CFR working paper NO. 21-05

on the valuation skills of corporate Bond Mutual Funds

G. cici • P. zhang

centre for financial Research
cologne

On the Valuation Skills of Corporate Bond Mutual Funds

by

Gjergji Cici and Pei (Alex) Zhang*

March 13, 2021

Abstract

We introduce a new measure to assess the valuation skills of investment-grade corporate bond funds. Our measure recognizes funds that ex-ante hold a higher fraction of undervalued bonds as having better valuation skills. The measure predicts future fund performance, is stable over time, and is unrelated to other sources of skill. Fund investors recognize such skill by responding more to the past performance of funds with better valuation skills. Consistent with the equilibrium model of Gârleanu and Pedersen (2018), our evidence suggests that as growing capital gets allocated to skilled bond funds, the corporate bond market is becoming more efficient.

* Gjergji Cici is from the School of Business, University of Kansas, 1654 Naismith Drive, Lawrence, Kansas, 66045, U.S., phone: 785-864-3873, email: gjergji.cici@ku.edu. Pei (Alex) Zhang is from the School of Business, University of Kansas, 1654 Naismith Drive, Lawrence, Kansas, 66045, U.S., phone: 608-571-9789, email: pzhang85@ku.edu. Cici is also a member of the Centre for Financial Research (CFR), Cologne, Albertus-Magnus-Platz, 50923 Cologne, Germany. For helpful comments and discussions we thank Scott Gibson and seminar participants at the University of Kansas.

1. Introduction

Corporate bond mutual funds are becoming increasingly important in the corporate bond market as their assets under management grew from $382 billion in 2000 to approximately $3 trillion in 2019 (Investment Company Institute (2020)). In contrast to active equity funds from which money has migrated to passive equity funds over the last 10 years, active corporate bond funds have been rewarded with equal investment flows as their passive counterparts (Mauboussin (2019)). Apparently, investors collectively believe that investment skills exist among active corporate bond mutual funds, but have given up on the idea that such skills are present among actively managed equity funds. What investors seem to believe, however, contrasts with a lack of clear evidence from academic research concerning the abilities of active corporate bond funds. Exploiting unique features of the corporate bond market, we introduce a novel holdings-based measure of the valuation abilities of corporate bond mutual funds, which identifies whether corporate bond mutual funds correctly identify and exploit mispriced bonds. By doing so, we shed new light on the debate concerning the investment abilities of this important group of institutional investors and reconcile the behavior of mutual fund investors with new evidence on the investment abilities of corporate bond funds.

The corporate bond market is large, illiquid, and deemed by many to be less efficient than the equity market. These features are conducive to numerous profit opportunities that are unique to the corporate bond market.[2] Despite this, the evidence from previous research on the investments abilities of corporate bond mutual funds is mixed. Most of the research to date has

[2] Examples of such opportunities include: (1) exploiting underpricing of corporate bonds in primary offerings, an activity which is far more active than in the equity market (e.g., Nikolova, Wang, and Wu (2020)); (2) trading against uninformed counterparties that transact for non-economic reasons (e.g., Spiegel and Starks (2016); Nanda, Wu, and Zhou (2019); Girardi, Hanley, Nikolova, Pelizzon, and Sherman (2020); Murray and Nikolova (2021)); and (3) providing liquidity during periods of sustained customer imbalances (e.g., Anand, Jotikasthira, and Venkataraman (2020)).

taken a skeptical stance, documenting that corporate bond funds, on average, generate returns that do not outperform their benchmarks or they are unable to pick bonds that outperform other bonds of similar characteristics.[3] Only recently has evidence emerged pointing to the presence of differential skills in the cross-section of corporate bond funds, the source of which is not well understood.[4] A notable exception to this is a study by Anand, Jotikasthira, and Venkataraman (2020) documenting that a subset of corporate bond funds earn positive alpha by supplying liquidity. Still, there is no evidence that corporate bond funds have valuation skill such that they can identify and profitably trade mispriced bonds, which encompasses one of their core activities. This is an open question of importance given the resources expended by active fund management on the analysis of corporate bonds. Our paper is the first to measure and document the presence of valuation skill in the cross-section of corporate bond mutual funds (hereafter referred to as corporate bond funds).

The idea behind our novel measure we use to identify valuation skills is straightforward. Consider a bond fund that is skilled at accurately valuing individual corporate bonds. The fund will exploit this particular advantage by identifying and buying bonds that are undervalued. Therefore, its portfolio ought to reveal such skill by exhibiting a higher fraction of undervalued bonds among all its bond positions that are mispriced. For example, a fund's portfolio that at a given point in time includes mispriced bonds that are all undervalued would indicate that this particular fund has the highest possible level of valuation accuracy. In contrast, the portfolio of another fund holding mispriced bonds that are all overvalued would indicate the lowest possible

[3] See Blake, Elton, and Gruber (1993); Elton, Gruber, and Blake (1995); Ferson, Henry, and Kisgen (2006); Gutierrez, Maxwell, and Xu (2008); Huij and Derwall (2008); Chen, Ferson, and Peters (2010); and Cici and Gibson (2012); Rohleder, Scholz, and Wilkens (2018); and Natter, Rohleder, and Wilkens (2021).
[4] See Choi, Cremers, and Riley (2020); Anand, Jotikasthira, and Venkataraman (2020); and Huang, Lee, and Rennie (2019).

level of valuation accuracy. Based on this insight, for each fund and date pair for which a reported portfolio exists, we compute the valuation accuracy score (VAS) as the fraction of mispriced bonds held that are undervalued. A higher VAS indicates a higher level of valuation accuracy.

The construction of our measure hinges on the ability to ex-ante identify mispricing in corporate bonds. We do so by exploiting a unique feature of the corporate bond market that many firms have multiple bonds outstanding.[5] Exploiting within-issuer variation of individual bonds' credit spreads at each point in time, we measure mispricing by isolating the part of the credit spread unexplained by common firm fundamentals and a number of bond characteristics. We confirm that this part of the credit spread is indeed due to mispricing and unlikely due to omitted bond or firm characteristics related to persistent risk by documenting that unexplained credit spreads predict economically significant future excess bond returns that materialize only in the short term, i.e., one month.

The focus of our study is on investment-grade bonds and investment-grade (IG) bond funds. The main reason for this is that our methodology for identifying mispriced bonds relies on the presence of multiple bonds issued by the same firm, which is more common among firms with IG credit ratings.[6] This requirement also means that we cannot determine mispricing for all bonds in a fund's portfolio; we can do so only for those issued by a firm with multiple bonds outstanding. Nonetheless, a fund that is skilled at valuing corporate bonds ought to benefit from such skill by holding undervalued bonds, regardless of whether these bonds can be identified as mispriced by

[5] For example, Verizon had over 100 bonds outstanding as of 6/31/2020. The large number of bonds per issuer and the possible mispricing among certain bonds of the same issuer are often presented by industry professionals and commentators as one of the unique opportunities to generate excess returns in the corporate bond market (e.g., Mauboussin (2019)).

[6] The median high-yield (HY) firm satisfying our data requirements has only 1.3 concurrently outstanding bonds, while the median IG firm has 3.5 issues outstanding. There is yet another reason for our focus on IG firms. The vast majority of HY firms' bonds are refinanced/called long before their maturity date (e.g., Xu (2018)), which means that credit spreads based on yield-to-maturity of HY bonds are systematically biased. A more appropriate yield measure of HY bond should be yield-to-worst or option-adjusted spread, which are both practically difficult to calculate.

our methodology. Thus, we expect our valuation accuracy measure to represent overall corporate bond valuation skill.

Covering a comprehensive sample of 381 IG bond funds during the 2003-2018 sample period, we conduct three sets of analyses. First, we document that our valuation accuracy score predicts future fund performance as bond funds with higher VAS exhibit significantly better gross and net return alphas than funds with lower VAS over the next quarter. For example, funds in the top VAS quintile outperform funds in the lowest quintile by a significant 31 basis points gross alpha per year. Not only is this performance differential highly significant in a statistical sense, but it is also economically significant, especially when considering that the gross alpha of the average active bond fund is just 23 basis points per year.

Our results are robust to controlling for a number of fund and family characteristics. Importantly, they persist even after we control for the ability of certain funds to profit from supplying liquidity as documented in Anand et al. (2020), confirming that our measure is indeed capturing a different type of skill. An additional test rules out a mechanical effect resulting from short-term outperformance of mispriced bonds employed for the construction of VAS: delaying fund performance measurement by one month does not change our main results. Our results are robust to controlling for unobserved fund heterogeneity using fund fixed effects, different benchmarks used for risk adjustment, and different windows to estimate fund alphas. In further robustness tests, we construct two alternative VAS measures based, respectively, on the number instead of the market values of mispriced holdings and on fund trades over the last twelve months. Our results remain unchanged.

We next investigate the most likely mechanism through which the valuation skills measured by VAS affect fund performance. Intuitively, we expect bond funds with valuation skills to exploit such skill by selecting undervalued bonds that will then outperform bonds with similar characteristics. In other words, such funds are expected to generate better performance through superior bond selection. Following Daniel, Grinblatt, Titman, and Wermers (1997) and Cici and Gibson (2012), we decompose a fund's holdings return into components that are attributable to bond-selection and characteristic-timing ability. Consistent with the "superior bond selection" mechanism, we find that VAS predicts fund holdings returns attributable to corporate bond selection but not returns attributable to characteristic timing.

Second, we examine the relation between our valuation accuracy measure and a number of other fund characteristics. The VAS of a given fund is highly persistent over time, consistent with the notion that it reflects a skill type that is stable. This analysis also suggests that VAS reflects skill that stems from the active trading of mispriced bonds. Specifically, VAS can be predicted by an alternative valuation accuracy measure that is based on the trades of a given fund in mispriced bonds over the last twelve months. In addition, funds with higher turnover exhibit higher VAS. This is consistent with the notion that funds with better valuation skills will rationally seek to benefit from such skills by trading more. Other fund variables, including the liquidity score of Anand et al. (2020), which captures the ability of certain funds to profit from providing liquidity, do not predict VAS. Thus, our measure represents a dimension of skill that is orthogonal to other factors known to affect fund performance.

Finally, we examine how, if at all, fund investors are responding to the presence of valuation skills in the cross section of IG bond funds and whether this has broader implications for the efficiency of the corporate bond market. Analyzing investor flows, we find evidence suggesting that investors are learning about the skills of IG bond funds through a combination of two sources of information. In particular, we document that flows exhibit a stronger performance-chasing behavior for funds with higher VAS, which means that investors perceive the past performance of funds with higher VAS to be a stronger indicator of skill and pursue it even more aggressively. Thus, investors learn about the skills of IG corporate bond funds utilizing information from portfolio holdings to infer valuation accuracy in conjunction with information from past fund performance. These results are consistent with learning mechanisms proposed in previous research. The fact that investors are utilizing information from portfolio holdings, suggests that they are incurring search costs in an attempt to find skilled funds, which is consistent with Gârleanu and Pedersen (2018), while their performance-chasing behavior is consistent with the Berk and Green (2004) framework whereby investors learn about skill from past performance.

Exploring implications that our findings could have for the efficiency of the corporate bond market, we find evidence that is largely consistent with the equilibrium model of Gârleanu and Pedersen (2018). The idea is that as search costs have been declining in later years due to technological advances (e.g., Gârleanu and Pedersen (2018)) and consequently investors can more easily find skilled managers, the capital flows to skilled active managers make asset prices more efficient. This is consistent with our evidence. That is, we find that the corporate bond market has become more efficient as bond fund investors allocate more capital to skilled IG corporate bond funds. In particular, we document that the profitability of portfolio strategies exploiting bond mispricing identified with our methodology has gone down in the later years. This evidence is further corroborated by a decline in the alphas of funds with the best valuation skills in the later years, indicating that it has become harder for skilled funds to generate alpha in a market that is becoming more efficient.

Our paper contributes to a growing literature that studies the performance of corporate bond funds.[7] While the methodologies employed in this literature largely mirror those from the far more extensive literature that studies the performance of active equity mutual funds, we introduce a methodological innovation to uncover valuation skills across bond funds that relies on unique features of the corporate bond market. This allows us to present novel evidence of skill in the active management of corporate bonds by documenting that the differential abilities to value individual corporate bonds accurately translate into differential performance in the cross-section. Thus, at a general level, our evidence contributes to the debate on whether skill exists among corporate bond mutual funds.

Our paper is also related to a recent literature strand documenting evidence of ability among subsets of corporate bond funds. Applying methodologies from the equity mutual fund literature, Huang, Lee, and Rennie (2019) and Choi, Cremers, and Riley (2020) present evidence of ability among corporate bond funds.[8] The source of this ability is not well understood, however, with the exception of Anand et al. (2020) who show that some funds are skilled at providing liquidity in a profitable manner. Our contribution is that we document another source of ability among bond funds that materializes in the form of superior valuation skills. Our finding that valuation skills exist in the cross-section of bond funds is new to the literature and thus contributes to furthering our understanding of the investment abilities and their sources among corporate bond mutual funds.

[7] Studies of corporate bond mutual fund performance include: Blake, Elton, and Gruber (1993); Elton, Gruber, and Blake (1995); Ferson, Henry, and Kisgen (2006); Gutierrez, Maxwell, and Xu (2008); Huij and Derwall (2008); Chen, Ferson, and Peters (2010); Cici and Gibson (2012); Moneta (2015); Rohleder, Scholz, and Wilkens (2018); Huang, Lee, and Rennie (2019); Choi, Cremers, and Riley (2020); Anand et al. (2020); and Natter, Rohleder, and Wilkens (2021).

[8] Huang et al. (2019) employ the bootstrap methodology of Fama and French (2010) to account for luck and document a higher fraction of skilled funds among active bond funds than what Fama and French (2010) document for equity funds. Choi, Cremers, and Riley (2020) employ a modified version of the active share measure of Cremers and Pettajisto (2009), documenting a positive relation between the active share of bond funds and their future performance.

Another contribution of our paper is that we provide supporting empirical evidence for the equilibrium model of Gârleanu and Pedersen (2018), which links the efficiency of asset prices to the efficiency of the asset management market. Our findings of increasing pricing efficiencies in the corporate bond market, differential valuation skills across IG bond funds, and investors' ability to identify skilled funds support major elements of their model. Even more important in the context of market efficiency, our findings provide support for one of the key predictions of their equilibrium model that as more capital goes to skilled active managers, asset prices become more efficient.

2. Data, Sample, and Construction of the Valuation Accuracy Score

2.1. Corporate Bond Sample Used to Identify Mispricing

To construct the corporate bond sample used to identify mispriced bonds, we combine information from four databases: the Mergent Fixed Income Securities (FISD) Database, the enhanced version of the Trade Reporting and Compliance Engine (TRACE) Database, the Bloomberg Database, and the Compustat Database. From FISD, we collect bond characteristics. Our corporate bond sample includes non-puttable, non-convertible, fixed-coupon, non-perpetual, senior unsecured U.S. Corporate Debentures ("CDEB"). We exclude bonds that: are not listed or traded in the US, i.e., Rule 144A and private placement bonds; are preferred securities; do not trade in US dollars; are issued by firms outside the jurisdiction of the United States; have less than one year of time-to-maturity; and have less than three months of age.[9]

[9] As documented by Bai, Bali, and Wen (2019), once a bond's time-to-maturity is less than one year, it is removed from major US corporate bond indexes. To avoid potential return distortions mechanically caused by index-tracking investors, we remove them from our sample. We also remove bonds with less than three months of age for similar reasons. Nikolova et al. (2020) document that newly-issued bonds are systematically underpriced in the offering process and institutional investors with better relation with underwriters tend to get larger allocations, which may cause a bias when identifying fund-level valuation skills.

For the resulting subset of bonds, we construct returns of monthly frequency from January 2003-December 2018 using pricing information obtained from TRACE and Bloomberg. We provide details on the additional filtering procedure we use to construct bond returns in Appendix A. We refer to this broader sample of corporate bonds as the *bond returns* sample and use it later in our holdings-based return decomposition.

Next, we calculate the yield to maturity and duration for each bond from the bond returns sample based on month-end prices, coupon information, and maturity. We compute the credit spread as the difference between the corporate bond yield and the Treasury bond yield of the same maturity.[10] Using the Bond CRSP link table provided by the WRDS Bond Return Database, we match bonds to firms and construct firm-level variables to be used in later analysis using accounting data collected from Compustat. Detailed information on the construction of firm-level variables is presented in Appendix B. Finally, since our method for identifying mispriced bonds requires the presence of multiple bonds outstanding per firm every month, we identify firms with at least two outstanding IG bonds with non-missing month-end prices in a given month and include all the IG bonds of these firms.[11] The resulting sample, which we refer to as the *mispricing-analysis* sample, consists of 7,822 IG bonds issued by 600 firms from January 2003 to December 2018.

Table 1 provides summary statistics for the mispricing-analysis bond sample. We have 376,394 monthly observations with non-missing values needed for the subsequent analysis. The average bond has an outstanding amount of $595 million, age of six years, ten years to maturity,

[10] Following Collin-Dufresne, Goldstein, and Martin (2001), we linearly interpolate the Treasury bond yield curve using 1-year, 2-year, 3-year, 5-year, 7-year, 10-year, 20-year, and 30-year constant maturity yields from the St. Louis Fed whenever possible.

[11] We convert bond ratings to numerical scores, where 1 refers to an AAA rating and 22 refers to a D rating. Numerical ratings of 10 or below (BBB- or better) are considered investment-grade, and ratings of 11 or higher (BB + or worse) are considered high yield.

and an average credit rating of A-. Unreported results confirm that our sample bonds are largely comparable to the greater universe of IG bonds.

2.2 Steps in the Construction of the Valuation Accuracy Score

In this section, we discuss the steps involved in the construction of our valuation accuracy score. We first explain and provide support for the procedure we use to identify mispriced bonds and then explain how we use fund portfolio holdings of mispriced bonds to construct the valuation accuracy score, which we use to assess the accuracy of bond funds' valuation assessments.

2.2.1. Methodology for Identifying Mispriced Bonds

A corporate bond spread is a function of three sets of factors: firm fundamentals, bond characteristics, and general market conditions. To identify mispriced bonds, ideally, we want to find bonds with credit spreads that are not fully explained by these determinants. This is challenging, however, because firm fundamentals are, for the most part, unobservable. To circumvent this limitation, we follow previous research and exploit a unique feature of the corporate bond market, namely that many firms have multiple bonds outstanding at a given point in time.[12] This feature allows us to compare bonds of the same firm at the same time that effectively have exposure to the same fundamental risk and market-wide factors, while controlling for observable bond characteristics.

Consistent with these insights, we isolate the unexplained part of the credit spread by running the following cross-sectional regression with issuer fixed effects every month:

$$CS_{i,j,t} = \alpha_{j,t} + \sum_{k=1}^{n} \beta_{t,k} \boldsymbol{Bond_{i,j,t,k}} + \mu_t TTM_{i,j,t} + \sum_{k=1}^{n} \gamma_{t,l} TTM_{i,j,t} \boldsymbol{Firm_{j,t,k}} + \varepsilon_{i,j,t} \quad (1)$$

[12] Examples of studies that use this feature include Helwege and Turner (1999); Dick-Nielson, Feldhütter, and Lando (2012); Helwege, Huang, and Wang (2014); Choi, Hoseinzade, Shin, and Tehranian (2020) and Chen and Choi (2020).

where *i*, *j*, and *t* denote, respectively, bond issue, firm, and month. $CS_{i,j,t}$ is the credit spread and $TTM_{i,j,t}$ is the natural log of time-to-maturity in years. Firm fixed effects denoted by $\alpha_{j,t}$ allow us to compare bonds of the same firm and thus control for firm fundamentals at time *t*. To control for bond heterogeneity, we include $\boldsymbol{Bond_{i,j,t,k}}$, a vector of the following bond-level variables: *rating number dummies*, *percentage of zero trading days in a month*, *coupon rate*, *natural log of current amount outstanding*, *natural log of bond age in years*, and *duration in years*.

Furthermore, as in Covitz and Downing (2007), we include interactions of the natural log of time-to-maturity with proxies for firm fundamentals to control for the possibility that longer-term bonds have greater sensitivity to firm fundamentals (e.g., Almeida and Philippon (2007)). These firm-level proxy variables denoted by $\boldsymbol{Firm_{j,t,k}}$ consist of two sets. The first set, which controls for firm credit risk largely following Dick-Nielsen, Feldhütter, and Lando (2012) includes *the ratio of operating income to sales*, *the ratio of long-term debt to assets*, *the ratio of total debt to capitalization*, *four pretax interest coverage dummies*, and *equity volatility*.[13] We also draw on Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017) and Choi and Kim (2017), who, inspired by the q-theory of the firm (Hou, Xue, and Zhang (2015)), identify a number of variables that explain bond returns in the cross-section. Thus, the second set includes *asset growth*, *investment-to-assets*, *gross profitability*, *momentum*, and *past month's equity return*. We provide detailed definitions of these firm-level variables in Appendix B.

It is important to note that running Equation 1 every month not only allows us to control for general market conditions but also allows the parameters to be time-varying if the relation

[13] Other studies that use these similar control variables include Blume, Lim, and Mackinlay (1999), Campbell and Taksler (2003), and Chen et al. (2007).

between credit spreads and the explanatory variables depends on market conditions, thus allowing for greater flexibility in estimation.

We use the residuals (*residual spreads*) from Equation 1 to determine a bond's valuation status.[14] A positive (negative) residual spread suggests that a bond's credit spread cannot be fully explained by its common determinants, and we hypothesize that such a bond has a temporarily higher (lower) credit spread than it should be, indicating potential underpricing (overpricing). Alternately, omitted risk factors could explain the residual spread. However, we can empirically assess the efficacy of our method for identifying mispricing by studying the future risk-adjusted returns of separate portfolios that include bonds, respectively, with positive and negative residual spreads. If the alphas of these portfolios are short-lived, then their residual spreads are more likely to indicate mispricing than omitted persistent risk.

At the end of each month *t*, we construct two portfolios, one consisting of bonds with positive residual spreads (*Pos-RS*) and the other consisting of bonds with negative residual spreads (*Neg-RS*). Both portfolios are value-weighted based on the amount outstanding of each portfolio bond and are held for one month. To examine persistence of alphas, we delay the construction of these portfolios by one to eleven months. Thus, in effect, we are tracking 12 Pos-RS portfolios and 12 Neg-RS portfolios depending on the delay of portfolio construction. The monthly return series of these portfolios are evaluated using a two-factor model where we regress the portfolio return in excess of the one-month risk-free rate on the following factors: *TERM*, the monthly return difference between the Bloomberg Barclays Long Treasury Bond Index and one-month risk-free rate and *DEF*, the monthly return difference between the Bloomberg Barclays US Corporate High Yield Index and the Bloomberg Barclays Treasury Bond Index (Fama and French (1993)). For

[14] The average R-square of monthly regression of Equation 1 is 84%, indicating that our methodology can explain the cross-sectional variation in bond credit spread fairly well.

robustness, we also estimate portfolio alphas based on a six-factor model, which includes TERM, DEF, and the four common risk factors introduced by Bai, Bali, and Wen (2019): bond market factor (*MKT*), downside risk factor (*DRF*), credit risk factor (*CRF*), and liquidity risk factor (*LRF*).

The portfolio alphas are reported in Table 2. In an efficient bond market, residual spreads should reflect mere noise, providing no information about future bond returns. This is not the case, however, as Column 1 shows that the Pos-RS portfolio generates a significant 28bps two-factor alpha while Column 2 shows that the Neg-RS portfolio generates a significant -22bps alpha in the next month. The signs of the alphas are consistent with the direction of mispricing implied by the sign of the residual spreads. In other words, the positive (negative) alpha generated by the Pos-RS (Neg-RS) portfolio in the next month indicates that this portfolio included undervalued (overvalued) bonds, the prices of which were pushed closer to their intrinsic value in the next month. Importantly, the fact that the alphas quickly disappeared beyond one month is inconsistent with residual spreads capturing omitted risk factors.[15]

Results from Columns 3 and 4, where we use the 6-factor model to estimate alphas are very similar. Taken together, our findings suggest that our approach based on residual spreads can identify, on average, temporarily mispriced bonds, and the bond market, in general, corrects such mispricing within a month. We provide additional support for the evidence from Table 2 in a series of robustness tests reported in Appendix C.

2.2.2. Valuation Accuracy Score Methodology

[15] Although it is not the focus of our investigation, in unreported results we observe a statistical difference in the performance of the two portfolios that lasts until month t+7 (t+6) under the 2-factor (6-factor) model. However, these alpha differences (2~7bps) are not economically meaningful since they do not survive transaction costs, which, based on Dick-Nielson et al. (2012), amount to a median roundtrip cost of 22bps.

To identify valuation skill across bond funds, our novel measure exploits information from fund portfolio holdings of bonds that we identify to be mispriced following the approach introduced in the previous section. The intuition is straightforward. A fund that has the ability to accurately identify undervalued or overvalued bonds ought to rationally exploit this ability by consistently buying underpriced bonds and selling overpriced bonds. Consequently, we would expect such a fund to hold a higher fraction of undervalued bonds among all the mispriced bonds we see in its portfolio. In other words, a higher fraction suggests a higher accuracy in the valuation assessments of the said fund.

Relying on fund *f*'s reported portfolio holdings and bond *i*'s valuation status at time *t* determined from Equation 1, we calculate the Valuation Accuracy Score ($VAS_{f,t}$) as follows:

$$VAS_{f,t} = \frac{\$\sum_{i=1}^{n} Underpriced\_bond_{i,f,t}}{\$\sum_{i=1}^{n} Underpriced\_bond_{i,f,t} + \$\sum_{i=1}^{n} Overpriced\_bond_{i,f,t}} \qquad (2)$$

where $\$\sum_{i=1}^{n} Underpriced\_bond_{i,f,t}$ ($\$\sum_{i=1}^{n} Overpriced\_bond_{i,f,t}$) is the sum of the market values of all underpriced (overpriced) bond holdings at time *t*. The market value of each holding is as reported by Morningstar. Consistent with our intuition presented above, by measuring the importance of undervalued bonds in the sub-portfolio of all mispriced bonds held by a fund, VAS helps us capture the accuracy of a fund's valuation assessments. Using market values places greater weight on larger holdings, which should reflect a fund's valuation assessment more accurately. In a robustness test, we consider a version of VAS based purely on the number of underpriced and overpriced bond holdings and find similar results. Possible values of VAS range by construction between zero and one. If every mispriced bond held in the portfolio is underpriced, a fund has a VAS of one. In contrast, if every mispriced bond held in the portfolio is overpriced, a fund has a VAS of zero.

An alternative approach to evaluate a fund's valuation skill is to assess valuation accuracy of fund trades inferred from portfolio changes. Although this approach may arguably better capture the active decisions of a given fund, one major drawback is that we do not observe the exact timing of fund trading activities. In the context of our study, such a drawback is likely to create substantial noise given the evidence from Table 2 that the bond market corrects bond mispricing within a month. Nonetheless, in a robustness test, we construct an alternative valuation accuracy measure based on fund trades of mispriced bonds.

2.3. Corporate Bond Mutual Fund Sample

We employ two mutual fund data sources. From Morningstar, we obtain detailed portfolio holdings for both live and dead mutual funds from January 2003 to December 2018. Other mutual fund characteristics come from the CRSP mutual fund (CRSP MF) database. We merge the two databases using fund tickers and CUSIPs. The steps for the selection of our corporate bond fund sample are as follows. We first select a comprehensive list of IG corporate bond funds using CRSP MF objective codes and Morningstar categories.[16] To ensure that we include funds that invest primarily in IG corporate bonds, we exclude funds that invest on average more than 50% of their corporate bond portfolio in HY bonds (e.g., Cici and Gibson (2012)).

Next, we exclude index-based funds, pure index funds, index enhanced funds, exchange-traded funds, exchange-traded notes, and variable annuity funds and require each remaining fund to have at least four Morningstar portfolio observations and invest, on average, at least 30% of its

[16] Specifically, following Goldstein, Jiang, and Ng (2017), we select funds with a Lipper objective code of 'A', 'BBB', 'SII', 'SID', 'IID' or a CRSP MF objective code with 'IC' for its first two characters. We also select funds with the Morningstar categories of "Corporate Bond", "Multi-sector Bond", "Nontraditional Bond", "Bank Loan", "Short-Term Bond", "Intermediate-Term Bond", and "Long-Term Bond".

portfolio in corporate bonds during the sample period (e.g., Anand et al. (2020)).[17] Furthermore, for the purpose of computing the valuation accuracy score, we exclude fund portfolio reports with no holdings in the bond sample that we used to identify mispriced bonds.

Finally, we apply two additional filters. One applies to fund flow, which we compute as the percentage change in a fund's assets not related to fund performance. As fund flow will be one of our control variables, we remove observations with extreme fund flows, i.e., greater than 50% or smaller than -50% in a month, which could be due to misreported fund mergers and splits (e.g., Chen and Qin (2017)). The other filter, intended to avoid incubation bias, excludes observations before a fund's TNA reaches five million dollars and its age reaches 12 months (e.g., Evans (2010)). Our final sample with non-missing values for the control and dependent variables used in subsequent analysis includes 381 IG corporate bond funds.

We combine multiple share classes of the same fund into a single fund and weight distinct share class characteristics by the lagged assets of each share class to compute fund-level characteristics. We construct a number of fund characteristics: *Fund Size*, total net assets under management in $ millions; *Fund Age*, the number of years since the inception of the oldest fund share class; *CRSP Turnover*, the annual portfolio turnover ratio reported in percent in the CRSP Mutual Fund Database; *Expense Ratio*, the fund's annual expense ratio in percent; *Family Size*, the aggregated total net assets (in $ millions) of all the family funds; *Net Return*, the monthly reported net-of-fee return of the fund; and *Flow*, the monthly percentage change in fund assets not related to fund performance. To capture trading activity in corporate bonds, we introduce *Corp Bond Turnover*, which is computed as the minimum of total purchases or total sales of all corporate

[17] As in Choi, Hoseinzade, Shin, and Tehranian (2020), we consider positions of bonds with FISD type of "CDEB", "CMTN", "CMTZ", "CCOV", "CP", "CLOC", "CPAS", "CPIK", and "CS" as corporate bond holdings. We also consider positions of bonds with FISD type of "USBN" as corporate bond holdings (e.g., Anand et al. (2020)). In addition, we extend the corporate bond holdings categorization to bonds with FISD bond type of "CZ" and "CCPI".

bonds in a reporting period, excluding bonds' expirations, divided by the average value of total corporate bond holdings of the fund during the reporting period.[18] The values of transactions and holdings are based on par values and expirations include maturing, calling, or any activity that reduces the total amounts of bonds outstanding to zero.

Table 3 provides summary statistics for the fund sample. If the average fund has no valuation skill, we expect the average VAS to be 50%. Both the mean and median VAS are about 53%. Thus, the average fund holds slightly more undervalued than overvalued bonds in its portfolio, an indication that the average fund has some valuation skill. The VAS interquartile range of 44.09% to 61.54%, suggests that some funds are more skilled at identifying and exploiting mispriced bonds but could also be due to random variation of VAS. Whether heterogeneity in skill is behind the observed dispersion in VAS is the subject of our analysis in the next sessions.

The average fund has assets of $1.6 billion and has been around for 17 years. The average CRSP portfolio turnover is 112%, while the corporate bond portfolio turnover is just 40%, which is sensible since the average fund holds almost half of its portfolio in corporate bonds. The average expense ratio of 73% is the same as the one reported for the IG sample of Choi, Hoseinzade, Shin, and Tehranian (2020).

3. Performance Predictability of VAS

3.1. Main Result

In this section, we investigate the relation between our Valuation Accuracy Score and future fund performance while controlling for fund characteristics that might also influence fund performance.

---

[18] Cici and Gibson (2012) document that CRSP turnover includes maturing bonds in sales and is based on all fund holdings, which may include treasuries and mortgage-backed securities.

Our performance measure is the alpha estimated using the following four-factor model, typically used by previous research for corporate bond fund performance evaluation:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,STK} STK_t + \beta_{i,BOND} BOND_t + \beta_{i,DEF} DEF_t + \beta_{i,OPTION} OPTION_t + \varepsilon_{i,t} \quad (3)$$

$R_{i,t}$ is the fund gross return in month *t* computed by adding one twelfth of the annual total expense ratio to the fund net-of-fee return, $R_{f,t}$ is the one-month treasury bill rate, STK_t is the excess return of the CRSP value-weighted stock index, $BOND_t$ is the excess return of the Bloomberg Barclays Aggregate Bond Index, DEF_t is the default factor measured as the monthly return difference between the Bloomberg Barclays US Corporate High Yield Index and the Bloomberg Barclays Treasury Bond Index, and $OPTION_t$ is the option factor calculated as the return spread between the Bloomberg Barclays US MBS Index and the Bloomberg Barclays Treasury Bond Index. We compute monthly alpha for each fund in a given month as the difference between the actual gross return and the expected return, whereby expected return is the sum of the products of factor realizations in that month and the respective factor betas estimated over the previous 18 months. We require at least 12 non-missing monthly fund returns over the previous 18 months for the factor beta estimation.

To examine whether VAS predicts future fund performance in the cross-section, we use the following model:

$$\alpha_{i,(t+1,t+3)} = \beta_{VAS} VAS_{i,t} + \gamma' \boldsymbol{X_{i,t}} + \varepsilon_{i,t} \quad (4)$$

where $\alpha_{i,(t+1,t+3)}$ is fund *i* 's average monthly gross alpha between *t+1* and *t+3*. $VAS_{i,t}$, the explanatory variable of interest, is fund *i*'s VAS at time *t*. $\boldsymbol{X_{i,t}}$ is a vector of fund control variables, some of which are described in the previous section, but also includes additional variables tailored to this analysis described below. To control for certain funds profiting from strategic liquidity provision, we add the fund's quintile rank of average liquidity supply score (*LS_score*) over the last 12 months (*t-11, t*) (*LS_scoreQ*), which is constructed following Anand et al. (2020).[19] Also following Anand et al. (2020), we include the average monthly gross alpha over the last 12 months (*Past Alpha*). In addition, we include the average monthly fund flow over the last 12 months (*Past Flow)*, the standard deviation of monthly fund flows over the last 12 months (*Flow Volatility*) and the standard deviation of monthly gross fund returns over the last 12 months (*Return Volatility*). We include month fixed effects to control for unobservable time-specific effects and fund style fixed effects based on Lipper objective codes to control for unobservable style-specific effects. Standard errors are double clustered by fund and month.

Estimation results for Model 4 are reported in Table 4. To illustrate the economic significance and to account for possible non-linearity in the VAS-performance relation, we also include specifications where we replace VAS with VAS Quintile, which captures the quintile ranks of VAS. Both VAS Quintile and VAS are significant predictors of future fund alphas at the 1% significance level regardless of whether we include control variables or not in the regression. Their predictive power is also economically significant. Focusing on the specification with control variables in Column 3, we infer that funds in the top VAS quintile outperform funds in the bottom VAS quintile by 2.6 basis points (0.65 * 4) per month over the next quarter, which translates to 31.2 basis points per year (2.6 * 12). This is highly significant in an economic sense considering that the annualized gross alpha of the average active bond fund is just 23 basis points per year.

Looking at the coefficients of the control variables, we confirm the findings of Anand et al. (2020) that funds can also earn additional alpha by strategically providing liquidity. Most importantly, though, the fact that our results hold even when we control for strategic liquidity

[19] A fund that neither provides nor absorbs liquidity has an *LS_score* of zero, while a fund with a positive *LS_score* exhibits a trading style that on average helps alleviate large dealer positions. We follow the Anand et al. (2020) convention and use *LS_scoreQ* in our main analysis. However, if we replace *LS_scoreQ* with its continuous version, average *LS_score* over the last 12-month, we find similar results.

provision confirms that our measure captures a different type of skill. Interestingly, past return volatility negatively predicts future fund alpha, but this is only statistically significant at the 10% level.

3.2. Measurement Issues

Admittedly, our methodology cannot determine the valuation status of every position in a fund's portfolio. However, such limitation should introduce noise in detecting skill and bias against us finding a relation between VAS and fund performance. For example, if a fund has a high VAS purely due to luck or measurement noise instead of its superior valuation skill, such a fund is unlikely to outperform other funds in the future. Hence, our key assumption is that VAS estimated based on funds' holdings in a subset of corporate bonds is still informative about fund managers' overall valuation skills to identify mispricing opportunities. We assess the validity of this assumption in the following tests.

A natural question is whether the results discussed above are simply a manifestation of short-term outperformance of underpriced bonds employed for the construction of our measure, which some funds happen to hold by pure chance alone. Funds with higher VAS at time t hold by construction more underpriced bonds, which, as shown in Table 2, outperform at time t+1. If our results are mainly driven by the outperformance of those underpriced bonds that some funds happen to hold by chance, then the outperformance of high-VAS funds is not related to fund manager skills.

Table 2 shows that the outperformance of underpriced bonds does not extend beyond one month. Thus, if we document future fund outperformance beyond one month, then fund outperformance cannot be attributed to the underpriced bonds per se. We address this concern by delaying fund performance measurement by one month. Thus, in Table 5 we test whether VAS at time *t* significantly predicts fund alphas between time *t*+2 and *t*+4.

Column 3 of Table 5 shows that funds in the top VAS quintile still outperform funds in the bottom VAS quintile by 2.1 basis points (0.53 * 4) monthly gross alpha over the next quarter or 25.4 basis points per year. The result is significant at 1% level. Since the underpriced bonds we employed to construct VAS at time *t* do not generate significant alpha during time *t*+2 and *t*+4, the fund outperformance during that time implies the outperformance of other positions of high VAS funds, further indicating that our VAS measure captures fund managers' overall valuation skills.

3.3. Robustness Checks

We perform a series of tests to confirm robustness of our main result. In Columns 1 and 2 of Table 6, we replace fund style fixed effects with fund fixed effects to control for unobserved fund heterogeneity when estimating Equation 4. In Columns 3 to 12, we estimate Equation 4 with alpha-related variables computed from different estimations. Specifically, in Columns 3 and 4, we estimate fund alphas using fund net-of-fee returns rather than gross returns. In Columns 5 and 6, we use a 36-month rolling window rather than an 18-month rolling window to estimate factor loadings in Equation 3 that are needed for the estimation of expected fund returns in a given month. In Columns 7 to 10, we use an 18-month rolling window and estimate fund alpha by sequentially adding two additional factors, *Term* factor and the liquidity risk factor (*LRF*)—which are defined in Section 2.2.1— to the original four-factor model laid out in Equation 3. Moving to Columns 11 and 12, we replace fund alpha with style-adjusted return. Style-adjusted return is the fund return minus the average return of the funds with the same Lipper objective code. Our results remain similar both in terms of economic and statistical magnitude across all columns.

The second set of tests addresses robustness with respect to the measurement of our explanatory variable of interest, VAS. To that end, we replace VAS with two alternative valuation accuracy measures in Equation 4 and examine their relation with future fund performance. Specifically, In Columns 1 and 2 of Table 7, using Equation 2, we calculate another valuation accuracy measure based on the number of underpriced and overpriced bond holdings instead of the market value of holdings. We refer to this measure as the number valuation accuracy score (*VAS_NUM*). Although market-value based VAS may reflect funds' convictions regarding bonds' valuation status more accurately, it may favor certain larger funds since larger funds are more likely to get larger bond allocations from the dealers due to their better relationships (e.g., Nikolova et al. (2020)). For example, a small fund and a large fund both bid for 10 million of an underpriced bond with the same dealer. The small fund may only get 2 million but the large fund gets 8 million due to its better relation with the dealer. In other words, market-value based VAS may underestimate the valuation accuracy of small funds. Thus, VAS_NUM can address this potential concern.

In Table 7 Columns 3 and 4, we construct an alternative valuation accuracy measure that is based on fund trades in mispriced bonds over the last twelve months rather than holdings. Since we do not observe the exact timing of each trade, following previous research, we make the assumption that each trade, inferred from two reporting periods, happens at the end of the most recent reporting period (e.g., Chen, Jegadeesh, and Wermers (2000)). Then, a trading-based VAS is computed as the sum of the par amount of all underpriced bonds bought and all the overpriced bonds sold by a fund divided by the total par amount of all trades in mispriced bonds for that fund over the last 12 months. We refer to this measure as the trade valuation accuracy score (*TVAS*). Although trading is arguably more likely to reflect active fund decisions, this measure may be subject to significant noise. For example, assume a fund bought a bond at the beginning of July according to its "underpriced" status at the end of June. Subsequently, at the end of July, the bond valuation status switched to "overpriced" and we observe the holding change based on the fund's July holdings report. According to our assumption, we will misclassify the true motivation of this trade.

As shown in Table 7, our results remain robust when we use the two alternative measures and their quintile ranks. In unreported analysis, we find similar results if we omit the control variables.

3.4. Potential Mechanism

We next propose and investigate the most likely mechanism through which the valuation skills measured by VAS affect fund performance. The mechanism we propose is straightforward: Funds with superior valuation skills simply generate better performance through superior bond selection. The idea is that bond funds with superior valuation skill are expected to exploit such skill by selecting undervalued bonds that will subsequently outperform bonds with similar characteristics.

To confirm that the outperformance of high VAS funds documented so far indeed comes from superior bond selection, we investigate each fund's corporate bond holdings following Daniel, Grinblatt, Titman, and Wermers (1997), and Cici and Gibson (2012). We decompose fund reported monthly returns into "Bond-Selection" (BS) return and the "Characteristic-Timing" (CT) return, which are hypothetical monthly returns based on funds' most recently reported corporate bond holdings. To construct the benchmark bond portfolios, we first independently sort all corporate bonds in our corporate bond returns sample into quintiles based on their duration and rating groups

(AAA, AA, A, BBB, BB, B, CCC, CC, C, D). We then compute monthly value-weighted return for the resulting 50 benchmark portfolios.

Next, $BS_{f,t}$, measuring whether a fund *f* can select bonds that will outperform other bonds with similar characteristics in month *t*, and $CT_{f,t}$, measuring fund *f*'s characteristic timing ability, are computed as follows:

$$BS_{f,t} = \sum_{i=1}^{N} w_{i,t-1}(R_{i,t} - R_t^{b,t-1}) \qquad (5)$$

$$CT_{f,t} = \sum_{i=1}^{N}(w_{i,t-1}R_t^{b,t-1} - w_{i,t-13}R_t^{b,t-13}) \qquad (6)$$

where $w_{i,t-1}$ is the weight of bond *i* relative to all corporate bond holdings in our bond return sample at the end of month *t* –1, $R_{i,t}$ is the month *t* return of bond *i*, and $R_t^{bi,t-1}$ is the month *t* return of the benchmark portfolio that is matched to bond *i* during month *t* –1. The weight of bond *i* at month *t* –13 is multiplied by $R_t^{b,t-13}$, the month *t* return of the benchmark portfolio that is matched to bond *i* during month *t* –13.

We then estimate Equation 4 using the average BS and CT over the next three month as the dependent variables, respectively. Results are reported in Table 8. Panel A Columns 1 to 4 show that both VAS Quintile and VAS significantly predict future fund Bond-Selection return at the 1% significance level regardless of whether we include control variables or not in the regression. For economic magnitude, funds in the top VAS quintile can outperform funds in the bottom quintile by 4bps per month (48 bps per year) over the next quarter in terms of BS return. In contrast, there is no consistent evidence that VAS Quintile and VAS predict Characteristic-Timing return as shown in Panel B.

In sum, the evidence collectively suggests that funds with high VAS achieve outperformance by successfully selecting bonds that can outperform other bonds with similar characteristics instead of tilting portfolio toward certain characteristics according to bond market conditions.

4. Determinants of VAS

In this section, we examine possible determinants of the accuracy of valuation assessments of bond fund managers and whether this type of skill is persistent. For this, we use the following model:

$$VAS_{i,t+1} = AVAS_{i,(t-11,t)} + TVAS_{i,t} + \gamma' \boldsymbol{X_{i,t}} + \varepsilon_{i,t} \qquad (7)$$

where $VAS_{i,t+1}$ is the valuation accuracy score computed using the first available fund holdings report within 3 months after month *t*. We include $AVAS_{i,(t-11,t)}$, the last 12-month average VAS, to examine the persistence of VAS. $TVAS_{i,t}$ is computed as discussed in the previous section and measures the valuation accuracy with respect to trades in mispriced bonds over the last twelve months (*t-11, t*). $\boldsymbol{X}$ is the same vector of fund characteristics introduced in Equation 3 plus the fund expense ratio.

Table 9 reports results. Column 1 reports results with $AVAS_{i,(t-11,t)}$ and $TVAS_{i,t}$ excluded for comparison. Columns 2 reports results for the full specification of Equation 7. If luck plays a role, a high VAS driven by luck in one period will tend to fall in the next period. Hence, if there is no persistent skill behind our VAS, its past average value should have no predictive power for future VAS. Column 2 shows that VAS is highly persistent as its average over the last 12 months, $AVAS_{i,(t-11,t)}$, has strong predictive power for VAS in the next period, supporting the notion that VAS reflects a skill type that is stable over time. This result also holds when in Column 3 we replace $VAS_{i,t+1}$with the average *VAS* over the next 12 months, $AVAS_{i,(t+1,t+12)}$, as the dependent variable. A concern is that the persistence of VAS is due to the persistence of the valuation status of the bonds we employed to construct the VAS. For example, if many bonds have been identified as underpriced for several months, then funds can achieve high VAS by passively holding such bonds. In unreported analysis, we find 70% of our bond observations have at least two valuation status switches in the next 12 months. In other words, in order to maintain a high VAS, a fund has to actively adjust its positions. This is indeed confirmed by the significance of TVAS, which is constructed based on trades over the last 12 months.

The only other fund characteristic that is significantly related to future valuation accuracy is *CRSP Turnover* in all specifications corresponding to Columns 1 to 3. *Return Volatility* is significant in Column 1. *Corp Bond Turnover* is significantly related to future valuation accuracy but only in the Column 3 and at the 10% level. All three variables are related to fund activeness. However, once we include our valuation accuracy measures in Column 2, the statistical significance of *Return Volatility* disappeared and the economic significance of *CRSP Turnover* reduced by 50% compared to Column 1. Thus, these results further suggest that a fund achieves higher VAS by consistently identifying and actively acting on mispriced opportunities instead of holding underpriced bonds by chance. The evidence is consistent with Pastor, Stambaugh, and Taylor (2017) who argue that a fund that is better at identifying mispricing opportunities would want to exploit such skill by trading more.

Turning to the other explanatory variables, we observe that *LS_scoreQ* does not explain future VAS, confirming again that VAS is not related to the ability of certain funds to strategically provide liquidity and profit from doing so. The same holds for the other fund characteristics. In addition, the adjusted R^2 of 7% from the specification of Column 1 shows that these fund characteristics explain very little of the variation of VAS. This suggests that VAS captures a unique dimension of skill that is not explained by other factors known to affect fund performance.

5. Investors' Response and Implications for Market Efficiency?

In this section, we examine how, if at all, the presence of valuation skills in the cross section of IG bond funds affects the decision-making of investors and whether this has broader implications for the efficiency of the corporate bond market.

5.1. How do Investors Respond?

In light of the evidence presented so far, a natural question is: How do investors respond to differential valuation skills across funds? The answer depends on how investors are learning about the skills of fund managers. Although different mechanisms have been proposed, it is largely unknown how this happens. If investors incur a search cost, as in the model of Gârleanu and Pedersen (2018), to find skilled funds, we would expect their flows to largely follow our *VAS* measure or some other similar indicators that reflect the valuation accuracy of these fund managers. If, on the other hand, investors infer skill primarily through past performance, as in the model of Berk and Green (2004), flows might simply respond to past performance without consideration to *VAS*. Another possibility is that investors learn through a combination of both approaches, utilizing information from portfolio holdings to infer valuation accuracy in conjunction with past fund performance. The idea is that information drawn from one approach could help validate inferences from the other approach or vice versa. For example, an investor who finds a fund with high valuation accuracy might also want to consult the fund's past performance as a way of validating the belief that the fund is skilled. On the other hand, an investor who has found a fund with great past performance might also want to consult the fund's valuation accuracy to rule out that performance was simply due to luck.

We explore the investors' reaction by estimating the following regression model:

$$Flow_{i,(t+1,t+3)} = \beta_V VAS_{i,t} + \beta_{INT} VAS_{i,t} * Past\ Alpha_{i,t} + \beta_{PA} Past\ Alpha_{i,t} + \gamma' \boldsymbol{X_{i,t}} + \varepsilon_{i,t} \quad (8)$$

The dependent variable, $Flow_{i,(t+1,t+3)}$, is the average flow of fund i over the next three months and the rest of the variables are described in Section 3.

Results from the estimation of Equation 8 are reported in Table 10. Results from Column 1, which regresses fund flow on past performance and other controls, confirm the empirical regularity that fund flows follow past performance. A 1% increase of the average last 12-month alpha leads to a 2% increase of average monthly flow in the next quarter. This performance-chasing behavior of flows is consistent with investors learning about manager skill from past performance (e.g., Berk and Green (2004)). Results from Column 2, which estimates Equation 8, show that flows do not directly follow the valuation accuracy score, suggesting that the valuation accuracy of bond funds is not a direct input in the decision-making of fund investors. However, the interaction term between VAS and *Past Alpha* is positive and significant, indicating a stronger performance-chasing behavior for funds with higher VAS. For a fund with no skill (VAS = 0), a 1% increase of past alpha leads to a 1% increase of average monthly flow in the next quarter. In sharp contrast, for a fund with a perfect skill (VAS = 1), a 1% increase of past alpha leads to a 3% (0.02 + 0.01) increase of average monthly flow in the next quarter. These results suggest that investors perceive the past performance of high-VAS funds as a stronger indicator of skill and pursue it even more aggressively. This is consistent with investors using a combination of past performance and information contained in the accuracy score to infer the valuation skills of fund managers.

5.2. Implications for Market Efficiency

To summarize, so far we have documented that pricing inefficiencies exist in the corporate bond market; differential valuation skills exist across IG bond funds, as indicated by the relative outperformance of funds with higher valuation accuracy scores; and investors are able to identify skilled managers. This evidence is largely consistent with the equilibrium setting of Gârleanu and Pedersen (2018) that links the efficiency of asset prices to the efficiency of the asset management market. Moreover, a key prediction of their equilibrium model is that as search costs decline and it becomes easier to find skilled managers, more capital goes to skilled active managers, which, in turn, makes asset prices more efficient. As argued by Gârleanu and Pedersen (2018), search costs have been going down in the mutual fund sector due to technological advances. Furthermore, we know that unlike equity mutual funds, capital from investors has been moving to active corporate bond funds at an accelerated pace over the last 10 years (e.g., Mauboussin (2019)) and, based on our evidence, this capital is able to identify skilled managers. Given all these considerations, we would expect that the allocation of capital to skilled active corporate bond funds over the last years has contributed to greater efficiency in the corporate bond market. If this is true, then we would expect the degree of mispricing, proxied by the profitability of portfolios exploiting the bond mispricing that we identify in Section 2.2.1, to decline in the later part of our sample period.

To examine this possibility, we proceed as follows. Following Section 2.2.1, at the end of each month *t*, we construct Pos-RS and Neg-RS portfolios containing bonds that were, respectively, identified to be undervalued and overvalued at the end of month *t* using our methodology. We hold each portfolio for one month. We then evaluate portfolio alphas by regressing the resulting monthly series of excess returns on the same six bond factors as in Section 2.2.1, separately for each of the four equal subperiods during 2003-2018. For completeness, we also report alphas estimated over the entire sample period.

Results reported in Table 11 show that the magnitude of the alphas of the two portfolios and their difference is particularly strong during 2007 and 2010. This result is likely driven by the financial crisis and is consistent with Brunnermeier and Pedersen (2009), who argue that market frictions and financial constraints can contribute to mispricing. More importantly, these portfolio alphas exhibit a sharp decline in magnitude after 2010. To illustrate, the average monthly alpha of the Pos-RS portfolio, which invests in undervalued bonds, declines from a positive and significant 56 basis points during 2007-2010 to a positive and significant 12 basis points for the 2015-2018 period. This, almost five-fold, decrease in alpha is economically meaningful given that the full period Pos-RS portfolio alpha is 29 basis points. Similarly, we see a two-fold decrease in the alpha magnitude for the Neg-RS portfolio, from -26 basis points to -11 basis points, and a four-fold decrease in the alpha difference of the two portfolios from 82 basis points to 23 basis points. Taken together, the results of Table 11 confirm that both underpricing and overpricing are diminishing since the profits of strategies that exploit bond mispricing have declined significantly in the later years. This is consistent with the notion that the corporate bond market has become more efficient as bond fund investors allocate more capital to skilled IG bond funds.

Bond market becoming more efficient as a result of capital flows to skilled IG bond funds could also have implications for the performance of the skilled funds in the later years. Lower profit opportunities in the later years would suggest a decline in the performance of the skilled funds over the same period.

To assess whether such a pattern is indeed present, we use a portfolio approach following Jegadeesh and Titman (1993). Specifically, we sort our sample funds into quintiles based on their

VAS at the end of every month and form equal-weighted portfolios. We hold these portfolios for three month. Thus, the month t portfolio is the equal-weighted average return of the portfolios formed in months $t-1$, $t-2$, and $t-3$. We then estimate alphas of these portfolios using Equation 3, separately for each of the four equal subperiods during 2003-2018. For completeness, we also estimate portfolio alphas over the entire sample period.

Results are reported in Table 12. As shown in Columns 1, the portfolio of funds in the top VAS quintile consistently earns significantly positive gross monthly alphas during the entire sample period and in each of the four subperiods. Over the entire sample period, funds in the top VAS quintile generate a monthly alpha of 7 basis points per month (84 basis points per year) and outperform funds in the bottom VAS quintile by a significant 8 basis points per months (96 basis points per year). The alphas of funds in other quintiles are largely indistinguishable from zero over the entire sample period and in the subperiods. Altogether, these results support the presence of skill among funds with higher valuation accuracy scores and also confirm our earlier results based on regression analysis.

More importantly, we observe a similar decline in the performance of top quintile funds after 2010 as the bond mispricing portfolios we show above. Specifically, while performance in the first three subperiods covering 2002 until 2015 hovers around 7 to 13 basis points, the performance drops to just 4 basis points during the last four years of the sample period. We see a similar pattern of decline for the return difference between top and bottom quintile funds, with the difference dropping to an insignificant 2 basis point in the last subperiod relative to a significant 19 (11) basis point difference in the 2007 – 2010 (2011-2014) subperiod. All in all, the evidence of performance decline for the funds with greater valuation skills suggests that it has become harder for these funds to generate alpha in a market that is becoming more efficient, perhaps in part due to capital flows following active management more aggressively in later years.

6. Conclusion

We develop a novel measure to identify investment-grade corporate bond funds with superior valuation skills. Focusing on fund holdings of corporate bonds deemed to be mispriced by our methodology, our valuation accuracy score recognizes funds that hold a higher fraction of undervalued bonds as having better valuation skills. Key to the construction of our measure is a unique feature of the corporate bond market that many firms have multiple bonds outstanding, which we exploit to identify mispriced bonds.

We find that our valuation accuracy score has strong predictive power for future fund performance, a result that is economically and statistically significant and robust to a number of methodological choices. In addition, the valuation accuracy score of a given fund is: highly persistent over time, related to active trading in mispriced corporate bonds, and unrelated to other sources of skill. Taken together, these findings suggest that our valuation accuracy measure reflects a type of skill that is stable over time and unique in relation to other possible sources of skill. Furthermore, fund investors seem to recognize the differential valuation skills of investment-grade corporate bond fund managers, as they consider the past performance of funds with higher valuation accuracy scores a stronger indicator of skill.

Being the first to document the presence of differential valuation skills in the cross-section of investment-grade corporate bond funds, our paper contributes to the larger debate on the investment abilities of corporate bond funds. Furthermore, by singling out this particular skill type and documenting its presence among investment-grade corporate bond funds, our paper furthers our understanding of the types of skills that these funds possess. This is important in light of the fact that prior research has documented only one particular type of skill among these funds that is related to liquidity provision, which falls outside the purview of these funds' core responsibilities.

Our findings can also explain why investors have been rewarding active corporate bond funds in the recent years to the extent that they have. The massive aggregate capital flows allocated to active corporate bond funds in the last few years can be explained by our finding that differential valuation skills exist across corporate bond funds and that investors are seemingly able to infer and chase these abilities. This evidence, combined with our finding that the level of corporate bond mispricing has declined in the last few years, suggests that capital being increasingly allocated to skilled investment-grade corporate bond funds has contributed to greater efficiency in the corporate bond market.

References

Almeida, Heitor, and Thomas Philippon. 2007. The Risk-Adjusted Cost of Financial Distress. *The Journal of Finance* 62 (6): 2557–2586.

Anand, Amber, Chotibhak Jotikasthira, and Kumar Venkataraman. 2020. Mutual Fund Trading Style and Bond Market Fragility. *The Review of Financial Studies*.

Bai, Jennie, Turan G. Bali, and Quan Wen. 2019. Common Risk Factors in the Cross-Section of Corporate Bond Returns. *Journal of Financial Economics* 131 (3): 619–642.

Berk, Jonathan B., and Richard C. Green. 2004. Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy* 112 (6): 1269–1295.

Bessembinder, Hendrik, Kathleen M. Kahle, William F. Maxwell, and Danielle Xu. 2009. Measuring Abnormal Bond Performance. *Review of Financial Studies* 22 (10): 4219–4258.

Blake, Christopher R., Edwin J. Elton, and Martin J. Gruber. 1993. The Performance of Bond Mutual Funds. *The Journal of Business* 66 (3): 371–403.

Blume, Marshall E., Felix Lim, and A. Craig Mackinlay. 1998. The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality? *The Journal of Finance* 53 (4): 1389–1413.

Brunnermeier, Markus K., and Lasse Heje Pedersen. 2009. Market Liquidity and Funding Liquidity. *Review of Financial Studies* 22 (6): 2201–2238.

Campbell, John Y., and Glen B. Taksler. 2003. Equity Volatility and Corporate Bond Yields. *The Journal of Finance* 58 (6): 2321–2350.

Chen, Long, David A. Lesmond, and Jason Wei. 2007. Corporate Yield Spreads and Bond Liquidity. *The Journal of Finance* 62 (1): 119–149.

Chen, Qianwen, and Jaewon Choi. 2020. Reaching for Yield and Bond Returns. working paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3225209

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers. 2000. The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers. *Journal of Financial and Quantitative Analysis* 35 (3): 343-368.

Chen, Yong, Wayne Ferson, and Helen Peters. 2010. Measuring the Timing Ability and Performance of Bond Mutual Funds. *Journal of Financial Economics* 98 (1): 72–89.

Chen, Yong, and Nan Qin. 2017. The Behavior of Investor Flows in Corporate Bond Mutual Funds. *Management Science* 63 (5): 1365–1381.

Choi, Jaewon, K J Martijn Cremers, and Timothy B Riley. 2020. Active Share and Bond Mutual Funds. working paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3557235

Choi, Jaewon, Saeid Hoseinzade, Sean Seunghun Shin, and Hassan Tehranian. 2020. Corporate Bond Mutual Funds and Asset Fire Sales. *Journal of Financial Economics* 138 (2): 432–457.

Choi, Jaewon, and Yongjun Kim. 2018. Anomalies and Market (Dis)Integration. *Journal of Monetary Economics* 100: 16–34.

Chordia, Tarun, Amit Goyal, Yoshio Nozawa, Avanidhar Subrahmanyam, and Qing Tong. 2017. Are Capital Market Anomalies Common to Equity and Corporate Bond Markets? An Empirical Investigation. *Journal of Financial and Quantitative Analysis* 52 (4): 1301–1342.

Cici, Gjergji, and Scott Gibson. 2012. The Performance of Corporate Bond Mutual Funds: Evidence Based on Security-Level Holdings. *Journal of Financial and Quantitative Analysis* 47 (1): 159-178.

Cici, Gjergji, Scott Gibson, and Rabih Moussawi. 2017. Explaining and Benchmarking Corporate Bond Returns. working paper, https://www.ssrn.com/abstract=2995626.

Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spencer Martin. 2001. The Determinants of Credit Spread Changes. *The Journal of Finance* 56 (6): 2177–2207.

Covitz, Dan, and Chris Downing. 2007. Liquidity or Credit Risk? The Determinants of Very Short-Term Corporate Yield Spreads. *The Journal of Finance* 62 (5): 2303–2328.

Cremers, K. J. Martijn, and Antti Petajisto. 2009. How Active Is Your Fund Manager? A New Measure That Predicts Performance. *Review of Financial Studies* 22 (9): 3329–3365.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52 (3): 1035-1058.

Dick-Nielsen, Jens, Peter Feldhütter, and David Lando. 2012. Corporate Bond Liquidity before and after the Onset of the Subprime Crisis. *Journal of Financial Economics* 103 (3): 471–492.

Elton, Edwin J, Martin J Gruber, and Christopher R Blake. 1995. Fundamental Economic Variables, Expected Returns, and Bond Fund Performance, *The Journal of Finance,* 50(4): 1229-1256.

Evans, Richard B. 2010. Mutual Fund Incubation. *The Journal of Finance* 65 (4): 1581–1611.

Fama, Eugene F., and Kenneth R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1): 3–56.

Fama, Eugene F., and Kenneth R. French. 2010. Luck versus Skill in the Cross-Section of Mutual Fund Returns. *The Journal of Finance* 65 (5): 1915–1947.

Ferson, Wayne, Tyler R. Henry, and Darren J. Kisgen. 2006. Evaluating Government Bond Fund Performance with Stochastic Discount Factors. *Review of Financial Studies* 19 (2): 423–455.

Gârleanu, Nicolae, and Lasse Heje Pedersen. 2018. Efficiently Inefficient Markets for Assets and Asset Management: Efficiently Inefficient Markets for Assets and Asset Management. *The Journal of Finance* 73 (4): 1663–1712.

Girardi, Giulio, Kathleen W Hanley, Stanislava Nikolova, Loriana Pelizzon, and Mila Getmansky Sherman. Forthcoming. Portfolio Similarity and Asset Liquidation in the Insurance Industry. *Journal of Financial Economics*.

Goldstein, Itay, Hao Jiang, and David T. Ng. 2017. Investor Flows and Fragility in Corporate Bond Funds. *Journal of Financial Economics* 126 (3): 592–613.

Green, Jeremiah, John R. M. Hand, and X. Frank Zhang. 2017. The Characteristics That Provide Independent Information about Average U.S. Monthly Stock Returns. *The Review of Financial Studies* 30 (12): 4389–4436.

Gutierrez, Roberto C., William F. Maxwell, and Danielle Xu. 2008. On Economies of Scale and Persistent Performance in Corporate-Bond Mutual Funds. working paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1133959

Helwege, Jean, and Christopher M. Turner. 1999. The Slope of the Credit Yield Curve for Speculative-Grade Issuers. *The Journal of Finance* 54 (5): 1869–1884.

Helwege, Jean, Jing-Zhi Huang, and Yuan Wang. 2014. Liquidity Effects in Corporate Bond Spreads. *Journal of Banking & Finance* 45: 105–116.

Hou, Kewei, Chen Xue, and Lu Zhang. 2015. Digesting Anomalies: An Investment Approach. *Review of Financial Studies* 28 (3): 650–705.

Huang, Lifa, Wayne Y. Lee, and Craig G. Rennie. 2019. Evidence from Bootstrap Simulations. working paper, University of Arkansas.

Huij, Joop, and Jeroen Derwall. 2008. "Hot Hands" in Bond Funds. *Journal of Banking & Finance* 32 (4): 559–572.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48 (1): 65–91.

Li, Erica X. N., Dmitry Livdan, and Lu Zhang. 2009. Anomalies. *Review of Financial Studies* 22 (11): 4301–4334.

Mauboussin, Michael J. 2019. Looking for Easy Games in Bonds. *BlueMountian Investment Research*

Moneta, Fabio. 2015. Measuring Bond Mutual Fund Performance with Portfolio Characteristics. *Journal of Empirical Finance* 33: 223–242.

Murray, Scott, and Stanislava Nikolova. Forthcoming. The Bond Pricing Implications of Rating-Based Capital Requirements. *Journal of Financial and Quantitative Analysis*.

Nanda, Vikram K., Wei Wu, and Xing (Alex) Zhou. 2019. Investment Commonality across Insurance Companies: Fire Sale Risk and Corporate Yield Spreads. *Journal of Financial and Quantitative Analysis* 54 (6): 2543-2574.

Natter, Markus, Martin Rohleder, and Marco Wilkens. Forthcoming. Maturity-Matched Bond Fund Performance. *Financial Analyst Journal.*

Nikolova, Stanislava, Liying Wang, and Juan (Julie) Wu. 2020. Institutional Allocations in the Primary Market for Corporate Bonds. *Journal of Financial Economics* 137 (2): 470–490.

Novy-Marx, Robert. 2013. The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics* 108 (1): 1–28.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor. 2017. Do Funds Make More When They Trade More? *The Journal of Finance* 72 (4): 1483–1528.

Rohleder, Martin, Hendrik Scholz, and Marco Wilkens. 2018. “Success and Failure on the Corporate Bond Fund Market.” *Journal of Asset Management* 19 (6): 429–43.

Schestag, Raphael, Philipp Schuster, and Marliese Uhrig-Homburg. 2016. Measuring Liquidity in Bond Markets. *The Review of Financial Studies* 29 (5): 1170–1219.

Spiegel, Matthew, and Laura Starks. 2016. Institutional Rigidities and Bond Returns around Rating Changes. working paper, Yale School of Management.

Wang, Z. Jay, Hanjiang Zhang, and Xinde Zhang. 2018. Fire Sales and Impediments to Liquidity Provision in the Corporate Bond Market. *Journal of Financial and Quantitative Analysis* 55 (8): 2613-2640.

Xu, Qiping. 2018. Kicking Maturity Down the Road: Early Refinancing and Maturity Management in the Corporate Bond Market. *The Review of Financial Studies* 31 (8): 3061–3097.

Table 1: Corporate Bond Mispricing-Analysis Sample Summary Statistics

This table reports summary statistics for the sample of IG corporate bonds that we use to identify mispricing. Statistics are based on monthly observations of IG corporate bonds. The sample includes 7,822 IG bonds issued by 600 firms from January 2003 to December 2018. *Yield* and *Duration* (Modified duration) are based on the bond's month-end price. *Amount Outstanding* is the bond's dollar amount outstanding (in $ millions) at the end of the month. *Bond Age* is the number of years since issuance. *Coupon* is the coupon rate. *ZTD* (Zero Trading Days) is the percentage of days when a bond did not trade during a month. *Rating* is a numerical score, where 1 refers to an AAA rating and 22 refers to a D rating. Numerical ratings of 10 or below (BBB- or better) are considered investment-grade, and ratings of 11 or higher (BB + or worse) are considered high yield.

Bond Characteristic	N	Mean	Std Dev	25^{th} Pctl	Median	75^{th} Pctl
Yield (%)	376,394	3.98	1.79	2.74	3.99	5.10
Duration (years)	376,394	6.71	4.22	3.33	5.74	9.57
Amount Outstanding ($M)	376,394	595	564	250	450	750
Bond Age (years)	376,394	5.81	5.36	2.00	4.08	7.69
Time-to-maturity (years)	376,394	10.27	8.63	3.76	7.03	15.60
Coupon (%)	376,394	5.40	1.81	4.13	5.55	6.70
ZTD (Zero Trading Days %)	376,394	51.78	28.94	26.92	50.00	76.92
Rating	376,394	7.38	2.05	6.00	8.00	9.00

Table 2: Alphas of Pos-RS and Neg-RS Portfolios

This table reports average monthly alphas of portfolios formed based on bond residual spreads from January 2003 to December 2018. At the end of each month *t*, we construct two portfolios, one consisting of bonds with positive residual spreads (*Pos-RS*) and the other consisting of bonds with negative residual spreads (*Neg-RS*). Residual spreads are estimated form Equation 1. Both portfolios are value-weighted based on the amount outstanding of each portfolio bond and are held for one month. We also delay the construction of these portfolios by one to eleven months. In effect, we are tracking 12 *Pos-RS* portfolios and 12 *Neg-RS* portfolios depending on the delay of portfolio construction. In Columns 1 and 2, portfolio alphas are estimated from regressing portfolio excess returns on the *TERM* factor, which is the monthly return difference between the Bloomberg Barclays Long Treasury Bond Index and one-month risk-free rate, and *DEF* factor, which is the monthly return difference between the Bloomberg Barclays US Corporate High Yield Index and the Bloomberg Barclays Treasury Bond Index. In Columns 3 and 4, portfolio alphas are estimated from regressing portfolio excess returns on the *TERM* factor; *DEF* factor; and bond factors introduced by Bai et al. (2019), including the bond market factor (*MKT*), downside risk factor (*DRF*), credit risk factor (*CRF*), and liquidity risk factor (*LRF*). We obtain these factors from Bai et al. (2019). Newey-West (1987) adjusted t-statistics with 6 lags are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

# Months After Valuation Status Determination	2-Factor Alphas		6-Factor Alphas	
	(1) Pos RS	(2) Neg RS	(3) Pos RS	(4) Neg RS
1	0.0028***	-0.0022***	0.0029***	-0.0020***
	(3.41)	(-5.03)	(3.39)	(-4.64)
2	0.0007	0.0000	0.0008	0.0001
	(1.36)	(0.02)	(1.58)	(0.25)
3	0.0008	0.0001	0.0009*	0.0002
	(1.60)	(0.13)	(1.78)	(0.38)
4	0.0005	0.0002	0.0006	0.0003
	(1.03)	(0.50)	(1.23)	(0.69)
5	0.0005	0.0001	0.0006	0.0002
	(0.90)	(0.25)	(1.10)	(0.54)
6	0.0005	0.0001	0.0006	0.0002
	(0.92)	(0.12)	(1.10)	(0.40)
7	0.0004	0.0002	0.0005	0.0003
	(0.73)	(0.31)	(0.97)	(0.58)
8	0.0004	0.0003	0.0005	0.0003
	(0.74)	(0.51)	(0.90)	(0.69)
9	0.0006	0.0001	0.0007	0.0002
	(0.95)	(0.19)	(1.14)	(0.40)
10	0.0003	0.0004	0.0004	0.0005
	(0.65)	(0.77)	(0.74)	(0.92)
11	0.0003	0.0004	0.0004	0.0005
	(0.66)	(0.84)	(0.77)	(0.98)
12	0.0003	0.0004	0.0004	0.0005
	(0.63)	(0.95)	(0.73)	(1.06)

Table 3: Corporate Bond Fund Summary Statistics

This table reports summary statistics for our investment-grade (IG) bond fund sample. Our sample includes 381 IG corporate bond funds from January 2003 to December 2018. The Valuation Accuracy Score ($VAS_{f,t}$) of fund *f* at time *t* is calculated as follows:

$$VAS_{f,t} = \frac{\$\sum_{i=1}^{n} Underpriced\_bond_{i,f,t}}{\$\sum_{i=1}^{n} Underpriced\_bond_{i,f,t} + \$\sum_{i=1}^{n} Overpriced\_bond_{i,f,t}}$$

where $\$\sum_{i=1}^{n} Underpriced\_bond_{i,f,t}$ ($\$\sum_{i=1}^{n} Overpriced\_bond_{i,f,t}$) is the sum of the market values of all underpriced (overpriced) bond holdings at time *t*, such that the valuation status of bond *i* in fund *f*'s reported portfolio holdings at time *t* is estimated from Equation 1. *Fund Size* captures the total net assets under management in $ millions. *Fund Age* is the number of years since the inception of the oldest fund share class. *CRSP Turnover* is the annual portfolio turnover ratio in percent reported in the CRSP Mutual Fund Database. *Corp Bond Turnover* is an annualized modified portfolio turnover computed as the minimum of total purchases or total sales of all corporate bonds in a reporting period, excluding bonds' expirations, divided by the average total corporate bond holdings of the fund during the reporting period, all based on par values. Expiration includes maturing, calling, or any activity that reduces the total amounts of bonds outstanding to 0. *Expense Ratio* is the fund's annual expense ratio in percent. *Family Size* reported in $ millions aggregates the total net assets under management of all the family funds. *Net Return* is the monthly reported net-of-fee return of the fund. *Flow* is the monthly percentage change in fund assets unrelated to fund performance.

Fund Characteristic	N	Mean	Std Dev	25^{th} Pctl	Median	75^{th} Pctl
VAS (%)	22,721	53.02	15.24%	44.09	52.66	61.54
Fund Size ($M)	22,721	1,596	4,177	135	422	1,184
Fund Age (Years)	22,721	16.6	11.5	9.0	15.0	22.0
CRSP Turnover	22,721	111.65%	120.62%	40.00%	68.00%	132.00%
Corp Bond Turnover	22,721	40.38%	44.10%	11.23%	28.62%	55.24%
Expense Ratio	22,721	0.73%	0.28%	0.54%	0.69%	0.88%
Family Size ($M)	22,721	1,860,580	7,355,892	27,012	141,942	680,657
Net Return	22,721	0.29%	1.11%	-0.17%	0.25%	0.79%
Flow	22,721	0.27%	4.68%	-1.25%	-0.05%	1.39%

Table 4: Valuation Accuracy Score and Future Fund Performance

This table reports results from regressions relating future fund performance with the fund valuation accuracy score (*VAS*) for IG corporate bond funds from January 2003 to December 2018. Observations are based on each fund's reporting period. The dependent variable is the average gross alpha between *t+1* and *t+3* in basis points. *VAS Quintile* is the fund's quintile rank of *VAS* at time *t*. *VAS* is the fund's continuous valuation accuracy score at time *t*. All control variables are measured at time *t*. Most control variables are described in Table 3. Additional control variables include: *LS_scoreQ*, the fund's quintile rank of average liquidity supply score (*LS_score*) over the last 12 months constructed following Anand et al. (2020); *Past Alpha*, the average gross alpha over the last 12 months; *Past Flow*, the average flow over the last 12 months in percent; *Flow Volatility*, the standard deviation of monthly fund flows over the last 12 months; and *Return Volatility*, the standard deviation of monthly gross fund returns over the last 12 months. All regressions include month and fund style (Lipper objective code) fixed effects. Standard errors (double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	Dependent variable: Avg Gross Alpha (*t+1*, *t+3*)			
	(1)	(2)	(3)	(4)
VAS Quintile	0.56***		0.65***	
	(2.86)		(3.85)	
VAS		6.49***		7.10***
		(3.37)		(4.01)
LS_scoreQ			0.38*	0.38*
			(1.89)	(1.88)
Past Alpha			0.23***	0.23***
			(4.20)	(4.20)
log(Fund Size)			-0.09	-0.09
			(-0.36)	(-0.36)
log(Fund Age)			-0.66	-0.66
			(-1.45)	(-1.45)
CRSP Turnover			0.18	0.16
			(0.39)	(0.36)
Corp Bond Turnover			0.88	0.87
			(1.04)	(1.03)
log(Family Size)			0.13	0.13
			(0.87)	(0.88)
Past Flow			-0.12	-0.12
			(-0.76)	(-0.78)
Flow Volatility			-0.10	-0.09

			(-0.99)	(-0.97)
Return Volatility			-0.06*	-0.06*
			(-1.82)	(-1.82)
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	22,721	22,721	22,721	22,721
Adjusted R^2	0.18	0.18	0.20	0.21

Table 5: Valuation Accuracy Score and Future Fund Performance (One Month Skipped)

This table reports results from regressions relating future fund performance with the fund valuation accuracy score (*VAS*) for IG corporate bond funds from January 2003 to December 2018. Observations are based on each fund's reporting period. The dependent variable is the average gross alpha between *t+2* and *t+4* in basis points. *VAS Quintile* is the fund's quintile rank of *VAS* at time *t*. *VAS* is the fund's continuous valuation accuracy score at time *t*. All control variables are the same as Table 4 and measured at time *t*. All regressions include month and fund style (Lipper objective code) fixed effects. Standard errors (double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	Dependent variable: Avg Gross Alpha (t+2, t+4)			
	(1)	(2)	(3)	(4)
VAS Quintile	0.44**		0.53***	
	(2.37)		(3.13)	
VAS		4.46***		5.11***
		(2.61)		(3.23)
Controls	No	No	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	22,529	22,529	22,529	22,529
Adjusted R^2	0.18	0.18	0.20	0.20

Table 6: Valuation Accuracy Score and Future Fund Performance (Robustness Tests)

This table reports results from regressions relating future fund performance with the fund valuation accuracy score (*VAS*) for IG corporate bond funds from January 2003 to December 2018. Observations are based on each fund's reporting period. In Columns 1 and 2, the dependent variable is the same as Table 4. In Columns 2 to 12, the dependent variables are the average alphas from different estimations between *t+1* and *t+3* in basis points. In Columns 3 and 4, we estimate fund alpha using fund net-of-fee return based on Equation 3. In Columns 5 and 6, we use a 36-month rolling window to estimate factor loadings in Equation 3 that are needed for the estimation of expected fund returns in a given month. In Columns 7 to 10, we use an 18-month rolling window and estimate fund alpha by sequentially adding two additional factors, *Term* factor and the liquidity risk factor (*LRF*), defined in Section 2.2.1, to the original four-factor model in Equation 3. In Columns 11 and 12, we use style-adjusted return as fund alpha. Style-adjusted return is the fund return minus the average return of the funds with the same Lipper objective code. *Past Alpha* is the average alpha estimated as the dependent variable over the last 12 months. All other variables are described in Table 3 and 4 and measured at time *t*. Columns 1 and 2 include month and fund fixed effects. Column 3 to 12 include month and fund style (Lipper objective code) fixed effects. Standard errors (double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	Dependent variable:											
	Original		Net Alpha		36-month		5 Factor		6 Factor		Style-adj	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VAS Quintile	0.73***		0.67***		0.65***		0.57***		1.06**		0.94***	
	[3.63]		[4.03]		[3.74]		[2.97]		[2.47]		[3.81]	
VAS		8.03***		7.28***		7.54***		6.90***		10.91**		7.81***
		[3.80]		[4.17]		[4.04]		[3.06]		[2.55]		[3.00]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE:	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE:	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Observations	22,721	22,721	22,721	22,721	21,366	21,366	22,721	22,721	21,035	21,035	22,721	22,721
Adjusted R^2	0.23	0.23	0.20	0.20	0.20	0.20	0.18	0.18	0.38	0.38	0.06	0.06

Table 7: Alternative Valuation Accuracy Measures and Future Fund Performance

This table reports results from regressions relating future fund performance with two alternative measures of fund valuation accuracy for IG corporate bond funds from January 2003 to December 2018. Observations are based on each fund's reporting period. The dependent variable is the average gross alpha between *t+1* and *t+3* in basis points. *VAS_NUM Quintile* is the fund's quintile rank of *VAS_NUM* at time *t*. *VAS_NUM* is the fund's continuous valuation accuracy score based on the number of underpriced and overpriced bond holdings at time *t*. *TVAS Quintile* is the fund's quintile rank of *TVAS* at time *t*. *TVAS* is computed as sum of the par amount of all underpriced bonds bought and all the overpriced bonds sold by a fund divided by the total par amount of all trades in mispriced bonds for that fund over the last 12 months. All control variables are the same as Table 4 and measured at time *t.* All regressions include month and fund style (Lipper objective code) fixed effects. Standard errors (double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	Dependent variable: Avg Gross Alpha (t+1, t+3)			
	(1)	(2)	(3)	(4)
VAS_NUM Quintile	0.61***			
	(3.15)			
VAS_NUM		7.24***		
		(3.26)		
TVAS Quintile			0.54**	
			(2.60)	
TVAS				5.33**
				(2.28)
Controls	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	22,721	22,721	22,647	22,647
Adjusted R^2	0.20	0.20	0.20	0.20

Table 8: Valuation Accuracy Score and Return Decomposition

This table reports results from regressions relating future fund bond-selection (BS) and characteristic-timing (CT) return with the fund valuation accuracy score (*VAS*) for IG corporate bond funds from January 2003 to December 2018. Observations are based on each fund's reporting period. In Panel A, the dependent variable is the average BS between *t+1* and *t+3* in basis points. In Panel B, the dependent variable is the average CT between *t+1* and *t+3* in basis points. BS and CT are calculated, respectively, according to Equations 5 and 6. *VAS Quintile* is the fund's quintile rank of *VAS* at time *t*. *VAS* is the fund's continuous valuation accuracy score at time *t*. All control variables are the same as Table 4 and measured at time *t*. All regressions include month and fund style (Lipper objective code) fixed effects. Standard errors (double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panel A

	Dependent variable: Avg BS (t+1, t+3)			
	(1)	(2)	(3)	(4)
VAS Quintile	1.00***		0.99***	
	[3.48]		[3.45]	
VAS		11.79***		11.83***
		[2.89]		[2.88]
Control	No	No	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	20,550	20,550	20,550	20,550
Adjusted R^2	0.04	0.04	0.04	0.05

Panel B

	Dependent variable: Avg CT (t+1, t+3)			
	(1)	(2)	(3)	(4)
VAS Quintile	0.27		0.28	
	[1.51]		[1.64]	
VAS		3.99		4.20*
		[1.64]		[1.69]
Control	No	No	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	20,550	20,550	20,550	20,550
Adjusted R^2	0.08	0.08	0.08	0.08

Table 9: Determinants of Valuation Accuracy Score

This table examines the determinants of valuation Accuracy Score (*VAS*) for IG corporate bond funds from January 2003 to December 2018. Observations are based on each fund's reporting period. The dependent variable in Column 1 and 2 is the first available *VAS* within 3 months after month *t* in percent. In Column 3, the dependent variable is the average *VAS* over the next 12 months in percent. *AVAS (x,y)* is the fund's average *VAS* between time *x* and time *y* in percent. *TVAS* is described in Table 7. All other variables are described in Tables 3 and 4 and measured at time *t*. All regressions include month and fund style (Lipper objective code) fixed effects. Standard errors (double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	Dependent variable:		
	VAS (t+1)		AVAS (t+1, t+12)
	(1)	(2)	(3)
AVAS (t-11, t)		0.71***	0.53***
		(32.13)	(20.17)
TVAS		0.04***	0.02**
		(4.00)	(2.00)
LS_scoreQ	0.15	0.09	0.06
	(0.86)	(0.96)	(0.53)
Past Alpha	0.01	-0.01	0.00
	(0.45)	(-1.05)	(0.05)
log(Fund Size)	0.04	0.01	0.05
	(0.18)	(0.06)	(0.34)
log(Fund Age)	0.27	0.25	0.21
	(0.51)	(1.21)	(0.68)
CRSP Turnover	0.96***	0.46***	0.51***
	(3.67)	(3.47)	(2.95)
Corp Bond Turnover	0.86	0.27	0.59*
	(1.51)	(0.81)	(1.82)
Expense Ratio	-0.02	-0.01	-0.01
	(-1.33)	(-1.13)	(-0.95)
log(Family Size)	0.15	0.04	0.03
	(1.02)	(0.67)	(0.31)
Past Flow	0.09	0.05	0.04
	(0.93)	(0.95)	(0.57)

Flow Volatility	0.04	0.01	-0.00
	(0.41)	(0.17)	(-0.04)
Return Volatility	0.02***	0.00	0.00
	(2.69)	(1.04)	(0.79)
Month FE:	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes
Observations	22,296	22,296	22,406
Adjusted R^2	0.07	0.30	0.35

Table 10: Valuation Accuracy Score and Future Fund Flow

This table reports results from regressions relating future fund flow with the fund valuation accuracy score (*VAS*) for IG corporate bond funds from January 2003 to December 2018. Observations are based on each fund's reporting period. The dependent variable is the average fund flow between t+1 and t+3 in percent. *VAS* is the fund's continuous *VAS* at time *t*. All control variables are the same as Table 4 and measured at time *t*. All regressions include month and fund style (Lipper objective code) fixed effects. Standard errors (double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	Dependent variable: Avg Flow (t+1, t+3)	
	(1)	(2)
VAS		0.07
		(0.40)
VAS * Past Alpha		0.02^{***}
		(2.62)
Past Alpha	0.02^{***}	0.01^{*}
	(7.53)	(1.76)
LS_scoreQ	0.01	0.01
	(0.29)	(0.30)
log(Fund Size)	-0.05^{*}	-0.05^{*}
	(-1.73)	(-1.74)
log(Fund Age)	-0.24^{***}	-0.25^{***}
	(-3.77)	(-3.81)
CRSP Turnover	-0.03	-0.04
	(-0.96)	(-1.03)
Corp Bond Turnover	-0.09	-0.09
	(-1.15)	(-1.15)
log(Family Size)	0.05^{***}	0.05^{***}
	(3.09)	(3.12)
Past Flow	0.51^{***}	0.51^{***}
	(22.20)	(22.44)
Flow Volatility	-0.02	-0.02
	(-1.36)	(-1.36)
Return Volatility	-0.00	-0.00
	(-1.13)	(-1.18)

Month FE:	Yes	Yes
Style FE:	Yes	Yes
Observations	22,721	22,721
Adjusted R^2	0.22	0.22

Table 11: Profitability from Mispricing by Subperiod

This table reports average monthly alphas of portfolios of bonds formed based on bond residual spreads in four equal subperiods during January 2003 to December 2018. At the end of each month *t*, we construct two portfolios, one consisting of bonds with positive residual spreads (*Pos-RS*) and the other consisting of bonds with negative residual spreads (*Neg-RS*). Residual spreads are estimated form Equation 1. Both portfolios are value-weighted based on the amount outstanding of each portfolio bond and are held for one month. The last column reports the alpha difference between the *Pos-RS* portfolio and the *Neg-RS* portfolio. We estimate portfolio alphas using the same six-factor model as in Table 2, separately for each of the four equal subperiods during 2003-2018. Newey-West (1987) adjusted t-statistics with 6 lags are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Pos RS	(2) Neg RS	(3) Difference
Full Period	0.0029***	-0.0020***	0.0049***
	(3.39)	(-4.64)	(5.22)
2003 - 2006	0.0021***	-0.0015***	0.0036***
	(3.79)	(-3.69)	(7.73)
2007 - 2010	0.0056***	-0.0026***	0.0082***
	(3.96)	(-4.64)	(4.70)
2011 - 2014	0.0017***	-0.0014***	0.0031***
	(3.49)	(-3.79)	(7.03)
2015 - 2018	0.0012*	-0.0011*	0.0023***
	(1.85)	(-1.97)	(14.55)

Table 12: Valuation Accuracy Score and Future Fund Performance by Subperiod

This table reports average monthly alphas of portfolios of funds formed based on funds' valuation accuracy scores (*VAS*) in four equal subperiods during January 2003 to December 2018. We sort our sample funds into quintiles according to their *VAS* at the end of every month and form equal-weighted portfolios. We hold these portfolios for three month. Thus, the month *t* portfolio is the equal-weighted average return of the portfolios formed in months $t-1$, $t-2$, and $t-3$.We estimate alphas of these fund portfolios using Equation 3, separately for each of the four equal subperiods during 2003-2018. Columns 1 and 3 report alphas for the top and bottom *VAS* quintile funds, respectively. Column 2 reports alphas of the portfolio comprising funds from the rest of the quintiles. The last column reports the alpha difference between Column 1 and Column 3. Newey-West (1987) adjusted t-statistics with 6 lags are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) VAS Q5	(2) VAS Q2 to Q4	(3) VAS Q1	(4) Difference
Full Period	0.0007***	0.0000	-0.0001	0.0008***
	(3.67)	(0.17)	(-0.55)	(3.72)
2003 – 2006	0.0007***	0.0004***	0.0001	0.0006
	(2.75)	(4.30)	(0.56)	(1.56)
2007 - 2010	0.0013***	-0.0001	-0.0006	0.0019***
	(2.75)	(-0.24)	(-1.02)	(4.26)
2011 - 2014	0.0012***	0.0003	0.0001	0.0011***
	(3.54)	(1.17)	(0.48)	(4.52)
2015 - 2018	0.0004**	0.0002*	0.0002	0.0002
	(2.21)	(1.87)	(1.18)	(1.05)

Appendix A: Corporate Bond Returns Sample

For the set of corporate bonds we identify from FISD, we construct monthly returns based on the following steps: First, we select all transaction data from the enhanced version of TRACE between January 2003 and December 2018. We follow Bai, Bali, and Wen (2019), and Anand et al. (2020) and impose the following transaction-level filtering criteria by removing: (1) bonds trading under \$5 or above \$1000; (2) transactions flagged as primary market transactions; (3) transactions labeled as when-issued, locked-in, or having special sales conditions together with dealer-customer transactions without commissions or transactions having more than a two-day settlement; (4) canceled transactions (we adjust records that are subsequently corrected or reversed); (5) transactions with trading volume less than \$10,000; and (6) transactions reported after the bond's amount outstanding is recorded by FISD as zero.

Next, using TRACE intraday data, we follow Bessembinder et al. (2009) and calculate daily clean price as the trading volume-weighted average of intraday prices. We then convert bond prices from daily to monthly frequency using the following procedure. For each bond in a given month, we set its month-end price equal to its last available daily TRACE price observed during the last five days of the month. When such a price is not available due to lack of trading, we then use the Bloomberg's quote price as its month-end price.[20] If neither a TRACE price during the last five days of the month nor a Bloomberg price is available, we drop the bond-month observation to avoid using a stale price.[21]

[20] Bloomberg has multiple pricing sources for bonds' quote prices. Following Schestag, Schuster, and Uhrig-Homburg (2016), we first use the Composite Bloomberg Bond Trade (CBBT) prices, calculated by Bloomberg using only the most recently updated executable prices in Bloomberg trading platform. If such prices are not available, we then use the Bloomberg Generic Quote (BGN) prices, which are calculated by Bloomberg using the quote prices from market contributors/participants. The exact methods of calculation are not disclosed by Bloomberg. We do not use other pricing sources from Bloomberg.

[21] In Appendix C, we conduct a robustness that excludes all Bloomberg prices.

Following the construction of monthly prices, we compute monthly corporate bond returns as follows:

$$RET_{i,j} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1$$

where $P_{i,t}$ is the month-end price, $AI_{i,t}$ is the accrued interest, and $C_{i,t}$ is the coupon payment, if any, of bond *i* during month *t*. We also follow Cici, Gibson and Moussawi (2017) in computing a composite default returns for all defaulted bonds.

Appendix B: Firm-level Variables

We collect several firm-level characteristics from Compustat and CRSP mainly using the SAS code posted by Green, Hand, and Frank (2017), and construct the following firm-level variables used to estimate Equation 1. *Operating income to sales* is operating income before depreciation to net sales. *Long-term debt to assets* is the total long-term debt to total assets. *Total debt to capitalization* is the total long-term debt plus debt in current liabilities plus average short-term borrowings scaled by total liabilities plus the market value of equity. We create four *pretax interest coverage dummies* using the procedure outlined by Dick-Nielsen et al. (2012) based on *pretax interest coverage*, which is operating income after depreciation plus interest expense scaled by interest expense. *Equity volatility* is estimated using the last year's daily returns requiring at least 180 observations. *Asset growth* is the percentage change in total assets (Cooper, Gulen, and Schill (2008)). *Investment to assets* is calculated as the annual change in gross property, plants, and equipment plus the annual change in inventories scaled by the lagged assets (Li, Livdan, Zhang (2009)). *Gross profitability* is calculated as revenues minus costs of goods sold divided by lagged assets (Novy-Marx (2013)). *Momentum* is the cumulative 11-month return on equity skipping the most recent month (Jegadeesh and Titman (1993)). *Reversal* is last month's equity return.

Appendix C: Bond Mispricing Robustness Checks

In order to utilize more within-firm variation in our estimation of Equation 1, in a first test we construct a subsample by identifying firms with more than 10 outstanding IG bonds with non-missing month-end price in a given month and including all the IG bonds of these firms. Using this subsample, we re-estimate Equation 1 and repeat our bond portfolio analysis of Table 2. More within firm variation should help generate more precise coefficient estimates and residuals from Equation 1. In other words, we should get more accurate signals to determine bonds' valuation status. As shown in Appendix Table C1, we obtain similar results as in Table 2.

In the second test, we address concerns regarding the use of Bloomberg quote prices, which we employ as month-end prices when TRACE transaction prices are not available. Although we tried our best to make sure the pricing sources we choose from the Bloomberg are executable by the market participants, it is still possible that the quoted price of a given bond uses prices of other bonds, including bonds of the same firm, as reference points. However, if the Bloomberg quoted price of a given bond incorporates the information from the prices of other bonds, we should be less likely to find potential mispricing. Nevertheless, we construct a subsample by identifying firms with at least two outstanding IG bonds with non-missing month-end TRACE price in a given month and including all the IG bonds of these firms. We then rerun Equation 1 and repeat our bond portfolio analysis in Table 2 using only TRACE transaction prices to calculate bond yields, duration, and monthly returns. As shown in Appendix Table C2, our results remain the same as Table 2.

Another two unreported robustness tests are as follows: (1) We construct another version of monthly returns following the methodology of Bai et al. (2019); and (2) we use 6 bond factors plus 4 traditional stock factors, including market factor, size factor, value factor, and momentum factors, to measure bond portfolio alphas. In both tests, we continue to find very similar results that residual spreads identified from Equation 1 predict economically significant future excess bond returns that materialize only in one month.

Appendix Table C1: Table 2 Replication Using Sample Firms with More Than 10 Bonds

This table replicates the results of Table 2 utilizing a stricter data requirement for the sample construction. Specifically, the sample used for this analysis is constructed by identifying firms with more than 10 outstanding IG bonds with non-missing month-end prices in a given month and including all the IG bonds of these firms. Newey-West (1987) adjusted t-statistics with 6 lags are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

# Months After Valuation Status Determination	2-Factor Alphas		6-Factor Alphas	
	(1) Pos RS	(2) Neg RS	(3) Pos RS	(4) Neg RS
1	0.0026***	-0.0023***	0.0027***	-0.0022***
	(2.77)	(-4.56)	(2.80)	(-4.34)
2	0.0006	-0.0002	0.0006	-0.0002
	(1.03)	(-0.41)	(1.09)	(-0.29)
3	0.0009	-0.0002	0.0008	-0.0001
	(1.40)	(-0.31)	(1.34)	(-0.19)
4	0.0002	0.0003	0.0003	0.0003
	(0.40)	(0.48)	(0.52)	(0.48)
5	0.0006	-0.0001	0.0007	0.0000
	(0.80)	(-0.13)	(0.89)	(-0.04)
6	0.0006	-0.0002	0.0006	-0.0001
	(0.79)	(-0.32)	(0.81)	(-0.12)
7	0.0002	0.0002	0.0002	0.0003
	(0.24)	(0.24)	(0.38)	(0.40)
8	0.0003	0.0001	0.0004	0.0002
	(0.46)	(0.15)	(0.55)	(0.24)
9	0.0004	0.0000	0.0005	0.0001
	(0.55)	(-0.04)	(0.65)	(0.10)
10	0.0005	0.0001	0.0005	0.0001
	(0.66)	(0.14)	(0.70)	(0.19)
11	0.0003	0.0003	0.0003	0.0004
	(0.41)	(0.55)	(0.46)	(0.60)
12	0.0004	0.0001	0.0005	0.0002
	(0.58)	(0.28)	(0.60)	(0.35)

Appendix Table C2: Table 2 Replication Using Only Trace Prices

This table replicates the results of Table 2 utilizing a stricter data requirement for the computation of credit spreads used in Equation 1. In particular, we use only TRACE transaction prices to calculate bond yields, duration, and monthly returns. Newey-West (1987) adjusted t-statistics with 6 lags are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

# Months After Valuation Status Determination	2-Factor Alphas		6-Factor Alphas	
	(1) Pos RS	**(2) Neg RS**	**(3) Pos RS**	**(4) Neg RS**
1	0.0024***	-0.0020***	0.0025***	-0.0019***
	(3.05)	(-4.72)	(3.05)	(-4.28)
2	0.0006	-0.0001	0.0008	0.0000
	(1.18)	(-0.19)	(1.43)	(-0.03)
3	0.0008	-0.0001	0.0009	0.0000
	(1.40)	(-0.30)	(1.61)	(0.02)
4	0.0004	0.0002	0.0005	0.0003
	(0.77)	(0.44)	(0.89)	(0.59)
5	0.0004	0.0000	0.0005	0.0002
	(0.64)	(-0.02)	(0.89)	(0.33)
6	0.0004	0.0000	0.0005	0.0001
	(0.74)	(-0.02)	(0.89)	(0.25)
7	0.0003	0.0001	0.0004	0.0002
	(0.53)	(0.15)	(0.75)	(0.40)
8	0.0003	0.0002	0.0004	0.0002
	(0.54)	(0.30)	(0.68)	(0.48)
9	0.0005	0.0000	0.0005	0.0001
	(0.78)	(0.08)	(0.88)	(0.22)
10	0.0005	0.0002	0.0005	0.0003
	(0.78)	(0.47)	(0.84)	(0.57)
11	0.0002	0.0003	0.0003	0.0004
	(0.40)	(0.53)	(0.59)	(0.76)
12	0.0003	0.0004	0.0004	0.0004
	(0.60)	(0.72)	(0.68)	(0.77)

cfr working paper series

centre for financial research
cologne

cfr working papers are available for download from www.cfr-cologne.de.

2021

No.	Author(s)	Title
21-05	G. Cici, P. Zhang	On the Valuation Skills of Corporate Bond Mutual Funds
21-04	V. Agarwal, P. Hanouna, R. Moussawi, C.W. Stahel	Do ETFs Increase the Commonality in Liquidity of Underlying Stocks?
21-03	M. Saglam, T. Tuzun, R. Wermers	Do ETFs Increase Liquidity?
21-02	C. Andres, D. Bazhutov, D. Cumming, P. Limbach	The M&A Rumor Productivity Dip
21-01	T. Bali, F. Weigert	Hedge Funds and the Positive Idiosyncratic Volatility Effect

2020

No.	Author(s)	Title
20-14	V. Agarwal, Y. Lu, S. Ray	Are hedge funds' charitable donations strategic?
20-13	M. Jagannathan, W. Jiao, R. Wermers	International Characteristic-Based Asset Pricing
20-12	E. Theissen, L. Zimmermann	Do Contented Customers Make Shareholders Wealthy? - Implications of Intangibles for Security Pricing
20-11	M. Hendriock	Implied Cost of Capital and Mutual Fund Performance
20-10	J. Fink, Stefan Palan, E. Theissen	Earnings Autocorrelation and the Post-Earnings-Announcement Drift – Experimental Evidence
20-09	E. Theissen, C. Yilanci	Momentum? What Momentum?
20-08	V. Agarwal, L. Jiang, Q. Wen	Why Do Mutual Funds Hold Lottery Stocks?
20-07	V. Agarwal, S. Ruenzi, F. Weigert	Unobserved Performance of Hedge Funds
20-06	M. Ammann, S. Fischer, F. Weigert	Factor Exposure Variation and Mutual Fund Performance
20-05	P. Limbach, P. R. Rau, H. Schürmann	The Death of Trust Across the U.S. Finance Industry
20-04	A. Y. Chen, T. Zimmermann	Open Source Cross-Sectional Asset Pricing

20-03	L. Ahnert, P. Vogt, V. Vonhoff, F. Weigert	Regulatory Stress Testing and Bank Performance
20-02	P. Schuster, E. Theissen, M. Uhrig-Homburg	Finanzwirtschaftliche Anwendungen der Blockchain-Technologie
20-01	S. Ruenzi, M. Ungeheuer, F. Weigert	Joint Extreme Events in Equity Returns and Liquidity and their Cross-Sectional Pricing Implications

2019

No.	Author(s)	Title
19-06	S. Greppmair, E. Theissen	Small Is Beautiful? How the Introduction of Mini Futures Contracts Affects the Regular Contract
19-05	G. Cici, M. Hendriock, A. Kempf	Finding your calling: Skill matching in the mutual fund industry
19-04	O. Korn, P. M. Möller, Ch. Schwehm	Drawdown Measures: Are They All the Same?
19-03	G. Cici, M. Hendriock, S. Jaspersen, A. Kempf	#MeToo Meets the Mutual Fund Industry: Productivity Effects of Sexual Harassment
19-02	T. Johann, S. Scharnowski, E. Theissen, C. Westheide, L. Zimmermann	Liquidity in the German Stock Market
19-01	A. Betzer, P. Limbach, P. R. Rau, H. Schürmann	Till death (or divorce) do us part: Early-life family disruption and investment behavior

2018

No.	Author(s)	Title
18-06	M. Goergen, P. Limbach, M. Scholz-Daneshgari	On the Choice of CEO Duality: Evidence from a Mandatory Disclosure Rule
18-05	F. Brochet, P. Limbach, D. Bazhutov, A. Betzer, M. Doumet	Where Does Investor Relations Matter the Most?
18-04	G. Cici, A. Kempf, C. Peitzmeier	Knowledge Spillovers in the Mutual Fund Industry through Labor Mobility
18-03	T. Rischen, E. Theissen	Underpricing in the Euro Area Corporate Bond Market: New Evidence from Post-Crisis Regulation and Quantitative Easing
18-02	S. Lesmeister, P. Limbach, M. Goergen	Trust and Shareholder Voting
18-01	G. Cici, M. Hendriock, A. Kempf	The Impact of Labor Mobility Restrictions on Managerial Actions: Evidence from the Mutual Fund Industry

This document only covers the most recent CFR working papers. A full list can be found at www.cfr-cologne.de.

centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de