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Missing the marks? Dispersion in corporate bond valuations across mutual funds

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Missing the Marks? Dispersion in Corporate Bond Valuations Across Mutual Funds

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Missing the Marks? Dispersion in Corporate Bond Valuations Across Mutual Funds*

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Abstract

We study the dispersion of month-end valuations placed on identical corporate bonds by different mutual funds. Such dispersion is related to bond-specific characteristics associated with liquidity and market volatility. TRACE may have contributed to the general decline in dispersion over our sample period, though other factors most likely played roles. Further tests reveal marking patterns to be consistent with returns smoothing behavior by managers. Funds with ambiguous marking policies and those holding “hard-to-mark” bonds appear more prone to smooth reported returns. From a regulatory perspective, we see little downside to requiring funds to explicitly state their marking standards.

1. Introduction

How hard is it to mark illiquid securities for position valuation purposes? The issue of marking accuracy by banks, hedge funds, and mutual funds became a focal point for company boards, regulators and the financial press during the credit crisis that began in August 2007. The SEC is actively examining how institutional investors "value their hard-to-value" securities.[1] Indeed, two investment advisers recently settled charges of negligent mispricing of certain mortgage-backed bonds and high-yield municipal bonds in their respective mutual funds in ways that caused artificially high prices for their funds' shares.[2] This paper offers direct insights into important aspects of pricing securities for position valuation purposes by examining the dispersion of month-end valuations simultaneously placed on identical US corporate bonds by an important set of traders, the managers of US bond mutual funds.

We first examine the cross-fund pricing dispersion of individual bonds. Marking corporate bonds *is* hard. After controlling for differences related to choice of marking standards, we show that pricing dispersion is related to bond-specific characteristics typically associated with market liquidity. Specifically, cross-fund pricing dispersion is higher for lower credit quality bonds, longer maturity bonds, and smaller-sized issues. Price dispersion for individual bonds also increases during periods when bond market return volatility is high.

We next study the time series of bond price dispersion. Bond price dispersion declined during our sample period. Of course, a decline in price dispersion over the entire sample period would be consistent with a number of explanations. Interestingly, during this same time period, Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engine (TRACE) for collecting and disseminating corporate bond transaction details expanded. There is some evidence that the declines in price dispersion were faster during the six months after the TRACE expansions. However, the declines were gradual and there is no evidence that the directly affected bonds dropped more rapidly.

[1] As reported in Volz (2009) and Pulliam, Smith and Siconolfi (2007).
[2] See the SEC's actions versus Evergreen Investment Management Company, LLC and Evergreen Investment Services, Inc. (http://www.sec.gov/litigation/admin/2009/34-60059.pdf) and Heartland Advisors, Inc. (http://www.sec.gov/litigation/admin/2008/33-8884.pdf).

Finally, we investigate whether bond mutual funds strategically mark bonds to smooth reported returns. Returns smoothing involves marking positions such that the net asset value (NAV) is set above or below the true value of fund shares, resulting in wealth transfers across existing, new and redeeming fund investors. Moreover, returns smoothing distorts a fund's risk-return profile, such as its Sharpe ratio, perhaps leading investors to make sub-optimal allocation decisions.

Like their hedge fund brethren, mutual fund managers compete with each other to attract new fund inflows on the basis of risk-adjusted performance statistics. Thus, all mutual fund managers have an incentive to smooth returns. However, while the motive to smooth returns exists, the means and opportunity for mutual fund managers to engage in discretionary returns management may be significantly more limited than those of unregulated hedge fund managers. One important constraint is SEC oversight of mutual funds regarding marking policies, especially with respect to adherence to each fund's statements to investors about how it will mark securities. While the majority of funds explicitly describe their security marking practices in their prospectuses (such as the use of bid prices or the midpoint of bid and ask price indications contributed by professional bond pricing services), some funds provide only ambiguous statements (such as a practice of marking debt securities at "fair value"). Of course, managers of funds concentrating on US Treasury bond investments have little scope to shade their marks. However, corporate bond fund managers may have substantial room to adjust prices of their illiquid, thinly traded securities upward or downward to smooth returns.

We present two sets of tests of returns smoothing behavior. Our first tests focus on the individual bond marks. The results reveal that the probability of observing a "high mark" is larger when a fund reports a return that underperforms the index. The results also show that the probability of observing a "low mark" is larger when a fund reports a return that outperforms the index. These patterns in the individual bond marks are consistent with returns smoothing.

Our second tests of returns smoothing behavior focus directly on the fund returns themselves. Our study is the first to provide returns smoothing evidence using direct holdings-based estimates of delegated portfolio managers' true economic returns. To date, researchers have focused on hedge fund reported returns. Lacking access to individual hedge fund holdings, Getmansky, Lo and Makarov (2004) rely heavily on econometric techniques to make indirect inferences about the relationship between reported and true economic returns of hedge funds. They find significant serial correlation in hedge fund returns and suggest that their findings may be driven either by problems in valuing illiquid assets or by discretionary returns management. Empirically distinguishing between the illiquidity and discretionary returns management explanations using only reported returns data may be difficult. Bollen and Pool (2008, 2009) make inferences using reported returns and find evidence consistent with hedge funds actively delaying or avoiding the reporting of small losses. Adding to the literature on returns management by delegated portfolio managers, our paper uses actual portfolio holdings data and develops direct tests to distinguish between the illiquidity and return smoothing explanations.

We develop a holdings-based "custom benchmark" to study fund performance using common bond marks that allows for a direct test of returns smoothing behavior. Our estimates for a variant of Getmansky, Lo and Makarov's (2004) model imply that the idiosyncratic part of a fund's reported return moves in the opposite direction of the contemporaneous true economic return. This is consistent with returns smoothing. The quantitative importance of such smoothing is larger for funds that we classify as "ambiguous" markers. In addition, the quantitative impact of such smoothing is larger for funds holding portfolios of "hard-to-mark" bonds. Such funds have greater leeway in marking bonds up or down because the wider range of marks by other funds makes it easier to justify one's own marking choice as reasonable. Taken altogether, these results suggest that managers of funds that lack an explicitly stated marking policy (i.e., have the "means") and hold portfolios of bonds that have the widest marking uncertainty (i.e., have the "opportunity") are most prone to smoothing reported fund returns.

The remainder of the paper is organized as follows. Section 2 provides a review of the related literature and discusses some specific issues related to valuing the individual holdings of bond funds. Section 3 discusses our data and summary statistics on bond fund holdings. Section 4 discusses the impact of bid-price versus mid-price bond marking standards. Section 5 presents our main empirical findings on cross-fund individual bond price dispersion, fund-by-fund portfolio marking practices and the impact of TRACE on bond valuation precision. Section 6 investigates the relationship between marking patterns of certain funds and possible returns smoothing behavior. Section 7 concludes.

2. The setting

Some students of equity markets and equity mutual funds may already be puzzled with our focus on the *dispersion* of month-end prices of identical bonds. Unlike equities, the overwhelming majority of bond trading takes place in over-the-counter dealer markets instead of on centralized exchanges. Thus, bond mutual funds do not share common access to a single exchange-determined closing price for each individual bond issue.[3] For some issues, this lack of an exchange-determined closing price is not an important impediment to valuing a fund's holding. For example, trading in each of the most recently auctioned (on-the-run) US Treasury securities is highly liquid and transparent. Dealer-to-dealer and dealer-to-customer electronic trading platforms and the ubiquitous Bloomberg terminal offer continuous pictures of bid and asked prices for these securities. In stark contrast, most high-yield corporate bond issues trade infrequently in thin, illiquid markets. Indeed, many individual corporate bond issues are held mainly as long-term investments in insurance company portfolios and trade rarely after an initial distribution period. So a mutual fund may need to produce daily valuations for some specific issues that have not traded for days or even weeks.

2.1. Related literature

Our research touches on themes that have stimulated a number of recent studies in the academic literature including mutual fund valuation fairness, the relationship between market transparency and pricing efficiency, and the specific impacts of TRACE on the US corporate bond market. Problems associated with fairly setting daily mutual fund NAVs have been addressed in the academic literature, especially with regard to the activities of market-timing traders. Market-timing activity has been particularly severe for funds that naturally hold illiquid securities – e.g., international equity funds, small-

[3] Valuing equities based upon exchange-determined closing prices can also be problematic since such prices for many thinly-traded stocks may be stale. See the fair value discussion below.

capitalization equity funds and high-yield corporate bond funds. Previous studies find evidence of large fund trading flows and large excess returns to stale price-oriented mutual fund trading strategies.[4] These results have focused attention on the need to accurately value securities positions for mutual fund NAV calculations. Our focus on the cross-fund dispersion of mutual fund valuations on a given security offers direct observations and insights into NAV calculation problems at the *individual security* level.

The literature has also investigated the relationship between market transparency and pricing efficiency and, as relates to corporate bonds, the specific impacts of TRACE on trading costs in the US corporate bond market. This literature distinguishes between *pre-trade* transparency (e.g., dissemination of bid and ask quotations, market depth, etc.) and *post-trade* transparency (e.g., timely public reporting of price and quantity data from actual trades). In this light, the impact of TRACE's introduction of post-trade price transparency in the secondary corporate bond market is of particular interest. Indeed, TRACE has already attracted attention in the market microstructure transactions costs literature. Bessembinder, Maxwell and Venkataraman (2006) estimate that TRACE eligibility reduces trade execution costs by one-half, and that a spillover liquidity effect results in a one-fifth cost reduction even for non-eligible bonds.[5] Edwards, Harris and Piwowar (2007) show that corporate bond transaction costs, measured as a function of trade size, are lower for bonds with transparent trade prices and that such costs drop when TRACE starts to publicly disseminate bond prices. Goldstein, Hotchkiss and Sirri (2007) investigate the last-sale trade reporting impact on BBB-rated corporate bond market liquidity. They find that the effect of post-trade transparency varies with trade size and has a neutral or positive effect on market liquidity. Except for the case of the most infrequently traded issues, bid-ask spreads on bonds whose prices become transparent decline by more than that of a control group. Our investigation of TRACE impacts on price dispersion relates most directly to Bessembinder, Maxwell and Venkataraman's (2006) framework since they motivate a presumed salutary impact of TRACE on

[4] See, for example, Bhargava, Bose and Dubofsky (1998), Boudoukh, Richardson, Subrahmanyam and Whitelaw (2002), Chalmers, Edelen and Kadlec (2001), Goetzmann, Ivkovic and Rouwenhorst (2001), Green and Hodges (2002) and Zitzewitz (2003)

[5] This finding is consistent with a related *liquidity externality* found for Tel Aviv Stock Exchange securities by Amihud, Mendelson and Lauterbach (1997) since improved price discovery for one security improves price discovery for other related securities.

transactions costs by focusing on the role of improved precision in estimating corporate bond value.[6]

2.2. Pricing bond holdings for mutual fund NAV purposes

Under the Investment Company Act of 1940, the definition of "value" for mutual fund securities holdings is construed in one of two ways. Securities for which "readily available" market quotations exist must be valued at market levels. All other securities must be priced at "fair value" as determined in good faith according to processes approved by the fund's board of directors. Marking a particular security at a fair value requires a determination of what an arm's-length buyer, under the circumstances, would currently pay for that security. SEC Accounting Series Release Nos. 113 and 118 recognize that no single standard exists for determining fair value. By the SEC's interpretation, a board acts in good faith when its fair value determination is the result of a sincere and honest assessment of the amount that the fund might reasonably expect to receive for a security upon its current sale, based upon all of the appropriate factors that are available to the fund. Fund directors must "satisfy themselves that all appropriate factors relevant to the value of securities for which market quotations are not readily available have been considered" and "determine the method of arriving at the fair value of each such security."

As a practical matter, a mutual fund could comply with the Investment Company Act's mandate to mark bond positions using "readily available" market quotations by relying on a single pricing service or multiple securities pricing services and/or securities dealers for the fund's holdings.[7] Securities pricing services produce and offer marks derived from analysis of various sources. Pricing services are for-profit firms that provide prices and pricing-related data to financial institutions like mutual funds for a fee. Pricing services compete for business along dimensions of pricing quality, security coverage and data transmission reliability.[8] These data cover both listed market price

[6] Bessembinder, Maxwell and Venkataraman (2006) analyze the relationship between market transparency and price efficiency in the context of a world in which transactions costs increase with the variance of valuation errors. They offer two channels for such a relationship: greater valuation errors (1) may increase the inventory risks of market-making and (2) may increase the likelihood that dealers can extract rents from less-well-informed counterparties.

[7] For more institutional details on bond pricing issues please see Appendix A.

[8] Current and past providers of evaluated pricing services over our sample period include Interactive Data Corporation, Standard & Poor's Security Evaluations, Thomson Reuters DataScope Evaluated Pricing Service, JPMorgan's

data for exchange-traded securities and "evaluated" price data for over-the-counter market securities. The price data for the exchange-listed securities are collected from the exchanges. An "evaluated" price for an over-the-counter market security is produced from firm-specific methodologies that combine information from a number of sources as well as professional judgment. A price needs to be produced each day even if the security in question did not trade that same day.

The fund could adhere to mechanical rules to use a predetermined single source or combine information from a number of sources, or else sometimes utilize discretion in adjustments to the individual security marks. Some funds outsource the actual fund accounting function to firms specializing in that function, while other funds, especially those organized within a large fund family, perform the fund accounting function in-house. Thus, mutual funds have substantial discretion in the marking of bonds. Moreover, such discretion may be useful when legitimate differences exist among competing external pricing sources for particular securities. Conversations with industry professionals revealed that individual traders, analysts and portfolio managers responsible for specific security positions routinely investigate and sometimes challenge the standard pricing source for any particular security when that default price feed result appears unreasonable. Such challenges involve questioning the pricing service responsible and obtaining "market color" on the security from a number of dealers. A portfolio manager identified with a decision to buy a particular security position has an incentive to investigate adverse marks on that security in order both to understand price moves as well as to protect his/her reputation within the firm. Such an investigation may result in a fund's decision to override the default price feed result.

3. Data and mutual fund corporate bond ownership statistics

3.1. Data

We use five databases in our study: (1) the Morningstar mutual fund holdings database, (2) the CRSP Survivor-Bias Free US Mutual Fund Database, (3) the Mergent

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PricingDirect, Markit, SIX Telekurs, SVC Corp. and FRI Corp. (In addition, Bloomberg delivers pricing information aggregated from various sources.) Some providers focus on specific asset classes. Nelson (2007) provides an overview of the pricing service industry.

Fixed Income Securities Database (FISD), (4) the TRACE database, and (5) Bloomberg corporate bond price data.

From Morningstar, we obtained mutual fund holdings data from January 1995 to December 2006 for 2,268 funds classified as fixed income funds. For each fund and date, the Morningstar mutual fund holdings database reports the CUSIP identifier of each security held and both the market and par values of each particular security holding. Based on the available Morningstar investment categories, each fund falls into one of four broad groups: Corporate Bond Funds, Government Bond Funds, Municipal Bond Funds, and Foreign Bond Funds. The database includes both surviving and dead funds and reports many additional statistics for each period in which a fund had a holdings report. Some of these fund statistics include an average maturity score, average credit quality, average duration, and several additional portfolio composition variables such as percentage invested in government bonds, corporate bonds, bonds of a particular credit rating (e.g., AAA or BBB), etc. Although funds were mandated to publicly report holdings only semiannually until 2004 and quarterly thereafter, some funds voluntarily reported holdings to Morningstar monthly.

We obtained monthly mutual fund returns from the CRSP Survivor-Bias Free Mutual Fund Database. We merged the Morningstar and CRSP databases using algorithms based on matching fund tickers and fund names. Over the 2003-2006 period when both databases reported bond holdings, our matching algorithm was supplemented with matches for holding positions. Out of the 2,268 funds in Morningstar we were able to find a match for 2,123 funds from the CRSP Database.[9]

From FISD, we obtained the credit rating, coupon rate, maturity date and issue size for a given bond at a particular point in time. We merged FISD with Morningstar holdings using bond CUSIPs.

From the TRACE database, we obtained trade-related information for each corporate bond such as the date and time of trade. FINRA, which is responsible for maintaining the TRACE database, provided us with additional data detailing the dates when corporate bonds became eligible for dissemination in the TRACE system.

[9] CRSP mutual fund return data is reported at the fund share class level and not at the portfolio level. We computed a single portfolio return each month by averaging the returns of all share classes belonging to a common portfolio after weighting the returns of each share class by the assets of each share class.

Finally, from Bloomberg, we downloaded historical end-of-month bid and ask prices for each corporate bond. The Bloomberg and TRACE data were linked with the FISD data using bond CUSIPs.

3.2. Mutual fund ownership profiles of corporate bonds

We use two measures to quantify and assess bond mutual fund ownership characteristics for different types of bonds. This first measure, *Own Ratio,* is calculated for each bond in a given year as the percentage of the issue size held by all 2,268 bond mutual funds. The second measure, *Own Number,* is calculated for each bond in a given year as the number of funds holding that bond. As in Falkenstein (1996), both of these measures are calculated every year and use the latest holdings report in a given year for a given mutual fund. The average and median values reported in Table 1 are taken across 71,758 year-bond observations corresponding to a set of 15,291 non-convertible corporate bonds.

<Insert Table 1 about here>

Panel A of Table 1 reports ownership statistics for all bonds. Panel B reports mean and median values for the ownership statistics by credit rating group. Each credit rating group suppresses the half-step distinctions (e.g., BBB-, BBB, and BBB+ bonds are all categorized as BBB). Panel C reports statistics categorized by the size of the issue. Each year, bonds are ranked on issue size and placed into deciles: the highest-issue-size bonds are placed in Decile 1 and lowest-issue-size bonds are placed in Decile 10. Ownership statistics categorized into four groups defined by the time to maturity are reported in Panel D.

The results in Table 1 reveal that the bond mutual fund ownership of corporate bonds tends to be relatively more concentrated in the intermediate maturity and high-yield sectors. For example, the median *Own Ratio* for high-yield bonds is more than four times the corresponding value for investment grade bonds. Perhaps more striking, the median *Own Ratio* for B-rated bonds is almost ten times the corresponding value for AAA-rated bonds. Across the maturity spectrum, mutual funds own substantially higher fractions of outstanding issues in the intermediate 5-to-10-year sector than they do in other maturity sectors. There does not appear to be any issue size-related tendency regarding mutual fund participation as measured by the *Own Ratio*. However, the results for *Own Number* measure clearly reveal that the largest issues are the most widely held. The *Own Number* results for our sample of mutual funds suggest that large-sized, 5-to-10-year maturity high-yield bonds are the most widely held corporate issues.

4. "Mid" versus "bid" bond pricing

4.1. Institutional details

Systematic pricing practices employed by mutual funds can affect the measured bond-pricing dispersion among mutual funds. SEC Accounting Series Release No. 118 provides guidance on how investment companies should value over-the-counter securities like corporate bonds to be in compliance with the Investment Act of 1940:

> *"Because of the availability of multiple sources, a company frequently has a greater number of options open to it in valuing securities traded in the over-the-counter market than it does in valuing listed securities. A company may adopt a policy of using a mean of the bid prices, or of the bid and asked prices, or of the prices of a representative selection of broker-dealers quoting on a particular security; or it may use a valuation within the range of bid and asked prices considered best to represent value in the circumstances. Any of these policies is acceptable if consistently applied. Normally, the use of asked prices alone is not acceptable."*

SEC guidance requires funds to mark bond values at a price equal to or greater than bid prices and less than ask prices. Beyond this limitation, however, funds are given considerable discretion in the method they choose to mark bond values. The marking method chosen can produce substantial pricing differences of the same security across funds in markets like high-yield corporate bonds where bid-ask spreads can be relatively wide.

<Insert Table 2 about here>

4.2. Categorizing funds by marking standard

We checked the SEC marking guidelines against how funds reported their bond marking practices in their prospectuses. Some funds explicitly described a practice of marking their debt securities using mid marks. Other funds explicitly described a practice of marking debt securities using bid marks. Alternatively, a third group of funds provided only general information, such as a practice of marking debt securities at fair value.

Bond mutual funds do not use boiler-plate language to describe their marking practices within their prospectuses. For each of the 946 corporate bond funds in our sample, we searched the historical prospectuses filed with the SEC for information about how it marked bond values for NAV purposes. Each fund was categorized each reporting period as following one of four marking standards: *mid markers* clearly stated the use of averaged bid and ask quotes when valuing debt securities for NAV purposes; *bid markers* clearly stated the use bid quotes; *mid/bid markers* used language that implied a combination of averages of bid and ask quotes and/or bid quotes; and *ambiguous markers* used only general language to describe their marking policy.

Panel A of Table 2 reports the frequency of marking standards based on information from the last prospectus filed during the sample period. Interestingly, we find that funds are fairly evenly distributed across three marking categories: mid markers (27.91%), bid markers (35.41%), and ambiguous markers (32.45%). Fewer funds fall into the mid/bid marker category (4.23%). Panel B reports the frequency of changes in marking standards and shows that the vast majority of funds started and ended with the same marking policy. Specifically, 824 of the 946 funds in our sample (87%) began and finished with the same marking policy.

Panel C reports statistics on scaled prices derived from the actual prices reported separately by bid, mid, and ambiguous markers. We standardize each bond's fund-reported prices based upon a scale where the corresponding Bloomberg bid and ask prices are set equal to zero and one, respectively. The mean scaled price of 0.204 reported by bid-marking funds is significantly lower than the 0.635 reported by mid-marking funds. On average, the bid-marking funds slightly overshoot the Bloomberg bid and mid-marking funds slightly overshoot the Bloomberg mid. But note that the difference between mean scaled prices for bid-markers versus mid-markers of 0.431 is roughly the size of the Bloomberg half spread. The median scaled prices tell a similar story. The median scaled prices of 0.150 reported by bid-marking funds is significantly lower than the 0.690 reported by mid-marking funds, and the difference of 0.540 is roughly the size of the Bloomberg half spread. These results reinforce the idea that there is content to the mid versus bid prospectus language. Moreover, the mean and median scaled prices for ambiguous markers of 0.452 and 0.433, respectively, fall roughly in the middle of those for bid markers and mid markers. Furthermore, the standard deviation of scaled prices within ambiguous markers is significantly higher than that for both bid and mid markers. Thus, the bond marks of ambiguous markers appear to vary more from period to period than do the corresponding marks of bid and mid markers. In contrast, the standard deviations of scaled prices of bid markers and mid markers are statistically indistinguishable.

4.3. Marking standards and fund characteristics

An interesting question is what motivates a fund to choose one marking policy over another? Table 3 provides summary characteristics for bid, mid and ambiguous markers. Dramatic differences are not apparent. Thus, fund characteristics do not appear to be related to the choice of marking policy in an obvious way. Noteworthy in light of our later investigation of whether pricing patterns are consistent with returns smoothing, all three marking subgroups show positive serial correlation of monthly returns and daily returns. Positive serial correlation is consistent with returns smoothing, but not the only possible cause. Positive serial correlation, for example, is also consistent with the hypothesis that less liquid securities are somehow more susceptible to special security marking problems resulting in stale prices. We later try to disentangle active returns smoothing from the potential presence of stale prices.

<Insert Table 3 about here>

4.4. Marking standards and auditors

Perhaps the fund's auditor matters with respect to the choice of marking policy? Table 4 reports information on the auditing firms used by bid, mid and ambiguous markers. The auditor information was hand-collected from fund prospectuses and N-

SARs. The client base of each of the big-four auditors is comprised of sizable percentages of funds in each of the three bid, mid and ambiguous marking subgroups. The frequency of marking standard is also reported for big-four and non-big-four auditors as separate groups. A chi-square test fails to reject the null hypothesis that the frequencies of bid, mid and ambiguous marking clients are related to the use of a big-four versus a non-big-four auditor. Thus, the type of a fund's auditor does not appear to explain the choice of marking standard in an obvious way. Nevertheless, we later explore the possibility that the use of other than a big-four auditor was associated with returns smoothing behavior.

<Insert Table 4 about here>

4.5. Marking standards and price clusters

Given the earlier discussion of how bonds are priced for NAV purposes, it is also interesting to know the extent to which bid, mid and ambiguous markers clustered on the same price when marking bonds. If several funds received a feed from a common pricing service and did not exercise discretion in adjusting individual bond marks, then price clustering would result. Table 5 presents price cluster information for all bonds.[10] We measure the number of price clusters as the number of unique prices observed across funds for the same bond on the same date. We see evidence of clustering, but still find a considerable spread of different prices across funds. Across all funds, we observe three or more price clusters just over half the time. When we focus only on bid or mid markers, the incidence of three or more clusters drops by roughly half. The drop is expected given the elimination of incidences where two funds used marks from the same pricing service without modification, but one fund used the bid price and the other used the mid price. When we focus only on ambiguous markers, we observe three or more clusters slightly more than 40 percent of the time regardless of whether the bond was investment grade or high yield. Table 5 also presents information on the fraction of positions priced at the mode conditional on there being more than one cluster. On average, regardless of how we split the data, more than half of the positions are priced at the mode. Under the presumption that these mode prices were supplied by a pricing

[10] Results were not different when we repeated this analysis separately for investment grade and high yield bonds.

service without modification by the funds, we can construct a proxy for exercising discretion. In our later examination of possible return smoothing behavior, we separately examine funds that tended to mark bonds at prices different from mode prices.

<Insert Table 5 about here>

5. Cross-fund price dispersion for the overall sample of funds

In this section, we examine the cross-fund pricing dispersion of individual bonds. As part of this analysis we control for differences related to choice of marking standards, and relate pricing dispersion to bond-specific characteristics. We conclude this section by examining the properties of cross-fund pricing dispersion through time.

5.1. Measures of bond price dispersion

For each fixed income fund and each reporting period, the Morningstar mutual fund holdings database reports the market and par values of each bond position. We calculate the reported price of bond i held by fund j at date t by dividing the reported market value of that bond holding by the reported par value of the holding and then multiplying by 100. In other words, the reported price measure that we use can be interpreted as the price per each 100 dollars of par value. For a bond to be included in our sample, three or more funds must report the price of the identical bond as of the same date.[11] Our sample includes 11,116 distinct corporate bonds and 252,765 bond-date observations that satisfy this condition.

We use the interquartile range (IR) of prices reported by all the funds holding the same bond on the same date to measure bond price dispersion across funds. The resulting dispersion statistics are then averaged across bond-date observations. We report results using the interquartile range because the distribution of bond prices across funds is negatively skewed and normality is strongly rejected by both the Smirnov-Kolmogorov and Anderson-Darling tests. Nonetheless we also examined the standard deviation and

[11] We also ignored all bond positions that were smaller than $10,000 in par value and round our calculated bond prices to the fourth decimal point to avoid spurious differences due to rounding errors.

average median absolute deviation of prices. The unreported results using these alternative measures of dispersion are qualitatively similar.

As described above, some funds explicitly state that they mark bonds at mid-market prices (i.e., the average of the bid and ask prices), whereas other funds explicitly state that they mark bonds at bid prices. Thus if we were to calculate dispersion using prices reported by all funds, our dispersion measure would be affected by the magnitude of the bid-ask spread. To control for the different marking standard used by funds, bond price dispersion is calculated separately using prices reported by three groups of funds: all funds; mid-marking funds; and bid-marking funds.

5.2. Bond price dispersion and bond characteristics

Table 6 reports bond price dispersion statistics based on univariate sorts related to bond characteristics. Panel A reports dispersion statistics by credit rating group. As expected, pricing dispersion across funds is generally decreasing in bond credit quality. With but one exception, dispersion is significantly lower when computed using marks reported exclusively by mid-marking or bid-marking funds. This finding is consistent with a dispersion measure based on all funds' prices being driven to some extent by the bid-ask spread. Nonetheless, dispersion generally decreases in bond credit quality regardless of whether the measure is computed based on all funds, mid-marking funds, or bid-marking funds. Interestingly, pricing dispersion for bonds in default (D-rated) is lower relative to even CCC or C-rated bonds. This is consistent with funds or pricing services using marks based on similar recovery rates estimated from similar bonds-in-default universes.

Panel B reports dispersion statistics by the size of the issue. Bonds are ranked on issue size annually and then placed into deciles. The highest-issue-size bonds are placed in Decile 1 and the lowest-issue-size bonds are placed in Decile 10. Also as expected, dispersion is nearly monotonically decreasing in issue size. Again, consistent with dispersion based on all funds' prices being driven to some extent by the bid-ask spread, dispersion is significantly lower when computed from marks reported exclusively by mid-marking or bid-marking funds.

Panel C reports dispersion statistics categorized into four groups defined by the time-to-maturity. Again as expected, dispersion is increasing in time-to-maturity. Once more we find that dispersion is significantly lower when computed from marks reported exclusively by mid-marking or bid-marking funds.

<Insert Table 6 about here>

We also examine bond price dispersion using multivariate regression analysis. The dependent variable is the cross-fund bond price interquartile range. Explanatory variables include: *Issue Size*, the log of the original par value of the bond issue expressed in millions of dollars; *Maturity*, the remaining time to maturity of the bond expressed in years; *Age,* the time elapsed since the bond's issuance expressed in years (see Hotchkiss, Jostova and Warga (2007)); *Volatility*, the annualized standard deviation of daily percentage price changes for the 10-year Treasury Note Futures during the concurrent observation month; and a time trend. Unreported results show, as expected, that the cross-fund pricing dispersion is higher for lower credit quality bonds, longer maturity bonds, smaller-sized issues, and older bonds. Dispersion is also higher during periods of higher market volatility.

5.3. A closer look at the time-series of bond price dispersion

We next take a detailed look at the time-series of bond price dispersion, particularly with respect to the impact of TRACE. TRACE was rolled out on separate schedules for four groups of bonds over a 27-month period extending from July 1, 2002 to September 30, 2004.[12] The first wave of bonds reported through TRACE encompassed all investment grade bonds greater than $1 billion in original issue size.[13] On July 1, 2002 FINRA required dissemination of transaction information for bonds meeting these criteria. Second-wave bonds include all investment grade bonds rated A or higher with original issue size of at least $100 million. These bonds became permanently disseminated as of March 1, 2003. Third-wave bonds comprise all issues rated BBB- to

[12] The rollout of TRACE began in July 2002 under the auspices of the NASD (National Association of Securities Dealers) to improve corporate bond transparency. FINRA was formed through the consolidation of NASD and the member regulation, enforcement and arbitration functions of the New York Stock Exchange in July 2007.
[13] Prices for a refreshed set of 50 highlighted non-investment grade bonds also began being disseminated at this time. We incorporate these bonds into our discussion of the full set of high-yield bonds below (the fourth wave).

BBB+ with an original issue size less than $1 billion. The third-wave rolled out in two phases. The initial phase began on April 14, 2003 when FINRA required dissemination for a subset of 120 third-wave bonds. The secondary phase began on September 30, 2004 when all other bonds meeting third-wave criteria became permanently disseminated. TRACE's fourth wave, the rollout for high-yield bonds, also occurred in two parts. FINRA began requiring dissemination of a special subset of 50 highlighted high-yield bonds on July 1, 2002.[14] The secondary phase began on September 30, 2004 when all other bonds meeting fourth-wave criteria became permanently disseminated.

Figure 1 shows the time series of the average dispersion for the four Trace bond waves.[15] We observe a general pattern of decreasing dispersion for each Trace bond wave around the implementation of TRACE. While the pattern is consistent with the transparency-enhancing TRACE system increasing pricing precision, dispersion may have fallen for other reasons. A gradual decline over the entire sample period is consistent with other more long-run factors. For example, the corporate bond market may have simply experienced a steady increase in the number of credit analysts and/or gradual improvements in credit-scoring models throughout the sample period. In contrast, an abrupt dispersion decrease coincident with first dissemination would be consistent with dispersion decreases being related to TRACE.

Unreported tests examine the pattern of pricing dispersion in tight six-month event windows immediately before and after the TRACE dissemination event dates. Although the unreported evidence shows a more rapid dispersion decrease for disseminated bonds in the tight event windows, non-disseminated bonds also show decreases that differ insignificantly from disseminated bonds. The evidenced is consistent with the view that the transparency-enhancing TRACE system contributed to increasing pricing precision, including a spillover effect for non-disseminated bonds. However, the observed gradual decline over our sample period and the similar dispersion

[14] While the number of highlighted high-yield bonds disseminated through TRACE remained constant from July 1, 2002 to September 30, 2004, the identities of the 50 bonds within this set changed. A total of 177 different highlighted high-yield bonds were disseminated at some point over the transition period.

[15] Since there is a high incidence of dispersion data missing for some of the bond waves prior to December 1998, the chart reflects data from December 1998 through December 2006, when the underlying quarterly data was consistently available for each of the four bond waves.

decline documented for the non-disseminated bonds suggest that TRACE might not have been the only source of the decline in pricing dispersion.

6. Do funds strategically mark bonds to smooth returns?

Returns smoothing involves managerial use of discretion over marks on individual holdings to alter the distribution of reported fund returns. The presumed goal of such returns management is to artificially enhance a fund's performance statistics to attract additional investment inflows. The mechanics of returns smoothing are based on the fact that fund performance is typically measured by comparing reported returns to an appropriate index. When the fund's underlying assets perform poorly relative to the index, marking discretion is used to boost reported returns by pricing individual holdings higher. Conversely when the fund's underlying assets perform well relative to the index, marking discretion is used to "bank" returns for the future by pricing individual holdings lower.

Thus, the returns smoothing hypothesis makes several testable predictions. When the fund reports returns that underperform the index, we ought to observe high marks on individual bond positions. When the fund reports returns that outperform the index, we ought to observe low marks on individual bond positions. Our first set of tests examines whether we observe this pattern of marks for individual bond positions.

Returns smoothing will also alter the returns reported by funds. When the fund's underlying assets show weak performance, the fund will use marking discretion to boost reported returns. Conversely when the fund's underlying assets show strong performance, the fund will use marking discretion to hold back on the reported returns. As argued by Getmansky et al., returns smoothing will thus cause reported returns to not fully incorporate the available economic information, leading to a less than one-for-one relation between reported returns and the true economic returns of the underlying assets. Our second set of tests examines whether we observe this pattern of marks for the returns reported by funds.

In the analysis that follows, we separately examine several fund subgroups that may have more discretion in the marking of bonds. These funds may use such discretion to more aggressively manage fund performance statistics through returns smoothing. The first subgroup we examine separately is ambiguous markers. Recall that SEC guidance gives funds discretion in the method used to mark bond values for NAV purposes. SEC case precedent, however, suggests that deviation from policies stated in the prospectus exposes fund management companies to potential legal liability.[16] Thus, we might expect bid and mid markers to closely follow their explicitly stated policies when marking bonds for NAV purposes. Ambiguous markers, in contrast, do not disclose details about marking policies in their prospectuses. Thus, these funds do not operate under any self-imposed, explicitly stated policy. Fair value guidance under SEC Accounting Series Release No. 118 is not extraordinarily restrictive, especially as it permits funds to "*use a valuation within the range of bid and asked prices considered best to represent value in the circumstances.*" Thus, ambiguous markers may retain more discretion in the marking of bonds than bid or mid markers.

<Insert Table 7 about here>

We also examine whether the tendency to mark positions differently from prices at which other funds cluster is associated with returns smoothing behavior. The presumption is that if we observe a cluster of funds marking a bond at the same price on the same date, then the cluster price was likely supplied by a pricing service without modification by the funds. Funds that tend to mark bonds at prices different from cluster prices therefore more likely exercise marking discretion.

Following similar logic, we also explore the possibility that the tendency for a fund to mark positions differently from other funds in the same family is associated with returns smoothing behavior. The presumption is that funds that mark at prices different from other funds in the same family more likely exercise marking discretion.

Finally, we investigate whether the use of other than a big-four auditor is associated with returns smoothing behavior. Under the presumption that big-four

[16] For example, Nevis Capital allocated all shares of IPOs that it acquired to only two of its clients, the Nevis Fund and Snowdon, but failed to disclose this practice to its other clients that were eligible to participate in IPOs. This practice was contrary to the Nevis Capital's claims in its Form ADV filed with the SEC that the firm would treat all of its clients equally, on a pro-rata basis. This provided the basis for the legal action taken against Nevis Capital by the SEC which accused this investment adviser of fraudulent conduct by making false and misleading statements and engaging in fraudulent and deceptive practices (see, for example, http://www.sec.gov/litigation/admin/ia-2214.htm).

auditors are more exacting in their pricing standards, funds that used a smaller auditor have more marking discretion.

6.1. Individual bond marks: Test design

Our analysis of individual bond marks treats each holding by each fund on each date as a separate observation. For this part of the analysis, we focus on observations marked at a price either greater than or equal to the Bloomberg mid price or less than or equal to the Bloomberg bid price.[17] Eighty percent, or 405,026, of the observations satisfy these criteria. We specify the relationship between individual bond marks and explanatory variables using a logit model. The dependent variable is constructed as an indicator variable, taking a value of one if the price is equal to or greater than the Bloomberg mid price and zero if the price is equal to or less than the Bloomberg bid price.

Key in the tests for returns smoothing are explanatory variables that reflect whether the fund underperformed or outperformed relative to an appropriate index. We benchmark the returns reported by funds invested primarily in investment-grade bonds against the Lehman Corporate Bond Index and the returns reported by funds invested primarily in high-yield bonds against the Lehman High-Yield Bond Index. We compute an index-adjusted return for each fund each month based on the fund's reported return over the prior twelve-months relative to the index. We then rank all positive index-adjusted returns. We construct an indicator variable, *Positive Return*, set equal to one if the observation is in the top third of the positive index-adjusted returns and to zero otherwise. We then separately rank all negative index-adjusted returns and construct an indicator variable, *Negative Return*, in an analogous manner.

We also construct indicator variables for the calendar and fiscal year ends. Fiscal year ends were hand-collected from each fund's prospectus or N-SAR report. The rationale for including *Calendar Year* end is that funds may have been more apt to engage in returns smoothing at a time when investors were more likely attuned to fund

[17] We excluded observations lying between the Bloomberg bid and mid quotes to remove any ambiguity related to whether those observations represented bid or mid quotes. Nevertheless, we also conducted our tests using a two-level categorization based on whether a price is strictly above or below the average of the Bloomberg bid and mid quotes, and the results were qualitatively similar.

performance. The rationale for including *Fiscal Year* end is that funds may have faced increased auditor scrutiny and were hence less apt to engage in returns smoothing.

The final explanatory variables are based on the fund subgroups described above. *Ambiguous Marker* is an indicator variable equal to one if the fund is categorized as an ambiguous marker. *Cluster Divergent* is an indicator variable used to identify funds that tended to mark bonds at prices different from cluster prices. To construct the variable *Cluster Divergent*, for each fund and each period we calculate the fraction of bonds held that are marked differently from the two most populated price clusters (divergent fraction). We then average the divergent fraction across all report dates for a particular fund. We rank all funds based on their average divergent fraction and split the sample into terciles. *Cluster Divergent* is set equal to one for funds in the top tercile. *Family Disagreement* is an indicator variable used to identify funds that tended to mark bonds at prices different from funds in the same family. To construct the variable *Family Disagreement*, for each fund and each period we calculate the fraction of bonds held that are marked differently from at least one other fund belonging to the same mutual fund family (disagreement fraction). We then average the disagreement fraction across all report dates for a particular fund. We rank all funds based on their average disagreement fraction and split the sample into terciles. *Family Disagreement* is set equal to one for the top tercile. *Not Big Four Auditor* is an indicator variable set equal to one if the underlying fund is not audited by one of the big four auditors.[18] Each of the subgroup indicator variables are interacted with the *Positive Return* and *Negative Return* variables to test for differential returns smoothing behavior.

6.2. Individual bond marks: Evidence

The results in Table 7 show a positive and significant loading on *Negative Return* for all of the logit model specifications. These results imply that the probability of observing a bond price equal to or above the Bloomberg mid (a "high mark") is larger when the fund reports returns that underperform the index. Results also show a negative and significant loading on *Positive Return* for all of the logit model specifications. These

[18] An alternative version of this variable based on whether the underlying fund is audited by PricewaterhouseCoopers versus other auditors produced qualitatively similar results.

results imply that the probability of observing a bond price equal to or below the Bloomberg bid (a "low mark") is larger when the fund reports returns that outperform the index. Both results are consistent with the returns smoothing hypothesis.

These Table 7 results are inconsistent with either random mispricing or stale pricing. To see this, consider a fund that did not exercise discretion over marks and held a portfolio that mirrored the index. Suppose that, because of either random mispricing or stale pricing, the fund marked the bonds it held either higher or lower than the prices used to calculate the index return. If the fund exhibited a random or stale-pricing-induced downward marking bias at the end of a given period, then it would show a negative index-adjusted return for the period. Conversely an upward marking bias would result in a positive index-adjusted return. Thus, random mispricing or stale pricing hypotheses generate testable predictions that run counter to the positive and significant loading on *Negative Return* and the negative and significant loading on *Positive Return.*

In model (2), the loadings on *Calendar Year* and *Fiscal Year* differ insignificantly from zero. The implication is that the pattern of marks consistent with return smoothing behavior does not differ over the course of the year.

In models (3) through (6), the loadings differ insignificantly from zero for the coefficients on the fund subgroups possibly having more marking discretion. Caveats, however, are warranted when interpreting these results. First, the subgroups singled out for separate examination may not differ from the rest of the sample with respect to the degree of marking discretion. Perhaps, for example, the bond marking scrutiny applied by Big Four auditors was no different than those applied by smaller auditors. Second, the logit model only provides evidence on the probability of observing a high or low bond price given certain conditions; it does not estimate the full economic impact of smoothing on the returns reported by funds. We now turn to an examination of whether reported returns exhibit evidence consistent with return smoothing.

6.3. Reported returns: Test design

Getmansky, Lo and Makarov (2004) estimate a returns model for hedge funds applicable to all funds that hold illiquid assets (such as our corporate bond mutual funds). In the model, fund j's reported or observable return in month t is denoted $R^0_{j,t}$. The fund's true economic return, which is assumed to be unobservable in their sample of hedge funds, is denoted $R_{j,t}$. The true economic return reflects the flow of information that would determine the equilibrium value of the fund's securities in a frictionless market. The observable reported returns are modeled as a finite moving average of the unobservable true economic returns. For example, regression equation (1) is a returns smoothing model using a specification that allows for two lagged months of true economic returns:

$$\mathrm{R}^{0}_{\mathrm{j,t}} = \alpha + \theta_{\mathrm{j,0}}\, \mathrm{R}_{\mathrm{j,t}} + \theta_{\mathrm{j,1}}\, \mathrm{R}_{\mathrm{j,t-1}} + \theta_{\mathrm{j,2}}\, \mathrm{R}_{\mathrm{j,t-2}} + \varepsilon_{j,t}. \tag{1}$$

The key coefficient in equation (1) is $\theta_{j,0}$, which indicates how much of the true economic return is reported in the current month. A $\theta_{j,0}$ value less than one means that, consistent with smoothed returns, on average fund *j* reported less than 100% of the current month's true economic return. A $\theta_{j,0}$ value equal to one means that on average fund *j* reported the current month's true economic return.[19]

Since hedge fund assets are not observable, Getmansky *et al.* fit their model using only reported returns and employ econometric techniques in multiple steps to estimate the $\theta_{j,0}$ coefficients. Our procedure differs from Getmansky *et al.* in that we estimate equation (1) directly using true economic returns based on actual bond holdings. For our sample of bond mutual funds, we develop a "custom benchmark" to derive each fund's true economic return since we directly observe the underlying assets held on all report dates.

For robustness, we apply two alternative measures for the bond prices used to value each bond position held by any fund. One measure is a "consensus" price calculated as the cross-fund median price of all bond prices reported by all funds. The other measure is the Bloomberg mid price.[20] Using these Bloomberg prices in the

[19] A $\theta_{j,0}$ value greater than one would imply that fund *j* marked its positions in a way that increased its returns volatility relative to its contemporaneous true economic returns (technically feasible but hard to motivate).

[20] Bloomberg reports end-of-month bond bid and ask quotes that combine information from different dealers or price sources. Sometimes when quotes are not available (especially post-TRACE), a trade price is provided in which case both the reported bid and ask prices are set equal to each other.

context of a robustness check makes sense since these prices are independent of any fund manager's specific endogenous decisions about how to mark bonds for NAV purposes.

Our two estimates of each fund's true economic return are the returns that the fund would have experienced had it marked its own individual bond holdings at either consensus prices or Bloomberg prices. Our exact procedure for estimating the true economic return begins by calculating a "portfolio spread" measured as the percentage difference between the value of a fund's portfolio of corporate bond positions using the fund's own marks and the value of those same positions remarked using either consensus prices or Bloomberg prices. As discussed above, for a bond to be included in our sample, three or more funds must report the price of the identical bond as of the same date. For each bond *i* meeting this requirement at date *t*, we calculate a price measure, $Price_{i,t}$, either as the consensus price (measured as the median price reported by all funds) or the Bloomberg price (measured as the average of the Bloomberg bid and ask quotes). Next, for each fund *j* at each date *t*, we identify all bonds held with valid prices. The independently computed value of all such bonds held by fund *j* at date *t* is calculated as follows:

$$Value_{j,t} = \sum_{i=1}^{N_j} Price_{i,j,t} \times ParValue_{i,j,t}, \qquad (2)$$

where $ParValue_{i,j,t}$ is the reported par value of bond *i* held by fund *j* at date *t.* Employing the same set of bonds used to calculate $Price_{j,t}$ we compute the reported value for fund *j* at date *t* as follows:

$$Reported\ Value_{j,t} = \sum_{i=1}^{N_j} Reported\ Price_{i,j,t} \times Par\ Value_{i,j,t}\ . \qquad (3)$$

The reported value reflects the prices used in the fund NAV calculation. The portfolio spread, defined as the percentage difference between the reported and independently computed values for fund *j* at date *t,* is calculated as

$$Portfolio\ \ Spread_{j,t} = \frac{Reported\ \ Value_{j,t} - Value_{j,t}}{Value_{j,t}} \tag{4}$$

and computed for each fund holding at least ten bonds with valid dealer prices in a given month.

We next calculate the percentage change in the portfolio due to the change in the portfolio spread as

$$\Delta\ Spread_{j,t} = \frac{Portfolio\ \ Spread_{j,t} - Portfolio\ \ Spread_{j,t-1}}{Portfolio\ \ Spread_{j,t-1}}. \tag{5}$$

Finally, we calculate our estimate of the true underlying portfolio return as

$$R_{j,t} = \frac{(1 + R^0_{j,t})}{(1 + \Delta\ Spread_{j,t})} - 1 \tag{6}$$

Under our method, $R_{j,t}$ reflects the component of the portfolio return that is not affected by the idiosyncratic marking behavior of the fund manager.

6.4. Reported returns: Evidence

In Table 8, we estimate regression equation (1) to generate returns smoothing profiles for all funds and for fund subgroups possibly having different marking discretion. Results using Bloomberg prices and consensus prices to estimate economic returns are reported in Panels A and B, respectively. Our estimation period covers the entire sample period and includes all funds with ten or more valid (non-missing) Bloomberg-based and consensus-based return observations. Two hundred sixty-six funds meet these criteria.

<Insert Table 8 about here>

Again, as in Table 7, the sub-groups of funds that we examine are based on marking policy; tendency to mark positions differently from the most popular prices used by all funds; tendency to mark positions differently from other funds in the family; and tendency to use a big four versus a non-big four auditing. We classify funds based on the tendency to mark positions differently from the most popular prices used by all funds by ranking all funds based on their average cluster divergent fraction into terciles. Funds classified as High Cluster Divergent funds are funds in the top tercile and Low Cluster Divergent funds are funds in the bottom tercile. We classify funds based on the tendency to mark positions in disagreement with other funds from the same family by ranking all funds based on their average disagreement fraction into terciles. Funds classified as High Family Disagreement funds are funds in the top tercile and Low Family Disagreement funds are funds in the bottom tercile.

In Panel A of Table 8, the first column shows that the θ_0 coefficient for all funds is 0.925, significantly less than one in both economic and statistical terms. The result implies that the idiosyncratic part of the typical funds' reported return moved in the opposite direction of the contemporaneous true economic return calculated using Bloomberg prices. The remaining columns in Panel A show that the θ_0 coefficient regardless of subgroup is also significantly less than one. Panel B shows that the key result that the θ_0 coefficient is less than one holds when consensus prices are used to calculate true economic returns. The result that the idiosyncratic part of a funds' reported return moved in the opposite direction of the contemporaneous true economic return is consistent with returns smoothing. Of course, the result is also consistent with a fund holding illiquid bonds susceptible to stale pricing problems.

Thus, in Table 9, where we compare the value of θ_0 coefficients across fund subgroups, we are careful to control for the characteristics of bonds held by the fund. We first estimate equation (1) for each fund separately. The resulting θ_0 coefficient for each fund serves as the dependent variable in regressions employing both the subgroup indicator variables and controls for the characteristics of bonds held. The *Cluster Divergent* and *Family Disagreement* indicator variables are constructed as in Section 6.1.

In the first specification, we directly control for bond characteristics associated with liquidity: *Non-Investment Grade* is the value-weighted percentage of the fund portfolio invested in non-investment grade bonds; *Issue Size* is the value-weighted average of the issue size of all bonds in the fund portfolio; and *Maturity* is the value-weighted average of the time-to-maturity of bonds in the portfolio. In the second specification, we control for differences associated with liquidity using TRACE trade characteristics: *Trades* is the weighted average number of trades reported in TRACE in the month prior to the fund holdings report date; and *Last Trade Distance* is the weighted average number of days from the last trade reported in TRACE. In the third specification, we use a summary measure of liquidity, *Price Range*. We calculate the price range of a given bond on a given date as the difference between the highest and lowest price reported by all funds holding the bond on the same date. Earlier evidence presented in this study suggests that bonds with higher price ranges are the most illiquid bonds. For each fund and each report date, we calculate *Price Range* as the value-weighted price range for all the bonds in the underlying portfolio.

<Insert Table 9 about here>

Results when Bloomberg prices and consensus prices are used to estimate economic returns are reported in Panels A and B, respectively, of Table 9. An interesting result is the negative and significant coefficient on *Ambiguous Marker* regardless of model specification and regardless of whether Bloomberg prices or consensus prices are used to calculate economic returns.[21] The smaller θ_0 coefficient for ambiguous markers compared to bid and mid markers is consistent with the hypothesis that the lack of an explicitly stated marking policy provided managers with increased cover to strategically smooth reported fund returns.

Another interesting result is the negative and significant coefficient on *Price Range* regardless of whether Bloomberg prices or consensus prices are used to calculate

[21] The negative and significant coefficient on *Ambiguous Marker* in Table 9 does not conflict with the logit results presented in Table 7. The logit model only provides evidence on the probability of observing a high or low bond price given certain conditions; it does not estimate the full economic impact of smoothing on the returns reported by funds. In contrast, Table 9 results reflect the economic magnitude of marking divergences for individual positions, market value of individual positions relative to fund net asset value, and strategic coordination of marks across multiple positions on a given date.

economic returns. Although *Price Range* serves as a proxy for liquidity and potential stale-price problems, it also has another interpretation in the context of the returns smoothing hypothesis. Funds holding portfolios of high price range bonds possess greater leeway in marking bonds up or down because the range of marks reported by other funds is wider. The wider the range of marks by other funds, the easier it is to justify one's own marking choice as reasonable.

7. Conclusions

This paper has analyzed important aspects of US corporate bond pricing by mutual funds and related issues in bond market structure and transparency. Our analysis focused on the dispersion of month-end valuations placed on identical bonds by different funds for NAV purposes. We uncovered and analyzed some systematic differences in bond-holdings valuations that incorporate the impact of differences in fund bid versus mid bond value marking standards. More fundamentally, our mutual fund bond valuation data allowed us to assess the difficulty of marking illiquid securities. Our results indicate that cross-fund bond price dispersion falls as bond credit quality increases, rises for longer bond time-to-maturity, and falls for larger bond issue size. Furthermore, price dispersion for individual bonds tends to be higher when underlying market volatility is high.

We also find that bond price dispersion declined over our sample period. A gradual decline over the entire sample period is consistent with a number of explanations. One contributing factor to this decline in dispersion may have been the dramatic improvement in corporate bond market transparency due to the roll-out of FINRA's TRACE system beginning in July 2002. While previous research has focused on the salutary impacts of TRACE on bond trade execution costs, the improvement in market transparency may have had more general benefits. This decrease in price dispersion over time is consistent with the hypothesis that the trade transparency generated by TRACE has increased the precision of bond pricing for NAV purposes, an "unanticipated consequence" of TRACE implementation that is beneficial to mutual fund investors. Nevertheless, the observed gradual decline over our entire sample period and associated dispersion declines documented for the uninvolved bonds strongly suggest that TRACE was not the only factor behind the decline in bond price dispersion.

Finally, we investigated whether the marking patterns of bond mutual funds may be associated with returns smoothing behavior. Tests focused on the individual marks revealed that (1) the probability of observing a "high mark" was larger when the fund reported returns that underperformed the index and (2) the probability of observing a "low mark" was larger when the fund reported returns that outperformed the index. Both results are consistent with returns smoothing. A second set of tests of the returns smoothing hypothesis focused instead on explaining observed fund returns. We employed a variant of Getmansky, Lo and Makarov's (2004) approach to generate returns smoothing profiles for all funds and for fund subgroups possibly having different levels of marking discretion. We constructed a "custom benchmark" for each fund's true economic return based upon revaluing actual fund holdings for each fund on all report dates using a common set of bond marks. Our estimates imply that the idiosyncratic part of a fund's reported return moved in the opposite direction of the contemporaneous true economic return. This is consistent with returns smoothing. The quantitative importance of such smoothing was larger for funds that we classify as "ambiguous" markers. This finding is consistent with the hypothesis that the lack of an explicitly stated marking policy (e.g., always mark at "bid" or "mid") provided managers with increased cover to strategically smooth reported fund returns. Furthermore, the quantitative importance of such smoothing was larger for funds holding portfolios of bonds with wide price ranges (i.e., "hard-to-mark" bonds). Such funds have greater leeway in marking bonds up or down because the wider the range of marks by other funds makes it easier to justify one's own marking choice as reasonable. Taken altogether, the results suggest that managers of funds that lack an explicitly stated marking policy and hold portfolios of bonds that have the largest marking uncertainty are most prone to smooth reported fund returns.

Our finding of a differential impact of ambiguous versus explicit fund marking policies on returns smoothing is of immediate practical interest. From a regulatory perspective, we see little downside to requiring each mutual fund to explicitly state its marking standard in its prospectus. Regulatory strategies for dealing with returns smoothing by funds that specialize in hard-to-mark bonds may be more difficult to formulate. Moreover, hedge fund managers generally share the motive, means and mismarking opportunities available to those mutual fund managers with ambiguous marking standards and/or that hold hard-to-mark bonds. Thus, taken together with the Getmansky *et al.* and Bollen and Pool (2008, 2009) evidence, our findings suggest that an in-depth evaluation of the security valuation practices of individual hedge funds may be a worthwhile endeavor for both the hedge fund industry itself and its would-be regulators towards the goal of identifying and eliminating returns smoothing by managers.

Table 1
Corporate Bond Ownership Statistics

The following table reports ownership statistics for bonds that are held by 2,268 bond mutual funds that reported their holdings to Morningstar during the 1995-2006 period. The reported statistics are for the set of 15,291 non-convertible corporate bond securities categorized as such by FISD. Data on bond credit ratings, issue sizes, and maturity dates came from FISD. The *Own Ratio* is calculated for each bond in a given year as the percentage of the total outstanding issue size held by all 2,268 bond mutual funds. The *Own Number* is calculated for each bond in a given year as the number of funds holding that bond. As in Falkenstein (1996), both these variables are calculated every year and use the latest holdings report in a given year for a given mutual fund. The average and median values reported below are taken across year-bond observations (there are 71,568 year-bond observations). Panel A reports ownership statistics for all bonds. Panel B reports mean and median values for the ownership statistics by credit rating group. Each credit rating group is constructed such that, for example, all BBB-, BBB and BBB+ bonds are categorized as one group, BBB. Panel C reports statistics categorized by the size of the issue. Each year bonds are ranked on issue size and sorted into deciles where the highest-issue-size bonds are placed in Decile 1 and lowest-issue-size bonds are placed in Decile 10. Ownership statistics categorized into 4 groups defined by the time to maturity are reported in Panel D.

Panel A. Overall Ownership Statistics

Ownership Statistic	Mean	Min	25th Percentile	Median	75th Percentile	Max
Own Ratio (%)	9.50	0.002	1.67	5.10	12.77	99.95
Own Number	12	1	2	6	15	204

Panel B. Ownership Statistics By Credit Quality

Credit	Own Ratio (%)		Own Number		
Rating	Mean	Median	Mean	Median	Observations
AAA	4.75	2.23	6.83	3.00	1,670
AA	4.26	2.29	6.27	3.00	5,018
A	4.69	2.80	8.06	4.00	20,245
BBB	7.12	4.79	11.72	6.00	20,534
BB	15.89	13.61	19.19	12.00	6,986
B	21.86	20.75	21.35	16.00	8,477
CCC	19.03	16.24	18.12	13.00	2,499
CC	13.21	10.18	11.93	8.00	359
C	15.07	12.44	14.56	11.00	185
D	10.53	6.79	7.99	5.00	1,400
NR	10.94	6.25	8.55	4.00	3,219
Inv. Grade	5.64	3.35	9.22	4.00	46,730
High-yield	18.39	16.14	19.01	13.00	19,906

Table 1-Continued

Panel C. Ownership Statistics By Issue Size					
Issue Size	Own Ratio (%)		Own Number		
Decile	Mean	Median	Mean	Median	Observations
1 (Highest)	7.29	5.14	29.61	21.00	7,306
2	8.58	5.42	18.36	13.00	7,295
3	9.18	5.35	15.29	10.00	6,831
4	9.62	5.21	13.36	8.00	6,815
5	8.78	4.47	9.57	5.00	8,543
6	9.88	4.86	9.07	5.00	6,300
7	10.33	5.20	8.76	5.00	7,406
8	11.44	6.28	8.40	5.00	6,223
9	9.80	5.00	5.19	3.00	8,073
10(Lowest)	10.58	4.80	2.70	1.00	6,776

Panel D. Ownership Statistics By Time to Maturity					
Time to	Own Ratio (%)		Own Number		
Maturity	Mean	Median	Mean	Median	Observations
≤2 years	7.08	3.66	8.14	4.00	16,003
(2, 5]	9.55	5.70	12.55	7.00	19,350
(5,10]	13.08	7.67	16.65	9.00	22,846
>10 years	6.19	3.59	8.18	4.00	13,157

Table 2
Frequency Analysis by Pricing Standard

This table reports information on the pricing standards that funds use to compute their net asset values. Fund-specific pricing standard information was hand-collected from prospectuses filed by funds with the Securities and Exchange Commission (SEC), available on the SEC website. A fund is classified as a *Mid Marker* if its prospectus states clearly that it uses the average of bid and ask quotes or prices when valuing debt securities for the purposes of calculating its net asset values. A fund is classified as a *Bid Marker* if its prospectus clearly states that the fund uses bid quotes or prices. A fund is classified as *Mid/Bid Marker* when language from its prospectus implies a combination of pricing standards (bid quotes and/or averages of bid and ask quotes). A fund is classified as an *Ambiguous Marker* when its prospectus does not disclose whether the fund specifically uses a bid or mid-marking standard, but rather uses general language to describe its pricing policy. Panel A reports the frequency of pricing standards based on information from the latest prospectus filed by each fund. Panel B reports the frequency of changes in pricing standards. Panel C reports statistics on standardized bond prices for prices reported separately by bid-marking, mid-marking, and ambiguous-marking funds. For a particular bond-date observation to be included in our analysis, we require that a price is reported for that bond by at least one mid-marking, one bid-marking, and one ambiguous marker fund. Next, using Bloomberg bid and ask quotes, we normalize reported prices relative to Bloomberg quotes such that Bloomberg bid price equals 0 and the Bloomberg ask price equals one for a particular bond. We first aggregate and compute statistics for all prices reported for a particular bond on a given date and then average these statistics across all bond-date observations.

Panel A. Frequency by Pricing Standard

Pricing Standard	#	%
Bid Marker	335	35.41
Mid Marker	264	27.91
Mid/Bid Marker	40	4.23
Ambiguous Marker	307	32.45
Total	946	100%

Panel B. Frequency of Changes in Pricing Standards

	Ending Pricing Standard							
	Bid Marker		Mid Marker		Mid/Bid Marker		Ambiguous Marker	
Beginni1ng Pricing Standard	#	%	#	%	#	%	#	%
Bid Marker	287	30.34	18	1.9	1	0.11	23	2.43
Mid Marker	27	2.85	235	24.84	1	0.11	20	2.11
Mid/Bid Marker	0	0	0	0	38	4.02	0	0
Ambiguous Marker	21	2.22	11	1.16	0	0	264	27.91

Panel C. Comparisons of Standardized Prices Across Different Pricing Standards

				Mid vs. Bid Markers		Ambiguous vs. Bid Markers		Ambiguous vs. Mid Markers	
Statistic	Bid Markers	Mid Markers	Ambiguous Markers	Difference	p-value	Difference	p-value	Difference	p-value
Mean	0.204	0.635	0.452	0.431	(0.00)	0.247	(0.00)	-0.183	(0.00)
Median	0.150	0.690	0.433	0.540	(0.00)	0.283	(0.00)	-0.257	(0.00)
St.Dev.	0.622	0.625	0.873	0.003	(0.93)	0.252	(0.00)	0.249	(0.00)

Table 3
Characteristics of funds with ambiguous and explicitly stated marking policies

This table reports fund characteristics for funds classified by transparency of marking standard. Funds with ambiguous marking policies are funds that never disclosed their pricing standard in any of their prospectuses. Funds with explicitly stated marking policies are funds that disclosed their pricing standard in their prospectus filed with the SEC. Mid markers and bid markers are funds that used mid or bid marking standards consistently through time. Fund characteristics are averaged across all observations belonging to a particular fund and the statistics reported in this table are based on the cross-section of funds. Credit rating, issue size, time to maturity, number of trades, and distance from last trade are calculated as the weighted average of the bond characteristics comprising each portfolio each date, with weights equal to the market value of each bond position as reported by the fund. Number of trades and distance from last trade for each bond in each portfolio are computed using TRACE data for the period October 2004-December 2006. Serial correlations of daily returns are computed using daily fund returns, available in the CRSP Mutual Fund database for the January 2001-December 2006 period. For comparability, serial correlations of monthly fund returns have also been computed over the January 2001-December 2006 period. Bond Issue Size, Fund Family Assets, and Fund Assets are reported in $ millions.

	Funds with Ambiguous Marking Policies		Funds with Explicitly Stated Marking Policies		Bid Markers		Mid Markers	
Characteristic	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Bond Credit Rating	BBB	BBB+	BBB	BBB+	BBB	BBB+	BBB	BBB+
Bond Issue Size ($ millions)	702	672	743	707	741	703	736	729
Bond Time to Maturity (Years)	7	7	8	7	7	7	8	8
Portfolio % in Non-Investment Grade Bonds	42.62	28.86	38.18	23.95	36.26	19.70	38.31	23.77
Bond Number of Trades	125	110	134	123	136	129	126	119
Bond Distance from Last Trade (days)	13	10	11	9	11	9	11	9
Family Assets ($ millions)	104,985	21,714	104,394	25,440	146,995	30,714	83,028	25,189
Number of Family Funds	149	134	204	121	216	98	201	144
Fund Assets ($ millions)	548	149	488	146	389	128	439	135
Fund Turnover (%)	137	98	176	112	183	117	185	121
Fund Expense Ratio (%)	0.88	0.85	0.87	0.80	0.84	0.81	0.91	0.81
Average Fund Return (%)	0.44	0.44	0.44	0.44	0.42	0.43	0.43	0.44
Standard Deviation of Fund Returns (%)	1.17	1.11	1.17	1.09	1.16	1.07	1.15	1.08
Serial Correlation of Monthly Returns (%)	11.53	7.78	10.84	7.45	10.82	7.11	10.61	8.11
Serial Correlation of Daily Returns (%)	7.48	3.79	6.60	2.47	6.11	2.42	6.97	2.32
Fraction of Load Funds (%)	59.75		64.51		60.08		68.28	
Number of Funds	264		682		284		233	

Table 4
Frequency analysis by auditor

This table reports information on the firms used by mutual funds to audit their annual statements. Fund-specific auditor information was hand-collected from N-SAR reports and prospectuses filed by funds with the Securities and Exchange Commission (SEC), available on the SEC website. Statistics on the frequency funds audited by the various auditors are reported. The frequency of funds audited by each auditor that are Bid Marker, Mid Marker, or Ambiguous Marker Funds are also reported.

Frequency of Funds and Marking Standards by Auditor					
			By Pricing Standard		
	All Funds		Bid Markers	Mid Markers	Ambiguous Markers
Auditor Name	#	%	%	%	%
Big Four Auditors:					
PRICEWATERHOUSECOOPERS LLP	352	37.21	37.50	18.47	44.03
ERNST & YOUNG LLP	218	23.04	36.24	35.78	27.98
DELOITTE & TOUCHE LLP	155	16.38	29.03	37.42	33.55
KPMG LLP	149	15.75	30.87	42.28	26.85
All Big Four Auditors:	877	92.71	34.55	30.22	35.23
Not Big Four Auditors:	69	7.29	37.68	26.09	36.23
Total	946	100.00	34.78	29.92	35.31

Table 5
Frequency of positions by cluster

This table reports the frequency of bonds with a given number of price clusters. For each date and bond held by at least three mutual funds, the number of price clusters is determined based on the prices reported by all the mutual funds that hold positions in that particular bond. Identification of clusters is conducted for the positions of all funds, of only Bid Markers, only Mid Markers, and only Ambiguous Markers. The last column reports the fraction of all positions that are priced at the most popular price conditional on there being more than one distinct price reported by all mutual funds.

	Fraction of Bonds with a Given Number of Price Clusters			Fraction of Positions Priced at Mode
	Number of Price Clusters			
	1	2	3 or more	
All Funds	12.30	36.67	51.03	57.46
Bid Markers	34.35	41.81	23.84	65.67
Mid Markers	21.86	50.88	27.26	63.39
Ambiguous Markers	15.80	44.10	40.10	58.16

Table 6
Bond Price Dispersion-Univariate Sorts

This table reports price dispersion statistics for bonds that are held by at least 3 mutual funds at the same date. There are 252,765 bond-date observations that satisfy this condition, corresponding to 11,116 corporate bonds. Bond price dispersion is calculated separately using prices reported by three groups of funds: all funds; mid-marking funds; and bid-marking funds. For a particular bond at a particular date we calculate the interquartile range (IR) of the prices reported by the various mutual funds that reported ownership of that bond. The resulting dispersion statistics are then averaged across bond-date observations. Panel A reports dispersion statistics by credit rating group. Each credit rating group is constructed such that, for example, all BBB-, BBB, and BBB+ bonds are categorized as one group, BBB. Panel B reports statistics categorized by the size of the issue. Each year bonds are ranked on issue size and sorted into deciles where the highest-issue-size bonds are placed in Decile 1 and lowest-issue-size bonds are placed in Decile 10. Panel C reports dispersion statistics categorized into 4 groups defined by the time to maturity. *** and ** denote statistical significance at the 1% and 5% level for the difference in dispersion between All Funds' prices and Bid Markers' and Mid Markers' prices.

Panel A. Price Dispersion Statistics By Credit Quality

	All Funds' Prices		Bid Markers' Prices		Mid Markers' Prices	
Credit Rating	Dispersion	Obs.	Dispersion	Obs.	Dispersion	Obs.
AAA	0.228	4,211	0.130***	1,696	0.167***	1,176
AA	0.255	10,874	0.143***	4,385	0.162***	2,733
A	0.281	59,612	0.174***	26,490	0.198***	17,215
BBB	0.332	73,847	0.210***	36,663	0.255***	26,758
BB	0.542	32,831	0.364***	16,444	0.386***	17,141
B	0.554	46,754	0.401***	23,650	0.349***	28,763
CCC	0.604	11,350	0.489***	5,402	0.346***	6,574
CC	0.679	911	0.352***	207	0.428***	447
C	0.712	620	0.668	143	0.521**	393
D	0.571	3,674	0.425***	669	0.493**	1,709
NR	0.503	6,733	0.329***	1,898	0.358***	2,891
Inv. Grade	0.303	148,544	0.190***	69,234	0.227***	47,882
High-yield	0.559	96,140	0.399***	46,515	0.367***	55,027

Table 6-Continued

Panel B. Price Dispersion Statistics By Issue Size

	All Funds' Prices		Bid Markers' Prices		Mid Markers' Prices	
Issue Size Decile	Dispersion	Obs.	Dispersion	Obs.	Dispersion	Obs.
1 (Highest)	0.241	24,105	0.141***	11,615	0.206***	10,505
2	0.301	26,434	0.193***	11,793	0.247***	10,564
3	0.369	23,500	0.240***	11,881	0.285***	10,748
4	0.370	27,525	0.260***	11,806	0.277***	11,288
5	0.436	24,603	0.281***	12,025	0.302***	10,245
6	0.422	25,650	0.327***	10,825	0.335***	10,260
7	0.442	24,757	0.309***	12,253	0.320***	10,695
8	0.454	26,842	0.322***	11,843	0.328***	10,707
9	0.513	24,056	0.350***	12,042	0.345***	10,801
10(Lowest)	0.511	25,293	0.328***	11,834	0.380***	10,595

Panel C. Price Dispersion Statistics By Time to Maturity

	All Funds' Prices		Bid Markers' Prices		Mid Markers' Prices	
Time to Maturity	Dispersion	Obs.	Dispersion	Obs.	Dispersion	Obs.
≤2 years	0.192	42,766	0.140***	17,428	0.158***	13,059
(2, 5]	0.369	71,938	0.254***	34,250	0.277***	30,055
(5,10]	0.472	100,788	0.321***	51,840	0.334***	51,534
>10 years	0.546	36,913	0.323***	14,333	0.393***	11,627

Table 7
Return smoothing and fund characteristics

This table presents results from a logit regression that relates the tendency for funds to mark above the Bloomberg bond mid quotes to fund characteristics. The analysis is done at the position level with each bond in each mutual fund portfolio at a given report data representing a distinct unit of observation. The dependent variable is an indicator variable that equals one for each bond position that is marked at or above the *mid* quote price reported by Bloomberg and zero for each bond position marked at or below the *bid* quote reported by Bloomberg. The main set of independent variables include: *Mid*, an indicator variable that equals one if a fund uses a mid pricing standard, *Ambiguous*, an indicator variable that equals one if a fund has an ambiguous pricing standard; *Negative Return*, an indicator variable that equals one if the fund's past 12 month benchmarked return is in the lowest negative return tercile; and *Positive Return*, an indicator variable that equals one of the fund's past 12 month benchmarked return is in the highest positive return tercile. To construct the *Negative Return* and *Positive Return* indicator variables, each month we first benchmark the past 12 month returns of each fund against either the Lehman Corporate Index or the Lehman High Yield Index, depending on whether the fund invests primarily in investment grade or high yield bonds. Next, for each fund, we group all the negative and positive benchmarked returns separately and rank them within each group into terciles. A return is defined as *Extreme Negative* if the benchmarked past 12 month return as of that particular month is in the bottom tercile of all negative returns. Similarly, we define a return as *Extreme Positive* if the benchmarked past 12 month return as of that particular month is in the top tercile of all positive returns. Additional independent variables include *Cluster Divergent, Family Disagreement, Not Big Four Auditor, Calendar, and Fiscal*. To construct the *Cluster Divergent* variable, for each fund and each period we calculate the fraction of bonds in its portfolio that are marked differently from the two most popular prices reported by all funds (cluster divergent fraction). Next, we average the cluster divergent fraction across all report dates of a particular fund to compute a single metric per fund. We rank all funds based on their average cluster divergent fraction into terciles and for funds in the top tercile cluster divergent is set equal to one and zero for the other funds. To construct the *Family Disagreement* variable, for each fund and each period we calculate the fraction of bonds in its portfolio that are marked differently from at least another fund belonging to the same mutual fund family (disagreement fraction). Next, we average the disagreement fraction across all report dates of a particular fund to compute a single metric per fund. We rank all funds based on their average disagreement fraction into terciles. *Family Disagreement* is set equal to one for funds in the top tercile and zero for the other funds. *Not Big 4 Auditor* is an indicator variable that equals one if the underlying fund is not audited by one of the big four auditors. *Calendar* is a dummy variable that equals one if the bond position is reported at the end of December and *Fiscal* is an indicator variable that equals one if the bond position is reported at the end of a month that corresponds with the fund's fiscal year-end. The marginal probabilities for the independent variables are reported along with the associated *t*-statistics. Standard errors are clustered by fund family and period.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Mid	0.167	(5.40)	0.167	(5.38)	0.167	(5.40)	0.171	(5.43)	0.170	(5.43)	0.168	(5.42)
Ambiguous	0.070	(2.80)	0.069	(2.76)	0.077	(3.22)	0.061	(2.27)	0.072	(3.03)	0.070	(2.81)
Negative Return	0.036	(2.21)	0.032	(1.84)	0.043	(2.23)	0.036	(2.25)	0.040	(2.42)	0.036	(2.21)
Positive Return	-0.037	(2.70)	-0.039	(-2.65)	-0.030	(-2.25)	-0.041	(-2.73)	-0.035	(-2.25)	-0.037	(-2.68)
Calendar			0.038	(1.16)								
Calendar × Negative Return			0.025	(0.56)								
Calendar × Positive Return			0.032	(0.85)								
Fiscal			-0.016	(-1.17)								
Fiscal × Negative Return			0.008	(0.46)								
Fiscal × Positive Returns			-0.020	(-0.70)								
Calendar × Fiscal			-0.017	(-0.57)								
Ambiguous × Negative Return					-0.020	(-1.29)						
Ambiguous × Positive Return					-0.022	(-1.56)						
Cluster Divergent							-0.028	(-0.94)				
Cluster Divergent × Negative Return							0.003	(0.16)				
Cluster Divergent × Positive Return							0.013	(1.27)				
Family Disagreement									0.051	(1.84)		
Family Disagreement × Negative Return									-0.013	(-0.79)		
Family Disagreement × Positive Return									-0.006	(-0.37)		
Not Big 4 Auditor											0.020	(0.61)
Not Big 4 Auditor × Negative Return											0.024	(0.91)
Not Big 4 Auditor × Positive Return											0.011	(0.46)
Observations = 405,026												

Table 8
Return smoothing regressions:

This table reports coefficient estimates from the returns smoothing model of Getmansky, Lo, and Makarov (2004). The specification for the regression model is

$$R^0_{j,t} = \alpha + \theta_0 R_{j,t} + \theta_1 R_{j,t-1} + \theta_2 R_{j,t-2} + \varepsilon_{j,t}$$

where $R^0_{j,t}$ and $R_{j,t}$ are the reported and economic returns of fund *j* during period *t*. In Panel A, consensus bond prices (computed as the cross-sectional median of all prices reported by mutual funds with ownership in a particular bond in a particular period) were used to compute economic returns. In Panel B, bond prices from Bloomberg were used to compute economic returns. Funds with ambiguous marking policies are funds that did not disclose their pricing standard in at least one of their prospectuses. Funds with explicitly stated marking policies are funds that always disclosed their pricing standard in their prospectus filed with the SEC. Funds are also classified by their tendency to mark positions differently from the most popular prices used by all funds. To construct this classification, for each fund and each period we calculate the fraction of bonds in its portfolio that are marked differently from the two most popular prices reported by all funds (cluster divergent fraction). Next, we average the cluster divergent fraction across all report dates of a particular fund to compute a single metric per fund. We rank all funds based on their average cluster divergent fraction into terciles: funds classified as High Cluster Divergent funds are those in the top tercile and Low Cluster Divergent funds are those in the bottom tercile. Funds were also classified by their tendency to mark positions in disagreement with other funds from the same family. To construct this classification, for each fund and each period we calculate the fraction of bonds in its portfolio that are marked differently from at least one other fund belonging to the same mutual fund family (disagreement fraction). We rank all funds based on their average disagreement fraction into terciles. Funds classified as High Family Disagreement funds are those in the top tercile and Low Family Disagreement funds are those in the bottom tercile. In addition funds were classified based on whether they were audited by one of the big four auditors or not. All results are based on pooled regressions and standard errors are clustered by fund family and period. T-statistics are presented in parentheses.

Panel A. Economic Returns Computed Using Bloomberg Bond Prices

		Marking Policy		Cluster Divergent		Family Disagreement		Auditor Size	
Variables	All Funds	Ambiguous	Explicitly Stated	High	Low	High	Low	Not Big 4	Big 4
Intercept	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.21)	(1.69)	(0.96)	(0.98)	(1.02)	(0.76)	(1.37)	(0.77)	(1.22)
θ_0	0.925	0.850	0.964	0.952	0.938	0.924	0.912	0.952	0.924
	(28.04)	(15.12)	(37.59)	(30.43)	(25.94)	(21.07)	(17.09)	(36.82)	(27.26)
θ_1	-0.021	-0.004	-0.031	-0.020	-0.022	0.002	-0.020	-0.006	-0.022
	(-0.99)	(-0.11)	(-1.75)	(-0.99)	(-0.72)	(0.06)	(-0.88)	(-0.50)	(-0.98)
θ_2	0.002	0.021	-0.008	-0.016	0.004	-0.002	0.000	0.000	0.002
	(0.10)	(0.74)	(-0.44)	(-0.79)	(0.15)	(-0.11)	(-0.02)	(-0.01)	(0.11)
p-value H_0: $\theta_0 = 1$	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
R^2	86.16%	80.17%	89.30%	88.66%	87.20%	87.30%	85.33%	89.12%	86.03%
Observations(Funds)	7,567(266)	2,227(79)	5,430(187)	2,452(88)	2,439(89)	2,435(88)	2,568(97)	430(17)	7,227(249)

Panel B. Economic Returns Computed Using Consensus Bond Prices

		Marking Policy		Cluster Divergent		Family Disagreement		Auditor Size	
Variables	All Funds	Ambiguous	Explicitly Stated	High	Low	High	Low	Not Big 4	Big 4
Intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.97)	*(2.01)*	*(1.54)*	*(1.83)*	*(1.03)*	*(1.21)*	*(2.03)*	*(-0.12)*	*(2.10)*
θ_0	0.962	0.931	0.974	0.966	0.987	0.957	0.946	0.985	0.960
	(87.34)	*(28.16)*	*(148.14)*	*(93.43)*	*(128.52)*	*(52.16)*	*(39.64)*	*(163.58)*	*(82.23)*
θ_1	0.014	0.018	0.013	0.017	0.008	0.022	0.013	0.018	0.014
	(3.50)	*(1.77)*	*(4.12)*	*(4.61)*	*(1.48)*	*(2.59)*	*(2.18)*	*(1.66)*	*(3.29)*
θ_2	-0.002	0.006	-0.005	-0.005	-0.005	-0.003	0.002	0.001	-0.002
	(-0.46)	*(0.79)*	*(-1.76)*	*(-1.22)*	*(-1.91)*	*(-0.72)*	*(0.29)*	*(0.26)*	*(-0.48)*
p-value H_0: $\theta_0 = 1$	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
R^2	97.21%	94.94%	98.17%	97.68%	98.99%	97.09%	95.95%	98.54%	97.13%
Observations(Funds)	9,137(266)	2,562(79)	6,575(187)	2,975(88)	2,805(89)	2,805(88)	3,332(98)	569(17)	8,568(249)

Table 9
Theta regressions

This table reports coefficients from regressions of fund θ_0 on dummy variables used to classify funds and liquidity-related control variables. The estimation of θ_0 was done separately using Bloomberg prices in Panel A and consensus prices in Panel B. *Ambiguous Marker* is a dummy variable that takes a value of one for all funds with ambiguous marking policies, i.e., funds that did not disclose their pricing standard in at least one of their prospectuses. To construct the Cluster Divergent variable, for each fund and each period we calculate the fraction of bonds in its portfolio that are marked differently from the two most popular prices reported by all funds (cluster divergent fraction). Next, we average the cluster divergent fraction across all report dates of a particular fund to compute a single metric per fund. We rank all funds based on their average cluster divergent fraction into terciles; Cluster Divergent is set equal to one for funds in the top tercile and zero for the other funds. To construct the Family Disagreement variable, for each fund and each period we calculate the fraction of bonds in its portfolio that are marked differently from at least another fund belonging to the same mutual fund family (disagreement fraction). Next, we average the disagreement fraction across all report dates of a particular fund to compute a single metric per fund. We rank all funds based on their average disagreement fraction into terciles; Family Disagreement is set equal to one for funds in the top tercile and zero for the other funds. *Not Big 4 Auditor* is an indicator variable that equals one if the underlying fund is not audited by one of the big four auditors. *Price Range* is a continuous variable that equals the value-weighted average price range of the underlying bonds in a fund's portfolio. The additional bond liquidity control variables are based on the underlying bond characteristics and these fund characteristics are averaged across all observations belonging to a particular fund: *Non-Investment Grade* represents the weight of non-investment grade bonds in a fund portfolio; *Issue Size* is the weighted average issue size of all bonds in a fund portfolio; and *Maturity* is the value-weighted average time to maturity of bonds in the portfolio. Other bond liquidity control variables are based on the underlying bond trade characteristics reported in the TRACE database: *Trades* is the weighted average number of trades for all the bonds in a portfolio reported in TRACE in the last month prior to the fund holdings report date and *Last Trade Distance* is the distance in days from the last trade for each particular bond averaged (value-weighted) across all the bonds in the portfolio. Standard errors are clustered by fund family. T-statistics are in parentheses.

Panel A. Economic Returns Computed Using Bloomberg Prices

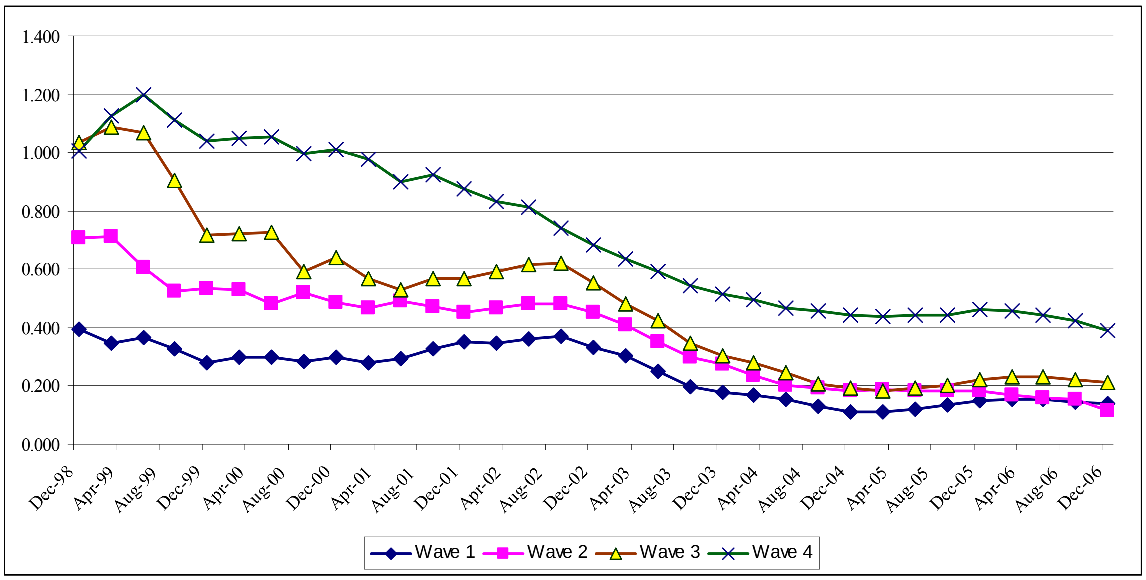
Variable	1	2	3	4
Intercept	0.972	0.970	0.989	0.864
	(65.32)	*(67.21)*	*(4.44)*	*(8.65)*
Ambiguous Marker	-0.062	-0.050	-0.060	-0.046
	(-2.67)	*(-2.29)*	*(-2.51)*	*(-2.26)*
Cluster Divergent	-0.015	-0.012	-0.016	-0.006
	(-0.81)	*(-0.63)*	*(-0.86)*	*(-0.28)*
Family Disagreement	-0.007	-0.001	-0.004	-0.005
	(-0.31)	*(-0.03)*	*(-0.20)*	*(-0.26)*
Not Big 4 Auditor	-0.015	-0.020	-0.017	-0.017
	(-0.63)	*(-1.00)*	*(-0.70)*	*(-0.68)*
Log(Price Range)		-0.086		
		(-2.86)		
Non-Investment Grade			-0.021	
			(-0.54)	
Log(Issue Size)			0.003	
			(0.10)	
Log(Maturity)			-0.013	
			(-0.51)	
Log(Trades)				0.020
				(1.15)
Log(Last Trade Distance)				0.005
				(0.26)
R^2	4.09%	9.02%	4.58%	3.44%
Funds (Obs.)	266	266	266	252

Table 9-Continued

Panel B. Economic Returns Computed Using Consensus Prices				
Variable	1	2	3	4
Intercept	0.992	0.991	0.989	0.990
	(172.36)	*(172.97)*	*(7.33)*	*(15.20)*
Ambiguous Marker	-0.031	-0.024	-0.032	-0.029
	(-1.89)	*(-1.82)*	*(-1.96)*	*(-2.07)*
Outmode	-0.014	-0.012	-0.015	-0.010
	(-1.50)	*(-1.25)*	*(-1.54)*	*(-1.02)*
Family Disagreement	-0.006	-0.002	-0.009	0.000
	(-0.31)	*(-0.10)*	*(-0.51)*	*(0.01)*
Not Big 4 Auditor	0.005	0.002	0.007	0.002
	(0.57)	*(0.17)*	*(0.71)*	*(0.17)*
Log(Price Range)		-0.050		
		(-2.05)		
Non-Investment Grade			0.010	
			(0.43)	
Log(Issue Size)			-0.009	
			(-0.47)	
Log(Maturity)			0.027	
			(1.13)	
Log(Trades)				0.002
				(0.13)
Log(Last Trade Distance)				-0.003
				(-0.25)
R^2	2.46%	6.44%	3.87%	2.43%
Funds (Obs.)	266	266	266	252

Figure 1
Time Series of Dispersion for the Four TRACE Bond Waves

Figure 1 shows the time series of the average dispersion for the four Trace bond waves. The *first wave* of bonds reported through TRACE encompassed all investment grade bonds greater than $1 billion in original issue size. On July 1, 2002 FINRA required dissemination of transaction information for bonds meeting these criteria. *Second-wave* bonds include all investment grade bonds rated A or higher with original issue size of at least $100 million. These bonds became permanently disseminated as of March 1, 2003. *Third-wave* bonds comprise all issues rated BBB- to BBB+ with an original issue size less than $1 billion. The third-wave rolled out in two phases. The initial phase began on April 14, 2003 when FINRA required dissemination for a subset of 120 third-wave bonds. The secondary phase began on September 30, 2004 when all other bonds meeting third-wave criteria became permanently disseminated. TRACE's *fourth wave*, the rollout for high-yield bonds, also occurred in two parts. FINRA began requiring dissemination of a special subset of 50 highlighted high-yield bonds on July 1, 2002. The secondary phase began on September 30, 2004 when all other bonds meeting fourth-wave criteria became permanently disseminated.



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Appendix A

Additional Institutional Bond Pricing Details

Bond dealer firms and securities pricing services compile daily marks on individual issues. Dealers compile these marks for internal profit and loss determination, repurchase agreement transaction collateral valuation, bond index construction and client servicing purposes. Within each dealer firm, the trading desk responsible for dealing in a given security generally sets the end-of-day marks on that security. Traders use available quotes from inter-dealer broker screens on the subject security or related securities, their own customer flows and any available "market color" – stories behind the day's transactions relayed from a variety of sources – as inputs to the marking process. Furthermore, compliance and risk management professionals within the dealer firm typically review the appropriateness of these marks, especially with regard to the integrity of internal daily profit and loss figures.[22] Dealers provide a great deal of information concerning prices, relative value and insights to institutional buy-side customers. Generally, there is effective best-in-class price knowledge for buy-side customers that have multiple (e.g., five) dealer relationships and access to price quotes from dealer sources.[23]

As it happens, the over-the-counter dealer market arrangement of bond markets and general reliance on dealer and/or pricing service marks for individual securities make bond funds generally less susceptible to stale pricing problems that are related to overall market volatility. In particular, bond dealers and bond pricing services will mark individual securities on an option-adjusted yield spread ("OAS") basis against the heavily-traded US Treasury benchmark issues. In this manner, the entire set of bond universe marks will reflect the latest available general market moves through Treasury benchmarks. But because so many corporate bond issues are illiquid and infrequently traded, there tends to be substantial variation in valuations nonetheless. For example, different dealers will experience different customer flows and therefore may form different opinions about the underlying value of any infrequently traded issue. The

[22] See Pulliam (2007).
[23] See "An analysis and description of pricing and information sources in the securitized and structured finance markets," The Bond Market Association and The American Securitization Forum, October 2006.

information a bond dealer collects through seeing specific customer trading flow goes beyond the trade's price. The size of the trade, the identity of the customer, and any explanations from the customer about the reasons behind the trade all matter. Thus, a dealer who has not traded a particular illiquid bond for an extended period will have a less informative opinion on its current value than one who has recently traded it.

Zitzewitz (2003) finds some evidence of NAV predictability in high-yield bond funds. Such evidence is at least partially consistent with the view that some price staleness may still be a problem for bond funds. Nevertheless, grossly inefficient extrapolative valuation rules should not survive competitive pressures within the pricing services industry. Indeed, such pricing services should seek to distinguish themselves by doing a good job of hand-pricing infrequently traded "hard-to-mark" securities. Thus, given the incentives in place, we would expect that pricing services would generate unbiased valuations of even the hardest-to-mark securities.

Variation among the valuations produced by different pricing services for the same corporate bond can be attributed to a number of factors. Some of these factors relate to the underlying valuation analytics. Important differences may exist in the specific inputs and models used by price providers for individual corporate bonds. Pricing services seek to differentiate themselves in the eyes of subscribing funds through offering "best-in-class" methodologies. But other factors driving variation in bond valuations will relate to choices made by the funds themselves. Specifically, pricing services may provide a menu of marking alternatives that permit any subscribing fund to choose either 3:00 PM or 4:00 PM benchmark Treasury yield curves as the "closing" benchmark curve. Furthermore, some pricing services offer funds the choice of marking the positions either at "bid" prices or at "mid" prices. We provide insights into the importance of this "bid" versus "mid" choice in section 5.

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