On the Valuation Skills of Corporate Bond Mutual Funds

by

Gjergji Cici and Pei (Alex) Zhang[*]

April 15, 2022

Abstract

We introduce a novel measure, *valuation accuracy score (VAS)*, to assess the valuation skills of investment-grade corporate bond mutual funds. VAS recognizes funds holding a higher (lower) fraction of underpriced (overpriced) corporate bonds as ex-ante having better valuation skills. VAS is predictive of future fund performance, is stable over time, and is unrelated to other sources of skill. Investors recognize valuation skills behind VAS by chasing the performance of higher-VAS funds more aggressively and exhibiting a convex flow-performance relation among these funds.

[*] 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 Vikas Agarwal, Christopher Anderson, Isarin Durongkadej (discussant), Scott Gibson, Alexander Kempf, Paul Koch, David Maslar, Andy Puckett, Nan Qin, David Rakowski (discussant), Tim Riley (discussant), Thad Sieracki, Russ Wermers, Yaoyi Xi, Jinming Xue, and seminar participants at the University of Cologne, University of Kansas, 2021 FMA Annual Meeting, 2021 SFA Annual Meeting, and 2022 EFA Annual Meeting.

1. Introduction

Corporate bond mutual funds (hereafter bond funds) are becoming increasingly important in the corporate bond market.[1] Furthermore, the corporate bond market is larger, more illiquid, and presumably less efficient than the equity market, providing numerous profit opportunities for bond funds that are unique to this market.[2] The consensus from the literature, however, is that active 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] In contrast to the academic consensus, investment flow patterns over the last 10 years (see Figure 1) suggest that investors see value in the active management of bond funds but not in the active management of equity funds. Motivated by these flow patterns, a new line of research has recently started to investigate whether at least some bond funds in the cross-section have investment skills.[4]

No work to date has explored whether valuation skills exist in the cross-section of bond funds whereby some funds can identify and exploit mispriced bonds, which is supposed to be one of their core activities. Our paper investigates whether cross-sectional differences exist in the valuation abilities of bond funds and how such abilities affect fund performance. Exploiting unique features of the corporate bond market, we develop a novel holdings-based measure of the valuation abilities of investment-grade bond funds. This is important given the resources expended by active fund management on the analysis of corporate bonds. Being the first to measure and document the presence of valuation skills in the cross-section of bond funds, we shed new light on the debate concerning the

[1] Assets under management of corporate bond funds grew from $382 billion in 2000 to approximately $3 trillion in 2019 (Investment Company Institute (2020)).

[2] Examples include: (1) exploiting underpricing of corporate bonds in the primary bond market, which is far more active than the primary equity market (e.g., Nikolova, Wang, and Wu (2020)); (2) trading against uninformed counterparties that transact for non-economic reasons (e.g., Murray and Nikolova (2021)); and (3) providing liquidity during periods of sustained customer imbalances (e.g., Anand, Jotikasthira, and Venkataraman (2021)).

[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 (2021); Anand et al. (2021); and Huang, Lee, and Rennie (2019).

investment abilities of this increasingly important group of institutional investors and help reconcile the behavior of mutual fund investors (e.g., steady inflow to active bond funds) with new evidence on the investment abilities of bond funds.

The idea behind our measure is straightforward. Consider a bond fund that is skilled at accurately valuing individual corporate bonds. This fund will systematically identify and buy (sell) bonds that are underpriced (overpriced). Therefore, its portfolio ought to reveal a higher (lower) fraction of underpriced (overpriced) bonds, meaning that this particular fund is forming more accurate valuation assessments compared to other funds. Based on this insight, for each fund and date pair with a reported portfolio, we compute the valuation accuracy score (VAS) as the fraction of underpriced bonds out of all underpriced and overpriced bond holdings. Funds simultaneously holding a high fraction of underpriced bonds and a low fraction of overpriced bonds have a high VAS, indicating a higher level of valuation accuracy.

To identify mispriced corporate bonds, we exploit a unique feature of the corporate bond market, namely that many firms have multiple bonds outstanding.[5] Exploiting within-firm variation of individual bonds' credit spreads at each point in time, we measure mispricing by estimating each bond's *residual spread*, the part of the credit spread unexplained by common (unobservable) firm fundamentals and bond characteristics. We confirm that the residual spread is caused by temporary mispricing and not by omitted risk factors by documenting that residual spreads predict future excess bond returns that materialize only in the short term, i.e., one month. Additional tests rule out the possibility that the documented mispricing and the future excess returns that follow immediately are due to temporary price pressure or asynchronous trading.

[5] For example, Verizon had over 100 bonds outstanding as of 6/31/2020. The large number of bonds per firm and the possible mispricing among certain bonds of the same firm 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)).

We focus on IG corporate bonds and IG bond funds because our identification of 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] Even though IG corporate bonds have relatively lower risk and are more liquid than high-yield corporate bonds, we still document a considerable amount of mispricing among IG corporate bonds with our methodology, suggesting that there is significant room for IG bond funds to exploit mispricing among IG corporate bonds.

Covering a comprehensive sample of 395 IG bond funds during the 2002.7-2019.12 sample period, we conduct three sets of analyses. First, we document that our valuation accuracy score predicts future fund performance. Specifically, funds in the top VAS quintile (high-VAS funds) outperform funds in the lowest quintile (low-VAS funds) in the next quarter by a significant 34 bps annualized gross alpha. This performance differential is economically significant, as the gross alpha of the average active bond fund is just 26 bps per year. The outperformance of higher-VAS funds extends beyond the one-month window over which alphas of mispriced bonds we use to construct VAS materialize, suggesting that these funds do not generate superior alpha simply because they were coincidentally holding underpriced bonds identified as such by our methodology. This provides a first indication that our VAS measure captures valuation skills extending beyond the mispriced bonds we use to construct our measure.

Our results are robust to controlling for a comprehensive list of fund and family characteristics. Importantly, they persist after we control for the propensity of certain funds to profit from supplying liquidity as documented in Anand et al. (2021). Our results are also robust to controlling for unobserved fund heterogeneity with fund fixed effects and different models or windows to estimate fund alphas.

[6] The median high-yield (HY) firm satisfying our data requirements has only 1.3 concurrently outstanding bonds, while the median IG firm has 3.7 bonds 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.

The outperformance of high-VAS funds is not driven by differences in their portfolio bond characteristics. Nor is it driven by them consistently tilting their portfolios towards other asset classes as our main result continues to hold for a subsample of funds that typically hold most of their portfolio in corporate bonds, among which the majority are IG corporate bonds. In further robustness tests, we construct alternative versions of VAS that, respectively, require larger numbers of bonds for the VAS calculation; use the number instead of the market values of bond holdings; and rely on fund trades instead of holdings. Our results remain unchanged.

We next investigate the most likely mechanism through which the skills measured by VAS affect fund performance. Intuitively, we expect high-VAS funds to generate better performance through superior bond selection. Following Daniel et al. (1997) and Cici and Gibson (2012), we decompose a fund's corporate bond holdings return into components attributable to bond-selection and characteristic-timing ability. Consistent with the "superior bond selection" mechanism, we find that VAS predicts fund returns attributable to corporate bond selection but not to characteristic timing. In a related test, we control for the part of fund return that comes from exploiting mispricing identified by our methodology by including an additional bond return factor based on bond residual spreads in our fund alpha estimation. We still find that VAS has significant predictive power for fund performance. Thus, high-VAS funds perform better because they have superior general bond selection ability that is not restricted to the mispriced bonds identified by our methodology. In other words, although it uses a subset of bonds for which we can determine valuation status, VAS provides a window into the overall valuation abilities of bond funds.

In our second set of analyses, we examine how our valuation accuracy measure relates to its past realizations and several fund characteristics. We find that VAS is highly persistent, which is consistent with it reflecting a stable skill. In addition, VAS is positively related to overall portfolio turnover, supporting 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.

(2021), which captures the propensity of certain funds to provide liquidity, are not related to VAS. Thus, our measure represents a new dimension of skill that is orthogonal to other factors known to affect fund performance.

Finally, we examine how, if at all, fund investors respond to the valuation skills of IG bond funds. We find 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 a higher VAS, which means that investors perceive the past performance of funds with a higher VAS to be a stronger indicator of skill and pursue it even more aggressively. Thus, investors learn about the skills of IG bond funds utilizing information from portfolio holdings to infer valuation accuracy in conjunction with information from past fund performance. Investors learning 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. Investors' recognition of high-VAS funds as skilled is further supported by analysis of the flow-performance sensitivity in the negative and positive performance regions. We find that for higher-VAS funds the flow-performance relation becomes more convex. This is consistent with the notion that, as investors identify skilled funds, they become less sensitive to poor performance relative to good performance of these funds.

Our paper contributes to a growing literature on the performance of bond funds.[7] While the methodologies employed in this literature largely mirror those from the far more extensive literature on 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

[7] See Blake et al. (1993); Elton et al. (1995); Ferson et al. (2006); Gutierrez et al. (2008); Huij and Derwall (2008); Chen et al. (2010); Cici and Gibson (2012); Moneta (2015); Rohleder et al. (2018); Huang et al. (2019); Choi et al. (2021); Anand et al. (2021); and Natter et al. (2021).

novel evidence of skill in the active management of corporate bonds by documenting that the differential abilities to accurately value individual corporate bonds translate into differential performance in the cross-section. Thus, at a general level, our evidence contributes to the debate on whether skill exists among bond funds.

Our paper is also related to a nascent literature strand documenting evidence of outperformance among subsets of bond funds. Huang et al. (2019) document a higher fraction of outperforming bond funds than expected by pure luck, which is much higher than for equity funds (e.g., Fama and French 2010). Choi et al. (2021) show that bond funds with higher active share exhibit better performance. Anand et al. (2021) document that a subset of funds follow a distinct strategy of providing liquidity from which they earn positive alpha. We contribute to this literature by documenting a new type of skill—valuation skill—in the cross-section of bond funds, which is distinct from the liquidity providing skill documented by Anand et al. (2021). Thus, our research furthers our understanding of the investment abilities of bond funds and the nature of their abilities.

Finally, our paper is related to the literature studying the flow-performance relation of bond funds. Goldstein et al. (2017) and Chen and Qin (2017) document that unlike for equity funds, the flow-performance relation is concave or linear for bond funds. We contribute to this literature by showing that investors' performance chasing behavior is not homogenous among corporate bond funds. In fact, flows of funds that investors believe to be skilled exhibit a convex flow-performance relation, which we attribute to investors' perception of skill causing outflows to be less sensitive to poor performance than inflows are to good performance of these funds.

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

2.1. Corporate Bond Samples

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 US public, non-puttable, non-convertible, fixed-coupon, non-perpetual, senior unsecured U.S. Corporate Debentures ("CDEB"). We exclude bonds that have less than one year of time-to-maturity, and have less than three months of age.[8]

For the resulting subset of bonds, following the literature, we first calculate the daily clean price as the trading volume-weighted average of intraday TRACE prices to minimize the effect of bid-ask spreads on prices. We then construct returns of monthly frequency from July 2002-December 2019 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 analysis of holdings-based return decomposition.

Next, we compute the credit spread as the difference between the corporate bond yield and the Treasury bond yield of the same maturity.[9] Using the Bond CRSP link table from WRDS, we match bonds to firms and construct firm-level variables 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 having at least two outstanding IG bonds with a non-missing month-end price in a given month and include all their bonds meeting this condition.[10] The resulting

[8] Bai, Bali, and Wen (2019) document that a bond is removed from major US corporate bond indexes once its time-to-maturity is less than one year. To avoid potential return distortions mechanically caused by index-tracking investors, we remove them from our sample. Nikolova et al. (2020) document that newly-issued bonds are systematically underpriced and institutional investors with better relations with underwriters tend to get larger allocations. This may cause a bias in the VAS of certain funds. For this reason, we remove bonds with less than three months of age.

[9] Corporate bond yields are calculated based on month-end prices, coupon information, and maturity. 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.

[10] 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.

sample, which we refer to as the *classified bond* sample and later use to classify the valuation status of its bonds, consists of 8,521 IG bonds issued by 616 firms from July 2002 to December 2019.

Table 1 provides summary statistics for the classified bond sample. We have 396,498 monthly observations with non-missing values needed for the subsequent analysis. The average bond has an outstanding amount of $637 million, age of five years, eleven years to maturity, 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

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 a credit spread that is not fully explained by these determinants. However, 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.[11] This feature allows us to compare bonds of the same firm at the same time, which effectively have exposure to the same fundamental risk and market-wide factors while controlling for observable bond characteristics.

We isolate the unexplained part of the credit spread by running the following cross-sectional regression with firm fixed effects, every month for all bonds in the classified bond sample:[12]

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

[11] Examples of studies that use this feature in other contexts include Helwege and Turner (1999); Dick-Nielsen, Feldhütter, and Lando (2012); Helwege, Huang, and Wang (2014); Choi et al. (2020); and Chen and Choi (2020).

[12] Running monthly regressions not only allows us to control for general market conditions but also allows the parameters to be time-varying if the relation between credit spreads and the explanatory variables depends on market conditions, thus allowing for greater flexibility in estimation.

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 bond-level variables that captures: *rating number dummies* to control for credit risk; *percentage of zero trading days in a month*, *natural log of current amount outstanding* and *natural log of bond age in years* to control for liquidity risk; and *coupon rate* and *duration in years* to control for interest rate risk. 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 bonds with a longer maturity 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 et al. (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 et al. (2017) and Choi and Kim (2018), who 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 variables in Appendix B.

We use the residuals from Equation 1 (hereafter *residual spreads*) to proxy for a bond's valuation status. A positive (negative) residual spread suggests that a bond's credit spread cannot be fully explained by its common determinants, and we hypothesize that the credit spread is temporarily higher (lower) than it should be, indicating potential underpricing (overpricing). As the firm fixed effects in Equation 1 allow us to compare bonds of the same firm to control for common (unobservable)

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

firm fundamentals, it is possible that the residual spreads only capture the relative degree of mispricing within the firm in certain months. For example, a bond, classified as underpriced by our methodology, could be simply viewed as being the least overpriced among all the bonds of a given firm if the firm or the entire market is temporarily overpriced. However, to the extent that the firm-level or the market-level mispricing is unlikely to sustain, underpriced (overpriced) bonds identified by our proxy should still, on average, outperform (underperform) in the future. It is also possible that the residual spreads are caused by some omitted risk factors instead of mispricing. To address these issues, we study the future risk-adjusted returns of separate portfolios that include bonds, respectively, with positive and negative residual spreads. If their alphas are short-lived, then their residual spreads are likely to indicate mispricing instead of some omitted persistent risk.

At the end of each month *t*, we construct two portfolios, one consisting of bonds with a positive residual spread (*Pos-RS*) and the other consisting of bonds with a negative residual spread (*Neg-RS*). Both portfolios are value-weighted based on the market value of each portfolio bond and are held for one month. To examine the 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)). In addition to the two common bond factors, we also estimate portfolio alphas based on a seven-factor model, which includes the TERM factor, the DEF factor, four common stock factors such as the *MKT*, *SMB*, *HML*, and *MOM* factors (Fama and French (1993) and Carhart (1997)), and the bond liquidity risk factor (*LRF*) introduced by Bai, Bali, and Wen (2019).

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 27 bps two-factor alpha while Column 2 shows that the Neg-RS portfolio generates a significant -20 bps 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: the positive (negative) alpha generated by the Pos-RS (Neg-RS) portfolio in the next month indicates that this portfolio on average included underpriced (overpriced) bonds, the prices of which were pushed closer to their intrinsic value in the next month. Importantly, the fact that the alphas quickly disappear beyond one month is inconsistent with residual spreads capturing omitted risk factors. Results from Columns 3 and 4 based on the seven-factor model to estimate alphas are similar. In Appendix C1, we report similar results based on a model including recently proposed bond risk factors such as bond market factor (*MKT_BOND*), the bond liquidity risk factor (*LRF*), the bond downside risk factor (*DRF*), the bond credit risk factor (*CRF*), the bond return reversal factor (*BOND_REV*), and the bond momentum factor (*BOND_MOM*) (Bai et al. (2019) and Jostova et al. (2013)).[14]

It is possible that the alphas of the Pos-RS and Neg-RS portfolios reflect bond characteristics that are not fully accounted for by the factor models. To rule this out, in Panel B of Table 2 we report the time-series means of the monthly cross-sectional average characteristics related to credit quality, interest-rate sensitivity, and liquidity separately for bonds in the two portfolios along with their differences. We supplement the characteristics of Table 1 with three additional liquidity measures: *EstDay Turnover*, the ratio of a bond's daily trading volume over its amount outstanding on the day its residual spread is estimated; *Rel Turnover,* the ratio of a bond's trading volume on the day its residual spread is estimated over its average daily trading volume based on trading days over the previous three

[14] We chose to report these as robustness results in Appendix C1 since some of these factors such as the DRF and the CRF do not cover our entire sample period.

months;[15] and *Illiquidity,* the autocovariance of the daily TRACE price changes within each month, multiplied by -1 (Bao, Pan, and Wang (2011)). In the first two measures, we set the daily trading volume to zero if there was no trading on the day we estimate the residual spread.

In addition, following the methodology of Anand et al. (2021), we examine whether bonds in the two portfolios are subject to differential short-term liquidity pressure from customer trading activity. If the next-month positive (negative) alphas of the Pos-RS (Neg-RS) portfolio are related to return reversals due to temporary liquidity pressure in previous months, we should observe a higher fraction of bonds with a positive (negative) dealer inventory cycle, indicating sustained customer selling (buying), in the Pos-RS (Neg-RS) portfolio. Hence, we report an additional monthly average statistic, *IC Ratio*, the ratio of the percentage of bonds with a positive dealer inventory cycle over the percentage of bonds with a negative dealer inventory cycle. A higher *IC Ratio* suggests that a higher fraction of bonds in the portfolio are experiencing customer selling than customer buying.[16]

The bonds in the Pos-RS and Neg-RS portfolios are not different in terms of credit quality. Their interest-rate sensitivity measures are similar, with differences that are trivial in an economic sense albeit statistically significant. We observe statistically significant differences for two of the six liquidity measures. Bonds in the Pos-RS portfolio have larger outstanding amounts than bonds in the Neg-RS portfolio and a lower fraction of zero trading days, though the difference in zero trading days is not economically meaningful. The other four liquidity measures are not different between the two groups both in terms of statistical and economic significance. Given that five out of the six liquidity measures exhibit no meaningful differences, we cannot reject the null that bonds in both portfolios have similar liquidity. Also, the difference in the IC Ratio suggests that a lower fraction of bonds in the Pos-RS portfolio (underpriced bonds) than in the Neg-RS portfolio (overpriced bonds) experienced

[15] A high *Rel Turnover* means that a bond experienced abnormally high trading activity on the day we estimate its residual spread compared to its recent history, indicating a potential influence by unexpected news.
[16] Anand et al. (2021) identified 117,825 positive inventory cycles and 90,046 negative inventory cycles. Thus, in the absence of any systematic biases, we expect the Pos-RS and Neg-RS portfolios to have an *IC ratio* of 1.3 (117,825/90,046).

customer selling before the portfolio formation. If future return reversals tend to follow temporary price pressure, this difference works against us finding positive alphas in the Pos-RS portfolio. Overall, there is no apparent evidence that the alphas of the Pos-RS and Neg-RS portfolios can be explained by differences in various bond characteristics or liquidity pressure.[17]

Taken together, our findings suggest that our approach can identify, on average, temporarily mispriced bonds. In Appendix C and D we conduct a series of robustness tests where we repeat the analysis of Table 2 using: (1) a subsample with a greater degree of within-firm variation for the estimation of Equation 1; (2) only trade-based prices from TRACE; and (3) delays in the measurement of next month returns to account for asynchronous trading. Our inferences from Table 2 remain robust. Furthermore, consistent with the expectation that mispricing should be gradually arbitraged away as mispricing becomes more "observable" and competition increases in the corporate bond market, in Appendix E we show that the alphas of both portfolios decline in magnitude in the later part of the sample period.

Finally, it is important to note that Equation 1 is not a description of how bond funds value corporate bonds and does not aim to identify the source of this mispricing, which is beyond the scope of this paper. Rather, Equation 1 provides us with a benchmark to approximate bond mispricing. Funds with valuation skills are likely to possess a larger information set than what is reflected in Equation 1 and extract more precise bond valuation signals from a more elaborate and timely process that uses higher frequency information. Thus, our approximation of bonds' valuation status might contribute noise to the valuation accuracy measure introduced in the next section to estimate funds' valuation ability. However, such noise should make it more difficult for us to find a relation between fund performance and the valuation accuracy score.

[17] Since dealer inventory cycles mainly detect short-term liquidity pressure, in unreported analysis, we also investigate bonds' long-term liquidity pressure measures such as 12-month order imbalance and lagged IC ratios and we do not find any statistical difference between the Pos-RS and Neg-RS portfolios, which addresses the concern that the alphas in the Pos-RS and Neg-RS portfolios are driven by long-term liquidity shocks.

2.2.2. Valuation Accuracy Score Methodology

To identify valuation skills across bond funds, our novel measure exploits information from fund portfolio holdings of bonds for which we can determine their valuation status using our methodology. The intuition is straightforward. A fund that can accurately identify underpriced or overpriced bonds ought to rationally exploit this ability by consistently buying underpriced bonds and selling overpriced bonds. Consequently, we expect such a fund to hold a higher (lower) fraction of underpriced (overpriced) bonds in its portfolio, suggesting a higher accuracy in its valuation assessments.

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:

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

where $\$ \sum_{i=1}^{n} Underpriced\_bond_{i,f,t}$ ($\$ \sum_{i=1}^{n} Overprice\_bond_{i,f,t}$) is the sum of the market values of all underpriced (overpriced) bond holdings at time *t* using the methodology from the previous section. Using market values reported by Morningstar places greater weight on larger holdings, which should reflect a fund's valuation assessment more accurately. Consistent with our intuition, by measuring the importance of underpriced bonds in the sub-portfolio of all underpriced and overpriced bonds held by a fund, VAS helps us capture the accuracy of a fund's valuation assessments using information from both underpriced and overpriced bonds. Therefore, funds need to simultaneously hold a high fraction of underpriced bonds and a low fraction of overpriced bonds in order to achieve a high VAS. In a robustness test reported later, we consider a version of VAS based purely on the number of underpriced bonds and overpriced bonds in the portfolio and find similar results. Possible values of VAS range by construction between zero and one. If every classified bond held in the portfolio is underpriced (overpriced), a fund has a VAS of one (zero).

An alternative approach is to assess valuation accuracy based on fund trades inferred from portfolio changes. Although this approach may arguably capture the active decisions of a given fund better, one major drawback is that we do not observe the exact timing of fund trades. In our setting, such a drawback is likely to create substantial noise given the evidence from Table 2 that the mispricing is short-lived. 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 (Bond Fund) Sample

We employ two mutual fund data sources. From Morningstar, we obtain detailed portfolio holdings for both live and dead mutual funds from July 2002 to December 2019. 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 bond fund sample are as follows. We first select a comprehensive list of IG bond funds using CRSP MF objective codes and Morningstar categories.[18] 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, enhanced index 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 portfolio in corporate bonds during the sample period (e.g., Anand et al. (2021)).[19] Furthermore, for the purpose

[18] Specifically, following Goldstein et al. (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".

[19] As in Choi et al. (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. (2021)). In addition, we extend the corporate bond holdings categorization to bonds with FISD bond type of "CZ" and "CCPI".

of computing the valuation accuracy score, we exclude fund portfolio reports with no holdings in the classified bond sample that we used to determine bond valuation status.

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 395 IG bond funds.

We combine multiple share classes of the same fund into a single fund by weighting their characteristics by the lagged assets of each share class. 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 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.[20] 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.

[20] 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.

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 underpriced than overpriced bonds in its portfolio, an indication that the average fund has some valuation skill. The VAS interquartile range of 44.3% to 61.4%, 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 sections.

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 41%, which is sensible since the average fund holds almost half of its portfolio in corporate bonds. The average expense ratio of 0.72% is the same as the one reported for the IG sample of Choi et al. (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.

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

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

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 liquidity provision, we add the fund's quintile rank of average liquidity supply score over the last 12 months (*t-11, t*) (*LS_scoreQ*), which is constructed following Anand et al. (2021). Also following Anand et al. (2021), 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 (high-VAS funds) outperform funds in the bottom quintile (low-VAS funds) by 2.8 bps (0.69 * 4) per month over the next quarter, which translates to 33.6 bps per year (2.8 * 12). This is highly significant in an economic sense considering that the annualized gross alpha of the average active bond fund is just 26.4 bps per year.

Looking at the coefficients of the control variables, we confirm the findings of Anand et al. (2021) that funds can also earn additional alpha by providing liquidity. Most importantly, though, the fact that our results hold even when we control for the propensity of certain funds to provide liquidity confirms that our measure captures a different dimension of skill.

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 a higher VAS at time t hold by construction more underpriced bonds, which, as shown in Table 2, mainly outperform at time t+1. If our results are 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 high-VAS funds still outperform low-VAS funds by 2.4 basis points (0.60 * 4) monthly gross alpha over the next quarter or 28.8 basis points per year. The result is significant at the 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 most likely comes from the outperformance of other positions of high-VAS funds. This suggests that our VAS measure captures fund managers' valuation skills that extend beyond the underpriced bonds we use to construct it.

3.2. Robustness Checks

We perform a series of analyses to confirm robustness of our main result. In our first set of analyses reported in Table 6 we account for fund unobserved heterogeneity or use alternative performance measures. 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 14, 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 needed for the estimation of expected fund returns in a given month. In Columns 7 to 12, using a 36-month rolling window, we estimate fund alphas by sequentially including additional bond risk factors defined in Section 2.2.1 to the original four-factor model laid out in Equation 3. In Columns 7 to 8, we add the TERM factor. In Columns 9 to 10, we add the liquidity risk factor (*LRF*). In Columns 11 and 12, we further include the downside risk factor (*DRF*), the credit risk factor (*CRF*), the bond return reversal factor (*BOND_REV*), and the bond momentum factor (*BOND_MOM*).[21] Moving to Columns 13 and 14, 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 robust across all columns.

In Appendix F we examine the portfolio characteristics of high- and low-VAS funds to rule out the possibility that funds with a higher VAS are tilting their portfolios towards bonds with certain

[21] The lower number of observations in columns 9-12 is because these additional factors do not cover our entire sample period.

properties that can explain their performance. There we also rule out that our results are driven by high-VAS funds consistently tilting their portfolios towards other asset classes as our main result continues to hold for subsamples of funds that typically hold a higher fraction (e.g., over 80%) of their portfolio in corporate bonds, among which the majority (e.g., over 90%) are IG corporate bonds.

The third set of tests addresses robustness with respect to the measurement of our explanatory variable of interest, VAS. To that end, we replace VAS with alternative measures in Equation 4 and report results in Table 7. Admittedly, our methodology uses only a subset of the fund portfolio to construct VAS. To enhance the accuracy of VAS, in Panel A, we construct three other measures, *VAS_10, VAS_20,* and *VAS_30*, requiring, respectively, at least 10, 20, and 30 bonds for which we can determine valuation status according to Equation 2. The results are still similar to those of Table 4, alleviating the concern of potential measurement error of VAS.

Next, in Columns 1 and 2 of Panel B, using Equation 2, we calculate another version of the valuation accuracy measure based on the number of underpriced bonds and overpriced bonds in the portfolio instead of the market value of bonds. 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 multiple dealers due to their better resources and relationships. For example, a small fund and a large fund both bid for 10 million of an underpriced bond in the secondary market. The small fund may only get 2 million from the only dealer they have access to but the large fund gets 8 million due to its better relations with multiple dealers. In other words, market-value based VAS may underestimate the valuation accuracy of small funds, a problem that can be mitigated with VAS_NUM.

In Columns 3 and 4 of Table 7 Panel B, 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 Panel B, our results remain robust when we use the two alternative measures and their quintile ranks.

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. To confirm the presence of the bond-selection mechanism, we conduct two tests. In the first test, we follow Daniel et al. (1997) and Cici and Gibson (2012) and decompose fund monthly returns into "Bond-Selection" (BS) return and the "Characteristic-Timing" (CT) return. If the mechanism we propose is indeed present, we expect funds with a higher VAS to exhibit a stronger bond selection return component.

We investigate each fund's entire corporate bond portfolio, including bonds not in our classified bond sample. 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 returns for the resulting 50 benchmark portfolios. Next, $BS_{f,t}$, measuring whether 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:

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

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

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 months as 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. In terms of economic magnitude, high-VAS funds can outperform low-VAS funds by 3.7 bps per month (44 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. Thus, the evidence from Table 8 supports the superior bond-selection mechanism.

While the test above shows that high-VAS funds, on average, have superior bond selection abilities applicable to all bonds, in our next analysis we explicitly test for whether high-VAS funds have selection ability that goes beyond exploiting mispricing identified by our methodology. To this end, we add an additional bond return factor (hereafter *RS* factor) to the fund performance evaluation model in Equation 3 to account for the part of fund return that arises due to funds holding (selling) underpriced (overpriced) bonds classified as such based on Equation 1. Similar to Bai et al. (2019), to construct the RS factor, each month we form bivariate portfolios by independently sorting bonds into four groups based on their rating (AAA, AA, A, BBB) and into terciles based on their residual spreads estimated from Equation 1. Then, the RS factor is the average difference of value-weighted returns between the top and bottom tercile portfolios sorted on residual spreads across the rating portfolios.

After we adjust fund performance using Equation 3 augmented with the RS factor, we re-estimate Equation 4 and report results in Table 9. In the first two columns, we use an 18-month rolling window followed by a 36-month window in the last two columns to estimate the monthly five-factor alphas. Results from Table 9 show that the predictive power of VAS on fund performance remains even after we control for any performance effects due to the RS factor, suggesting that higher-VAS funds have superior bond selection ability that goes beyond exploiting mispricing identified by our methodology.

In sum, the evidence from this section collectively supports the superior bond selection mechanism. Said differently, higher-VAS funds achieve outperformance because they have superior general bond selection ability that is not restricted to the mispriced bonds identified by our methodology but extends to other bonds.

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. We use the following model:

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

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. $\boldsymbol{X}$ is the same vector of fund characteristics introduced in Equation 3 plus the fund expense ratio. We also include month fixed effects and fund style fixed effects. Standard errors are double clustered by fund and month.

Panel A of Table 10 reports results. Column 1 reports results with $AVAS_{i,(t-11,t)}$ excluded for comparison. Columns 2 reports results for the full specification of Equation 7. If luck plays a role and 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 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.

Another way to look at whether funds exhibit persistent valuation accuracy is to look at a transition matrix reporting the fraction of fund rankings based on AVAS in months [t-11, t] that stay in the same or different AVAS rankings in months [t+1, t+12]. If [t-11, t] rankings are random, then funds have a 20% probability of transitioning to any of the AVAS quintiles during [t+1, t+12]. The transition matrix reported in Panel B of Table 10 shows that Q5 funds have a 50% probability of being in the Q5 quintile and only a 5.7% probability of ending up in the Q1 quintile in the next 12 months. We observe a similar tendency for Q1 funds to preserve their ranking in the future. The Pearson's chi-square statistic rejects the null hypothesis that the valuation accuracy scores are driven by randomness and have no relation to future valuation accuracy scores.

The only other fund characteristic that is significantly related to future valuation accuracy in all specifications of Panel A is the CRSP turnover. In addition, the corporate bond portfolio turnover is significantly related to future valuation accuracy in Column 1 and Column 3. These two variables are related to fund activeness. However, once we include our valuation accuracy measures in Column 2, the economic significance of the CRSP turnover and the corporate bond portfolio turnover reduced by more than 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 propensity of certain funds to provide liquidity. The lack of a significant relation also suggests that funds with valuation skills do not exhibit a systematic overall tendency to demand liquidity either. Perhaps this is not surprising given the results from Panel B of Table 2 showing less customer-induced selling pressure among the underpriced relative to overpriced bonds that go into the calculation of VAS, providing additional evidence that high-VAS funds do not have a liquidity-providing style.

The other fund characteristics are not significantly related to VAS either. 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

In light of the evidence presented so far, a natural question is: How do investors respond to differential valuation skills across funds? This depends on how investors are learning about the skills of fund managers. If investors incur a search cost, as in the model of Gârleanu and Pedersen (2018), to find skilled funds, we 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 identifies a fund with a 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. Month fixed effects and fund style fixed effects are included and standard errors are double clustered by fund and month.

Results are reported in Table 11. 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 skills 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 a 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 view 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 VAS to infer the skills of fund managers.

If investor believe that higher-VAS funds are skilled, then the flow-performance relation of these funds should exhibit more convexity in the form of lower sensitivity to poor performance relative to good performance of these funds. The idea is that investors will likely respond less vigorously (in a more forgiving way) to the poor performance of a skilled fund relative to its good performance. To test this prediction and differentiate the fund performance between the positive and negative regions, we modify Equation 8 by including a three-way interaction term that includes VAS, Past Alpha, and a negative performance indicator (*Neg Alpha*). *Neg Alpha* equals to one if Past Alpha is negative and zero otherwise. Results from this specification are reported in Column 3 of Table 11. The coefficient for the three-way interaction term is negative and highly significant, suggesting that the higher the VAS, the more convex is the flow-performance relation a fund has. For a fund with no skill (VAS = 0) in the positive (negative) performance region, a 1% increase (decrease) in alpha is associated with 0% inflow (2% outflow), indicating a concave flow-performance relation. However, for a fund with perfect skill (VAS=1) in the positive (negative) performance region, a 1% increase (decrease) in alpha is associated with 5% inflow (2% outflow), indicating a convex flow-performance relation.

This pattern is further supported by analysis of the flow-performance relation within fund subsamples formed based on VAS. We split the sample based on each fund's VAS into three groups: funds in the top 30%VAS group, funds in the middle 40% VAS group, and funds in the bottom 30% VAS group. Then, in each group, we estimate the flow-performance relation using the interaction term between Past Alpha and Neg Alpha. Results are reported in Columns 4 to 6 of Table 11. We only find a significant convex flow-performance relation in Column 4 for funds in the top 30% group. For these funds in the positive (negative) performance region, a 1% increase (decrease) in alpha is associated with 3% inflow (1% outflow) increase. For the rest of funds, the flow-performance relation is linear.

In the context of previous research documenting a concave or linear flow-performance relation for bond funds (Goldstein et al. (2017) and Chen and Qin (2017)), our findings suggest that the flow-performance relation is not uniform across bond funds. In fact, the relation depends on investors' perception of skill, whereby funds perceived as more skilled by investors exhibit a convex flow-performance relation.

6. Conclusion

We develop a novel measure to identify investment-grade corporate bond funds with superior valuation skills. Our valuation accuracy score recognizes funds that hold a higher (lower) fraction of underpriced (overpriced) 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, an effect that materializes through superior bond selection. This result 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 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 IG bond fund managers: they consider good past performance of funds with higher valuation accuracy scores an even stronger indicator of skill while they become less sensitive to poor performance relative to good performance of these funds.

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 and 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 materializes in the form of liquidity provision, an activity that falls outside the purview of these funds' core responsibilities.

Our findings can also explain why investors have been rewarding active corporate bond funds in 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, as evidenced by a stronger return chasing behavior and a convex flow-performance relation among funds with high valuation accuracy score.

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. 2021. Mutual Fund Trading Style and Bond Market Fragility. *The Review of Financial Studies* 34 (6): 2993–3044.

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.

Bao, Jack, Jun Pan, and Jiang Wang. 2011. The Illiquidity of Corporate Bonds. *The Journal of Finance* 66 (3): 911-946.

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.

Carhart, Mark M, 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance* 52(1): 57-82.

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. 2021. Why Have Actively Managed Bond Funds Remained Popular. 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.

Cooper, Michael J, Huseyin Gulen, and Michael J Schill. 2008. Asset Growth and the Cross-Section of Stock Returns. *The Journal of Finance* 63 (4): 1609–1651.

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. *The 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.

Frazzini, Andrea, and Lasse Heje Pedersen. 2014. Betting against Beta. *Journal of Financial Economics* 111 (1): 1–25.

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.

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.

Huang, Lifa, Wayne Y. Lee, and Craig G. Rennie. 2019. Selection and Timing Skill in Bond Mutual Fund Returns: 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.

Jostova, Gergana, Stanislava Nikolova, Alexander Philipov, and Christof W. Stahel. 2013 Momentum in Corporate Bond Returns. *Review of Financial Studies* 26 (7): 1649–93.

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. 2021 Forthcoming. The Bond Pricing Implications of Rating-Based Capital Requirements. *Journal of Financial and Quantitative Analysis*.

Natter, Markus, Martin Rohleder, and Marco Wilkens. 2021. Maturity-Matched Bond Fund Performance. *Financial Analyst Journal* 77 (2): 83–96.

Newey, Whitney K., and Kenneth D. West. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55 (3): 703–708.

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.

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: Classified Bond 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 8,521 IG bonds issued by 616 firms from July 2002 to December 2019. *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. *Time-to-maturity* is the number of remaining years until the bond's maturity. *Coupon* is the coupon rate. *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. *ZTD* (Zero Trading Days) is the percentage of days when a bond did not trade during a month.

Bond Characteristic	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
Yield (%)	396,498	4.00	1.80	2.74	3.94	5.13
Duration (years)	396,498	6.8	4.3	3.3	5.8	10.2
Amount Outstanding ($M)	396,498	637	581	300	500	750
Bond Age (years)	396,498	5.3	4.8	1.9	3.9	7.2
Time-to-maturity (years)	396,498	10.5	8.9	3.7	7.0	17.2
Coupon (%)	396,498	5.3	1.8	4.0	5.4	6.6
Rating	396,498	7.3	2.1	6.0	8.0	9.0
ZTD (Zero Trading Days %)	396,498	47.6	26.7	25.0	46.2	70.0

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

Panel A reports average monthly alphas of portfolios formed based on bond residual spreads (estimated from Equation 1) from July 2002 to December 2019. At the end of each month *t*, we construct two portfolios, one includes bonds with a positive residual spread (*Pos-RS*) and the other includes bonds with a negative residual spread (*Neg-RS*). Both portfolios are value-weighted and are held for one month. We also delay the construction of the 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* and *DEF* factors. In Columns 3 and 4, portfolio alphas are estimated from regressing portfolio excess returns on the *TERM* and *DEF* factors; common stock factors such as the *MKT*, *SMB*, *HML*, and *MOM* factors; and the bond market liquidity risk factor (*LRF*). Newey-West (1987) adjusted t-statistics are given in parentheses. In Panel B, we report the time-series means of monthly cross-sectional average bond characteristics in the Pos-RS and Neg-RS portfolios and their difference along with t-stats, for which the underlying standard errors are Newey-West adjusted. *EstDay Turnover* is the ratio of a bond's daily trading volume over its amount outstanding on the day its residual spread is estimated. *Rel Turnover* is the ratio of a bond's trading volume on the day its residual spread is estimated over its average daily trading volume based on the trading days over the previous three months. In the above two measures, we set the daily trading volume to zero if there was no trading on the day we estimate the residual spread. *Illiquidity* is the autocovariance of the daily TRACE price changes within each month, multiplied by -1. *IC Ratio* is the ratio of the percentage of bonds with a positive dealer inventory cycle over the percentage of bonds with a negative dealer inventory cycle. All the other variables are described in Table 1. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Portfolio Alphas for the Pos-RS and Neg-RS Portfolios

# Months After Valuation Status Determination	Two-factor Alphas		Seven-factor Alphas	
	(1) Pos-RS	(2) Neg-RS	(3) Pos-RS	(4) Neg-RS
1	0.0027***	-0.0020***	0.0024***	-0.0021***
	(3.51)	(-4.05)	(4.08)	(-4.22)
2	0.0008	0.0000	0.0006	-0.0002
	(1.65)	(0.08)	(1.32)	(-0.53)
3	0.0009	0.0000	0.0006	-0.0002
	(1.58)	(0.11)	(1.41)	(-0.58)
4	0.0005	0.0003	0.0002	0.0000
	(1.00)	(0.54)	(0.55)	(-0.07)
5	0.0005	0.0001	0.0002	-0.0001
	(0.96)	(0.21)	(0.47)	(-0.36)
6	0.0005	0.0000	0.0001	-0.0002
	(0.83)	(0.11)	(0.27)	(-0.48)
7	0.0004	0.0002	0.0001	-0.0002
	(0.84)	(0.36)	(0.25)	(-0.36)
8	0.0004	0.0003	0.0000	0.0000
	(0.72)	(0.50)	(-0.05)	(-0.05)
9	0.0006	0.0001	0.0002	-0.0002
	(1.01)	(0.18)	(0.39)	(-0.55)
10	0.0005	0.0003	0.0001	-0.0001
	(0.84)	(0.53)	(0.15)	(-0.18)
11	0.0003	0.0003	-0.0001	0.0000
	(0.60)	(0.61)	(-0.15)	(0.02)
12	0.0003	0.0005	-0.0002	0.0002
	(0.49)	(0.94)	(-0.44)	(0.51)

Table 2. -continued

Panel B. Bond Characteristics of the Pos-RS and Neg-RS Portfolios

Characteristics	Pos-RS Mean	Neg-RS Mean	Avg Difference
Credit Quality			
Rating	7.3	7.3	-0.0
Interest-rate Sensitivity			
Duration (years)	6.7	6.6	0.1*
Time-to-maturity (years)	10.6	10.2	0.3***
Coupon (%)	5.5	5.6	-0.1***
Liquidity			
Amount Outstanding ($M)	648	569	79***
Bond Age (years)	5.3	5.3	0.0
ZTD (Zero Trading Days %)	46.9	47.8	-0.9***
EstDay Turnover (%)	0.41	0.41	0.00
Rel Turnover	1.52	1.54	-0.02
Illiquidity	2.01	1.84	0.17
Dealer Inventory Cycle			
IC Ratio	1.31	1.41	-0.10***

Table 3: Corporate Bond Fund Summary Statistics

Panel A reports summary statistics for our investment-grade (IG) bond fund sample. Our sample includes 395 IG bond funds from July 2002 to December 2019. 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*. 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. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Fund Characteristics	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
VAS (%)	24,735	53.1	15.0	44.3	52.6	61.4
Fund Size ($M)	24,735	1,606	4,276	134	424	1,180
Fund Age (Years)	24,735	16.6	11.6	8.0	15.0	22.0
CRSP Turnover (%)	24,735	112.3	121.6	41.0	69.0	133.0
Corp Bond Turnover (%)	24,735	40.8	44.6	11.5	29.0	55.6
Expense Ratio (%)	24,735	0.72	0.28	0.54	0.68	0.88
Family Size ($M)	24,735	135,856	386,917	7,932	28,617	95,214
Net Return (%)	24,735	0.34	1.12	-0.14	0.28	0.83
Flow (%)	24,735	0.29	4.72	-1.21	-0.04	1.41

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 bond funds from July 2002 to December 2019. 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 over the last 12 months constructed following Anand et al. (2021); *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. T-statistics (standard errors are 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	0.67***		0.69***	
	(3.42)		(3.62)	
VAS		7.25***		7.43***
		(3.14)		(3.24)
LS_scoreQ			0.32*	0.32*
			(1.73)	(1.70)
Past Alpha			0.23***	0.23***
			(4.32)	(4.33)
log(Fund Size)			-0.09	-0.09
			(-0.37)	(-0.37)
log(Fund Age)			-0.66	-0.67
			(-1.52)	(-1.54)
CRSP Turnover			-0.02	-0.04
			(-0.06)	(-0.12)
Corp Bond Turnover			0.64	0.64
			(1.54)	(1.53)
log(Family Size)			0.15	0.15
			(0.85)	(0.86)
Past Flow			-0.10	-0.10
			(-0.63)	(-0.65)
Flow Volatility			-0.06	-0.05
			(-0.62)	(-0.58)
Return Volatility			-0.05*	-0.05*
			(-1.72)	(-1.71)
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	24,735	24,735	24,735	24,735
Adjusted R^2	0.18	0.18	0.20	0.20

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 bond funds from July 2002 to December 2019. 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. T-statistics (standard errors are 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	0.57***		0.60***	
	(2.77)		(2.87)	
VAS		5.88**		6.11***
		(2.57)		(2.61)
Controls	No	No	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	24,300	24,300	24,300	24,300
Adjusted R^2	0.17	0.17	0.19	0.19

Table 6: Valuation Accuracy Score and Future Fund Performance under Various Robustness Checks

This table reports results from regressions relating future fund performance with the fund valuation accuracy score (*VAS*) for IG bond funds. 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 14, 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. From Columns 7 to 12, we use a 36-month rolling window and estimate fund alphas by sequentially adding more bond risk factors defined in Section 2.2.1 to the original four-factor model laid out in Equation 3. In Columns 7 to 8, we add the TERM factor. In Columns 9 to 10, we add the liquidity risk factor (*LRF*). In Columns 11 and 12, we further include the downside risk factor (*DRF*), the credit risk factor (*CRF*), the bond return reversal factor (*BOND_REV*), and the bond momentum factor (*BOND_MOM*). In Columns 13 and 14, 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 4 and 5 and measured at time *t*. Columns 1 and 2 include month and fund fixed effects. Column 3 to 14 include month and fund style (Lipper objective code) fixed effects. *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*. T-statistics (standard errors are 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		10 Factor		Style-adj	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
VAS Quintile	0.72***		0.70***		0.65***		0.61***		0.62**		0.60***		0.75***	
	(3.51)		(3.71)		(3.44)		(3.14)		(2.64)		(2.50)		(3.35)	
VAS		8.03***		7.50***		7.27***		6.72**		5.62**		6.02***		6.94***
		(3.18)		(3.30)		(3.04)		(2.61)		(2.01)		(2.39)		(3.04)
Controls	Yes	Yes	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	Yes	Yes
Style FE:	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE:	Yes	Yes	No	No	No	No	No	No	No	No	No	No	No	No
Observations	24,735	24,735	24,735	24,735	23,167	23,167	23,167	23,167	20,596	20,596	18,722	18,722	24,735	24,735
Adjusted R^2	0.23	0.23	0.20	0.20	0.20	0.20	0.17	0.17	0.21	0.21	0.20	0.20	0.07	0.07

Table 7: Alternative Valuation Accuracy Measures and Future Fund Performance

This table reports results from regressions relating future fund performance with alternative measures of fund valuation accuracy for IG bond funds from July 2002 to December 2019. 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. In Panel A, *VAS_X Quintile* is the fund's quintile rank of *VAS_X* at time t, which is the fund's continuous valuation accuracy score requiring at least *X* bonds for its calculation according to Equation 2. In Panel B, *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 bonds and overpriced bonds in the portfolio 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. T-statistics (standard errors are double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panel A: Requiring more Bonds for the Computation of VAS

	Dependent variable: Avg Gross Alpha (t+1, t+3)					
	(1)	(2)	(3)	(4)	(5)	(6)
VAS_10 Quintile	0.62***					
	(3.36)					
VAS_10		7.73***				
		(3.78)				
VAS_20 Quintile			0.61***			
			(2.93)			
VAS_20				8.16***		
				(3.12)		
VAS_30 Quintile					0.71***	
					(2.98)	
VAS_30						9.99***
						(3.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,998	21,998	17,299	17,299	12,792	12,792
Adjusted R^2	0.20	0.20	0.23	0.23	0.24	0.24

Table 7.-continued

Panel B: VAS Versions based on the Number of Bonds and Bond Trades

	Dependent variable: Avg Gross Alpha (t+1, t+3)			
	(1)	(2)	(3)	(4)
VAS_NUM Quintile	0.57***			
	(3.20)			
VAS_NUM		6.43**		
		(2.60)		
TVAS Quintile			0.59***	
			(2.96)	
TVAS				4.93**
				(2.26)
Controls	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	24,735	24,735	24,735	24,735
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 bond funds from July 2002 to December 2019. 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. T-statistics (standard errors are double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panel A: Bond Selection

	Dependent variable: Avg BS (t+1, t+3)			
	(1)	(2)	(3)	(4)
VAS Quintile	0.90***		0.92***	
	(3.73)		(3.80)	
VAS		7.86**		8.20***
		(2.52)		(2.62)
Control	No	No	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	22,883	22,883	22,883	22,883
Adjusted R^2	0.04	0.04	0.04	0.04

Panel B: Characteristic Timing

	Dependent variable: Avg CT (t+1, t+3)			
	(1)	(2)	(3)	(4)
VAS Quintile	0.30*		0.30*	
	(1.88)		(1.91)	
VAS		2.90		2.96
		(1.40)		(1.43)
Control	No	No	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	22,883	22,883	22,883	22,883
Adjusted R^2	0.10	0.10	0.10	0.10

Table 9: RS Factor and Future Fund Performance

This table reports results from regressions relating future fund performance adjusted for the *RS* factor with the fund valuation accuracy score (*VAS*) for IG bond funds from July 2002 to December 2019. 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. In Columns 1 to 2 (3 to 4), we use an 18-month (36-month) rolling window and estimate fund alpha by adding the RS factor to the original four-factor model in Equation 3. To construct the RS factor, each month, we form bivariate portfolios by independently sorting bonds into four groups based on their rating (AAA, AA, A, BBB) and ten terciles based on their residual spreads estimated from Equation 1. Then, the RS factor is calculated as the average difference between the value-weighted top tercile and bottom tercile portfolios sorted on residual spreads across the rating portfolios. *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. T-statistics (standard errors are double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	Dependent variable: Avg Gross Alpha adjusted for the RS factor (t+1, t+3)			
	(1) 18-month	(2) 18-month	(3) 36-month	(4) 36-month
VAS Quintile	0.63**		0.64***	
	(2.37)		(2.92)	
VAS		6.93**		6.35***
		(2.38)		(2.63)
Control	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	22,942	22,942	20,596	20,596
Adjusted R^2	0.19	0.19	0.23	0.23

Table 10: Determinants of Valuation Accuracy Score

Panel A examines the determinants of valuation Accuracy Score (*VAS*) for IG bond funds from July 2002 to December 2019. 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. 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. T-statistics (standard errors are double-clustered by fund and month) are presented in parentheses. In panel B, funds are sorted into five quintiles by their *AVAS (t-11, t)*. The first column reports the sorting variable. The next five columns report the likelihood of a fund in an *AVAS (t-11, t)* quintile during the sorting period falling into each *AVAS (t+1, t+12)* quintile in the subsequent period t +1 to t +12. The reported chi-square statistics are for the test of null hypothesis that the probability for being in each *AVAS (t+1, t+12)* quintile in the future is independent of the fund's *AVAS (t-11, t)* quintile today. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panel A: Determinants of VAS

	Dependent variable:		
	VAS (t+1)		AVAS (t+1, t+12)
	(1)	(2)	(3)
AVAS (t-11, t)		0.72***	0.55***
		(34.12)	(21.12)
LS_scoreQ	0.09	0.09	0.06
	(0.58)	(1.02)	(0.56)
Past Alpha	-0.00	-0.01	0.00
	(-0.11)	(-1.09)	(0.37)
log(Fund Size)	0.11	0.01	0.02
	(0.49)	(0.16)	(0.17)
log(Fund Age)	0.20	0.21	0.26
	(0.39)	(1.09)	(0.87)
CRSP Turnover	1.16***	0.36***	0.51***
	(4.23)	(3.25)	(3.28)
Corp Bond Turnover	0.49**	0.20	0.38***
	(1.99)	(1.53)	(2.74)
Expense Ratio	-0.01	-0.00	-0.01
	(-0.67)	(-1.00)	(-1.07)
log(Family Size)	0.11	0.03	0.02
	(0.58)	(0.37)	(0.18)
Past Flow	0.12	0.10**	0.11*
	(1.25)	(2.09)	(1.68)
Flow Volatility	0.03	-0.03	-0.04
	(0.33)	(-0.59)	(-0.76)
Return Volatility	0.01	0.00	0.00
	(0.90)	(0.60)	(0.40)
Month FE:	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes
Observations	24,525	24,525	24,639
Adjusted R^2	0.07	0.30	0.36

Table 10.-continued

Panel B: Transition Matrix of VAS

Quintile of AVAS (t-11, t)	Percentage in Quintile of AVAS (t +1, t +12) 1 (low)	2	3	4	5 (high)
1 (low)	50.0%	25.2%	11.6%	7.4%	5.7%
2	23.6%	30.5%	21.5%	15.4%	9.0%
3	12.2%	22.1%	29.3%	24.3%	12.1%
4	7.4%	14.8%	25.0%	31.8%	21.0%
5 (high)	5.5%	8.0%	13.3%	21.5%	51.7%

H0: Rows and Columns are Independent

$\chi 2 > 8{,}921$***

Table 11: Valuation Accuracy Score and Flow-Performance Relation

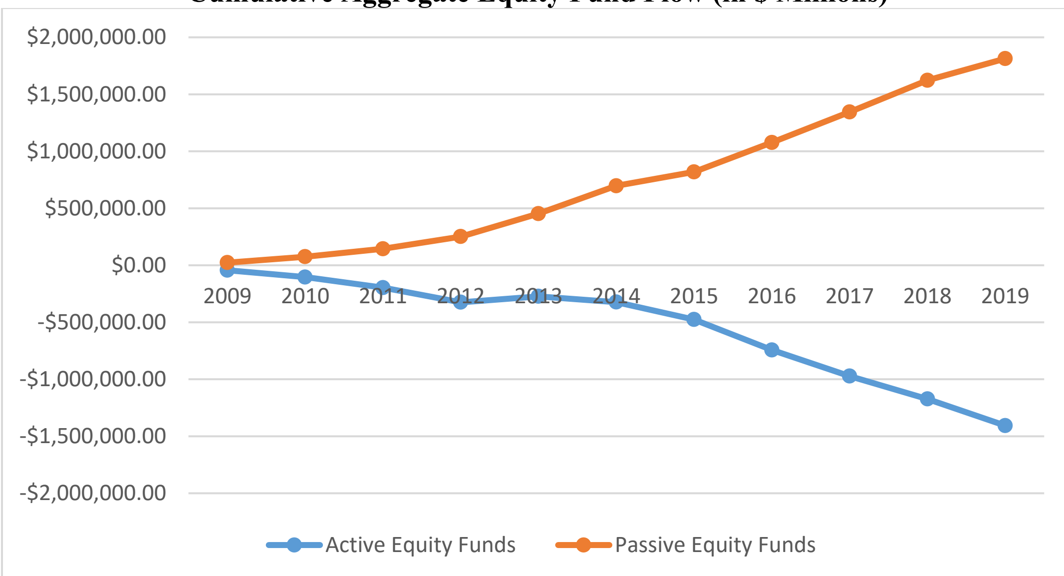
This table reports results from regressions relating future fund flow with the fund valuation accuracy score (*VAS*) and a number of interactive variables for IG bond funds from July 2002 to December 2019. Observations are based on each fund's reporting period. The dependent variable is the average fund flow between t+1 and t+3 in percent. *VAS* is the fund's continuous the continuous version of the Valuation Accuracy Score at time *t*. *Neg Alpha* is an indicator variable equal to one if *Past Alpha* is negative and zero otherwise. In columns 1 to 3. we use the full sample. In Columns 4 to 6, we split the sample based on each fund's VAS into three groups: funds in the top 30% VAS group, funds in the middle 40% group, and funds in the bottom 30% VAS group. 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. T-statistics (standard errors are 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) Full Sample	(2) Full Sample	(3) Full Sample	(4) Top 30% VAS	(5) Mid 40% VAS	(6) Bot 30% VAS
VAS		-0.01	-0.43			
		(-0.03)	(-1.61)			
VAS * Past Alpha		0.02**	0.05***			
		(2.05)	(3.03)			
Past Alpha	0.02***	0.01**	-0.00	0.03***	0.02**	0.02**
	(7.73)	(2.14)	(-0.24)	(5.05)	(2.87)	(2.59)
Past Alpha * Neg Alpha			0.02	-0.02**	0.00	-0.00
			(1.46)	(-2.27)	(0.54)	(-0.56)
VAS * Past Alpha * Neg Alpha			-0.05**			
			(-2.59)			
Neg Alpha			-0.29	-0.08	-0.21*	-0.15
			(-1.09)	(-0.59)	(-1.71)	(-1.28)
VAS * Neg Alpha			0.25			
			(0.52)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,735	24,735	24,735	7,190	9,906	7,639
Adjusted R^2	0.23	0.23	0.23	0.23	0.24	0.22

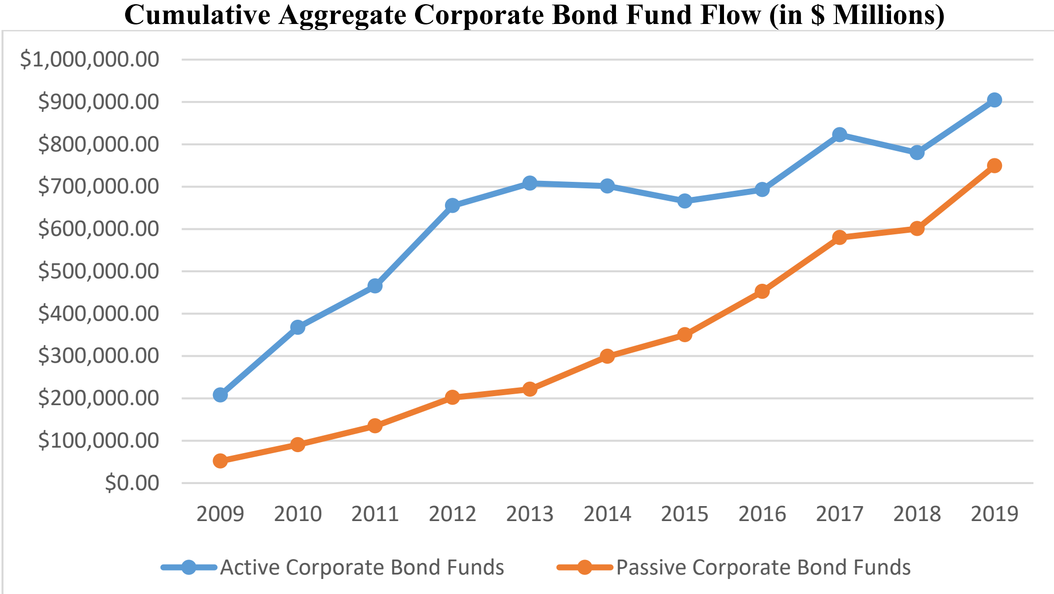
Figure 1: Active and Passive Flows for U.S. Equity and Corporate Bond Fund Sectors

This figure reports cumulative aggregate flows during 2009-2019 for active and passive mutual funds in the equity and corporate bond mutual fund sectors. Passive funds include index funds and ETFs. The aggregate annual flows are based on estimated fund-level annual flows obtained from Morningstar.

Cumulative Aggregate Equity Fund Flow (in $ Millions)



Cumulative Aggregate Corporate Bond Fund Flow (in $ Millions)



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 July 2002 and December 2019. We follow Bai, Bali, and Wen (2019), and Anand et al. (2021) and impose the following transaction-level filtering criteria by removing: (1) bonds that are preferred securities, asset-backed, structured notes, agency backed, or equity linked; (2) bonds trading under $5 or above $1000; (3) transactions flagged as primary market transactions; (4) 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; (5) canceled transactions (we adjust records that are subsequently corrected or reversed); (6) transactions with trading volume less than $10,000; and (7) 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 to minimize the effect of bid-ask spreads in 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 Bloomberg Generic Quote (BGN) price, which is calculated by Bloomberg using *real-time* executable and indicative quote prices from market contributors/participants as its month-end price.[22] 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.

[22] BGN prices are also used in Bao, Pan, and Wang (2011) and Chen, Lesmond, and Wei (2007).

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)). *Past month's equity return* is last month's equity return.

Appendix C: Bond Mispricing Robustness Checks

We first use recently proposed bond risk factor models to estimate bond portfolio alphas in Table 2. In Columns 1 and 2 of Appendix Table C1, we use the bond market factor (*MKT_BOND*), the bond liquidity risk factor *(LRF)*, the bond downside risk factor (*DRF*), the bond credit risk factor (*CRF*), the bond return reversal factor (*BOND_REV*), and the bond momentum factor (*BOND_MOM*) (Bai et al. (2019) and Jostova et al. (2013)) to estimate portfolio alphas.[23] In Columns 3 and 4, in addition to the bond risk factors in Columns 1 and 2, we further include the TERM factor, the DEF factor, and common stock factors such as the *MKT*, *SMB*, *HML*, and *MOM* (Fama and French (1993) and Carhart (1997)) to estimate portfolio alphas. Since the DRF and the CRF are only available after July 2004, the sample period in Appendix C1 is from July 2004 to December 2019. Using both factor models, we still find that residual spreads predict future excess bond returns that materialize only in one month.

Next, in order to utilize a greater degree of within-firm variation in our estimation of Equation 1, in the first test we construct a subsample by identifying firms having at least 10 outstanding IG bonds with a non-missing month-end price in a given month and including all these firms' bonds. Using this subsample, we re-estimate Equation 1 and repeat our bond portfolio analysis of Table 2. Greater 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 C2, we obtain similar results as in Table 2.

In the third 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 the pricing source we choose from Bloomberg is based on *real-time* executable and indicative quote prices that

[23] The *MKT_BOND* factor is the monthly return difference between the Bloomberg Barclays Corporate Bond Index and one-month risk-free rate. The downside risk factor (DRF) captures the lower tail of the historical distribution of returns, which proxies for the expected decline of bond returns over a given horizon of time and a given probability. We construct the bond return reversal factor (BOND_REV) and the bond momentum factor (BOND_MOM) based on our bond return sample following the methodology of Bai et al. (2019) and Jostova et al. (2013),

should reflect the consensus of market participants, it is possible that the quoted prices of some bonds may not be executable. To account for this concern, we first drop all observations that use Bloomberg prices for month-end prices. We then construct a subsample, the *TRACE classified bond* subsample, which includes firms having multiple bonds with a non-missing month-end TRACE daily price in a given month and only their bonds that meet this condition. Therefore, in the TRACE classified bond subsample, month-end prices are based only on the last TRACE daily price available during the last five trading days of each month and not on Bloomberg prices. Using this subsample, we re-estimate Equation 1 and repeat our bond portfolio analysis of Table 2. As shown in Appendix Table C3, our results remain the same as in Table 2.

Appendix Table C1: Table 2 Replication Using Different Factor Models

This table replicates the results of Table 2 utilizing different factor models. In Columns 1 and 2, portfolio alphas are estimated from regressing portfolio excess returns on recently proposed bond risk factors such as the bond market factor (*MKT_BOND*), the bond downside risk factor (*DRF*), the bond credit risk factor (*CRF*), the bond liquidity risk factor (*LRF*), the bond return reversal factor (*BOND_REV*), and the bond momentum factor (*BOND_MOM*). In Columns 3 and 4, portfolio alphas are estimated from regressing portfolio excess returns on common bond factors such as the *TERM* factor, the *DEF* factor, the *MKT_BOND* factor, the *DRF*, the *CRF*, the *LRF*, the *BOND_REV* factor, and the *BOND_MOM* factor, and common stock factors such as the *MKT*, *SMB*, *HML*, and *MOM* factors. Newey-West (1987) adjusted t-statistics are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

# Months After Valuation Status Determination	Six-factor Alphas		Twelve-factor Alphas	
	(1) Pos-RS	(2) Neg-RS	(3) Pos-RS	(4) Neg-RS
1	0.0015***	-0.0013***	0.0015***	-0.0015***
	(2.87)	(-3.98)	(4.35)	(-5.62)
2	0.0005	-0.0004	0.0004	-0.0004
	(1.38)	(-0.99)	(1.65)	(-1.53)
3	0.0004	-0.0003	0.0003	-0.0003
	(1.06)	(-0.81)	(1.21)	(-1.29)
4	0.0003	-0.0003	0.0001	-0.0003
	(0.63)	(-0.72)	(0.51)	(-1.08)
5	0.0001	-0.0003	0.0000	-0.0003
	(0.23)	(-0.71)	(0.07)	(-1.24)
6	0.0000	-0.0002	-0.0001	-0.0002
	(-0.07)	(-0.63)	(-0.45)	(-1.07)
7	0.0001	-0.0003	0.0000	-0.0003
	(0.30)	(-0.93)	(-0.04)	(-1.35)
8	0.0001	-0.0004	0.0000	-0.0004
	(0.39)	(-0.92)	(0.10)	(-1.20)
9	0.0000	-0.0002	-0.0001	-0.0002
	(0.00)	(-0.54)	(-0.28)	(-0.97)
10	0.0000	-0.0001	-0.0001	-0.0002
	(0.00)	(-0.39)	(-0.39)	(-0.64)
11	-0.0000	-0.0001	-0.0002	-0.0001
	(-0.04)	(-0.24)	(-0.60)	(-0.31)
12	-0.0001	0.0001	-0.0003	0.0001
	(-0.31)	(0.15)	(-0.89)	(0.29)

Appendix Table C2: Table 2 Replication Using Sample Firms with at least 10 Bonds

This table replicates the results of Table 2 utilizing a stricter data requirement for the sample construction. Specifically, the subsample used for this analysis is constructed by identifying firms having at least 10 outstanding IG bonds with a non-missing month-end prices in a given month and including all these firms' bonds. We then repeat the analysis as in Table 2. Newey-West (1987) adjusted t-statistics are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

# Months After Valuation Status Determination	Two-factor Alphas		Seven-factor Alphas	
	(1) Pos-RS	(2) Neg-RS	(3) Pos-RS	(4) Neg-RS
1	0.0026***	-0.0020***	0.0021***	-0.0023***
	(2.92)	(-4.26)	(3.58)	(-3.92)
2	0.0007	-0.0001	0.0004	-0.0005
	(1.29)	(-0.12)	(0.78)	(-1.10)
3	0.0008	0.0000	0.0004	-0.0005
	(1.29)	(0.02)	(0.97)	(-0.95)
4	0.0004	0.0002	0.0000	-0.0002
	(0.73)	(0.39)	(0.01)	(-0.53)
5	0.0005	0.0000	-0.0001	-0.0004
	(0.71)	(0.02)	(-0.13)	(-0.81)
6	0.0004	0.0000	-0.0002	-0.0005
	(0.58)	(-0.08)	(-0.41)	(-1.08)
7	0.0003	0.0003	-0.0002	-0.0003
	(0.53)	(0.43)	(-0.43)	(-0.58)
8	0.0002	0.0003	-0.0004	-0.0002
	(0.38)	(0.46)	(-0.72)	(-0.34)
9	0.0007	0.0000	-0.0001	-0.0004
	(0.86)	(0.05)	(-0.25)	(-0.92)
10	0.0007	0.0001	-0.0001	-0.0004
	(0.88)	(0.17)	(-0.14)	(-0.81)
11	0.0004	0.0002	-0.0002	-0.0003
	(0.59)	(0.39)	(-0.46)	(-0.56)
12	0.0001	0.0005	-0.0005	0.0000
	(0.20)	(0.83)	(-0.93)	(0.00)

Appendix Table C3: Table 2 Replication Using Only TRACE Prices

This table replicates the results of Table 2 utilizing a stricter data requirement for the sample construction. The subsample, *TRACE classified bond* subsample, includes firms having multiple bonds with a non-missing month-end TRACE daily price in a given month and only their bonds that meet this condition. We then repeat the analysis as in Table 2. Newey-West (1987) adjusted t-statistics are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

# Months After Valuation Status Determination	Two-factor Alphas		Seven-factor Alphas	
	(1) Pos-RS	(2) Neg-RS	(3) Pos-RS	(4) Neg-RS
1	0.0026***	-0.0018***	0.0022***	-0.0020***
	(3.30)	(-3.89)	(3.89)	(-3.94)
2	0.0008	0.0001	0.0005	-0.0002
	(1.56)	(0.28)	(1.10)	(-0.39)
3	0.0009	0.0000	0.0006	-0.0003
	(1.54)	(0.08)	(1.37)	(-0.70)
4	0.0004	0.0003	0.0002	0.0000
	(0.90)	(0.60)	(0.37)	(-0.06)
5	0.0005	0.0002	0.0001	-0.0002
	(0.87)	(0.33)	(0.32)	(-0.41)
6	0.0005	0.0000	0.0001	-0.0002
	(0.85)	(0.10)	(0.28)	(-0.56)
7	0.0004	0.0002	0.0001	-0.0002
	(0.78)	(0.40)	(0.17)	(-0.49)
8	0.0004	0.0002	0.0000	-0.0001
	(0.73)	(0.45)	(-0.07)	(-0.19)
9	0.0006	0.0001	0.0001	-0.0003
	(0.96)	(0.19)	(0.22)	(-0.63)
10	0.0006	0.0002	0.0001	-0.0002
	(1.02)	(0.49)	(0.30)	(-0.34)
11	0.0003	0.0004	-0.0001	0.0000
	(0.53)	(0.64)	(-0.31)	(-0.11)
12	0.0003	0.0004	-0.0002	0.0001
	(0.57)	(0.88)	(-0.42)	(0.32)

Appendix D: Controlling for Asynchronous Trading

Although the evidence from Appendix Table C3 conducted on the TRACE classified bond subsample is reassuring, asynchronous trading remains a potential candidate for explaining the alphas of the Pos-RS and Neg-RS portfolios documented in Table 2 and Appendix Table C3. The reason for this is that, even for different bonds of the same firm, trading (and their corresponding month-end prices we record) may take place on different dates. To illustrate this, consider a hypothetical scenario, whereby the Pos-RS and Neg-RS portfolios each have only one bond, respectively, A and B. Suppose that the last trade of bond A happens on 10/26/2020 (four days before the last trading day of October). Relevant positive (negative) news comes out on 10/29/2020 (one day before the last trading day of October) and bond B trades on the last trading day of the month. Compared to bond B, the month-end price of bond A does not reflect the latest news, which may cause bond A to appear underpriced (overpriced) due to its price reflecting stale information.

We conduct a number of tests to address asynchronous trading concerns by drawing different subsamples from the TRACE classified bond subsample used in Appendix Table C3 and delaying the buying or selling of bonds that do not trade on the last trading day (or the afternoon of the last trading day) of a month by modifying their next month returns when we construct the Pos-RS and Neg-RS portfolios.

In our first test, we condition on a subsample of bonds where asynchronous trading described above is less likely to be a problem. Starting with the TRACE classified bond subsample, we first identify all bonds that traded (i.e., that had a non-missing TRACE daily price) on the last trading day of a given month. Next, from this set we construct a subsample by identifying firms having multiple bonds that traded on the last trading day of a given month and including all these firms' bonds that meet this condition. As before, the starting price for the month $t+1$ return calculation is the TRACE daily price on the last trading day of month t. Because all the bonds in this subsample traded on the last day of the month, we expect their prices to reflect the latest news. Using this subsample, we re-estimate Equation 1 and repeat our bond portfolio analysis of Table 2. Results reported in Appendix Table D1 show that the Pos-RS (Neg-RS) portfolio continues to generate positive (negative) alphas in the next month that continue to be economically and statistically significant.

In our next tests reported in Appendix Table D2, we incrementally bring back bonds that did not trade on the last trading day of the month from the TRACE classified bond subsample while at the same time we delay their portfolio formation by modifying their next month return measurement. In Panel A, we require that each firm has at least one bond that traded on the last trading day of a given month and at least another one that did not. In this subsample, asynchronous trading is most likely to be a problem. In Panel B, we include bonds of firms having at least one bond that traded on the last trading day of a given month. Finally, in Panels C and D we use the entire TRACE classified bond subsample, i.e., including even firms that did not have a single bond that traded on the last trading day of a given month.

Next, for all bonds in Panels A through C that did not trade on the last trading day of a given month *t*, we modify their next month (*t+1*) return construction by delaying their return measurement using the TRACE daily price on the first trading day of month *t+1*, instead of the month-end TRACE price of month *t*, as the starting price. The reason for doing so is that the TRACE daily price we record as the month-end price for these bonds might be stale and therefore not reflect new information released between the day when the bond last traded and the day we estimate its valuation status. Moreover, to address the concern that new information may arrive during the last trading day of a month, in Panel D we introduce trading delays even for bonds that traded on the last day of the month but did not trade in the afternoon. In essence, when we construct the Pos-RS and Neg-RS portfolios at the end of each month *t*, we delay the buying or selling of bonds that do not trade on the last trading day (or the afternoon of the last trading day) of month *t* to the beginning of month *t+1* and then hold the portfolios during month *t+1*. For all the other bonds that traded on the last trading day of the month in Panels A through C or the afternoon of the last trading day of the month in Panel D, the month *t+1* return calculation is as in Appendix Table D1. For each of the four subsamples corresponding, respectively, to Panels A through D of Appendix Table D2, we re-estimate Equation 1 and repeat our bond portfolio analysis of Table 2 reporting alphas only for the first month after portfolio formation. The alphas of the Pos-RS and Neg-RS portfolios reported in Panels A through D are very similar to those of Appendix Table D1.[24]

It is worth noting that the magnitudes of alphas for the Pos-RS and Neg-RS portfolios in both Appendix Tables D1 and D2 dropped by roughly 3-10 bps compared to Table 2. One potential explanation is that part of the alphas in Table 2 could be due to asynchronous trading. It is also plausible that the trade delays we implement might not only help remove stale information from next month returns, but also remove part of the information associated with the bond valuation status. Nonetheless, they survive even after we control for asynchronous trading that occurs when bonds do not trade on the same day during the last five days of a month. In sum, the results from Appendix Table D2 provide confidence that the alphas of Pos-RS and Neg-RS portfolios reflect mispricing.

[24] In unreported analysis, we confirm that in Panel A through D of Appendix Table D2, the percentages of bonds with delayed return measurement in the Pos-RS and Neg-RS portfolios are quantitatively similar.

Appendix Table D1: Table 2 Replication Using Bonds with a TRACE Price on the Last Trading Day of the Month

This table replicates the results of Table 2 utilizing a stricter data requirement for the sample construction. We first identify all bonds that traded on the last trading day of a given month. Next, from this set we construct a subsample by identifying firms having multiple bonds that traded on the last trading day of a given month and including all the bonds of these firms that meet this condition. We then repeat the analysis as in Table 2. Newey-West (1987) adjusted t-statistics are given in parentheses. ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% levels, respectively.

# Months After Valuation Status Determination	Two-factor Alphas		Seven-factor Alphas	
	(1) Pos-RS	(2) Neg-RS	(3) Pos-RS	(4) Neg-RS
1	0.0019**	-0.0012***	0.0016***	-0.0014***
	(2.41)	(-2.81)	(2.76)	(-2.73)
2	0.0012	0.0004	0.0009	0.0002
	(1.64)	(0.68)	(1.58)	(0.40)
3	0.0011	0.0000	0.0009	-0.0005
	(1.28)	(0.07)	(1.42)	(-0.78)
4	0.0005	0.0006	0.0002	0.0002
	(0.70)	(0.78)	(0.32)	(0.32)
5	0.0005	0.0003	0.0000	-0.0001
	(0.76)	(0.46)	(0.06)	(-0.12)
6	0.0005	0.0001	0.0002	-0.0001
	(0.70)	(0.21)	(0.29)	(-0.24)
7	0.0004	0.0003	0.0000	-0.0001
	(0.57)	(0.38)	(0.06)	(-0.27)
8	0.0006	0.0003	0.0002	0.0000
	(0.82)	(0.44)	(0.45)	(-0.04)
9	0.0004	0.0003	-0.0001	-0.0002
	(0.57)	(0.46)	(-0.26)	(-0.39)
10	0.0009	0.0005	0.0002	-0.0001
	(0.93)	(0.71)	(0.32)	(-0.25)
11	0.0005	0.0003	0.0000	-0.0002
	(0.69)	(0.52)	(0.01)	(-0.29)
12	0.0004	0.0007	-0.0003	0.0002
	(0.54)	(0.97)	(-0.42)	(0.47)

Appendix Table D2: Accounting for Asynchronous Trading with Delayed Portfolio Formation

This table reports next-month alphas of Pos-RS and Neg-RS portfolios using different samples and different starting prices to measure next month returns from July 2002 to December 2019. The subsamples used for Panels A through D are drawn from the *TRACE classified bond* subsample, which includes firms having multiple bonds with a non-missing month-end TRACE daily price in a given month and only their bonds that meet this condition. In Panel A, we construct a subsample by identifying firms having at least one bond that traded and at least another one that did not trade on the last trading day of a given month. In Panel B, we construct another subsample by identifying firms having at least one bond that traded on the last trading day of a given month. In Panel C, we use the entire *TRACE classified bond* subsample. Depending on when a bond's month-end prices is recorded during month t, the starting price for the monthly return calculation for month $t+1$ is based on the TRACE daily price on the last trading day of month t or the TRACE daily price on the first trading day of month $t+1$. Specifically, In Panel A through C, for bonds that traded on the last trading day of month t, the starting price for $t+1$ month's return calculation is the TRACE daily price of the last trading day of month t. For bonds without trading on the last trading day of month t, the starting price for $t+1$ month's return calculation is the TRACE daily price on the first trading day of month $t+1$. In Panel D, the next month return construction is similar to that of Panels A through C. The only difference is that for bonds that traded in the afternoon of the last trading day of month t, the starting price for $t+1$ month's return calculation is the TRACE daily price of the last trading day of month t. For bonds without trading in the afternoon of the last trading day of month t, the starting price for $t+1$ month's return calculation is the TRACE daily price on the first trading day of month $t+1$. We then repeat the analysis as in Table 2. Newey-West (1987) adjusted t-statistics are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bonds of firms having at least one bond that traded and at least another one that did not trade on the last trading day of month t

Two-factor Alphas		Seven-factor Alphas	
Pos-RS	Neg-RS	Pos-RS	Neg-RS
0.0019**	-0.0016***	0.0015***	-0.0018***
(2.57)	(-3.52)	(2.91)	(-3.34)

Panel B: Bonds of firms having at least one bond that traded on the last trading day of month t

Two-factor Alphas		Seven-factor Alphas	
Pos-RS	Neg-RS	Pos-RS	Neg-RS
0.0020***	-0.0014***	0.0016***	-0.0016***
(2.63)	(-3.23)	(3.11)	(-3.16)

Panel C: Entire TRACE classified bond subsample

Two-factor Alphas		Seven-factor Alphas	
Pos-RS	Neg-RS	Pos-RS	Neg-RS
0.0019***	-0.0014**	0.0016***	-0.0016***
(2.66)	(-3.22)	(3.12)	(-3.28)

Panel D: Entire TRACE classified bond subsample with trade delays for bonds without trading in the afternoon of the last trading day of month t

Two-factor Alphas		Seven-factor Alphas	
Pos-RS	Neg-RS	Pos-RS	Neg-RS
0.0018**	-0.0011***	0.0014***	-0.0013***
(2.47)	(-2.74)	(2.87)	(-2.86)

Appendix E: Mispricing by Sample Subperiods

Our sample period covers close to 17 years. Given the trade reporting improvements introduced during our sample period (e.g., introduction of TRACE), we expect that mispricing has become easier to identify and exploit in the later part of our sample period. As a result, we expect the degree of mispricing to have diminished through time. 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 underpriced and overpriced at the end of month *t* using our methodology. Moreover, to gauge the overall degree of mispricing, we construct a difference portfolio that longs the Pos-RS portfolio and shorts the Neg-RS portfolio and thus captures both underpricing and overpricing. We hold each portfolio for one month. We then evaluate portfolio alphas by regressing the resulting monthly series of excess returns, separately, on the same two-factor and seven-factor models used in Section 2.2.1 for three roughly equal subperiods during 2002.7-2019.12. For robustness, we make sure that each subperiod has at least five years. For completeness, we also report alphas estimated over the entire sample period.

Results reported in Appendix Table E1 show that the magnitude of the alpha of the "difference" portfolio is higher during the first two subperiods than the last. The higher alphas in the second subperiod relative to the first subperiod are likely driven by the financial crisis, which is consistent with Brunnermeier and Pedersen (2009), who argue that market frictions and financial constraints can contribute to mispricing. Nevertheless, the much lower alphas of the difference portfolio in the last subperiod relative to the first two subperiods, which signifies an over two-fold decline relative to the first two subperiods, indicate that mispricing is shrinking. This evidence is consistent with the notion that as mispricing has become more observable and investors have increasingly traded to exploit part of it has been arbitraged away.

Appendix Table E1: Alphas of Pos-RS and Neg-RS Portfolios Bonds by Subperiod

This table reports average monthly alphas of portfolios of bonds formed based on bond residual spreads in three roughly equal subperiods during July 2002 to December 2019. At the end of each month *t*, we construct two portfolios, one consisting of bonds with a positive residual spread (*Pos-RS*) and the other consisting of bonds with a negative residual spread (*Neg-RS*). Residual spreads are estimated form Equation 1. Both portfolios are value-weighted based on the market value of each portfolio bond and are held for one month. Column 3 reports the alpha difference between the *Pos-RS* portfolio and the *Neg-RS* portfolio. In Panel A (B), we estimate portfolio alphas using the same two-factor (seven-factor) model as in Table 2, separately for each of the three roughly equal subperiods during 2002.7-2019.12. Newey-West (1987) adjusted t-statistics are given in parentheses. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A Two-factor	(1) Pos RS	(2) Neg RS	(3) Difference
Full Period	0.0027***	-0.0020***	0.0047***
	(3.51)	(-4.05)	(4.85)
2002.7 – 2007.12	0.0021**	-0.0025***	0.0046***
	(2.43)	(-6.15)	(8.63)
2008.1 – 2013.12	0.0045***	-0.0024***	0.0069***
	(2.75)	(-3.45)	(3.33)
2014.1 – 2019.12	0.0016**	-0.0007	0.0023***
	(2.53)	(-1.01)	(17.81)

Panel B Seven-factor	(1) Pos RS	(2) Neg RS	(3) Difference
Full Period	0.0024***	-0.0021***	0.0045***
	(4.08)	(-4.22)	(6.29)
2002.7 – 2007.12	0.0023**	-0.0026***	0.0049***
	(2.60)	(-7.11)	(8.63)
2008.1 – 2013.12	0.0029***	-0.0030***	0.0060***
	(3.50)	(-2.90)	(4.49)
2014.1 – 2019.12	0.0015**	-0.0009	0.0024***
	(2.49)	(-1.37)	(21.32)

Appendix F: Holdings Characteristics and Subsamples with Different Corporate Bond Weights

To rule out the possibility that funds with a higher VAS tilt their portfolios towards bonds with certain properties that can explain their performance, in Panel A of Appendix Table F1 we compare the portfolio characteristics of high- and low-VAS funds. For each fund and report date we value-weight each bond characteristic listed in Panel B of Table 2 using the market value of each position as its weight. We then report the time-series means of the monthly cross-sectional averages for high- and low-VAS funds. In the lower part of Panel A, we also report the time-series means of the monthly cross-sectional average portfolio weights in different asset classes (e.g., government bonds, corporate bonds, equity, etc.) for high- and low-VAS funds. To determine whether a bond is a corporate bond we rely on FISD classifications discussed in footnote 19. For the classification of bonds into other asset classes, we rely on the holding-type designation provided by Morningstar.

Panel A of Appendix Table F1 shows that the portfolio bonds of high- and low-VAS funds are not statistically different in credit quality. In terms of interest-rate sensitivity, we see no statistical difference in duration. Although high-VAS funds hold bonds with a slightly longer-term maturity, previous research shows that long-term bonds tend to underperform short-term bonds (e.g. Frazzini and Pedersen (2014)). The economic magnitude of the coupon rate difference is small. With respect to liquidity, we see only a slight tilt toward more liquid bonds in the portfolios of high-VAS funds when we look at the first four liquidity measures and find a statistically insignificant difference for the last two liquidity measures, Rel Turnover and Illiq. Overall, these comparisons rule out the possibility that the outperformance of high-VAS funds can be explained by their portfolio bond characteristics.

Comparisons of portfolio weights in the various asset classes suggest that high-VAS funds hold a slightly lower fraction in corporate bonds relative to low-VAS funds (46.6% vs. 48.8%) and a slightly higher fraction in cash (3.3% vs. 2.8%). The representation of the other asset classes is not different between the two groups.[25] Even though there are no big differences in the non-corporate bond holdings of high- and low-VAS funds, the averages reported for such holdings could mask temporal differences. For example, a high-VAS fund that is primarily in corporate bonds during the period we estimate our betas could move into stocks for a few months in the subsequent period. Because its stock market beta in the estimation period is low, it will generate positive and persistent alphas, albeit spurious, in the next few months. When the fund moves out of stocks, that would generate an opposite performance pattern.

To rule this possibility out, in Panel B of Appendix Table F1 we repeat the analysis of Table 4 for subsamples of IG bond funds with greater average corporate bond weights than the original sample used in Table 4 while maintaining all other requirements unchanged. The idea is that bond fund subsamples with greater average corporate bond weights will have greater stability in their corporate bond weights and will be less susceptible to the problem described above. We look at three subsamples of IG bond funds whose average portfolio allocations in corporate bonds are at least 40%, 60%, 80%, respectively, during the sample period. For these three subsamples, the corresponding weights of the corporate bond portfolio in IG bonds are 86.6%, 90.4%, and 92.4%, respectively. Results from Panel B of Appendix Table F1 confirm the results of Table 4 as the coefficient on VAS and VAS Quintile continue to be economically and statistically significant for all three subsamples. Their coefficients get significantly larger as the fraction of fund holdings in corporate bonds increases. For example, the coefficient on the VAS variable increases from 8.11 for the first subsample ($\geq$ 40% in corporate bonds) to 11.74 for the second subsample ($\geq$ 60% in corporate bonds) to 17 for the last subsample ($\geq$80 in corporate bonds). This pattern confirms that the performance effect we document comes primarily

[25] To formally rule out the possibility that differences in portfolio characteristics or weights in different asset classes explain our main performance results, in unreported tests we re-estimate Equation 4 after we augment it with the portfolio characteristics and weights of Panel A of Appendix Table F1. The coefficients on the VAS and VAS Quintile variables and their statistical significance do not change much relative to those reported in Table 4, ruling out that any of the variables in Panel A of Appendix Table F1 explain our findings.

from the ability of funds with a high VAS to skillfully analyze corporate bonds rather than other types of securities or temporarily shift to other securities.

Appendix Table F1: Holdings Characteristics and Subsamples with Different Corporate Bond Weights

In Panel A, sample funds are sorted into quintiles according to *VAS* at time *t*. We report portfolio characteristics for funds in the top and bottom VAS quintiles. First, for each fund and report date we value-weight each bond characteristic listed in Panel B of Table 2 using the market value of each position as its weight. Then, we report the time-series means of the monthly cross-sectional average characteristics for funds in the top and bottom quintiles. We also report the time-series means of the monthly cross-sectional average portfolio weights in different asset classes for funds in the top and bottom VAS quintiles. "Avg Difference" reports the time-series means of the monthly difference between the top and bottom VAS quintiles. Corresponding standard errors are Newey-West adjusted. *Government Bonds* is the fraction of the fund's assets held in government bonds. *Mortgage Bonds* is the fraction of the fund's assets held in mortgage bonds. *Corporate Bonds* is the fraction of the fund's assets held in corporate bonds that can be identified in FISD. *Equity* is the fraction of the fund's assets held in equity. *Cash* is the fraction of the fund's assets held in cash. All the other variables are described in Table 1. Panel B reports results from regressions relating future fund performance with the fund valuation accuracy score (*VAS*) for IG bond funds for the subsample of funds whose average portfolio allocations in corporate bonds are at least 40%, 60%, 80%, respectively, from July 2002 to December 2019. The row "Avg Corp Weight" reports the average fraction of the fund's assets held in corporate bonds that can be identified in FISD. The row "Avg IG/Corp Weight" reports the average fraction of the fund's investment-grade bonds held in the corporate bond portfolio. All control variables in Panel B are the same as in Table 4 and measured at time *t*. All regressions in Panel B include month and fund style (Lipper objective code) fixed effects. *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*. T-statistics (standard errors are double-clustered by fund and month) are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panel A. Holdings Characteristics of Extreme VAS Quintiles

Characteristics	VAS Q5	VAS Q1	Avg
	Mean	Mean	Difference
Credit Quality			
Rating	7.8	7.7	0.1
Interest-rate Sensitivity			
Duration (years)	5.3	5.2	0.1
Time-to-maturity (years)	8.1	7.4	0.7*
Coupon (%)	5.2	5.4	-0.2**
Liquidity			
Amount Outstanding ($M)	1,110	1,044	66***
Bond Age (years)	3.3	3.8	-0.4***
ZTD (Zero Trading Days %)	30.9	32.3	-1.5*
EstDay Turnover (%)	0.52	0.41	0.12**
Rel Turnover	1.15	1.10	0.05
Illiquidity	0.89	0.70	0.19
Asset Classes			
Government Bonds (%)	18.3	19.1	-0.8
Mortgage Bonds (%)	17.7	17.3	0.4
Corporate Bonds (%)	45.6	47.4	-1.9***
Equity (%)	1.1	1.0	0.1
Cash (%)	3.6	3.0	0.6

Appendix Table F1.-continued

Panel B. Performance Regressions for Fund Subsamples with Varying Corporate Bond Weights

	Dependent variable: Avg Gross Alpha (t+1, t+3)					
	Avg Corp >= 40%		Avg Corp >= 60%		Avg Corp >= 80%	
Avg Corp Weight	58.1%		76.9%		86.0%	
Avg IG/Corp Weight	86.6%		90.4%		92.4%	
	(1)	(2)	(3)	(4)	(5)	(6)
VAS Quintile	0.70***		1.16***		1.11***	
	(3.03)		(2.92)		(3.14)	
VAS		8.11***		11.74**		17.00***
		(2.90)		(1.99)		(3.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,327	14,327	4,582	4,582	1,920	1,920
Adjusted R^2	0.20	0.20	0.27	0.27	0.36	0.36