	(0.575)	(0.007)	(0.000)	
Junk	0.544	–0.011	–0.057	0.148	0.205
	(0.000)	(0.865)	(0.189)	(0.000)	

bid-ask bounce effect dominates, leading to negative coefficient estimates for the lagged bond returns.

A bond-by-bond examination of the predictability results provides further insight into the nature of the firms for which we find predictable bonds: Within the BBB- and junk-rated classes, by and large, the bonds of firms encountering financial difficulties are the ones that exhibit predictability. Here a "predictable bond" is defined as one for which the sum test and the Granger causality test both reject the null at the 5% level.

In the BBB-rated category, the majority of the predictable bonds are issued by Ford and GM, both companies that faced significant financial pressure over our sample period. Other firms with significant numbers of predictable bonds include Albertson's, Constellation Energy, Delphi, Provident, and Sungard Data Systems, all companies that encountered some degree of financial distress over our sample period.

General Motors also accounts for a sizable share of the predictable bonds in the junk category, a result of the downgrade of GM to junk over our sample period.[16] We also find predictable junk-rated bonds issued by Delta and Northwest Airlines, both companies that were operating close to bankruptcy during the period.[17] Calpine's bonds exhibit predictability, and again, Calpine was close to bankruptcy in our sample period. Delphi Corp. and Visteon Corp. both supply parts to automakers, and we also see a smattering of nearly failed technology and telecom companies in the junk-rated grouping.

We make the results of this informal analysis more precise in Table 7, which displays summary statistics for categories of predictable and unpredictable bonds. While the time to maturity and coupon rates of the bonds appear similar in the predictable and unpredictable categories, the mean stock return for predictable bonds in the junk and BBB categories is much lower than for the unpredictable bonds, suggesting that these firms indeed face some type of difficulty. To confirm this, we calculate two measures of financial distress commonly used in the literature. First, we use a modified Altman (1968) Z-score, calculated using the hazard model coefficient estimates found in Hillegeist, Keating, Cram, and Lundstedt (2004). We also employ the hazard model estimates in Shumway (2001) to calculate an alternative measure of financial distress. In both cases, a higher score indicates a greater probability of bankruptcy. Table 7 shows results separated by rating category. For the main categories of interest—BBB and junk—the predictable bonds have higher Altman and Shumway scores than the unpredictable bonds, with the difference being statistically significant in two of four cases. For the BBB category, the difference is significant for the Altman score but not the Shumway score. For junk, the difference is significant for Shumway but not Altman.[18]

This detailed analysis clarifies our earlier predictability results. Firms close to or in financial distress generate news with important implications for the expected cash flows of the firms' bonds and equity, as illustrated by our tests in Table 6. This news is of sufficient magnitude to generate trading in the firms' bonds in the face of steep transaction costs, and the price movements resulting from this trading reveal the relative informational inefficiency of the corporate bond market in the form of the lead-lag relation found between the firms' bond and equity returns.

In comparing our results to those of Hotchkiss and Ronen (2002), it is important to bear in mind that bond transactions' costs were likely higher during their sample period, and thus the news reflected in equity returns may not have been substantial enough to induce trading in the firms' bonds. Moreover, their sample period may not have included as many firms experiencing credit rating downgrades or bankruptcy as our sample period. Thus, the bonds in their FIPS sample do not exhibit the same predictability found for many of those in our TRACE sample.

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[16]Ford's bonds were also gradually downgraded to junk by the three ratings agencies we use. However, they remain in our BBB sample due to the methodology we use to average ratings across agencies.

[17]Bonds exit our sample at the time they enter bankruptcy.

[18]Note that, due to data availability, a different number of observations is sometimes available for the Altman and Shumway calculations. This is especially true in the AA category, where we can only calculate the Altman score for one bond in the predictable category.

TABLE 7

Summary Statistics for Predictable and Unpredictable Bonds

Table 7 displays summary information for the predictable ($P = 1$) and unpredictable ($P = 0$) bonds in each rating category. A predictable bond is one for which we reject both the sum test and the Granger causality test in the hourly returns regressions. Coupon rates, hourly bond returns, and hourly stock returns are expressed in percentage terms. The columns labeled $\rho_{S,B}$ show the mean and standard deviation of the contemporaneous correlations between stock and bond returns for the firms in the indicated category. The column labeled "Altman" shows the average Altman distress measure, where the measure is calculated for each firm using the hazard model coefficient estimates found in Hillegeist et al. (2004). The column labeled "Shumway" shows the average Shumway distress measure, which is calculated for each firm using the Hazard model estimates found in Shumway (2001). For the distress measures, we also present t-statistics from tests of the null hypothesis that the mean scores of the predictable and unpredictable samples are equal. The column N shows the maximum number of bonds in each category.

		Years to Maturity		Coupon		Bond Returns		Stock Returns		$\rho_{S,B}$		Altman			Shumway			
Rating	P	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t-Test	Mean	Std. Dev.	t-Test	N
AAA	0	13.5	8.5	5.1	1.5	0.001	0.00	0.001	0.01	0.002	0.02	0.009	0.00	N/A	0.001	0.01	N/A	166
	1	32.0	N/A	6.8	N/A	0.002	N/A	0.009	N/A	–0.017	N/A	0.012	N/A		0.001	N/A		1
AA	0	9.3	6.7	4.8	2.0	0.000	0.00	0.002	0.01	0.001	0.03	0.007	0.00	N/A	0.001	0.00	9.80	409
	1	4.7	3.2	0.7	1.5	0.004	0.00	0.002	0.00	0.013	0.01	0.009	N/A		0.000	0.00		14
A	0	12.2	8.5	5.6	1.5	0.000	0.00	0.003	0.01	0.004	0.05	0.009	0.00	0.79	0.001	0.00	–1.94	786
	1	10.0	7.4	5.3	1.6	–0.001	0.00	0.006	0.01	0.008	0.05	0.009	0.00		0.001	0.00		24
BBB	0	11.7	8.9	6.3	1.2	–0.001	0.00	–0.005	0.02	0.004	0.03	0.011	0.00	–0.99	0.001	0.00	–7.48	647
	1	13.5	8.0	6.5	1.2	0.002	0.01	–0.026	0.02	0.016	0.04	0.011	0.00		0.002	0.00		259
Junk	0	11.7	7.5	7.3	1.6	0.001	0.01	0.001	0.03	0.005	0.03	0.011	0.00	–5.77	0.013	0.08	–0.41	473
	1	11.9	6.7	7.0	1.8	0.003	0.01	–0.028	0.03	0.028	0.06	0.012	0.00		0.015	0.04		329

3. Convertible Bonds

Convertible bonds are of independent interest in this analysis because, in contrast to nonconvertible bonds, they become more equity-like as their credit quality improves. Intuitively, this is because the conversion option goes more deeply into the money as the prospects of the firm improve and the equity appreciates in value. Hence an analysis of these bonds sheds additional light on whether it is the sensitivity of a bond's return to firm-specific news, and not whether the news is on average good or bad, that governs whether we see predictability in a bond's returns.

As with the nonconvertible bonds, we estimate bond-by-bond regressions of hourly convertible bond returns and their associated equity returns on 10 lags of the bond and equity returns.[19] As before, the bond-level coefficient estimates (not reported) exhibit a good deal of cross-sectional variation. In contrast to the nonconvertible bond results, however, the signs are consistently positive and the magnitudes sizable for the coefficients on the lagged equity returns in the bond equations for all rating classes.

As these results suggest, we see in Table 8 that there is strong evidence of predictability for convertible bonds of all ratings. For AA-rated convertible bonds, we reject the null of equal informational efficiency under the sum test for 28.6% of the bonds and under the Granger test for 42.9% of the bonds (although there are only 7 bonds in this category). In the larger A-, BBB-, and junk-rated categories,

[19] Our sample for the hourly convertible bond-by-bond regressions is chosen in the same manner as the sample for the hourly nonconvertible regressions. This results in a sample of 190 unique bonds.

we reject the equal efficiency hypothesis under both tests for the vast majority of bonds in each rating category.

TABLE 8

Hypothesis Test Results: Convertible Bonds

Table 8 displays the results of hypothesis tests on the security-level coefficient estimates for the vector-autoregressive specification

$$z_{j,t} = c_j + \sum_{i=1}^{L} b_{i,j} R_{B,t-i,j} + \sum_{i=1}^{L} s_{i,j} R_{S,t-i,j} + \varepsilon_{j,t},$$

where $z_{j,t} = \left[R_{B,t,j}, R_{S,t,j}\right]'$, $R_{B,t,j}$ is the return on convertible bond j at time t and $R_{S,t,j}$ is the return on stock j. We set $L = 10$ based on the Akaike Information Criterion. The statistic "Sum" gives the proportion of bonds or stocks for which the F-statistic for the null hypothesis that the sum of the cross-market coefficients equals 0 is statistically significant at the 95% level. The statistic "Granger" gives the proportion of bonds or stocks for which the F-statistic for the null hypothesis that all of the cross-market coefficients are equal to 0 is statistically significant at the 95% level. The sample period is from October 1, 2004 through December 31, 2005, for a total of 2,173 hourly observation intervals over 312 trading days. Only bonds with at least 700 hourly return observations are included in the sample.

	Share of Sample Rejecting H_0	
	Sum	Granger
AA		
Stock	0.000	0.000
Bond	0.286	0.429
A		
Stock	0.000	0.038
Bond	0.808	0.769
BBB		
Stock	0.050	0.050
Bond	0.750	0.683
Junk		
Stock	0.010	0.150
Bond	0.740	0.720

Table 9 provides summary statistics on the convertible bonds stratified by rating and predictability.[20] It is clear from these statistics that the most important determinant of predictability for these bonds is the degree to which the conversion option is in-the-money. There are no consistent patterns in the average years-to-maturity or coupons of the predictable and unpredictable bonds within each rating category. The contemporaneous stock-bond return correlation patterns are also similar to those of the nonconvertible bonds in that they indicate that the dominant form of news concerns the mean value of the firm's assets.

The mean stock and bond returns are higher for predictable convertible bonds than for unpredictable convertible bonds. This fact is reflected in the greater in-the-moneyness of the conversion option for the predictable bonds. We measure the in-the-moneyness of the conversion option by subtracting the strike price of the conversion option from the stock price and averaging over the sample period. We form a "moneyness rank" measure that lies between 0 and 1 and ranks the bonds from least in-the-money (0) to most in-the-money (1). As can be seen from Table 9, for AA-rated convertibles, the unpredictable bonds have an average moneyness rank of 0.337, while the predictable bonds have an average rank of 0.528.

[20]Five fewer convertible bonds are used in calculating Table 9 compared to Table 8, as we are unable to find conversion prices for these bonds.

TABLE 9

Summary Statistics for Predictable and Unpredictable Convertible Bonds

Table 9 displays summary information for the predictable ($P = 1$) and unpredictable ($P = 0$) convertible bonds in each rating category. A predictable convertible bond is one for which we reject both the sum test and the Granger causality test in the hourly returns regressions. Coupon rates, hourly bond returns, and hourly stock returns are expressed in percentage terms. The columns labeled $\rho_{S,B}$ show the mean and standard deviation of the contemporaneous correlations between stock and bond returns for the firms in the indicated category. The column labeled "Conversion Option In-the-Moneyness" shows the average rank of how far in-the-money the conversion options are for the bonds in the indicated category, where we have normalized the ranks to lie between 0 and 1. The t-statistics are also shown for tests of the null hypothesis that the mean moneyness rank of the predictable and unpredictable samples are equal. The column N shows the number of bonds in each category.

		Years to Maturity		Coupon		Bond Returns		Stock Returns		$\rho_{S,B}$		Conversion Option In-the-Moneyness			
Rating	*P*	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	*t*-Test	*N*
AA	0	18.7	11.3	0.650	0.929	0.001	0.001	0.004	0.004	0.015	0.014	0.337	0.129	–2.94	5
	1	23.1	9.1	0.625	0.884	0.008	0.003	–0.000	0.000	0.015	0.002	0.528	0.011		2
A	0	25.3	5.4	0.716	1.222	0.003	0.004	0.002	0.009	0.013	0.028	0.406	0.126	–4.34	7
	1	22.3	5.6	1.198	1.124	0.013	0.008	0.012	0.012	0.058	0.031	0.721	0.238		19
BBB	0	21.9	7.7	2.018	1.934	0.005	0.008	0.004	0.012	0.025	0.057	0.522	0.286	–1.67	21
	1	19.9	5.6	1.576	1.441	0.010	0.009	0.009	0.013	0.058	0.047	0.646	0.226		39
Junk	0	12.1	9.1	3.842	1.864	0.004	0.006	0.005	0.015	0.013	0.024	0.204	0.133	–7.80	33
	1	15.1	7.6	3.447	1.894	0.006	0.022	0.004	0.038	0.073	0.074	0.529	0.281		67

For A-rated convertibles, the ranks are 0.406 and 0.721 for unpredictable and predictable bonds, respectively. For BBB- and junk-rated bonds, the differences across the predictability categories are of similar magnitude. In terms of statistical significance, we reject the null of no difference in means across the two groups for the A- and junk-rated bonds.

It is clear from these results that it is not the direction of news that determines whether the bond return is led by the associated equity return. Rather, it is the fact that there *is* news, and the fact that the bond value, either by virtue of the fact that the bond is close to default or contains a conversion option, is sensitive to news that carries implications for expected cash flows. The results are consistent with the notion that the bond market is in general less informationally efficient than the stock market.

C. Economic Significance

In this section we briefly examine whether the results presented here reflect potentially profitable trading strategies. That is, could one form portfolios of bonds based on observing past stock returns that would lead to excess profits? To test this, we form portfolios at the daily or hourly frequency based on returns on the associated equity in the last period. We follow the methodology of Lo and MacKinlay (1990) and invest the fraction

$$w_{i,t} \quad = \quad \frac{1}{N}(R_{i,t-1} - R_{m,t-1}) \tag{3}$$

in the bonds of firm i. Here, N represents the number of firms present in the sample with bonds in the given rating category, $R_{i,t-1}$ is the return on firm i's equity in period $t-1$, and $R_{m,t-1}$ is the return on an equally weighted portfolio of the firms with bonds in the given rating class. Thus the bonds of a firm with an above average equity return in the last period will receive positive weight in the portfolio.

Since a single firm may have many bonds in the sample, we equally weight firm i's share across all of its bonds. The end result is a zero-net investment portfolio that can be rebalanced periodically. For hourly returns, we track the returns on this portfolio when it is held for one hour or one full day. For daily returns, we trace the returns when the portfolio is held for one day or one full week. The results for nonconvertible and convertible bonds are shown in Table 10. The row labeled "Mean Profit" represents the average return generated by the strategy each time it is executed, while the row labeled "Total Profit" is the cumulative profits from executing this strategy over the October 1, 2004 to December 31, 2005 period. For nonconvertible bonds, Panels A and B show that the most profitability exists, not surprisingly, in the junk category. Also, the longer the holding period, the larger the total profits. For example, for both hourly and daily returns, the junk portfolio with the longer holding period generates total cumulative returns over the entire sample in excess of 1%. For all other ratings categories, the profits are close to 0. The convertible bond results in Panels C and D are a bit more impressive in economic terms. For example, the total cumulative 15-month profit generated by forming junk bond portfolios daily and holding for one week is 2.7%.

While these 1%–3% profits over 15 months are generated with zero net investment, it is worth noting that transaction costs would quickly shrink any profits.

TABLE 10

Profitability

Table 10 presents results concerning the economic profitability of a trading strategy that goes long (short) on the bonds of firms whose equity return is above (below) the average equity return in the prior period. Panel A (C) presents returns where portfolios are formed based on hourly returns for nonconvertible (convertible) bonds, while Panel B (D) presents results where portfolios are based on daily returns for nonconvertible (convertible) bonds. For hourly returns, the portfolios are held for either one hour or one full day. For daily returns, the portfolios are held for either one day or one full week. The average holding period percentage profit ("Mean Profit") and the total cumulative percentage profit for the entire sample period ("Total Profit") are shown for each rating category. There are no AAA-rated convertible bonds in the sample.

Panel A. Hourly Returns: Nonconvertible Bonds

	Hold for One Hour					Hold for One Day				
Profit	AAA	AA	A	BBB	Junk	AAA	AA	A	BBB	Junk
Mean	–0.000	0.000	–0.000	0.000	0.000	–0.000	0.000	–0.000	0.000	0.000
Total	–0.051	0.012	–0.008	0.008	0.408	–0.019	0.008	–0.002	0.043	1.021

Panel B. Daily Returns: Nonconvertible Bonds

	Hold for One Day					Hold for One Week				
Profit	AAA	AA	A	BBB	Junk	AAA	AA	A	BBB	Junk
Mean	0.000	–0.000	0.000	0.000	0.002	0.001	–0.000	0.000	0.000	0.003
Total	0.076	–0.016	0.019	0.014	0.559	0.175	–0.008	0.014	0.016	1.027

Panel C. Hourly Returns: Convertible Bonds

	Hold for One Hour					Hold for One Day				
Profit	AAA	AA	A	BBB	Junk	AAA	AA	A	BBB	Junk
Mean	N/A	0.000	0.000	0.000	0.001	N/A	0.000	0.001	0.001	0.002
Total	N/A	0.081	0.585	0.476	1.141	N/A	0.012	1.705	1.572	3.685

Panel D. Daily Returns: Convertible Bonds

	Hold for One Day					Hold for One Week				
Profit	AAA	AA	A	BBB	Junk	AAA	AA	A	BBB	Junk
Mean	N/A	0.000	0.001	0.002	0.005	N/A	–0.000	0.002	0.002	0.009
Total	N/A	0.032	0.455	0.618	1.532	N/A	–0.019	0.664	0.547	2.696

Given that Edwards et al. (2007) show the average transaction cost for a $100,000 trade in junk bonds to be around 50 basis points, as well as the additional costs of short-selling bonds, it is highly unlikely that one could profitably take advantage of the predictability documented in this paper.

IV. Conclusion

In this paper, we exploit comprehensive data on secondary market transactions in corporate bonds in order to examine the relative informational efficiency of bonds and stocks. We find that stock returns predict returns on BBB- and junk-rated nonconvertible bonds at both daily and hourly frequencies; stock returns do not predict returns for nonconvertible bonds rated above BBB. For convertible bonds, we find evidence that stock returns lead bond returns in all credit quality categories. These conclusions hold whether we use a portfolio, pooled time-series cross-sectional, or bond-by-bond approach.

In regressions including contemporaneous and lagged Treasury note and S&P 500 returns, we find that highly rated bond returns are driven primarily by Treasury returns, while the lower rated bond returns correlate with equity returns. These results are consistent with the hypothesis that, because the expected cash flows for safe bonds are relatively stable, movements in the prices of these bonds largely reflect changes in interest rates, while equity price movements respond in large measure to firm-level news on earnings, producing low correlations (contemporaneously and at a lag) between the bond and equity returns. Because the BBB- and junk-rated bonds are closer to default, the expected cash flows and hence prices of these bonds react to news about the firm's cash flows, albeit at a lag relative to their associated equity, owing to the relative inefficiency of the bond market. These results are reinforced by an analysis of convertible bonds. We find strong evidence of predictability for convertible bonds of all ratings, consistent with the fact that the presence of the conversion option renders such bonds highly sensitive to firm-specific news, while the inefficiency of the bond market relative to the equity market produces the lead-lag structure evident in the convertible bond and equity returns.

These results provide an important new perspective on the issue of how firm-specific information is incorporated into the prices of stocks and bonds. While Kwan (1996) finds that stock returns lead nonconvertible bond returns even for bonds that are solidly investment grade, we find no such predictability in our transaction-based returns data on AA- and A-rated nonconvertible bonds. And while Hotchkiss and Ronen (2002) find no evidence that stocks lead bonds using more recent data, we find that this result may be an artifact of their small sample of bonds and relatively short sample period. It may be the case that few of the firms in Hotchkiss and Ronen (2002) faced the degree of difficulties faced by the firms in our sample. The apparently conflicting conclusions reached in these previous studies are likely a result of the fact that the previous research relied upon less comprehensive data than those we employ in this study.

Our findings also have implications for the growing literature on credit derivatives. Acharya and Johnson (2007) find evidence that traders with inside information may use the credit default swap market to profit from their information.

Norden and Weber (2009) find that the credit default swap and stock markets tend to lead the bond market in reflecting information. Our results suggest that traders with information are most likely to trade first in the equity or credit default swap market, rather than incur the costs of trading in illiquid corporate bonds. Our results also suggest that it would be fruitful to focus on distressed firms when analyzing the relations among credit default swaps, bonds, and equity.

Finally, our results shed additional light on the impact of transparency on financial markets. At the outset, we noted the results of several studies suggesting that greater transparency in the corporate bond market has brought down transaction costs. Our results suggest that a lack of transparency alone cannot explain the relative inefficiency of corporate bonds, at least for distressed firms. However, it may be the case that increased transparency has improved the efficiency of A- and AA-rated bonds as compared to those studied by Kwan (1996) long before the implementation of TRACE.

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