The Informational Efficiency of the Corporate Bond Market: An Intraday Analysis

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Using a unique dataset based on daily and hourly high-yield bond transaction prices, we find the informational efficiency of corporate bond prices is similar to that of the underlying stocks. We find that stocks do not lead bonds in reflecting firm-specific information. We further examine price behavior around earnings news and find that information is quickly incorporated into both bond and stock prices, even at short return horizons. Finally, we find that measures of market quality are no poorer for the bonds in our sample than for the underlying stocks.

> The sad truth is that investors in the corporate-bond market do not enjoy the same access to information as a car buyer or a home buyer or, I dare say, a fruit buyer. Improving the transparency is a top priority for us.
>
> *Arthur Levitt, Chairman, Securities and Exchange Commission (Wall Street Journal 9/10/98)*

In April 1994 the National Association of Securities Dealers (NASD) began an electronic quotation and surveillance system for high-yield bonds known as the fixed income pricing system (FIPS). With the implementation of FIPS, investors are for the first time able to track bond prices, volume, and transactions for a limited number of corporate bonds. Not surprisingly, to date there has been relatively little research on the behavior of corporate bond prices, largely because reliable transactions data are rarely available.[1] Past studies that have sought to assess the accuracy and efficiency of the corporate bond market utilize data based on weekly or monthly quotes from a single dealer. In this article we take advantage of the unique NASD data to examine the

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[1] See Sarig and Warga (1989) for a discussion of bond data problems. In a survey of current market microstructure literature, Goodhart and O'Hara (1997) note the "serious omission" in research on fixed income markets due to the lack of adequate data, despite the size and importance of these markets.

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efficiency and price discovery process for corporate bond prices on the daily and intradaily level.

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

This article uses a dataset based on daily and hourly transactions for 55 high-yield bonds included on the NASD FIPS system between January 3, 1995, and October 1, 1995, to examine the informational efficiency of corporate bond prices relative to stock prices. As such, it represents the first empirical study of the daily and intradaily behavior of corporate bond returns and the evolution of bond prices.[2] Specifically we address the following questions:

- Do stocks lead bonds in reflecting firm-specific information?
- Is the speed of price adjustment to firm-specific information different for bonds and stocks?
- Are measures of market quality different for bonds than for stocks?

We find that overall, in terms of informational efficiency, the behavior of these bonds is similar to that of the underlying stock, even on an intraday level.

Several recent studies find a strong contemporaneous relationship between corporate bond returns and both government bond and stock returns using monthly or weekly quote data [Blume, Keim, and Patel (1991), Cornell and Green (1991), and Kwan (1996)]. Extending this work, Kwan (1996) suggests that lagged stock returns have explanatory power for current bond yield changes. Although we find that positive and significant correlations between bond and stock returns persist on the daily and intradaily level, we establish that these are not causal relationships. Granger causality tests indicate that lagged stock returns are not significant in explaining bond returns. Any contemporaneous relationship we observe is therefore best described as a joint reaction to common factors.

The results in this article may be surprising in light of previously reported evidence. However, our transactions-based bond data not only allow us to investigate relationships previously examined only on a lower-frequency level, but also to use techniques and consider issues that cannot be addressed with lower-frequency quote data. In particular, the statistical methods

[2] Alexander, Edwards, and Ferri (2000) use the FIPS data to study the determinants of bond trading volume. Alexander, Edwards, and Ferri (1999) examine the comovement of returns on the FIPS bonds and common stocks of the issuing firms using daily, weekly, and monthly returns.

employed in this article are carefully directed at addressing potential nontrading effects in the high-yield market.

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

Finally, to further examine the relative efficiency of the two markets, we calculate the pricing errors derived by Hasbrouck (1993) as a measure of market quality. We decompose bond and stock prices into random walk and stationary components, with the former representing the efficient price of the security. We consider two distinct identification restrictions on the pricing error to facilitate estimation of the intradaily pricing error variances. Overall these results suggest that low-grade bond market quality is not different from the market quality of those firms' stocks.

Analysis of the FIPS data provides an important first step toward understanding price behavior in this dealer market. Previous research into the intraday behavior of bond prices has been limited to the government bond market [Fleming and Remolona (1997), Nyborg and Sundaresan (1996), Balduzzi, Elton, and Green (2001)]. Using lower-frequency corporate bond quote data, Gehr and Martell (1992) argue that "the dealer market is characterized by extreme informational inefficiency," based on their finding that bid-ask spreads between dealers often do not intersect. Using transactions-based data, we find that the informational efficiency for the high-yield bonds in our dataset is similar to that observed for the underlying stocks.

Differences between our results and prior studies may be attributed to the fact that transactions-based data has been unavailable prior to the introduction of the FIPS system. A notable exception is the availability of daily transactions data for insurance company trades in corporate debt, which has been studied in a series of three recent articles. Rather than comparing bonds to the underlying stocks, Hong and Warga (2000) compare this set of institutional trades to trades on the NYSE's Automated Bond System (ABS) and find that bid-ask spreads are similar in both markets. Their conclusions are similar to ours in that trading costs do not appear to be higher in the dealer market for corporate bonds. Chakravarty and Sarkar (1999) and Schultz (2001) examine the insurance company trades and find slightly higher estimates of the bid-ask spread.

Our study of the informational efficiency of the bond market relative to that of the stock market also addresses issues in the ongoing debate concerning the benefits of market transparency. When two securities that are claims on the same underlying firm value are traded in different markets, an informed trader may strategically choose to trade in one of those markets. NASD's reporting requirements for the FIPS bonds provide a certain degree of posttrade transparency for those securities since hourly summaries of trades are disclosed, but this transparency is clearly less than that mandated for the underlying stocks. Despite the traditional view that greater transparency reduces adverse selection, encourages uninformed investors to enter the trading arena, and facilitates risk sharing, there has been considerable debate as to the overall effect of market transparency on informational efficiency. The lack of theoretical consensus on these effects clouds our ability to clearly predict differences across the two markets.[3] However, recent experimental evidence by Bloomfield and O'Hara (1999) does find that trade disclosure significantly improves informational efficiency. While data limitations preclude us from testing this hypothesis directly, our results do indicate that information is impounded quickly into both bond and stock prices, despite the lesser transparency for the bonds. It is possible that even the limited transparency introduced by the FIPS system has led to the informational efficiency of the securities we study. As future regulatory changes lead to increased transparency in the corporate bond market, researchers may then be able to further address these important issues.

This article is organized as follows. Section 1 describes the FIPS system and documents the trading frequencies for the bonds in our sample and for their underlying stocks. Section 2 examines tests of causality for bond and stock returns, while Section 3 examines the impact of earnings news on bond and stock prices. Section 4 provides measures of market quality. Section 5 concludes.

1. Data

Unlike stock prices, corporate bond transaction prices historically have not been publicly reported. Over time there has been increasing concern over the lack of transparency in the corporate bond market, which led to the introduction of the FIPS system in April 1994. FIPS began with 113 participating brokers and dealers, and participation grew to 134 by January 1995. The major objectives underlying the FIPS initiative were described as follows: (1) to bring transparency (i.e., more accessible and accurate information on prices and trading volume) to the over-the-counter dealer markets in selected high-yield bonds, (2) to provide an efficient price discovery mechanism, and (3) to establish a centralized database to support NASD surveillance of the market.

[3] For example, Madhavan (1995) predicts that informed traders benefit in less transparent markets because dealers in less transparent markets will price more aggressively in early rounds of trade so as to use their private knowledge from trades to extract rents in future rounds. On the other hand, Naik, Neuberger, and Viswanathan (1999) argue that in dealer markets, requiring prompt trade disclosure may reduce public investor welfare in some cases.

Table 1
Characteristics of FIPS bonds and issuing companies

	Mean	Median	Minimum	Maximum
Issuer total assets ($ millions)	3152.4	1820.3	331.6	28273.7
Issuer total liabilities/total assets	1.10	0.96	0.56	2.56
Coupon	9.6	9.875	0	13
Years remaining to maturity	10.2	10.0	4.5	20.0
Duration	5.1	5.4	2.4	7.5
Amount outstanding ($ millions)	374.1	275.0	100.0	1126.4
S&P rating	—	B+	D	BB+
Value of embedded options	1.02	0.19	0	6.86
Additional bond characteristics:		*N*	%	
Distribution by equity listing:	NYSE	28	50.9	(23 companies)
	AMEX	2	3.6	
	NASDAQ	9	16.4	(6 companies)
	Privately held	16	29.1	(13 companies)
Bond is callable:		42	76.4	
Bond has sinking fund provisions		9	16.4	
Bond listed on NY Bond Exchange or AMEX		16	29.1	

Sample includes 55 bonds from 44 companies included on the NASD FIPS between January 3, 1995, and October 31, 1995. Financial characteristics of issuing companies are based on data from Moody's Industrial Manuals. Bond characteristics are determined from *Salomon Brothers Yield Book* and *Moody's Manuals* as of January 3, 1995.

Under the FIPS system, the NASD requires transaction reports (within 5 minutes of execution) for all trades executed by NASD members in the over-the-counter market between 9 A.M. and 5 P.M. for approximately 50 high-yield bonds.[4] Based on these trade reports, hourly high and low trading ranges and the dollar volume of transactions are displayed on the FIPS terminal for seven hourly intervals beginning at 10:00 A.M. Our dataset consists of the hourly high and low prices and hourly volume for all bonds displayed on the FIPS system between January 3, 1995, and October 31, 1995.[5]

The bonds included on this system were chosen by the NASD advisory committee largely because they were the most liquid issues at the time the system began. Bonds were chosen based on volume, price, name recognition of the issuer, research following, and representation from diverse industry groups. Although these bonds constitute a small subset of the universe of high-yield bonds, these securities are characterized by "comparatively high trade volumes, multiple broker/dealers that are willing to trade the issue in block size, and trading patterns that more closely resemble the issuer's stock" (*BNA Securities Regulation and Law Report*, March 1994).

Table 1 provides summary characteristics for the 55 FIPS bonds from 44 issuing companies. The issuing companies are relatively large (median book

[4] We refer to the 50 mandatory reported bonds as the "FIPS bonds." Under the FIPS, trade reports are also required for all nonmandatory high-yield bonds by 5 P.M. on the trade date. Transaction information in nonmandatory bonds is monitored by the NASD for surveillance purposes only and not disseminated publicly.

[5] Bond dealers who register (through the FIPS terminal) as a market maker in a particular bond are also required to provide continuous quotes for that security. However, the displayed quote data were not initially considered to accurately reflect the market, since several major dealers did not participate in this aspect of the system. Given concerns regarding the accuracy of quote data, this article utilizes only the hourly transactions based data.

value of assets of \$1820.3 million) and are often highly levered, consistent with the firms' below-investment-grade credit ratings. All FIPS bonds are nonconvertible, issued between August 15, 1990, and March 30, 1994, and are on average 1.9 years old on January 3, 1995. While the remaining time to maturity ranges from 4.5 to 20 years, more than 90% of the bonds have more than 5 years to maturity. The sample includes two zero coupon bonds and three deferred interest bonds; the coupons of all other bonds range from 5% to 13%. Issue size is generally quite large, averaging \$374 million.[6] Finally, credit quality based on the S&P rating as of January 3, 1995, varies from BB+ to a low of D; although bonds in default were not originally selected for inclusion on the system, two issues subsequently defaulted but remained displayed on FIPS until the securities were redeemed.

High-yield bond structures typically have multiple embedded options. In our sample, 42 bonds (76.4%) are callable prior to maturity and 9 bonds (16.4%) have sinking fund provisions. We calculate option values using the option adjusted spread (OAS) model provided in the Salomon Brothers Yield Book and find that as of January 3, 1995, 31 bonds have no embedded options or options with little value (less than \$.25 per \$100 bonds) and that 24 bonds have options with values ranging from \$.40 to \$6.86 (\$2.21 on average).

Table 2 documents trading volume for the FIPS bonds. There is considerable variability in the number of sample period days in which a bond trades and in the average daily trading volume, even between bonds of the same issuer. While many of the bonds trade nearly 100% of the days, a few bonds trade much less frequently, with a low of 8.4% of days.[7] Fifteen bonds also trade on the NYSE's ABS; for these bonds, the average daily FIPS-reported volume is substantially greater than that on the exchange. The median reported exchange volume is only 25% of the total dealer market for those bonds, and there is considerable variability across these bonds (ranging from 0.2% to 81%).[8] These statistics indicate the relative importance of the dealer market compared with that of the exchange market for bonds. For comparative purposes, Table 2 also reports the stock trading volume matched by hourly time intervals with those of the 35 bonds (28 companies) for which the stock is publicly traded and included in the TAQ database. The average daily dollar volume for the equity is on average 19 times (median 5.6 times) the daily bond volume, and all but four companies have stock trades reported for 100% of days for which the corresponding bond is included on FIPS.

[6] We also compared the FIPS bonds to a sample of 846 high-yield bonds issued between 1991 and 1994 from Securities Data Corporation. The median bond principal amount and median issuer market capitalization for our sample of mandatory FIPS bonds is approximately two times that of the other high-yield bonds. The median time to maturity, coupon, and other characteristics, however, are not statistically different between these groups.

[7] Bonds with such a low volume of trade are generally removed from the FIPS system by the NASD at the next periodic review.

[8] Exchange volume is based on figures reported in the *Wall Street Journal Trading Summary for 1995* (1/2/96) and the *New York Stock Exchange 1995 Fact Book*. Bonds that are listed on the ABS but which did not trade there in 1995 are not included in these figures.

Table 2
Trading volume statistics for FIPS bonds and underlying stock

Company name	Coupon	Maturity	Bond volume: # days bond trades/ # days bond included on FIPS (%)	Bond volume: Average daily volume ($000)	Bond volume: Average daily volume on days traded	Bond volume: Average daily volume, NYSE's ABS	Stock volume: # days bond trades/ # days bond included on FIPS (%)	Stock volume: Average daily dollar volume ($000)
1. AK Steel Corp	10 3/4	4/1/04	87/143 (60.8%)	2753	4526	6		
2. American Standard	9 7/8	6/1/01	211/211 (100.0%)	1218	1218			
3. American Standard	0,10.5[a]	6/1/05	143/143 (100.0%)	6102	6102			
4. Bally's Health&Tennis	13	1/15/03	143/143 (100.0%)	1165	1165			
* 5. Best Buy Co[b]	8 5/8	10/1/00	198/211 (93.8%)	265	283	216	211/211 (100.0%)	15412
* 6. Bethlehem Steel	10 3/8	9/1/03	140/143 (97.9%)	365	373		143/143 (100.0%)	11324
7. Cablevision Systems	10 3/4	4/1/04	57/211 (27.0%)	735	2719		211/211 (100.0%)	2255
8. Century Communications	9 3/4	2/15/02	128/211 (60.7%)	706	1164			
* 9. Chiquita Brands	9 5/8	1/15/04	208/211 (98.6%)	424	430		211/211 (100.0%)	2384
10. Clark Oil & Refining	9 1/2	9/15/04	128/211 (60.7%)	143	235	46		
11. Comcast Corp	9 1/2	1/15/08	152/211 (72.0%)	584	810		211/211 (100.0%)	4306
12. Comcast Corp	10 5/8	7/15/12	98/211 (46.4%)	394	847		211/211 (100.0%)	4306
13. Container Corp	9 3/4	4/15/03	91/211 (43.1%)	297	689			
14. Continental Cable	8 7/8	9/15/05	98/211 (46.4%)	940	2024			
* 15. Eckerd Corp[b]	9 1/4	2/15/04	130/143 (90.9%)	318	350	149	143/143 (100.0%)	3868
* 16. Flagstar	10 3/4	9/15/01	192/211 (91.0%)	1876	2062		211/211 (100.0%)	651
* 17. Flagstar Corp	11 1/4	11/1/04	211/211 (100.0%)	5275	5275		211/211 (100.0%)	651
18. Food 4 Less	10 4/9	4/15/00	12/143 (8.4%)	6	73			
19. Fort Howard Corp	9	2/1/06	211/211 (100.0%)	2634	2634			
20. Fort Howard Corp	9 1/4	3/15/01	207/211 (98.1%)	237	241			
21. Fort Howard Corp	10	3/15/03	143/143 (100.0%)	1279	1279			
22. Healthtrust	8 3/4	3/15/05	97/119 (81.5%)	158	1357	35	47/119 (39.5%)	3077
* 23. Kroger Co	8 1/2	6/15/03	203/211 (96.2%)	366	380		211/211 (100.0%)	9264
24. Kroger Co	9 3/4	2/15/04	66/143 (46.2%)	32	69		143/143 (100.0%)	9415
25. K-lll Comms Corp	10 5/8	5/1/02	66/211 (31.3%)	509	1627			
26. Marvel Parnt Hld	0	4/15/98	116/143 (81.1%)	428	527			
* 27. NEXTEL Comms Corp	9 3/4[a]	8/15/04	132/143 (92.3%)	3945	4274		143/143 (100.0%)	24452
* 28. NEXTEL Comms Corp	11 1/2[a]	9/1/03	201/211 (95.3%)	2304	2419		211/211 (100.0%)	24705
29. NL Industries	11 3/4	10/15/03	115/211 (54.5%)	1775	3257		211/211 (100.0%)	748
30. OrNda	12 1/4	5/15/02	66/211 (31.3%)	1150	3676		211/211 (100.0%)	7153

Table 2
(continued)

Company name	Coupon	Maturity	Bond volume: # days bond trades/ # days bond included on FIPS (%)	Bond volume: Average daily volume ($000)	Bond volume: Average daily volume on days traded	Bond volume: Average daily volume, NYSE's ABS	Stock volume: # days bond trades/ # days bond included on FIPS (%)	Stock volume: Average daily dollar volume ($000)
31. Owens Illinois Inc.	10 1/4	4/1/99	126/211 (59.7%)	350	586	110	211/211 (100.0%)	1548
* 32. Owens Illinois Inc.	11	12/1/03	173/211 (82.0%)	7154	8726	93	211/211 (100.0%)	1548
33. Pathmark Stores	9 5/8	5/1/03	135/143 (94.4%)	2076	2199			
* 34. Payless Cashways[b]	9 1/8	4/15/03	196/211 (92.9%)	1097	1180	525	211/211 (100.0%)	661
* 35. Penn Traffic	8 5/8	12/15/03	177/211 (83.9%)	1295	1543		209/211 (99.1%)	509
36. Penn Traffic	10 1/4	2/15/02	121/211 (57.3%)	417	726		209/211 (99.1%)	509
* 37. Playtex Family	9	12/15/03	211/211 (100.0%)	2167	2167		211/211 (100.0%)	1761
38. Revlon Worldwide	0	3/15/98	143/143 (100.0%)	6827	6827			
39. Safeway Inc.	9 2/3	1/15/04	128/211 (60.7%)	153	252	86	211/211 (100.0%)	8353
* 40. Service Merchandise[b]	9	12/15/04	209/211 (99.1%)	1298	1310	726	211/211 (100.0%)	1934
41. Southland	5	12/15/03	162/211 (76.8%)	2229	2903		113/211 (53.6%)	229
* 42. Stone Container Corp[b]	9 7/8	2/1/01	211/211 (100.0%)	9371	9371	931	211/211 (100.0%)	24104
* 43. Stone Container Corp[b]	10 3/4	4/1/02	133/143 (93.0%)	1819	1956	294	143/143 (100.0%)	25430
44. Trans World Airlines	10	11/3/98	73/143 (51.0%)	165	324		76/143 (53.1%)	1075
45. Trump Plaza Funding	10 7/8	6/15/01	118/143 (82.5%)	3722	4510			
* 46. Unisys Corp	10 5/8	10/1/99	134/143 (93.7%)	720	768		143/143 (100.0%)	9989
* 47. US Air Inc.	10	7/1/03	141/143 (98.6%)	3272	3319		143/143 (100.0%)	12712
* 48. Viacom Intl	8	7/7/06	143/143 (100.0%)	7494	7494		143/143 (100.0%)	8757
* 49. Wheeling Pittsburgh Corp[b]	9 3/8	11/15/03	206/211 (97.6%)	1048	1073	272	211/211 (100.0%)	1674
50. Grand Union	12	9/1/04	15/16 (93.8%)	8038	8573			
51. Tenet Healthcare	10 1/8	3/1/05	8/13 (61.5%)	2982	4845	53		
52. Grand Union	11 1/4	7/15/00	114/195 (58.5%)	2661	4552			
53. Coltec Inds	10 1/4	4/1/02	11/68 (16.2%)	171	1055		68/68 (100.0%)	1907
54. Del Webb	9 3/4	3/1/03	55/68 (80.9%)	466	576	120	68/68 (100.0%)	1026
55. Transco Energy Corp	9 3/8	8/15/01	7/39 (17.9%)	37	209		39/39 (100.0%)	2504

Bond volume statistics are obtained for all bonds included on the NASD's FIPS from January 3, 1995, to October 31, 1995. Trade volume for the underlying stock is obtained for matching time intervals from the TAQ database. NYSE's Automated Bond Exchange (ABS) volume is based on figures reported in the *Wall Street Journal* and the *NYSE 1995 Fact Book.*

*Indicates subsample of 20 most actively traded bonds with publicly traded underlying equity.

[a] Deferred interest or step-up coupon bond.

[b] Also listed as one of NYSE's 50 most active bonds for 1995 and 1996.

Overall the trading volume statistics document considerable variability across bonds in trading frequency. To mitigate potential nonsynchronous trade effects, we construct a portfolio of the 20 most actively traded FIPS bonds which also have publicly traded equity (noted by an asterisk in Table 2). On average, these 20 bonds transact on 95% of the days in the sample period. Of the seven hourly time intervals reported on the FIPS system each day, these bonds trade on average in 3.5 of the hourly periods.[9] This portfolio of most actively traded bonds is used for our regressions and causality tests (Section 2) and for our market quality tests (Section 4).

2. Do Stock Returns Lead Corporate Bond Returns?

In this section we look at the relationship between high-yield bond returns and returns on the underlying stock. Both bonds and stocks are claims on the value of the firm's assets. From Merton (1974), we can view equity as a call on the firm's assets, and debt as a portfolio that consists of investing in a default risk-free asset and shorting a put on the value of the firm. Information that positively affects the value of the firm's assets, all things being equal, will increase the value of both the bond and stock and produce a positive contemporaneous relationship between bond and stock returns. Information which increases the variance of returns on the firm's assets, all things being equal, will lead to an increase in stock prices and a decrease in bond prices. Furthermore, if stock prices are more informationally efficient than bonds and reflect information faster, we expect to observe cross-serial correlations in returns (i.e., lagged stock returns will have explanatory power for current bond returns).

Previous research has established a positive contemporaneous relationship between bond and stock prices based on monthly dealer quotes. This suggests that it is primarily information about the value of the firm's assets that drives the observed positive relationship between bond and stock returns. More recently, Kwan (1996) extends this work and finds, in addition to this positive contemporaneous relationship, that lagged stock returns have explanatory power for current bond yield changes; based on this, he argues that individual stocks lead bonds in reflecting firm-specific information.

Our objective in this section is as follows. In Section 2.1 we define our return calculations. In Section 2.2 we reexamine the relationships studied in previous articles and establish that a positive contemporaneous relationship exists between bond and stock returns on both the daily and intraday level. In Section 2.3. we take up the issue of causality, but unlike the methods employed in the existing literature, we use a vector autorgression (VAR) approach.

[9] Using proprietary data provided directly by the SEC (rather than the publicly disseminated hourly summaries), Alexander, Edwards, and Ferri (2000) are able to determine that the average number of transactions per day for all FIPS bonds from October 1994 to July 1997 ranges from 0.45 to 41.16. Thus the most active FIPS bonds likely have a large number of transactions per hour.

2.1 Calculation of daily and hourly returns

Daily FIPS bond, treasury, and stock returns are calculated as follows. Daily bond returns, $RB_{i,t}$, are calculated using the midpoint of the high and low prices for the last hour of trade in bond i on day t. For the few cases in which a bond does not have a reported price for a given day, we assume that the price is equal to the last recorded price. Since prices are quoted without accrued interest, bond returns are adjusted for accrued interest and coupon payments. We isolate interest rate risk by calculating a time series of prices for a "default-free" bond by discounting the remaining high-yield bond cash flows at corresponding Treasury spot rates.[10] These prices generate a sequence of default-free bond returns, $RD_{i,t}$. Treasury spot rates are calculated by fitting a cubic spline to the observed on-the-run Treasury curve obtained from Telerate [see Fisher, Nychka, and Zervos (1994) for calculation details]. Our methodology ensures that, except for embedded options, the cash flows of the default-free security exactly match those of the high-yield bond. Lastly, to calculate stock returns including dividends, $RS_{i,t}$, we use the last transaction price reported on the TAQ database for the hour corresponding to the last hour of trade for FIPS bond i on day t. For comparison with prior research, we also measure daily stock returns using the S&P 500 index and treasury returns using the Lehman Brothers Intermediate Government Bond Index.

In addition to the daily return characteristics, our data allow us to examine characteristics of intradaily (hourly) returns. Hourly bond, stock, and default-free returns are calculated similarly to daily returns. To calculate stock returns, we use the last stock transaction price reported on TAQ for each of the seven hourly trade intervals. Bond returns are calculated using the midpoint of the high and low transaction prices reported in the FIPS hourly summary. This timing may in fact bias our results toward finding that stocks respond more quickly to new information (see note 14). When a bond or stock does not have a reported price for a given hour, we assume that the price remains unchanged from the most recent hour with a trade.[11] Since data for hourly treasury spot rates used to compute default-free returns are only available from May 19, 1995, to October 31, 1995, tests involving hourly default-free returns are therefore restricted to this time period.

[10] Alternatively, Blume, Keim, and Patel (1991) calculate a default-free bond price by computing the price of a portfolio of government bonds with closely matching cash flows. Kwan (1996) matches bonds to similar maturity riskless interest rates by interpolation from constant-maturity Treasury yields; however, since high-yield bonds have higher coupons and embedded options, durations will not be matched as closely using this approach.

[11] An alternative methodology to fill in missing prices is the "repeat sales" methodology used by Case and Schiller (1987) and Bailey, Muth, and Nourse (1963) to analyze data characterized by infrequent transactions. Rather than assuming a zero return for hours with no bond trade, returns from an index of bonds which trade that hour are used to infer the returns of the nontraded bond. Goetzmann (1995) and Goetzmann and Spiegel (1995) provide a detailed discussion of this methodology. As shown in earlier drafts, all results in this article are qualitatively similar with and without the repeat sales methodology.

2.2 Influence of government bond and equity returns

We first examine the relationship between bond price movements and equity and interest rate movements by regressing daily returns for the portfolio of the 20 most active FIPS bonds against contemporaneous and lagged stock and treasury returns. This allows us to compare the relationship between the bond and stock returns for our sample to previously documented results. We use the return-generating process as specified in Cornell and Green (1991), and measure stock and treasury returns using the S&P 500 and Lehman Intermediate Government Bond indices:

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^L RL_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \varepsilon_t, \qquad (1)$$

where RB_t is the equally weighted FIPS bond portfolio return, RL_t is the Lehman index return, and RM_t is the S&P 500 index return. We also run regressions using the default-free return, RD_t, rather than the Lehman index return to measure the interest rate risk corresponding to the FIPS securities.

In terms of informational efficiency, however, we need to compare bond returns to returns on the stock of the same firm. Therefore we also regress bond returns on the corresponding default-free securities, the S&P 500 index, and the underlying stocks:

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^D RD_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \sum_{i=0}^{ns} \beta_i^S RS_{t-i} + \varepsilon_t, \qquad (2)$$

where RS_t is the equally weighted underlying stock portfolio return. As in previous studies, we incorporate lags of all variables. The inclusion of the lagged bond returns (RB_{t-i}) allows us to consider autocorrelation-adjusted bond returns. We incorporate standard error adjustments to account for potential serially correlated and heteroscedastic errors using Hansen's (1982) generalized method of moments.

Summary statistics for the return series used in the regressions are reported in Table 3. For daily returns we observe that the standard deviation of returns is lower for the Lehman index than for the portfolio of FIPS bonds and higher for the S&P index and portfolio of underlying stocks. Dividing the 20 FIPS bonds into portfolios by credit rating, we also observe that the standard deviation of returns for both the FIPS bond and underlying stock portfolios increases as the credit rating falls. On an hourly basis we observe similar relationships, though the standard deviation of returns for the underlying stock portfolio is somewhat lower for the middle-rated group.

Panel A of Table 4 reports the results for the daily regressions. Based on Scholes and Williams (1977) and as in Cornell and Green (1991), we report the sum of the coefficients as opposed to individual coefficients, since interpretation of the individual lagged coefficients is inappropriate in this

Table 3
Summary statistics for daily and hourly returns

		Mean	Median	Standard deviation
A. Daily return on:				
RB_t	FIPS bond portfolio	0.00034	0.00028	0.00343
RL_t	Lehman Intermediate Government Bond Index	0.00046	0.00033	0.00197
RD_t	Default free treasury	0.00070	0.00042	0.00361
RM_t	S&P 500	0.00100	0.00061	0.00505
RS_t	Underlying stock portfolio	−0.00064	−0.00087	0.00895
Bonds rated BB− to BB:				
RB_t	FIPS bond portfolio	0.00046	0.00050	0.00372
RS_t	Underlying stock portfolio	−0.00094	−0.00044	0.01014
Bonds rated B− to B+:				
RB_t	FIPS bond portfolio	0.00031	0.00023	0.00407
RS_t	Underlying stock portfolio	−0.00023	0.00032	0.01388
Bonds rated CCC+ or lower:				
RB_t	FIPS bond portfolio	−0.00118	0.00044	0.02124
RS_t	Underlying stock portfolio	0.00119	0.00004	0.02069
B. Hourly return on:				
RB_t	FIPS bond portfolio	0.00003	0.00010	0.00167
RD_t	Default free treasury	0.00008	0.00000	0.00139
RM_t	S&P 500	0.00009	0.00014	0.00196
RS_t	Underlying stock portfolio	−0.00011	−0.00018	0.00426
Bonds rated BB− to BB:				
RB_t	FIPS bond portfolio	0.00003	0.00001	0.00182
RS_t	Underlying stock portfolio	−0.00037	−0.00050	0.00654
Bonds rated B− to B+:				
RB_t	FIPS bond portfolio	0.00002	0.00001	0.00218
RS_t	Underlying stock portfolio	−0.00013	−0.00012	0.00502
Bonds rated CCC+ or lower:				
RB_t	FIPS bond portfolio	0.00002	0.00017	0.00557
RS_t	Underlying stock portfolio	0.00028	0.00000	0.00839

Statistics are calculated for daily returns from April 10, 1995, to October 31, 1995, and for hourly returns from May 19, 1995, to October 31, 1995. The FIPS bond portfolio consists of the 20 most actively traded FIPS bonds as indicated on Table 2. Portfolios of bonds rated BB− to BB, B− to B+, and CCC+ or lower consist of 6, 10, and 4 bonds, respectively.

context. Results are insensitive to the inclusion of additional lags (or leads) of any variables. The return on the daily bond portfolio [Regression (1)] is significantly positively related to the Lehman Intermediate Index return ($\sum \beta^L = 0.58$), as well as to the daily S&P 500 index return ($\sum \beta^M = 0.49$). The magnitude of the sensitivity to interest rates and especially to stock market movements appears substantially higher than reported in previous work for monthly returns. For example, Blume, Keim, and Patel (1991) report regression results for portfolios of high-yield bonds on monthly government bond returns and small stocks (1982–1989), with coefficients of 0.33 and 0.17, respectively. Cornell and Green (1991) also conduct regressions of monthly low-grade bond fund returns on Treasury bond and S&P 500 Index returns for the years 1960–1989 and obtain significant coefficient estimates of 0.28 and 0.36. Regression (2) substitutes the default-free bond return for the Lehman index return. Although the coefficient is somewhat lower, this variable more closely measures the interest rate risk of the specific FIPS securities. Market-wide information is reflected in the coefficient for the S&P 500 return which is slightly greater in Regression (2).

Table 4
Two factor regression models relating daily FIPS bond returns to interest rate and equity movements

	α	$\sum\beta^B$ FIPS bond	$\sum\beta^L$ Lehman Int Govt	$\sum\beta^D$ Default free	$\sum\beta^M$ S&P	$\sum\beta^S$ Stock	Adjusted R^2	N
A. All bonds								
(1)	−0.0004	−0.1020	0.5803[a]		0.4903[a]		0.175	138
	(0.1637)	(0.5424)	(0.0001)		(0.0024)			
(2)	−0.0003	−0.1467		0.2513[a]	0.5377[a]		0.138	138
	(0.2458)	(0.3874)		(0.0098)	(0.0012)			
(3)	−0.0003	−0.1616		0.2624[b]	0.5476[a]	0.0209	0.138	137
	(0.2796)	(0.3413)		(0.0117)	(0.0015)	(0.7620)		
B. Bonds rated BB− to BB								
(4)	−0.0001	−0.3571[b]	0.7098[a]		0.4451[a]		0.204	138
	(0.6687)	(0.0381)	(0.0001)		(0.0020)			
(5)	0.0000	−0.3868[b]		0.2966[a]	0.4880[a]		0.161	138
	(0.9302)	(0.0189)		(0.0028)	(0.0010)			
(6)	0.0001	−0.3024[c]		0.3203[a]	0.4130[a]	0.0847	0.221	138
	(0.7777)	(0.0921)		(0.0007)	(0.0023)	(0.1490)		
C. Bonds rated B− to B+								
(7)	−0.0003	−0.1332	0.5561[a]		0.3396[c]		0.086	138
	(0.3131)	(0.4731)	(0.0012)		(0.0565)			
(8)	−0.0003	−0.1553		0.2691[b]	0.3665		0.065	138
	(0.4033)	(0.4064)		(0.0210)	(0.0445)[b]			
(9)	−0.0001	−0.2471		0.3769[a]	0.2752[c]	0.1465[b]	0.135	138
	(0.7516)	(0.1575)		(0.0024)	(0.0731)	(0.0247)		
D. Bonds rated CCC+ or lower								
(10)	−0.0004	−0.2509	0.5713		0.9061[a]		0.059	138
	(0.5705)	(0.1332)	(0.1449)		(0.0023)			
(11)	−0.0003	−0.2689		0.1974	0.9459[a]		0.052	138
	(0.6468)	(0.1051)		(0.3563)	(0.0019)			
(12)	−0.0002	−0.2408		0.2131	0.7140[b]	0.1154[b]	0.125	138
	(0.7309)	(0.1690)		(0.3030)	(0.0387)	(0.0363)		

Table reports results of the following regressions:

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^L RL_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \varepsilon_t$$

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^D RD_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \varepsilon_t$$

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^D RD_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \sum_{i=0}^{ns} \beta_i^S RS_{t-i} + \varepsilon_t,$$

where RB_t is the FIPS bond portfolio return, RL_t and RD_t are the Lehman Intermediate Government Bond Index and default free bond returns, and RM_t and RS_t are the S&P and underlying stock portfolio returns. nb, ni, and ns denote the number of lags for the bond, interest rate, and stock returns, respectively. Regressions include three lags of the bond return ($nb = 3$), the contemporaneous Lehman or default-free return ($ni = 0$), and the contemporaneous plus four lags of the S&P or stock return ($ns = 4$). Standard errors are calculated using Hansen's (1982) generalized method of moments. Regressions include returns from 4/10/95 to 10/31/95. a, b, c denote significance at the 1%, 5%, and 10% level, respectively. p-values are shown in parentheses.

Regressions (1) and (2) show a very strong interest rate and systematic risk component to the high-yield bond returns. Using monthly quote data from Lehman Brothers Fixed Income database, Elton et al. (2001) also find that corporate bonds have a large systematic risk component and offer two explanations for this finding. First, if default risk is systematic (as equity prices rise, default risk decreases and vice versa), the expected default loss will move with equity prices and induce a large systematic factor. Second, they find evidence of a risk premium not associated with default risk which changes over time and affects both corporate bonds and stocks. Therefore the return on corporate bonds appears to be subject to the same type of systematic risk that affects other assets (e.g., stocks).

Regression (3) includes the return on the portfolio of underlying equities. Since the returns are determined by both systematic and firm-specific risk, both the market and underlying stock returns are expected to be related to the high-yield bond returns. For the full sample of the 20 FIPS bonds, while the coefficient for the S&P 500 return continues to be significant, the coefficient for the underlying equity return is not significant.[12] The coefficient on the stock return variable is similar when we rerun Regression (3) using the Lehman index rather than the default-free bond return (not reported in table).

Our results contrast with Kwan (1996), who finds that bonds rated below investment grade are highly correlated with their issuing firms' stocks, but that changes in riskless interest rates have no marginal explanatory power. It is clear from our results that low-grade bonds are sensitive to movements in interest rates and stock markets at the daily level. If firm-specific information is important in determining high-yield bond returns, we would expect the stock return coefficient to be stronger for the lowest-rated bonds.

To examine this hypothesis, we partition the FIPS bond portfolio into three credit rating groups, BB$-$ or higher (6 bonds), B$-$ to B$+$ (10 bonds), and CCC+ or lower (4 bonds). For the highest-rated bonds [Regression (4)], the coefficient for the Lehman index ($\sum \beta^L = 0.7098$) is significantly different from the coefficients for the lower-rated bonds [Regressions (7) and (10)]; we reject the hypothesis that these coefficients are equal with p-values of 0.08 and 0.10. The coefficient for the default-free bond is significant only for the two higher-rated portfolios, though the differences in these coefficients from that of the lowest-rated bonds is not significant. The most striking difference we observe is for the S&P 500 coefficient, which is greater for the lowest-rated bonds. For example, in Regression (10), $\sum \beta^M = 0.9061$, which is significantly different from the coefficients for the highest- and mid-rated portfolios (p-values of 0.09 and 0.10). Lastly, the coefficient for the underlying stock portfolio is lowest for the highest-rated bonds; it is significantly different from the coefficient for the mid-rated bonds (p-value 0.10) but not the lowest-rated bonds. Overall we observe a stronger interest rate component and weaker equity component for higher-rated bonds, though the differences are only weakly significant.

[12] In Regressions (1) and (2), the coefficient for the contemporaneous Lehman index return is significant, while only the first, third, and fourth lagged S&P coefficients are individually significant. We define the contemporaneous return on the S&P 500 and Lehman indices based on the index level at the end of the day; if a bond only trades earlier in the day, index returns may incorporate more recent information than the bond returns. In Regression (3), coefficients for the contemporaneous default-free bond return, lags 1–4 of the S&P 500 return, and the contemporaneous stock return are individually significant. Further interpretation of lagged coefficients is deferred to Section 2.3, where we rely on a VAR approach.

Table 5
Two factor regression models relating hourly FIPS bond returns to interest rate and equity movements

	α	$\sum\beta^B$ FIPS bond	$\sum\beta^D$ Default free	$\sum\beta^M$ S&P	$\sum\beta^S$ Stock	Adjusted R^2	N
A. All bonds							
(1)	0.0000	−0.4137[a]	0.1083[b]	0.1979[b]		0.066	797
	(0.8542)	(0.0001)	(0.1222)	(0.0144)			
(2)	0.0000	−0.4233[a]	0.1074[b]	0.0610	0.1140[c]	0.083	797
	(0.5317)	(0.0001)	(0.1254)	(0.5617)	(0.0637)		
B. Bonds rated BB− to BB							
(3)	0.0000	−0.3302[a]	0.2518[a]	0.1669[b]		0.080	797
	(0.9159)	(0.0001)	(0.0016)	(0.0375)			
(4)	0.0000	−0.3242[a]	0.2492[a]	0.1462[c]	0.0224	0.091	797
	(0.7956)	(0.0001)	(0.0023)	(0.0851)	(0.5773)		
C. Bonds rated B− to B+							
(5)	0.0000	−0.4821[a]	0.0444	0.2318[b]		0.073	798
	(0.9318)	(0.0001)	(0.6121)	(0.0276)			
(6)	0.0000	−0.5012[a]	0.0777	0.0358	0.1353[a]	0.085	798
	(0.5465)	(0.0001)	(0.3938)	(0.7839)	(0.0083)		
D. Bonds rated CCC+ or lower							
(7)	0.0000	−0.5456[a]	0.1009	0.1553		0.080	797
	(0.8632)	(0.0001)	(0.6135)	(0.5272)			
(8)	0.0000	−0.5452[a]	0.1141	0.0206	0.1183	0.091	797
	(0.9347)	(0.0001)	(0.5699)	(0.9404)	(0.1727)		

Table reports results of the following regressions:

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^D RD_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \varepsilon_t$$

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^D RD_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \sum_{i=0}^{ns} \beta_i^S RS_{t-i} + \varepsilon_t,$$

where RB_t is the hourly FIPS bond portfolio return, RD_t is the default-free treasury return, RM_t is the S&P 500 return and RS_t is the underlying stock portfolio return. nb, ni, and ns denote the number of lags for the bond, interest rate, and stock returns, respectively. Regressions include three lags of the bond return, the contemporaneous and two lags of the default-free return, and the contemporaneous plus seven lags of the stock return. Standard errors are calculated using Hansen's (1982) generalized method of moments. Regressions include returns after May 19, 1995. a, b, c denote significance at the 1%, 5%, and 10% level, respectively. p-values are shown in parentheses.

Regressions for hourly returns are reported in Table 5. We use default-free returns to measure the effect of interest rate changes (hourly returns on the Lehman index are not available). For the hourly returns, both the interest rate and equity components are significant [in Regression (2), for example, $\sum\beta^D = 0.1074$, $\sum\beta^S = 0.1140$]. As with the daily returns, the interest rate component is significantly greater for higher-rated bonds; in Regression (3), $\sum\beta^D$= 0.2518, which is significantly greater than the coefficients for the middle- and lower-rated portfolios (p-values 0.09 and 0.10). While the S&P 500 coefficient is significant only for the highest- and middle-rated bonds, differences in the coefficients are not significant. For the underlying stock portfolio [Regressions (4), (6), and (8)], the coefficient for the highest rated bonds is significantly different (p-value 0.09) from the middle-rated group, though it is not significantly different from the coefficient for the lowest group.

For both the daily and hourly returns, we also examine the relationship between the significance of the equity component and the liquidity of the bonds. We rerun our general regression analysis [Equation (2)], dividing the 20 FIPS bonds into two portfolios based on the average number of hours per day with trades. On the daily level, the coefficient for the underlying stock portfolio for the higher-liquidity portfolio is significant while the coefficient for the lower-liquidity portfolio is not, and we reject the hypothesis that these coefficients are equal at the 10% level. On the hourly level, the coefficient for the underlying stock is not significant for either portfolio. Thus we only observe some relationship between the equity component and liquidity on the daily level.

Finally, we examine whether interest rate and equity movements are important in explaining individual bond returns by estimating Equation (2) for each bond separately. At the daily level, Table 6 documents that $\sum \beta^D$ is positive and significant in 12 of the 20 cases, with an average of 0.444 for those that are significant and 0.335 overall. The summed coefficient for the stock returns, $\sum \beta^S$, is positive and significant in 8 of the 20 cases, with an average of 0.206 for those cases and 0.117 overall. For the hourly returns, Table 7 again shows that measurement of the interest rate and equity risk is sensitive to the frequency of returns: $\sum \beta^D$ is positive and significant in 7 of the 20 cases; the average coefficient is 0.126 for those that are significant and 0.129 overall. Further, the sum of the stock variable coefficients ($\sum \beta^S$ averages 0.071 overall and 0.155 for seven cases where it is significant) still indicates a strong equity component for some individual bonds.

Since results for the individual bond regressions illustrate considerable variation across bonds in the sample, we also compare characteristics of the bonds that show a significant equity component with those that do not. The average standard deviation of underlying stock returns for bonds with (without) a significant equity component on the daily level is 0.032 (0.036); on the hourly level the average standard deviation is 0.014 (0.012). The differences in means are not significant in either case. We also find that on the hourly but not the daily level, there is a weak relationship between the equity component and the trading frequency (measured by the average number of hours with trade per day). Bonds with a significant equity component based on hourly returns trade on average 3.8 hours per day versus 2.9 for the remaining bonds, and the difference in means is significant at the 10% level.

2.3 Causality

In this section we extend our analysis of the link between high-yield bond and equity returns by testing for causality directly. We conclude that while the bond and equity returns are highly contemporaneously correlated, the relationship is not a causal one.

In the absence of an explicit price discovery model that predicts a specific relationship between high-yield bond returns and the stock and default-free returns, we assume a very general structure for the autocorrelations

Table 6
Regressions relating individual bond daily returns to interest rate and equity movements

Bond	Coupon, maturity	α	$\sum \beta^B$	$\sum \beta^D$	$\sum \beta^M$	$\sum \beta^S$	Adj R^2	N
Best Buy Co.	8.63%, 10/01/00	0.0009 (0.0785)^c	−0.5408 (0.0213)^b	0.4530 (0.0019)^a	0.1250 (0.5911)	0.0700 (0.0242)^b	0.156	205
Bethlehem Steel	10.38%, 09/01/03	0.0003 (0.7460)	−0.5966 (0.0022)^a	0.3736 (0.0721)^c	0.5488 (0.0668)^c	0.0258 (0.7462)	0.202	138
Chiquita Brands	9.63%, 01/15/04	0.0013 (0.0435)^b	−1.1207 (0.0001)^a	0.5106 (0.0179)^b	0.0911 (0.7890)	0.0921 (0.3380)	0.366	206
Eckerd Corp	9.25%, 02/15/04	0.0005 (0.0703)^c	−0.4889 (0.0039)^a	0.1244 (0.0282)^b	0.2769 (0.0250)^b	0.0250 (0.5708)	0.050	138
Flagstar	10.75%, 09/15/01	−0.0002 (0.7718)	−0.8522 (0.0001)^a	0.4026 (0.0687)^c	0.5275 (0.0687)^c	0.0020 (0.9369)	0.186	206
Flagstar Corp	11.25%, 11/01/04	−0.0013 (0.1745)	−0.5177 (0.0036)^a	0.4399 (0.1316)	0.8856 (0.0550)^c	0.0424 (0.3255)	0.154	206
Kroger Co.	8.50%, 06/15/03	0.0014 (0.0089)^a	−1.3323 (0.0001)^a	−0.0285 (0.8324)	0.2987 (0.2531)	0.0008 (0.9924)	0.291	206
NEXTEL Comms	9.75%, 08/15/04	0.0002 (0.8805)	−0.5844 (0.0039)^a	0.1176 (0.7965)	0.6814 (0.2930)	0.4395 (0.0001)^a	0.170	138
NEXTEL Comms	11.5%, 09/01/03	0.0017 (0.2825)	−0.1966 (0.1394)	0.6776 (0.0258)^b	0.6509 (0.3121)	0.2675 (0.0387)^b	0.137	206
Owens Illinois Inc.	11.00%, 12/01/03	0.0001 (0.6356)	−0.3868 (0.0246)^b	0.4133 (0.0001)^a	0.4586 (0.0015)^a	−0.0097 (0.8328)	0.226	206
Payless Cashways	9.13%, 04/15/03	−0.0013 (0.1824)	−0.5400 (0.0012)^a	0.1286 (0.7000)	0.7975 (0.1984)	0.0842 (0.3413)	0.136	206
Penn Traffic	8.63%, 12/15/03	0.0002 (0.7603)	−0.6849 (0.0010)^a	0.3051 (0.0488)^b	0.4328 (0.1693)	0.1050 (0.0691)^c	0.257	203
Playtex Family	9.00%, 12/15/03	0.0001 (0.8249)	−0.6059 (0.0004)^a	0.1216 (0.4246)	0.5237 (0.1241)	0.1030 (0.1296)	0.130	206
Service Merchandse	9.00%, 12/15/04	−0.0001 (0.9395)	−0.2299 (0.1702)	0.3745 (0.1888)	0.4398 (0.3429)	0.2287 (0.0048)^a	0.073	206
Stone Container	9.88%, 02/01/01	0.0003 (0.5742)	−0.4667 (0.0451)^b	0.5782 (0.0001)^a	0.2494 (0.2052)	0.0876 (0.0102)^b	0.207	206
Stone Container	10.75%, 04/01/02	0.0003 (0.6985)	−1.0811 (0.0001)^a	0.6821 (0.0174)^b	0.0834 (0.8317)	0.2141 (0.0033)^a	0.273	138
Unisys Corp	10.63%, 10/01/99	−0.0001 (0.9289)	−0.4892 (0.1607)	0.3569 (0.3698)	0.0452 (0.9249)	0.2574 (0.1349)	0.154	138
US Air Inc.	10.00%, 07/01/03	0.0013 (0.1897)	−0.4406 (0.0102)^b	−0.1485 (0.6834)	−0.3328 (0.4674)	0.2388 (0.0006)^a	0.260	138
Viacom Intl	8.00%, 07/07/06	0.0000 (0.9934)	−0.4001 (0.0565)^c	0.3749 (0.0001)^a	0.7014 (0.0013)^a	0.0363 (0.4775)	0.234	138
Wheeling Pittsburgh	9.38%, 11/15/03	−0.0003 (0.5729)	−0.3823 (0.0269)^b	0.4343 (0.0306)^b	0.6891 (0.0153)^b	0.0336 (0.5560)	0.119	206
Average		0.0003	−0.5969	0.3346	0.4087	0.1172		

Table reports results of the following regression:

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^D RD_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \sum_{i=0}^{ns} \beta_i^S RS_{t-i} + \varepsilon_t$$

where RB_t is the daily FIPS bond return, RD_t is the default-free Treasury returns, RM_t is the S&P 500 return, and RS_t is the underlying stock returns. Standard errors are calculated using Hansen's (1982) generalized method of moments. p-values are shown in parentheses.

Table 7
Regressions relating individual bond hourly returns to interest rate and equity movements

Bond	Coupon, maturity	α	$\sum\beta^B$	$\sum\beta^D$	$\sum\beta^M$	$\sum\beta^S$	Adj R^2	N
Best Buy Co.	8.63%, 10/01/00	0.0000 (0.6846)	−0.4485 (0.0001)[a]	0.3234 (0.0420)[b]	0.2896 (0.0451)[b]	0.0447 (0.3862)	0.094	801
Bethlehem Steel	10.38%, 09/01/03	0.0001 (0.4295)	−0.3362 (0.0001)[a]	0.1687 (0.3345)	−0.1013 (0.5851)	0.1187 (0.0673)[c]	0.061	801
Chiquita Brands	9.63%, 01/15/04	0.0001 (0.4175)	−0.4666 (0.0001)[a]	0.4480 (0.0394)[b]	−0.0494 (0.8454)	0.0224 (0.6325)	0.075	801
Eckerd Corp	9.25%, 02/15/04	0.0001 (0.1143)	−0.3490 (0.0002)[a]	−0.0641 (0.4272)	0.1278 (0.2435)	−0.0157 (0.3206)	0.100	801
Flagstar	10.75%, 09/15/01	0.0001 (0.6263)	−0.3581 (0.0001)[a]	−0.0444 (0.8333)	0.0975 (0.6036)	0.0180 (0.6916)	0.072	801
Flagstar Corp	11.25%, 11/01/04	0.0000 (0.8547)	−0.7111 (0.0001)[a]	−0.1453 (0.7515)	0.1138 (0.7729)	0.0010 (0.9930)	0.150	801
Kroger Co.	8.50%, 06/15/03	0.0001 (0.5672)	−0.5698 (0.0001)[a]	0.3100 (0.0948)[c]	−0.1030 (0.6279)	−0.0183 (0.6445)	0.101	801
NEXTEL Comms	9.75%, 08/15/04	−0.0001 (0.8828)	−0.3855 (0.0001)[a]	0.0813 (0.8276)	0.5738 (0.1254)	0.0024 (0.9795)	0.062	801
NEXTEL Comms	11.5%, 09/01/03	−0.0001 (0.7031)	−0.6400 (0.0001)[a]	0.2352 (0.5372)	0.0265 (0.9686)	0.1804 (0.4196)	0.130	801
Owens Illinois Inc.	11.00%, 12/01/03	0.0000 (0.4394)	0.0084 (0.9043)	0.1520 (0.0134)[b]	0.1521 (0.0354)[b]	0.0158 (0.7005)	0.040	801
Payless Cashways	9.13%, 04/15/03	−0.0001 (0.8151)	−0.8155 (0.0001)[a]	−0.9647 (0.0691)[c]	0.4777 (0.4821)	0.1790 (0.0399)[b]	0.164	801
Penn Traffic	8.63%, 12/15/03	−0.0001 (0.7864)	−0.2656 (0.0034)[a]	0.2930 (0.1000)[c]	0.1022 (0.5910)	0.0776 (0.0923)[c]	0.046	801
Playtex Family	9.00%, 12/15/03	0.0000 (0.7461)	−1.0988 (0.0001)[a]	0.1568 (0.3080)	0.3033 (0.2129)	0.1170 (0.0399)[b]	0.257	801
Service Merchandise	9.00%, 12/15/04	0.0000 (0.9642)	−0.5840 (0.0001)[a]	0.1690 (0.6301)	0.4312 (0.1955)	0.2111 (0.0005)[a]	0.110	801
Stone Container	9.88%, 02/01/01	0.0001 (0.5989)	−0.9682 (0.0001)[a]	0.4068 (0.1021)	0.1227 (0.5486)	0.1205 (0.0252)[b]	0.219	801
Stone Container	10.75%, 04/01/02	0.0001 (0.7925)	−0.4943 (0.0001)[a]	−0.1016 (0.8200)	−0.1128 (0.8012)	0.0148 (0.8749)	0.090	801
Unisys Corp	10.63%, 10/01/99	−0.0002 (0.4092)	−0.3193 (0.0001)[a]	0.3703 (0.1429)	0.0943 (0.7707)	0.0103 (0.9249)	0.078	801
US Air Inc.	10.00%, 07/01/03	0.0001 (0.6503)	−0.6224 (0.0001)[a]	0.3850 (0.2478)	−1.0351 (0.0412)[b]	0.2588 (0.0011)[a]	0.171	801
Viacom Intl	8.00%, 07/07/06	0.0001 (0.4223)	−0.7009 (0.0001)[a]	0.3202 (0.0281)[b]	0.3590 (0.0068)[a]	−0.0117 (0.7228)	0.151	801
Wheeling Pittsburgh	9.38%, 11/15/03	0.0000 (0.8369)	−0.4303 (0.0001)[a]	0.0831 (0.7228)	0.3317 (0.0474)[b]	0.0756 (0.1085)	0.098	801
Average		0.0000	–0.5278	0.1291	0.1101	0.0711		

Table reports results of the following regression:

$$RB_t = \alpha_t + \sum_{i=1}^{nb} \beta_i^B RB_{t-i} + \sum_{i=0}^{ni} \beta_i^D RD_{t-i} + \sum_{i=0}^{ns} \beta_i^M RM_{t-i} + \sum_{i=0}^{ns} \beta_i^S RS_{t-i} + \varepsilon_t,$$

where RB_t is the hourly FIPS bond return, RD_t is the default-free Treasury returns, RM_t is the S&P 500 return, and RS_t is the underlying stock returns. Standard errors are calculated using Hansen's (1982) generalized method of moments. p-values are shown in parentheses.

and cross-correlations of these returns. We examine the bond price impact of unexpected movements in the stock and the corresponding default-free returns. Given the positive correlations we observe between the bond and stock returns in the previous section, we now allow for the question of causality, that is, do stock returns themselves impact bond returns?

Statistically we rely on the VAR approach to examine the interrelationship of the bond and stock price returns, and we conduct an analysis of Granger causality patterns in the data. Specifically we examine the relationship between portfolios of the FIPS bonds and of the corresponding stocks on the daily and hourly levels. The VAR for the variable set $z_t = [RB_t, RS_t]'$ is estimated for all variables using the specification

$$z_t = B_1 z_{t-j} + B_2 z_{t-j} + \mu_t,$$

where RB_t and RS_t are the bond and stock returns, respectively, for day (hour) t, B_i are conformable matrices, and μ_t is a disturbance vector. Qualitatively identical results are obtained using both the S&P 500 index return and the stock portfolio return ($z_t = [RB_t, RM_t, RS_t]'$).

To test the null that (for example) the stock returns do not Granger cause the bond returns, we rely on the bivariate VAR model, and estimate by ordinary least squares (OLS)

$$RB_t = c_1 + \sum_{i=1}^{j} a_i RB_{t-i} + \sum_{i=1}^{j} b_i RS_{t-i} + \nu_{1,t},$$

where the as and bs are coefficients, c is the regression constant, ν_t is the disturbance, and j is the lag length. We then conduct an F-test of the null hypothesis: $H_0 = [b_i] = 0$, for all i. The coefficient results are not reported, as they are not significant at any reasonable level. The Granger causality tests indicate that neither bond returns are important in explaining stock returns, nor are stock returns important in explaining bond returns at these horizons. Specifically the F-statistic for the null hypothesis that hourly stock (bond) returns have no explanatory power for the bond (stock) returns is 0.84 (1.10) resulting in a p-value of 0.66 (0.37), implying that neither null can be rejected at any reasonable level of significance. Similar results are obtained on the daily level, with an F-statistic of 0.93 (0.77) and p-value of 0.51 (0.66), again implying that neither null can be rejected at any reasonable level of significance.[13]

Although our focus is on the causality between the bond and stock returns, we also examine an alternative analysis that includes the potential effect

[13] The results reported are for lag lengths of 20 for the hourly data and 10 for the daily data. Hamilton (1994) provides a discussion of the sensitivity of these tests in general to lag length choice. However, our results do not appear to be artifacts of the choice of lag length; F-statistics are statistically insignificant for all reasonable lag lengths (we let j vary from 2 to 30, at which point the regressions become insignificant).

of interest rate movements. The variable set becomes $z_t = [RB_t, RS_t, RD_t]'$, where RD_t is the default-free return. The results are not qualitatively different; the F-test for the null hypothesis that stock (bond) returns have no explanatory power for the bond (stock) returns results in a p-value of 0.27 (0.83) for the daily data and in a p-value of 0.48 (0.59) for the hourly data, again implying that neither null can be rejected at any reasonable level of significance.[14]

These results are critical in the interpretation of the regressions conducted in Section 2.2, as well as in the interpretation of previously documented findings regarding the links between the bond and equity markets: while strong significant relationships are observed among the bond and equity markets, these correlations should not necessarily be regarded as causal relationships. Any contemporaneous (or lagged) relationships observed by us (or other literature) are therefore attributed to the joint reaction to common factors.[15]

The results of this section do not negate the correlation between the markets, rather the intertemporal causality between them. Since both of these securities do react to common information events, we next investigate the reaction of each of the asset classes to firm-specific information. We estimate the impact of earnings information on both bond and stock returns, and determine how quickly this information is impounded into the prices of these securities.

3. Earnings Announcements

The previous sections indicate a strong contemporaneous correlation between bonds and the underlying stock. This section focuses on the effect of the firm-specific information contained in earnings announcements on bond prices at hourly and daily horizons. Our tests allow us to examine how quickly information is incorporated into bond relative to stock prices.

The lack of available data has made it difficult for researchers to study the impact of news announcements on bond prices. Recent exceptions are Fleming and Remolona (1997), Green (1999), and Balduzzi, Elton, and Green (2001), who examine the effects of economic news announcements

[14] Using returns based on stock prices at the end of the hour versus bond returns based on the average of the high and low prices during the hour may actually bias us toward finding that stocks lead bonds in reflecting information, particularly since the number of transactions within the hour is likely to be greater for the stock than for the bond. Despite this, the results for our dataset are not consistent with earlier research which concludes that lagged stock returns have predictive power for bond returns. We obtain similar results when the stock price is calculated as the first transaction of the hour matching the FIPS bond transactions hour, and when the stock price is calculated as the average of the high and low transactions price for the stock on the hour matching the FIPS transactions hour. Granger–Sims causality tests indicate that this lack of intertemporal causality persists even when the data is restricted to short intervals around earnings announcements.

[15] It is also possible that previous findings that lagged stock returns have explanatory power for bond returns can be attributed to the use of indicative bond prices supplied by traders rather than transactions data [Duffee (1999)].

on intraday government bond prices. Our data make it possible to examine the effect of firm-specific news on corporate bond prices at short horizons.[16]

Data on analyst's earnings forecasts are obtained from IBES. We report results for the entire sample of FIPS bonds, including the subset of 20 bonds examined in the previous section; although some bonds are not actively traded over the entire sample time period, they may become more active in response to earnings surprises. For each firm we obtain the time of the news wire story announcing quarterly corporate earnings from Dow Jones News Retrieval; almost all announcements for our sample occur early on the announcement day. We include only events where there is no additional news reported in the wire story other than that related to the earnings release. We also eliminate events for which there is significant news between the IBES forecast date and the earnings release date. This leaves us with a sample of 99 events, which covers 34 bonds from 26 companies. For 80 of these events, we have underlying stock return data.

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

$$FE_i = \ln(A_i/F_i),$$

where FE_i is the log forecast error for firm i, A_i is the announced earnings per share, and F_i is the forecast earnings per share.[17] The mean (median) earnings forecast error is 12.7% (3.6%); 71 events have positive forecast errors. Stock, bond, and market returns are calculated for different intervals around the announcement time. To examine whether earnings information is reflected in bond or stock returns, we first run the following cross-sectional regressions:

$$RB_{[-1,t]} = \alpha_0 + \alpha_1 * FE + \alpha_2 * RM_{[-1,t]} + \varepsilon \tag{3}$$

$$RS_{[-1,t]} = \alpha_0 + \alpha_1 * FE + \alpha_2 * RM_{[-1,t]} + \varepsilon, \tag{4}$$

where RB and RS are the bond and stock returns for the period starting at day (hour) -1 prior to the announcement. The ending point of the return interval, t, ranges from 0 to $+7$ for the daily data and from 0 to $+14$ for the hourly data. RM, the return on the S&P 500 index, is included to control for market movements over these return intervals.

[16] Warga and Welch (1993) show that studies measuring the timing and magnitude of bond price reactions to recent information are sensitive to the type of data used. In the context of leveraged buyout announcements and using monthly data, they show that studies which rely on exchange data or databases incorporating matrix pricing are unlikely to detect a significant impact on bond prices.

[17] We exclude from the analysis three observations where A_i or F_i is negative. Our results are insensitive to alternative definitions of the forecast error including $FE_i = (A_i - F_i)/F_i$ and $FE_i = (A_i - F_i)/S_i$, where S_i is the stock price 10 days prior to the announcement for observations where stock price data are available. Regression results are also not sensitive to the removal of any outliers (based on standardized residuals). We also examine regressions where we standardize both bond and stock returns by dividing by the standard deviation of returns in nonannouncement periods: results are qualitatively the same with this standardization.

We also run a second set of regressions, redefining our return window in a way that allows us to observe how quickly information is completely incorporated into prices. This is especially illuminating when dealing with microstructure data, where the focus is on the specific time frame within which price discovery takes place. We run regressions similar to Equations (3) and (4), except we examine one-day (one-hour) windows starting at the date (hour) prior to the announcement. For the daily data, the dependent variables for the regressions are $RB_{[t,\,t+1]}$ and $RS_{[t,\,t+1]}$, where t ranges from -1 to $+4$. For the hourly data, t ranges from -1 to $+13$. The S&P 500 returns are of course calculated over the same time intervals.

Table 8 reports results for regressions using daily data. Test statistics are computed using heteroscedastic-consistent variance estimates [White (1980)].

Table 8
Effect of corporate earnings announcements on daily returns of FIPS bonds and underlying stocks

Daily return interval	Intercept	Earnings forecast error	S&P 500 return	Adjusted R^2	N
Panel A: Bond returns					
[−1 : 0]	0.0010 (0.342)	0.0044 (0.000)[a]	0.1569 (0.329)	0.156	99
[−1 : 1]	0.0004 (0.809)	0.0053 (0.000)[a]	0.3523 (0.013)[b]	0.072	98
[−1 : 2]	0.0005 (0.778)	0.0050 (0.000)[a]	0.6208 (0.001)[a]	0.084	98
[−1 : 3]	0.0007 (0.745)	0.0058 (0.000)[a]	0.3982 (0.067)[c]	0.064	98
[−1 : 4]	0.0002 (0.940)	0.0051 (0.000)[a]	0.4183 (0.018)[b]	0.061	95
[−1 : 5]	−0.0007 (0.717)	0.0048 (0.002)[a]	0.4353 (0.004)[a]	0.054	93
[−1 : 6]	0.0014 (0.458)	0.0040 (0.002)[a]	0.1473 (0.513)	0.012	93
[−1 : 7]	0.0008 (0.745)	0.0037 (0.005)[a]	0.3540 (0.133)	0.020	91
[−1 : 0]	0.0010 (0.342)	0.0044 (0.000)[a]	0.1569 (0.329)	0.156	99
[0 : 1]	−0.0002 (0.868)	0.0005 (0.744)	0.1728 (0.280)	−0.015	98
[1 : 2]	0.0012 (0.212)	−0.0011 (0.227)	−0.1944 (0.364)	0.003	98
[2 : 3]	0.0001 (0.918)	0.0011 (0.294)	0.0583 (0.696)	−0.009	98
[3 : 4]	0.0006 (0.508)	−0.0008 (0.288)	0.0801 (0.721)	−0.012	95
[4 : 5]	−0.0004 (0.613)	−0.0005 (0.354)	0.2942 (0.119)	0.020	93
Panel B: Stock returns					
[−1 : 0]	0.0038 (0.454)	0.0192 (0.004)[a]	−0.4003 (0.563)	0.107	80
[−1 : 1]	0.0060 (0.327)	0.0271 (0.003)[a]	0.3393 (0.599)	0.128	79
[−1 : 2]	−0.0016 (0.801)	0.0278 (0.002)[a]	1.2181 (0.070)[c]	0.131	79
[−1 : 3]	−0.0047 (0.513)	0.0294 (0.000)[a]	1.4443 (0.039)[b]	0.140	79
[−1 : 4]	0.0034 (0.582)	0.0258 (0.001)[a]	0.5682 (0.397)	0.099	79
[−1 : 5]	0.0084 (0.339)	0.0243 (0.003)[a]	−0.2536 (0.736)	0.085	76
[−1 : 6]	0.0081 (0.399)	0.0233 (0.017)[b]	−0.8079 (0.344)	0.090	76
[−1 : 7]	−0.0004 (0.966)	0.0265 (0.009)[a]	−0.1182 (0.889)	0.063	74
[−1 : 0]	0.0038 (0.454)	0.0192 (0.004)[a]	−0.4003 (0.563)	0.107	80
[0 : 1]	0.0031 (0.214)	0.0082 (0.021)[b]	0.5663 (0.334)	0.055	79
[1 : 2]	−0.0059 (0.007)[a]	−0.0008 (0.773)	1.1743 (0.006)[a]	0.054	79
[2 : 3]	0.0011 (0.688)	−0.0001 (0.953)	−0.4250 (0.360)	−0.018	79
[3 : 4]	0.0015 (0.606)	−0.0006 (0.828)	1.8532 (0.002)[a]	0.066	79
[4 : 5]	−0.0018 (0.522)	0.0027 (0.118)	0.7460 (0.113)	−0.001	76

Table reports results of OLS regressions where the dependent variable is the FIPS bond or stock return over the interval specified. Sample includes observations for all FIPS bonds where analyst forecasts of quarterly earnings are available from IBES. Date 0 is the date of the earnings announcement obtained from Dow Jones Newswire. Earnings forecast errors are calculated as the log of the difference between the announced and forecast earnings. p-values are shown in parentheses.

Bond returns (panel A) are significantly positively related to the earnings forecast error variable starting at the one-day return. Increasing the window around the event time, the forecast error coefficient remains significant but begins to drop in magnitude through day +7. Results are nearly identical when we include the default-free return as an additional explanatory variable (not reported). For comparison, panel B reports the regressions for the underlying stock; the forecast error is significant over all the intervals reported. The R^2s for the stock return regressions are consistent with those reported in previous research [Lev (1989)].

The second set of regressions in each panel indicates that information is impounded quickly into both bond and stock prices. For the bond returns, the forecast error is positive and significant for the one-day interval ending on the announcement date, [–1, 0]. Returns for any subsequent time interval are not significantly related to the forecast error. These results suggest that the information related to the earnings news is fully reflected in bond prices by the end of the announcement day. For the stock returns, we find that returns past the [0, 1] interval are not related to the forecast error. Information is largely incorporated on the announcement date and to a smaller degree on the following date.

The daily regression results indicate that all information is quickly impounded into both bond and stock prices. We next examine how earnings information is reflected in the hourly bond and stock returns. Table 9 reports these regressions for the hourly data. For the first set of bond return regressions in panel A, the earnings forecast error variable is significant for the [–1, 1] interval covering the hour following the announcement through the [–1,14] interval. The stock return regressions (panel B) show that the earnings forecast error is also significant for each of the intervals examined.

As with the daily returns, we also examine the speed with which information is fully incorporated into prices. The bond return regressions show that information is fully incorporated into the high-yield bond prices by the end of the fourth hour following the earnings announcement.[18] The stock return regressions indicate that information is fully incorporated by the seventh hour following the announcement, though the significance levels decline substantially after the hour of the announcement. Although information is incorporated into stock prices over a slightly longer time interval, the greatest impact appears in the first hour. Since most announcements occur early on the announcement date, these results show that information is quickly incorporated into both bond and stock prices within that day. Most importantly, however, the evidence is inconsistent with the idea that information is incorporated into bond prices only slowly over time.

[18] We further examine the sensitivity of our results to the frequency of bond trading. When we run the same set of regressions including only the subset of events where the bond trades at both the announcement and the following hour, the results are qualitatively the same as those reported. We also do not observe any relationship between the size of the equity coefficient (as measured in Section 2.1) and the speed of adjustment to earnings news.

4. Pricing Errors and Relative Market Quality

In order to further examine the relative efficiency of the two markets, we measure the market quality for the FIPS bond and for the underlying stocks. Specifically we examine whether pricing errors of different magnitudes are

Table 9
Effect of corporate earnings announcements on hourly returns of FIPS bonds and underlying stocks

Hourly return interval	Intercept	Earnings forecast error	S&P 500 return	Adjusted R^2	N
Panel A: Bond returns					
[−1 : 0]	0.0014 (0.019)^b	−0.0005 (0.265)	0.0882 (0.444)	−0.013	98
[−1 : 1]	0.0008 (0.222)	0.0020 (0.015)^b	−0.0607 (0.743)	0.066	98
[−1 : 2]	0.0008 (0.324)	0.0032 (0.005)^a	−0.1189 (0.608)	0.120	99
[−1 : 3]	0.0010 (0.244)	0.0020 (0.026)^b	−0.0963 (0.574)	0.031	99
[−1 : 4]	0.0016 (0.168)	0.0045 (0.000)^a	0.2151 (0.146)	0.148	99
[−1 : 5]	0.0004 (0.710)	0.0046 (0.001)^a	0.1156 (0.443)	0.160	99
[−1 : 6]	0.0007 (0.491)	0.0045 (0.000)^a	0.1122 (0.465)	0.170	98
[−1 : 7]	0.0006 (0.529)	0.0045 (0.000)^a	0.1001 (0.394)	0.174	98
[−1 : 8]	0.0012 (0.393)	0.0051 (0.000)^a	0.2884 (0.026)^b	0.133	98
[−1 : 9]	−0.0005 (0.715)	0.0064 (0.000)^a	0.1703 (0.183)	0.154	98
[−1 : 10]	0.0003 (0.866)	0.0053 (0.000)^a	0.1664 (0.165)	0.094	98
[−1 : 11]	0.0021 (0.214)	0.0052 (0.000)^a	0.2629 (0.017)^b	0.088	98
[−1 : 12]	0.0015 (0.398)	0.0050 (0.000)^a	0.2931 (0.003)^a	0.073	98
[−1 : 13]	0.0008 (0.647)	0.0053 (0.000)^a	0.2861 (0.007)^a	0.067	98
[−1 : 14]	0.0015 (0.365)	0.0056 (0.000)^a	0.2909 (0.011)^b	0.084	98
[−1 : 0]	0.0014 (0.019)^b	−0.0005 (0.265)	0.0882 (0.444)	−0.013	98
[0 : 1]	−0.0004 (0.463)	0.0024 (0.001)^a	0.1701 (0.454)	0.164	98
[1 : 2]	−0.0002 (0.764)	0.0012 (0.047)^b	0.1156 (0.696)	0.025	98
[2 : 3]	0.0002 (0.752)	0.0022 (0.012)^b	−0.0928 (0.786)	0.040	98
[3 : 4]	0.0002 (0.807)	0.0027 (0.001)^a	0.1738 (0.201)	0.113	98
[4 : 5]	−0.0010 (0.194)	0.0000 (0.981)	−0.0209 (0.936)	−0.021	98
[5 : 6]	0.0007 (0.143)	−0.0003 (0.523)	−0.4004 (0.047)^b	−0.001	98
[6 : 7]	−0.0001 (0.652)	−0.0001 (0.363)	−0.1113 (0.207)	−0.010	98
[7 : 8]	0.0003 (0.714)	0.0004 (0.416)	−0.0728 (0.786)	−0.017	98
[8 : 9]	−0.0015 (0.036)^b	0.0013 (0.203)	0.0638 (0.822)	0.012	98
[9 : 10]	0.0008 (0.111)	−0.0011 (0.165)	0.1861 (0.299)	0.042	98
[10 : 11]	0.0018 (0.010)^a	−0.0002 (0.650)	0.2163 (0.030)^b	−0.010	98
[11 : 12]	−0.0006 (0.529)	−0.0005 (0.688)	−0.3075 (0.254)	−0.013	98
[12 : 13]	−0.0003 (0.686)	0.0002 (0.746)	−0.0390 (0.861)	−0.020	98
[13 : 14]	0.0009 (0.039)^b	0.0003 (0.673)	−0.0634 (0.722)	−0.016	98
Panel B: Stock returns					
[−1 : 0]	0.0021 (0.514)	0.0099 (0.005)^a	1.1990 (0.229)	0.070	80
[−1 : 1]	−0.0011 (0.738)	0.0104 (0.002)^a	−0.9900 (0.321)	0.064	80
[−1 : 2]	−0.0013 (0.681)	0.0115 (0.002)^a	−1.0934 (0.341)	0.082	80
[−1 : 3]	−0.0015 (0.652)	0.0134 (0.001)^a	−1.1169 (0.318)	0.107	80
[−1 : 4]	−0.0022 (0.557)	0.0168 (0.001)^a	−0.3898 (0.625)	0.130	80
[−1 : 5]	0.0003 (0.939)	0.0180 (0.001)^a	−0.8411 (0.279)	0.132	80
[−1 : 6]	0.0026 (0.580)	0.0167 (0.004)^a	−0.9254 (0.182)	0.093	80
[−1 : 7]	0.0075 (0.190)	0.0210 (0.005)^a	−0.8103 (0.223)	0.096	79
[−1 : 8]	0.0069 (0.209)	0.0212 (0.006)^a	−0.9330 (0.210)	0.112	79
[−1 : 9]	0.0069 (0.236)	0.0221 (0.004)^a	−0.7413 (0.156)	0.109	79
[−1 : 10]	0.0048 (0.406)	0.0218 (0.002)^a	−0.8148 (0.071)^c	0.114	79
[−1 : 11]	0.0066 (0.264)	0.0229 (0.002)^a	−0.2105 (0.456)	0.111	79
[−1 : 12]	0.0053 (0.389)	0.0231 (0.003)^a	−0.1451 (0.705)	0.103	79
[−1 : 13]	0.0047 (0.426)	0.0230 (0.003)^a	−0.1559 (0.718)	0.107	79
[−1 : 14]	0.0045 (0.446)	0.0224 (0.004)^a	−0.0139 (0.974)	0.098	79

Table 9
(continued)

Hourly return interval	Intercept	Earnings forecast error	S&P 500 return	Adjusted R^2	N
[−1 : 0]	0.0021 (0.514)	0.0099 (0.005)[a]	1.1990 (0.229)	0.070	79
[0 : 1]	−0.0035 (0.005)[a]	0.0006 (0.737)	−1.3196 (0.041)[b]	0.028	79
[1 : 2]	−0.0002 (0.856)	0.0008 (0.373)	0.7866 (0.360)	−0.012	79
[2 : 3]	0.0006 (0.681)	0.0018 (0.098)[c]	0.2328 (0.772)	0.017	79
[3 : 4]	−0.0012 (0.441)	0.0040 (0.069)[c]	0.4242 (0.350)	0.050	79
[4 : 5]	0.0027 (0.097)[c]	0.0008 (0.562)	0.2730 (0.711)	−0.022	79
[5 : 6]	0.0000 (0.985)	−0.0009 (0.397)	2.3675 (0.103)	0.045	79
[6 : 7]	0.0055 (0.002)[a]	0.0038 (0.061)[c]	1.5211 (0.034)[b]	0.064	79
[7 : 8]	−0.0004 (0.773)	0.0014 (0.274)	1.2444 (0.029)[b]	0.024	79
[8 : 9]	−0.0005 (0.714)	0.0015 (0.187)	1.2295 (0.296)	0.003	79
[9 : 10]	−0.0019 (0.075)[c]	−0.0002 (0.824)	−0.1012 (0.847)	−0.026	79
[10 : 11]	0.0016 (0.104)	0.0013 (0.108)	1.4186 (0.000)[a]	0.121	79
[11 : 12]	−0.0014 (0.173)	0.0003 (0.595)	0.6333 (0.207)	−0.004	79
[12 : 13]	−0.0005 (0.772)	−0.0002 (0.875)	−0.3251 (0.655)	−0.023	79
[13 : 14]	−0.0003 (0.811)	−0.0007 (0.644)	0.4124 (0.344)	−0.012	79

Table reports results of OLS regressions where the dependent variable is the FIPS bond (panel A) or stock (panel B) return over the interval specified. Hour 0 is the hour of the earnings announcement obtained from Dow Jones Newswire. *p*-values are shown in parentheses.

associated with the different markets. Clearly, complete resolution of this issue involves the ability to distinguish among the potential factors for any observed differences. For example, market mechanism effects may confound the comparison between the debt and equity markets (the bonds trade over the counter in a dealer-driven system, while the majority of the stocks trade on either the NYSE or the AMEX where the specialist mediates trade).

Hasbrouck (1993) decomposes security prices into random walk and stationary components, with the former representing the efficient price of the security. The second, transitory component is generally regarded as the pricing error, or the dispersion between the observed price and the "true" or efficient price, which is assumed to follow a random walk:

$$p_t^B = m_t^B + s_t^B \tag{5A}$$

$$p_t^S = m_t^S + s_t^S \tag{5B}$$

$$m_t^B = m_{t-1}^B + w_t^B \tag{5C}$$

$$m_t^S = m_{t-1}^S + w_t^S, \tag{5D}$$

where p_t is the logarithmic transaction price of the security at time t, B denotes the bond, S denotes the stock, m_t is the logarithmic value of the security at time t, and s is the pricing error. The variance of the pricing error, σ_s^2, is generally regarded as the inverse measure of market quality.

Hasbrouck (1993) makes two simplifying identification restrictions on the pricing error to facilitate the estimation of the pricing error and its variance.

We follow his identification process (as an illustrative application only), and assume that the pricing error is written:

$$s_t^B = \alpha^B w_t^B + \eta_t^B \tag{6A}$$

$$s_t^S = \alpha^S w_t^S + \eta_t^S, \tag{6B}$$

where η_t is a disturbance uncorrelated with w_t, w_t are uncorrelated increments representing innovations in the true price, $E(w_t) = 0, E(w_t^2) = \sigma_w^2$, and $E(w_t w_\tau) = 0$ for $t \neq \tau$. The first term, αw_t, can be thought of as the information-related term, and the second, η_t, can be thought of as the information-unrelated term.[19] When $\alpha = 0$, the pricing error is assumed to be completely information unrelated, and the specification corresponds to the Roll (1984) spread estimator ($\eta_t = \pm(spread)/2$), depending on whether the order represents a buy or a sell. Schultz (2000) finds that the Roll estimator performs well for intraday trade data for NASDAQ stocks. Since no evidence exists as to the estimator's performance for bond transactions, we also consider an alternative information-related pricing specification, where $\alpha \neq 0$.[20]

Since the log return can be written as $r_t = s_t - s_{t-1} + w_t$, and since w_t and s_t are serially uncorrelated, r_t, which has nonzero autocovariances at the first lag only, can be represented as a moving average process, where σ_ε^2 and A fully characterize the variance and serial covariance of the return process. Identification restrictions are imposed for estimation of this underidentified system. The first, that the pricing error is information uncorrelated (Roll spread estimator model), has $\alpha = 0$ and $\sigma_s^2 = \sigma_n^2$ and implies that $\sigma_w^2 = (1-A)^2\sigma_\varepsilon^2$, $\sigma_s^2 = A\sigma_\varepsilon^2$, and $\sigma_S = \sqrt{\rho_i}\sigma_{Ri}$, where ρ_i is the serial correlation coefficient and σ_{Ri} is the standard deviation of the security return. The second restriction, that the pricing error is information correlated is attributed to Beveridge and Nelson (1981) and imposes the restriction that $\eta_t = 0$. Under this specification, Hasbrouck (1993) shows that $\alpha = A/(1-A)$, $w_t = (1-A)\varepsilon_t$, $s_t = \alpha w_t$, $\sigma_w^2 = (1-A)^2\sigma_\varepsilon^2$, $\sigma_s^2 = A^2\sigma_\varepsilon^2$, and $\sigma_S = \sqrt{.5(1-\sqrt{1-4\rho_i^2})}\sigma_{Ri}$.

Estimating the hourly pricing errors for each market allows us to compare the quality of the two markets. We estimate the market quality measure, *MQ*, as 1 minus twice the ratio of the pricing error variance of the security to the total return variance of the security, $MQ_i = 1 - 2 * (\sigma_{si}^2/\sigma_{Ri}^2)$, where σ_{Ri}^2 is the variance of the return. This measure can be interpreted as the proportion

[19] Both terms may impound microstructure effects. The information-unrelated term is assumed to be determined by the trading mechanism and other microstructure effects, such as price discreteness, noise trading, and transient liquidity effects. The information-related term arises from asymmetric information (adverse selection effects in the presence of fixed transaction costs) and from partial (lagged) adjustment, or overreaction, of prices to information. In a Glosten and Milgrom (1985) world, this term may be interpreted as rising from the existence of asymmetric information in the presence of fixed costs ($\alpha > 0$), $\sigma_n^2 > 0$.

[20] Hasbrouck (1993) provides a discussion on the sensitivity of the results to the specification and on the lack of compelling economic evidence in favor of either model. In addition, Harris (1990) provides evidence on the poor performance of the Roll spread estimator in daily and weekly data.

of the total return variance due to fundamental variance. As the quality of the market worsens, this measure increases.[21]

For the information-unrelated (Roll) case, the average pricing error standard deviation estimate for the 20 FIPS bonds (σ_{sb}) is 0.0033, the average standard deviation estimate (σ_{Rb}) is 0.0063, and the average bond market quality measure (MQ_b) is 0.7156 (with a standard error of 0.0513). Similarly, for the 20 stocks, the average pricing error standard deviation estimate (σ_{ss}) is 0.0055, the average standard deviation estimate (σ_{Rs}) is 0.0125, and the average stock market quality measure (MQ_s) is 0.7583 (with a standard error of 0.0479).[22]

For the information-correlated case, the average pricing error standard deviation estimate for the 20 FIPS bonds (σ_{sb}) is 0.0017 and the average bond market quality measure (MQ_b) is 0.9284 (standard error of 0.0146). Similarly, for the 20 stocks, the average pricing error standard deviation estimate (σ_{ss}) is 0.0028 and the average stock market quality measure (MQ_s) is 0.8938 (standard error of 0.0775).[23]

As expected, the results are sensitive to the identification restrictions assumed. The information-related and unrelated cases represent two polar extremes in terms of pricing error specification restrictions. While in the information-uncorrelated case, the bond market is of lower quality than the stock market, the relationship is reversed in the information-correlated case. Furthermore, in both cases the average pricing error standard deviation estimate for the stocks (σ_{ss}) is greater than that for the bonds (σ_{sb}). We conclude that the market quality of the FIPS bond market is no poorer than that for the underlying stocks.

Other measures used in prior research to describe market quality include liquidity, the bid-ask spread and market depth. While data constraints limit our ability to examine these latter elements for corporate bonds, the time-series properties of the hourly data afford the computation of the pricing error variances that measure market quality. Our results are not inconsistent, however, with other recent findings on market quality for the high-yield debt markets. Hong and Warga (2000) estimate effective bid-ask spreads in the ABS market and the dealer market based on insurance company transactions and find that high-yield bonds have similar spreads in both markets. Chakravarty and Sarkar (1999) report similar bid-ask estimates for high-yield bonds for the same database of insurance company trades. Our finding that

[21] We are grateful to Larry Glosten for suggesting this market quality measure and its intuitive interpretation.

[22] The method used for construction of the hourly bond price series (using the midpoint of the high and low prices for the hour) could potentially cause a downward bias in the pricing error estimate for the bond return series of up to roughly half when there are two or more observations per hour. However, based on Alexander, Edwards, and Ferri (1999, 2000), who observe real-time FIPS transactions, for most hours and most bonds there is at most one transaction per hour, thereby mitigating the degree of bias expected.

[23] One bond (and corresponding stock) was removed from the sample for both specifications because a positive serial correlation was estimated.

market quality is no poorer for the bonds in our sample than for their underlying stocks is consistent with their findings that trading costs do not appear to be unusually high for insurance company trades in corporate bonds.

5. Conclusion

Using a unique dataset based on daily and hourly transaction prices for 55 high-yield bonds, we examine the informational efficiency of the corporate bond market relative to the market for the underlying stock. In contrast to previous research utilizing weekly or monthly dealer quotes, we find that stocks do not lead bonds in reflecting firm-specific information. Although we also find positive and significant correlations between bond and stock returns, even on the daily and intraday level, we establish that these are not causal relationships. We further consider the impact of firm-specific information on corporate bond prices by examining price behavior around earnings releases and find that this information is quickly incorporated into both bond and stock prices, even at short return horizons. Finally, we find that market quality is no poorer for the bonds in our sample than for the underlying stocks.

Our findings suggest that the market for actively traded bond issues such as those in our sample is informationally efficient, even relative to the market for the underlying stocks. There have been a number of studies that raise concerns over the quality of bond prices. Differences in our results and prior studies may be largely due to the unavailability of higher-frequency transaction-based data and perhaps different trading mechanisms. Previous samples also include many less actively traded bonds than studied here. Although increasing transparency in the corporate bond market through a centralized public source of price quotes such as FIPS may well reduce trading costs, the largest potential gains would most likely be for less-liquid issues. Also, the bonds studied here may have benefited from the transparency added by inclusion in the FIPS system. Of interest is that previous attempts to make the entire corporate bond market more transparent via electronic trading systems have been largely unsuccessful.[24] It would be useful in future research to compare the behavior of bonds in our sample to that of other high-yield bonds whose trades are reported to the NASD but which are not publicly displayed.

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[24] For a description of these attempts, see "Never Cross a Bond Dealer," *Business Week*, 3/9/98. As described in Section 2, the success of the NASD's FIPS as a useful quotation system has been limited. As of July 1, 2002, FIPS has been incorporated into a broader NASD initiative known as TRACE (Trade Reporting and Compliance Engine).

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