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Abstract

The corporate bond market is larger, more illiquid, and presumably less efficient than the equity market. These features provide numerous profit opportunities for corporate bond mutual funds that are unique to the corporate bond market. However, whether corporate bond mutual funds have the valuation skills needed to take advantage of these opportunities is unclear. We introduce a novel measure to assess the valuation skills of investment-grade corporate bond mutual funds, which we refer to as the valuation accuracy score (VAS). VAS recognizes funds holding more underpriced and less overpriced corporate bonds as ex-ante having better valuation skills. It predicts future fund performance, is stable over time, and is unrelated to other sources of skill. Investors chase the performance of higher-VAS funds more aggressively and exhibit a convex flow-performance relation among these funds.

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1. Introduction

Corporate bond mutual funds (hereafter bond funds) are becoming increasingly important in the corporate bond market, which is larger, more illiquid, and presumably less efficient than the equity market.[1] These features provide numerous profit opportunities for bond funds that are unique to the corporate bond market.[2] Whether bond mutual funds have the valuation skills needed to take advantage of these opportunities is unclear. The consensus from the literature 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 this view, investment flow patterns over the last 10 years (see Figure 1) suggest that investors see value in the active management of bond funds relative to the active management of equity funds. Motivated by this, new research has recently started to investigate whether at least some bond funds in the cross-section have investment skills.[4]

We exploit unique features of the corporate bond market to develop a novel holdings-based measure of the valuation abilities of investment-grade bond funds. With this measure we investigate whether cross-sectional differences in valuation skills exist among bond funds and how they relate to fund performance. This is important given that bond valuation is supposed to guide the core activities of bond funds and active fund management expends substantial resources on the analysis of corporate bonds. By measuring and documenting the presence of valuation skill in the cross-section of bond funds, we shed new light on the debate concerning the investment abilities

[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).

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 the most skilled relative to other funds at accurately valuing the fundamental value of individual corporate bonds. This fund will buy and sell bonds that are, respectively, underpriced and overpriced. Therefore, this fund ought to hold more underpriced bonds and less overpriced bonds compared to other funds that lack such skill. Based on this insight, for each fund and date pair with a reported portfolio, we compute the valuation accuracy score (VAS) as the dollar fraction of underpriced bonds out of all underpriced and overpriced bond holdings. Funds simultaneously holding a high dollar 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 estimate each bond's *residual spread*, the part of the credit spread unexplained by unobservable firm fundamentals and bond characteristics. We confirm that the residual spread is caused by temporary mispricing and not by omitted risk factors. We also show that the documented short-term return predictability of residual spreads is not driven by differences in: the characteristics of the underlying bonds—such as credit quality, interest rate sensitivity, and liquidity; asynchronous trading; and temporary price pressure due to liquidity shocks caused by sustained customer selling/buying activities documented by

[5] For example, Verizon had over 100 bonds (including different bond types and seniorities) 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).

Anand et al. (2021). Providing further confidence for residual spreads as a measure of mispricing, additional tests show that mispricing is more pronounced for firms that operate in a more opaque information environment.

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. Importantly, the predictive power of VAS is robust to controlling for a comprehensive list of fund and family characteristics along with other measures of ability from previous research, suggesting that VAS captures a dimension of ability that is unique from other sources of skill documented in the literature.[7] Using a battery of tests, we show that the outperformance of higher-VAS funds extends beyond bonds with short-term mispricing that are identified as such by our methodology and lasts longer than the abnormal

[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.
[7] These measures of mutual fund ability from previous research include: the liquidity providing skill measure of Anand et al. (2021); the Return Gap of Kacperczyk, Sialm, and Zheng (2008); Bond Selection and Characteristic Timing of Cici and Gibson (2012); and Issuer Active Share of Choi et al. (2021).

performance of those mispriced bonds. This suggests that VAS captures a more general type of valuation skill that extends to other bonds.

The performance predictability of VAS is robust to different approaches used to measure performance. Furthermore, the outperformance of high-VAS funds is not driven by differences in their portfolio bond characteristics or portfolio tilts towards other asset classes. Our results hold even when we conduct a number of methodological modifications in the construction of VAS. In addition, VAS is highly persistent, which is consistent with it reflecting a stable skill, and is not driven by other measures of skill from previous research. This further confirms that VAS represents a new dimension of skill that is unrelated to other factors known to affect fund performance.

In our second set of analyses, we investigate two potential mechanisms behind the performance-predicting power of VAS. The idea behind the first mechanism is that the short-term nature of the mispricing used to construct VAS and the pervasive illiquidity of corporate bonds make it likely that only funds with trading cost advantages exploit such mispricing. The idea behind the second mechanism is that funds with higher VAS simply generate better performance through superior bond selection facilitated by their valuation skills. We find no support for the trading-cost-advantage mechanism in several tests that we conduct. Specifically, we find that the ability of funds to identify and exploit mispriced bonds is not related to the Return Gap measure of Kacperczyk et al. (2008), a proxy of funds' trading costs or short-term trading advantages. Nor is it related to the propensity of certain funds to profit from providing liquidity. Furthermore, building on previous theoretical work (e.g., Constantinides 1986), we find no support for the notion that high-VAS funds have transaction cost advantages that enable them to hold more illiquid bonds in their portfolios, as high-VAS funds hold bonds that are as, if not more, liquid than low-VAS funds. We find support for the superior-bond-selection mechanism, however, when we decompose fund holdings returns into "Bond-Selection" and "Characteristic-Timing" components. We find that VAS predicts the holdings-based return component attributable to corporate bond selection but not the component attributable to timing, suggesting that the ability to identify mispriced bonds translates into superior bond selection.

Finally, we examine how, if at all, fund investors respond to the valuation skills of bond funds. We document that investment flows exhibit a stronger performance-chasing behavior for funds with higher VAS, which means that investors perceive the past performance of these funds to be a stronger indicator of skill. In addition, we find that for higher-VAS funds the flow-performance relation is more convex. This is consistent with an extension of the theoretical framework of Lynch and Musto (2003). Specifically, when fund performance is below a certain threshold, fund investors expect a calibration in strategy by the fund or the fund family. This means that as investors expect the next period return to reflect that calibration, they will be less sensitive to the recent poor performance since it is not informative about future performance. Applied to our setting, investors arguably expect the strategy calibration to be more consequential for funds they perceive to be more skilled, i.e., higher-VAS funds, thus making them even less sensitive to the poor performance of higher-VAS funds. We further document that the more convex flow-performance of higher-VAS funds is robust to controlling for the effect that fund costs such as transaction costs and investor costs such as load fees, 12b-1 fees, and tax burdens could have on the performance-flow convexity.

Our paper contributes to a growing literature that studies the performance of bond funds.[8] While the methodologies employed in this literature largely mirror those from the far more

[8] 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).

extensive literature of active equity mutual funds, we introduce a methodological innovation to uncover valuation skills across bond funds that relies on unique features of the corporate bond market. This allows us to present novel evidence of skill in the active management of corporate bonds by documenting that the differential abilities to 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.

Previous studies have looked at ex-post and indirect measures of valuation skills of corporate bond funds. These studies have either used reported fund returns with factor regressions (e.g., Ferson et al. 2010) or portfolio holdings (e.g., Cici and Gibson 2012) to isolate the performance component that is attributable to selection ability, which serves as an indication of valuation skill. Our contribution to this literature is two-fold. First, our valuation skill measure is more direct in that it tells us how funds' valuation assessments are shaping their portfolio decisions. Second, unlike previous measures described above that isolate selection return components from ex-post fund performance, our measure serves as an ex-ante predictor of performance.

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 issuer active share exhibit better performance. Anand et al. (2021) document that a subset of funds follows a distinct strategy of providing liquidity from which they earn positive alpha. We contribute to this literature by documenting that a subset of bond funds has valuation skill, which is supposed to guide the core activities of these institutional investors. We show that this skill is not only distinct from these other sources of skill documented by previous research but also from other potential sources of skill captured by traditional measures such as the Return Gap measure of Kacperczyk et al. (2008) or the Bond-Selection and Characteristic-Timing components of Cici and Gibson (2012). Thus, our research contributes by documenting a new type of ability among bond funds that is distinct from other sources of ability identified in the literature.

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 and that funds that investors believe to be skilled exhibit a convex flow-performance relation.

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").[9] We exclude bonds that have less than one year of time-to-maturity, and have less than three months of age.[10]

For the resulting subset of bonds, we follow the literature and first calculate the daily clean price as the trading volume-weighted average of intraday TRACE prices to minimize the effect of

[9] All sample bonds have the same seniority in the liability structure.
[10] Many bond indices exclude bonds with less than one year to maturity. 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.

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 Section A of the Internet Appendix. We refer to this broader sample of corporate bonds as the *bond returns* sample and use it later in our analysis of holdings-based analysis.

Next, we compute the credit spread as the difference between the corporate bond yield and the Treasury bond yield of the same maturity.[11] 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 Section B of the Internet Appendix. 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.[12] The resulting 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.

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[11] 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.

[12] 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.

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 firm fundamentals, bond characteristics, and general market conditions. To identify mispriced bonds, 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 exploit a unique feature of the corporate bond market, namely that many firms have multiple bonds outstanding at a given point in time. This 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:[13]

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

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

[13] 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.

and Downing (2007), we interact 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*.[14] 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 and include: *asset growth*; *investment-to-assets; gross profitability*; *momentum*; and *past month's equity return*. Detailed definitions of these variables are in Section B of the Internet Appendix.

We use the residuals from Equation 1 (hereafter *residual spreads*) to proxy for a bond's valuation status. A positive or negative residual spread suggests that a bond's credit spread cannot be fully explained by its common determinants, indicating potential temporary underpricing or overpricing, respectively. It is plausible that the residual spreads are caused by unknown omitted characteristics or risk factors representing certain stable equilibrium outcomes. To address this issue, we study the future risk-adjusted returns of separate portfolios that include bonds, respectively, with positive and negative residual spreads. If the residual spreads are correlated with some unknown omitted characteristics or risk factors, then the alphas of these portfolios would tend be long-lived because the influence of these omitted characteristics and factors would manifest itself as alpha rather beta. In what follows, we show that this is not the case.

At the end of each month t, we construct one portfolio consisting of bonds with a positive residual spread (*Pos-RS*) and another one consisting of bonds with a negative residual spread (*Neg-*

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

RS). Both portfolios are value-weighted based on the market value of each portfolio bond and held for one month. To examine the persistence of alphas, we delay portfolio construction by one to eleven months. Thus, in effect, we are tracking 12 Pos-RS portfolios and 12 Neg-RS portfolios depending on the delay. 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 (*LRF*) factor (Dickerson, Mueller, and Robotti 2023; Bai, Bali, and Wen 2023).

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, 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 or negative alpha generated by the Pos-RS or Neg-RS portfolio in the next month indicates that this portfolio on average included underpriced or overpriced bonds, respectively, the prices of which moved 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. Rather, it is consistent with arbitrage forces causing temporary mispricing to converge to fair values. Results from Columns 3 and 4 based on the seven-factor model to estimate alphas are similar. In Table C2 of the Internet Appendix, we report similar results based on a model that augments the seven-factor model with additional bond risk factors.

It is possible that the observed alphas 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 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 Anand et al. (2021), we examine whether bonds in the two portfolios are subject to differential short-term liquidity pressure from customer trading activity, reversals of which could give rise to the alphas that we document. To identify pressure from customer trading activity, we determine whether a given bond at a given time is in a positive or negative inventory dealer cycle. Following Anand et al. (2021), we define a positive dealer cycle as an episode in a bond with sustained customer selling, which leads to large positive dealer inventory for that bond. Similarly, we define a negative dealer cycle as an episode of sustained customer buying leading to large negative dealer inventories. If the next-month positive alphas of the Pos-RS portfolio are

[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.

related to return reversals because of temporary liquidity pressure due to sustained customer selling in previous months, we should observe a higher fraction of bonds with a positive dealer inventory cycle in the Pos-RS portfolio. Similarly, if the next-month negative alphas of the Neg-RS portfolio are related to return reversals because of temporary liquidity pressure due to customer sustained buying in previous months, we should observe a higher fraction of bonds with a negative dealer inventory cycle in the Neg-RS portfolio. 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 rather 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 hypothesis 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 customer selling before the portfolio formation. Thus, the positive alphas of the Pos-RS portfolio are not due to reversals following sustained

[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 of the bonds in this portfolio. Similarly, negative alphas of the Neg-RS portfolio are not due to reversals following sustained customer buying of the bonds in this 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 temporarily mispriced bonds. In Sections C and D of the Internet Appendix, we conduct a series of robustness tests where we repeat the analysis of Table 2 using: (1) Equation 1 augmented with bond factor betas; (2) additional risk factor to compute alphas; (3) a subsample with a greater degree of within-firm variation for the estimation of Equation 1; (4) only trade-based prices from TRACE; and (5) 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 Section E of the Internet Appendix we show that the alphas of both portfolios decline in magnitude in the later part of the sample period.

It is important to note that Equation 1 does not describe how bond funds value corporate bonds. Instead, it provides us with a benchmark to approximate bond mispricing. Funds with valuation skill 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 is a threshold that funds with valuation skill will likely improve upon. Finally, Equation 1 does not aim to identify the exact source of mispricing, as this is not the focus of our paper. Nonetheless, additional

[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.

tests reported in Section F of the Internet Appendix show that the degree of mispricing is larger in portfolios of firms that operate in a more opaque information environment (firms followed by fewer analysts). Suggesting that residual spreads are related to factors that impede information efficiency, this finding provides further confidence for residual spreads as a measure of mispricing.

2.2.2 Valuation Accuracy Score Methodology

To identify valuation skill—the ability to identify bonds that deviate from their fundamental values—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 fraction of underpriced bonds and lower fraction of 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 $\$\sum_{i=1}^{n} Underpriced\_bond_{i,f,t}$ is the sum of the market values of all underpriced bond holdings and $\$\sum_{i=1}^{n} Overprice\_bond_{i,f,t}$ is the sum of the market values of all 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

[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".

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 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

[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".

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.

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

[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.

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. 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, which we conduct using the following four-factor model, typically used by previous research for bond fund performance evaluation:

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

$R_{i,t}$ 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 $MORTG_t$ is the option factor calculated as the return spread between the Bloomberg Barclays US MBS Index and the Bloomberg Barclays Treasury Bond Index.

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

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

where $\alpha_{i,(t+1,t+3)}$ is fund *i* 's average monthly gross alpha between *t+1* and *t+3*. $VAS_{i,t}$, the explanatory variable of interest, is fund *i*'s VAS at time *t*. $\boldsymbol{X_{i,t}}$ is a vector of fund control variables, some of which are described in the previous section, but also includes additional variables tailored to this analysis described below. To control for certain funds profiting from 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.[21]

[21] Unreported results show some evidence that funds investing in bonds with longer maturities exhibit a stronger ability to deliver abnormal performance based on their VAS. A possible explanation is that bonds with longer

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, our results hold even when we control for the propensity of certain funds to provide liquidity.[22]

3.2 Performance Predictability of VAS Controlling for Other Measures of Ability

We examine the performance-predictability of VAS after controlling for additional measures of skill used in the literature, which include: (1) *Return Gap*; (2) *Bond Selection*; (3) *Characteristic Timing*; and (4) *Issuer Active Share*.

Return Gap is the fund's average return gap measure constructed and averaged over the last 12 months, as in Kacperczyk et al. (2008). *Return Gap* is computed for each fund in a given month as the difference between the reported return of the fund and the holdings return of the most recently disclosed fund's portfolio net of the fund's expense ratio.

Bond Selection is the fund's average bond-selection return and *Characteristic Timing* is the fund's average characteristic-timing return over the last 12 months. Their construction generally follows Cici and Gibson (2012). To construct the benchmark bond portfolios, we sort sequentially based on duration, rating, and illiquidity to form 125 benchmark portfolios. The illiquidity measure we use for sorting is the autocovariance of the daily TRACE price changes within each month, multiplied by -1 (Bao, Pan, and Wang 2011). We then compute monthly value-weighted returns for the resulting 125 benchmark portfolios. Next, $Bond\ Selection_{f,t}$, measuring whether fund f can select bonds that will outperform other bonds with similar characteristics in month t, and

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maturities face greater uncertainty, which likely subjects them to greater inefficiencies and related mispricing. Funds with better valuation skills are more likely to exploit such opportunities.

[22] This is consistent with our evidence from Section 2.2.1 showing that the mispricing we document is not driven by short-term liquidity pressure from customer trading activity, further suggesting that the exploitation of mispricing by high-VAS funds is not synonymous with funds exploiting sustained customary selling to provide liquidity in a profitable manner.

$Characteristic\ Timing_{f,t}$, measuring fund *f*'s characteristic timing ability, are computed as follows:

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

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

where $w_{f,i,t-1}$ is the weight of bond *i* in fund *f*'s portfolio 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.

Finally, *Issuer Active Share* is the fund's latest issuer active share, which is computed for fund *f* at time *t* as follows, in the spirit of Choi, Cremers, and Riley (2021):

$$Issuer\ Active\ Share_{f,t} = \frac{1}{2}\sum_{i=1}^{N^t}\left|w_{f,i,t} - w_{benchmark,i,t}\right|, \tag{7}$$

where $w_{f,i,t}$ denotes the weight of issuer *i* in fund *f*'s portfolio and $w_{benchmark,i,t}$ is the weight of issuer *i* in the benchmark. To construct corporate bond benchmark portfolios, we use the approach of Qin and Wang (2021). Specifically, following the Morningstar's 3 × 3 fixed income style box approach, we classify bonds into one of the nine cells of a three-by-three matrix constructed along duration and rating dimensions. Bonds in each of the nine cells categorized by duration and rating make up each of the nine benchmark portfolios, with weights determined by the bond market values. To determine the benchmark portfolio of a given fund at time *t*, we pick the benchmark portfolio that produced the lowest issuer active share for that fund over the last 12 months.

Results from the estimation of Equation 4 augmented with the four measures described above are reported in Table 5. The liquidity supply score of Anand et al. (2021) becomes more significant, indicating that funds' future performance is partly explained by their liquidity provision. However, it is important to note that the predictive ability of VAS remains statistically and economically important even after we add the additional measures of ability.[23]

3.3 Is Ability Restricted Only to Mispriced Bonds Identified by our Methodology?

It is unclear whether the relative outperformance of higher-VAS funds is attributable to the short-term outperformance of underpriced bonds identified based on Equation 1 or extends beyond these bonds. If it is attributable only to the short-term outperformance of underpriced bonds identified by our methodology, a concern is that funds with a higher VAS hold disproportionately more of these bonds by chance and their outperformance is not related to fund manager skills. We address this in three ways.

First, we examine buy-and-hold risk-adjusted returns for all mispriced bonds in our classified bond sample, mispriced bonds held by our sample funds, and other IG bonds held by our sample funds that are in our broader bond returns sample but not categorized as mispriced by our methodology (hereafter referred to as other bonds) over longer horizons of subsequent months. If VAS captures general valuation skill that goes beyond holdings of bonds with short-term mispricing identified by our methodology, we expect the buy-and-hold returns for the other bonds to persist at least as long as those of the bond holdings with short term mispricing.

We follow the approach of Jegadeesh and Titman (1993) and compute average monthly alphas of buy-and-hold strategies with overlapping holding periods. For a holding period of K months, at the end of each month t, a buy-and-hold return is the average monthly return of K value-weighted portfolios formed with bonds with a certain characteristic (e.g., positive or negative

[23] Our inferences regarding the performance predictability of VAS remain unchanged when we replace our computed issuer active share with the issuer active share used in Choi, Cremers, and Riley (2021) for the observations that overlap with our sample (roughly 50% of our sample). We thank Jaewon Choi, Martijn Cremers, and Timothy Riley for providing us with the issuer active share data used in Choi et al. (2021).

residual spread) identified in the current month *t* as well as in the previous *K - 1* months. Buy-and-hold strategy alphas are estimated from regressing portfolio excess returns on the factors of the 7-factor model introduced in Section 2.2.1 (Table 2). Results are presented in Table 6.

In Columns 1 and 2, we investigate the performance of portfolios that include all sample bonds with a positive residual spread (Pos-RS) in Column 1 and bonds with negative residual spread (Neg-RS) in Column 2. In Columns 3 and 4, the portfolios include mispriced bonds held by high-VAS and low-VAS funds, respectively. Finally, in Columns 5 and 6, the portfolios include other bond holdings held by high- and low-VAS funds, respectively. In Columns 3-6, we first use weights based on portfolio position sizes of a given fund when we construct a buy and hold portfolio for that fund. Then, we aggregate these buy-and-hold portfolios across funds by equally weighting them to come up with an aggregate buy-and-hold portfolio for a given holding period. Results from this table suggest that buy-and-hold alphas of the mispriced bonds, which are undervalued, in the all-bond sample are significant for holding periods of up to six months. Buy-and-hold alphas for the mispriced bonds, which are undervalued, in the portfolios of high-VAS funds are significant over longer holding periods, up to eight months. This suggests ability on the part of high-VAS funds that goes beyond picking bonds based on their residual spreads alone. Interestingly, the buy-and-hold alphas of the other bond holdings (that exclude mispriced bonds) of the high-VAS funds continue to be significant beyond eight months all the way to 12 months, with signs of tapering off in the more remote months. The fact that the buy-and-hold returns of the other bonds held by high-VAS funds are significant in the first place and also persist over a longer horizon than the buy-and-hold returns of the mispriced bonds further supports the notion that VAS captures general bond picking skills that go beyond holdings of bonds with short-term mispricing identified by our methodology.[24]

Second, moving from performance of holdings to fund performance, we examine the predictability of VAS for fund performance measured over the next 6, 9, and 12 months. We replace average alpha over the next three months in Equation 4 with average alpha over the next 6, 9, and 12 months and report results from the modified regressions separately for each alternative dependent variable in Table 7. Results suggest that the VAS signal preserves its value for 9 to 12 months. Both the continuous VAS and its quintile measure significantly and consistently predict future performance for the next 6 and 9 months and only the quintile measure predicts performance for the next 12 months. Table 6 shows that buy-and-hold alphas of bonds with short-term mispricing (undervalued) identified as such by Equation (1) are significant for up to six months. The fact that the predictability of VAS for performance, as shown in Table 7, extends beyond six months confirms that VAS reflects a more general measure of valuation skill.

Finally, in a test reported in Section G of the Internet Appendix, we add the return of a zero-investment, factor-mimicking portfolio for mispricing (hereafter *MP* factor) to the fund performance evaluation model in Equation 3 to account for the part of fund return that arises due to funds holding and selling, respectively, bonds with short-term underpricing and overpricing as determined by Equation 1. The *MP* factor is the average difference of value-weighted returns between the top and bottom tercile portfolios sorted on residual spreads across rating portfolios. After we adjust fund performance using Equation 3 augmented with the *MP* factor, we re-estimate Equation 4. Results show that the predictive power of VAS on fund performance remains even

[24] Unreported results are similar when we weight the buy-and-hold portfolios of individual funds in a way that reflects the size of these funds and when we control for fund style by ranking funds into VAS quintiles within fund style groups.

after we control for any performance effects due to the *MP* factor, suggesting that higher-VAS funds have ability that goes beyond exploiting short-term mispricing identified by our methodology.

3.4 Robustness Checks

Table 8 reports our first set of robustness tests for the fund performance results. In Columns 1 and 2 of Table 8, we replace fund style fixed effects with fund fixed effects to control for unobserved fund heterogeneity when estimating Equation 4. The evidence from these two specifications and from Table 4 suggest that there is both cross-sectional and within-fund variation in the VAS-performance relation. This is consistent with Pastor, Stambaugh, and Taylor (2017), who document both sources of variation in the turnover-performance relation and whose theoretical model predicts that funds trading to a greater extent in response to time-varying profit opportunities are also more skilled in the cross-section.[25] In Columns 3 to 14, we estimate Equation 4 with different performance measures. 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*) (Bai, Bali, and Wen 2023), and the bond momentum factor

[25] Another prediction of the theoretical model in Pastor et al. (2017) is that the within-fund variation of the skill-performance relation is stronger than its cross-sectional variation. This is indeed confirmed in our study based on a comparison of the VAS coefficients from Table 4 and the first two columns of Table 6.

(*BOND_MOM*) (Jostova et al. 2013).[26] 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 Section H of the Internet Appendix, we examine the portfolio characteristics of high- and low-VAS funds to rule out that funds with a higher VAS are tilting their portfolios towards bonds with certain 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.

Finally, in tests reported in Section I of the Internet Appendix we address robustness with respect to the measurement of VAS. Specifically, we replace VAS with alternative measures and re-estimate Equation 4. One alternative version of VAS requires a larger number of mispriced bonds in a fund portfolio to estimate VAS in order to reduce its measurement error. Another version is based on the number of underpriced bonds and overpriced bonds in the portfolio instead of the market value of bonds. Finally, the last alternative version of VAS is based on fund trades in mispriced bonds rather than holdings. Our results remain robust when we use these alternative measures of VAS.

3.5 Persistence and Determinants of VAS

In this section, we examine the persistence of VAS and its determinants. To examine persistence, we follow Anand et al. (2021) and construct a transition matrix reporting the fraction

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

of funds in quintiles based on average VAS in the last 12 months that stay in the same or different quintiles formed by ranking on average VAS over the next 12 months. If rankings in the past 12 months are random, then funds have a 20% probability of transitioning to any of the VAS quintiles during the next 12 months. The transition matrix reported in Table 9 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.[27]

To examine the determinants of VAS, we use the following model:

$$VAS_{i,t+1} = AVAS_{i,(t-11,t)} + \gamma' \boldsymbol{X_{i,t}} + \varepsilon_{i,t} \qquad (8)$$

where $VAS_{i,t+1}$ is the valuation accuracy score computed using the first available fund holdings report within 3 months after month *t*. $AVAS_{i,(t-11,t)}$ is the last 12-month average VAS. $\boldsymbol{X}$ is the same vector of fund characteristics introduced in Equation 3 plus the fund expense ratio and the four additional measures of ability from previous research introduced in Section 3.2. We also include month and fund style fixed effects and double cluster standard errors by fund and month.

Table 10 reports results. Consistent with the evidence from Table 9, the past average value of VAS has predictive power for future VAS. This suggests that VAS reflects a skill type that is stable over time. The CRSP turnover is significantly related to future valuation accuracy in all specifications. This suggests that a fund achieves higher VAS by consistently identifying and actively acting on mispriced opportunities instead of holding underpriced bonds by chance. The

[27] In unreported results, we also show that high VAS funds (in top VAS quintile) exhibit first-order autocorrelation that is 37% higher than that of low VAS funds (in bottom quintile).

evidence is consistent with Pastor et al. (2017), who argue that a fund that is better at identifying mispricing opportunities would want to exploit such skill by trading more. Past flow is also positively associated with future VAS.

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 skill 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 measures of ability do not explain future VAS either. This suggests that VAS captures a unique dimension of skill that is distinct from other sources of ability identified in previous research.

4. Potential Mechanisms

We next propose and investigate two potential mechanisms through which VAS affects fund performance. The first mechanism works through high-VAS funds having certain trading advantages that lower their trading costs. The idea is that, given the short-term nature of the mispricing employed to construct VAS and the pervasive illiquidity in the corporate bond market, only funds with trading advantages, i.e., funds that incur lower trading costs, can exploit such mispricing. The second mechanism is more direct: funds with superior valuation skill simply generate better performance through superior bond selection.

The evidence from the previous section, which looks at the determinants of VAS casts doubt on the presence of the trading-cost-advantage mechanism. If high-VAS funds are able to persistently generate lower transaction costs, we would expect to see a positive relation between

VAS and the return gap measure of Kacperczyk et al. (2008), which captures the effect of trading cost advantages or advantages due to profitable short-term trading skills. This is not corroborated by the evidence presented in Table 10, where we see that the coefficient on the return gap measure is insignificant. Similarly, if high-VAS funds are able to exploit mispricing caused by other investors demanding liquidity because they are able to provide liquidity, we should see a positive relation between VAS and the *LS_scoreQ* of Anand et al. (2021). Again, results from Table 10 show that VAS is not related to the propensity of certain funds to provide liquidity.

Another way to examine the presence of the trading-cost-advantage mechanism is to use guidance from previous theoretical work. Constantinides (1986) states that "transaction costs have a first-order effect on the assets' demand", meaning that, all else equal, investors will choose to trade less in assets that have higher transaction costs. Absent a transaction cost advantage among high-VAS, both high- and low-VAS funds should exhibit a similar preference for illiquid bonds. However, if high-VAS funds have a transaction cost advantage, we ought to see high-VAS funds holding more illiquid bonds, from which they can earn the illiquidity premium.

To examine whether high-VAS funds hold more illiquid bonds, in Table 11 we compare the portfolio liquidity characteristics of high- and low-VAS funds. For each fund and report date we value-weight each liquidity 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, along with differences between the two groups. Contrary to what we would expect if high-VAS funds had a transaction cost advantage, Table 11 shows that high-VAS funds have a slightly greater weight in more liquid bonds in their portfolios when we look at the first four liquidity measures and a statistically insignificant difference for the last two liquidity measures, *Rel Turnover* and *Illiquidity*. Overall, these comparisons do not support the notion that high-

VAS funds have a transaction costs advantage that enables them to hold more illiquid bonds in their portfolios.

Having shown that VAS is not related to transaction cost advantages, we next provide evidence confirming the superior-bond-selection mechanism. We use portfolio holdings to decompose fund monthly returns into “Bond-Selection” return and the “Characteristic-Timing” return (Daniel et al. 1997; Cici and Gibson 2012) based on Equations (5) and (6). If the bond selection mechanism is indeed present, we would expect funds with a higher VAS to exhibit a stronger bond selection return component.

We estimate Equation 4 using the average Bond Selection and Characteristic Timing over the next three months as dependent variables, respectively. Results are reported in Table 12. 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 outperform low-VAS funds by 3.9 bps (0.99 * 4) per month (47 bps per year) over the next quarter in terms of Bond Selection return. This evidence supports the superior-bond-selection mechanism. There is no evidence that VAS Quintile and VAS predict Characteristic Timing return as shown in Panel B. The fact that VAS is related to the bond selection component but not the timing component of holdings returns suggests that VAS captures a very specific source of skill that is related to bond selection resulting from valuation skills.

Additional evidence supporting the bond selection mechanism comes from another test reported in Section J of the Internet Appendix. This test employs the framework of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), which predicts that active funds focus on security selection during good market conditions and timing during poor market conditions. Extending this insight to our setting with corporate bond funds, if VAS captures valuation skill that materializes through superior selection, then we should expect to see that the performance predictability of VAS is noticeably higher during good market conditions than during poor market conditions. Providing further support for the bond selection mechanism, we do indeed find that VAS positively predicts fund performance during good market conditions, when funds are supposed to focus on bond selection, but not in bad times.

5. Investors' Response

Given the evidence presented so far, a natural question is: How do investors respond to differential valuation skills across funds? This likely 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 VAS or other similar indicators that reflect valuation accuracy. If, on the other hand, investors infer skill primarily through past performance, as in 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:

$$Flow_{i,(t+1,t+3)} = \beta_V VAS_{i,t} + \beta_{INT} VAS_{i,t} * Past\ Alpha_{i,t} + \beta_{PA} Past\ Alpha_{i,t} + \gamma' \boldsymbol{X_{i,t}} + \varepsilon_{i,t} \quad (9)$$

The dependent variable, $Flow_{i,(t+1,t+3)}$, is the average flow of fund i over the next three months, *Past Alpha* is the average monthly gross alpha over the last 12 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 13. Column 1, which regresses fund flow on past performance and other controls, confirms the empirical regularity that fund flows follow past performance. A 1% increase of the average last 12-month alpha leads to a 2% increase of average monthly flow in the next quarter. This performance-chasing behavior of flows is consistent with investors learning about manager skill from past performance (e.g., Berk and Green 2004). Results from Column 2, which estimates Equation 9, 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, which is consistent with investors using a combination of past performance and information contained in VAS to infer the skill of fund managers.

We next examine the shape of the flow-performance curve for funds with higher versus lower VAS. We differentiate fund performance between the positive and negative regions and modify Equation 9 by including a three-way interaction term that includes VAS, Past Alpha, and a negative performance indicator (*Neg Alpha*). *Neg Alpha* equals one if Past Alpha is negative and zero otherwise. Results from this specification are reported in Column 3 of Table 13. 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.

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 13. We only find a significant convex flow-performance relation in Column 4 for funds in the top 30% group.

The more convex flow-performance relation for higher-VAS is consistent with an extension of the theoretical framework of Lynch and Musto (2003). They suggest that when fund performance is below a certain threshold, fund investors expect a change or adjustment in strategy, which means that the next period return will reflect the strategy change, making fund investors less sensitive to recent poor performance since it is not informative about future performance. Extended to our setting, investors presumably expect the strategy change to be more consequential for funds that they perceive to be more skilled, i.e., higher-VAS funds, which in turn makes them even less sensitive to the poor performance of higher-VAS funds.

We control for the possibility that the convexity of the flow-performance relation for higher-VAS funds is driven by fund investor-level costs, some of which could be used by the fund or the fund family to market past fund performance in a selective manner. For example, Sirri and Tufano (1998) propose that funds, themselves or with the help of brokers, could engage in active marketing by promoting recent good performance and by emphasizing other services offered by the fund or the fund family when the fund had bad performance. This increases awareness of good performance but desensitizes investors to poor performance among funds with higher load fees.[28] Similarly, a fund generating a lower tax burden might cause investors to become less sensitive to poor performance. It is also possible that the flow-performance convexity of higher-VAS funds is driven by fund-level costs such as trading costs. When a fund incurs lower transaction costs, such benefits could similarly cause investors to become less sensitive to poor performance.

To control for investor-level and fund-level costs as potential drivers of the convexity of the flow-performance relation for higher-VAS funds, in Columns 7 and 8 we include Load Fees, 12b-1 Fees, Tax Burden, and Return Gap as additional control variables. Load is computed by summing the maximum front-end load and the maximum rear-load of each share class and then taking an asset-weighted average of this sum across all share classes of the same fund. Load reflects the compensation paid to brokers for selling the share classes of a given fund. 12b-1 Fee is the fund's 12b-1 fee, asset-weighted, across all share classes of the same fund. This fee is used to pay for the fund's marketing and distribution activities (part of which can go to compensate brokers on an ongoing basis). Tax Burden is computed as the sum of the product of the funds' dividend, short-term, and long-term capital gains distribution yields with the respective average marginal tax rates (Sialm and Stark 2012).[29] The Return Gap is the fund's average return gap computed as in Kacperczyk et al. (2008) and averaged over the last 12 months and is a proxy for trading costs and value added by the fund via short-term trading,

[28] The more active marketing by funds when they experience good performance is also likely to reduce the search costs for investors of funds that have experienced good performance.

[29] Bergstresser and Poterba (2002) show that funds with larger tax burdens experience lower subsequent fund flows.

In addition to adding the four variables described above, in Column 8, we replace all alpha-related variables with alphas estimated from fund net returns, which are net of the fund expense ratio. In unreported results, we also control for the effect that each of the four control variables described above could have on the sensitivity of flows to performance by including triple interactions between past alpha, negative performance, and each of the four control variables. No matter whether we simply include the four control variables or triple-interact them with past alpha and negative performance, the sign and size of the triple interaction VAS * Past Alpha * Neg remains unaffected, suggesting that the convexity of the flow-performance relation for high-VAS funds is robust to controlling for these additional variables.

In the context of previous research documenting a concave or linear flow-performance relation for bond funds (Goldstein et al. 2017; Chen and Qin 2017), our findings suggest that the flow-performance relation is not uniform across bond funds such that 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 dollar fraction of underpriced 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 several 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.

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.

The findings of our paper taken together contribute to the larger debate on the investment abilities of corporate bond funds, further our understanding of the types of skills that these funds possess and help us understand how investors respond to performance of skilled bond funds. How the valuation skills documented here develop in relation to the human capital traits of portfolio managers or organizational processes instituted by investment firms is worthy of future research.

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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***	0.0027***	-0.0021***
	(3.51)	(-4.05)	(4.67)	(-4.46)
2	0.0008	0.0000	0.0007	-0.0001
	(1.65)	(0.08)	(1.56)	(-0.27)
3	0.0009	0.0000	0.0007	-0.0001
	(1.58)	(0.11)	(1.54)	(-0.32)
4	0.0005	0.0003	0.0003	0.0001
	(1.00)	(0.54)	(0.70)	(0.25)
5	0.0005	0.0001	0.0004	-0.0001
	(0.96)	(0.21)	(0.75)	(-0.18)
6	0.0005	0.0000	0.0002	-0.0001
	(0.83)	(0.11)	(0.50)	(-0.30)
7	0.0004	0.0002	0.0002	0.0000
	(0.84)	(0.36)	(0.46)	(-0.04)
8	0.0004	0.0003	0.0001	0.0001
	(0.72)	(0.50)	(0.28)	(0.16)
9	0.0006	0.0001	0.0004	-0.0001
	(1.01)	(0.18)	(0.72)	(-0.31)
10	0.0005	0.0003	0.0002	0.0000
	(0.84)	(0.53)	(0.42)	(0.06)
11	0.0003	0.0003	0.0001	0.0001
	(0.60)	(0.61)	(0.14)	(0.27)
12	0.0003	0.0005	0.0000	0.0003
	(0.49)	(0.94)	(-0.07)	(0.71)

Table 2. -continued

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

Characteristics	Pos-RS	Neg-RS	Avg
	Mean	Mean	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: Performance Predictability of Valuation Accuracy Score Controlling for Other Skill Measures

This table replicates Table 4, modified to control for measures of ability from previous research. Control variables of interest include: *LS_scoreQ*, the fund's quintile rank of average liquidity supply score over the last 12 months; *Return GAP,* the fund's average return gap over the last 12 months; *Bond Selection,* the fund's average bond-selection return over the last 12 months; *Characteristic Timing,* the fund's average characteristic-timing return over the last 12 months; *Issuer Active Share,* the fund's latest issuer active share. All other control variables are the same as in 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+1, t+3)					
	(1)	(2)	(3)	(4)	(5)	(6)
VAS Quintile	0.67***		0.62***		0.62***	
	(3.49)		(3.01)		(3.01)	
VAS		7.22***		7.00***		6.96***
		(3.14)		(2.82)		(2.80)
LS_scoreQ	0.36*	0.35*	0.38**	0.38**	0.38**	0.38**
	(1.92)	(1.90)	(2.07)	(2.04)	(2.07)	(2.04)
Return Gap	0.06	0.06	0.06	0.06	0.06	0.06
	(1.36)	(1.35)	(1.33)	(1.32)	(1.32)	(1.31)
Bond Selection			0.03	0.03	0.03	0.03
			(0.73)	(0.74)	(0.72)	(0.73)
Characteristic Timing			0.03	0.02	0.03	0.02
			(1.09)	(1.09)	(1.09)	(1.08)
Issuer Active Share					6.05	5.50
					(0.69)	(0.62)
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	23,472	23,472	23,472	23,472
Adjusted R^2	0.20	0.20	0.21	0.21	0.21	0.21

Table 6: Buy-and-Hold Performance for Mispriced Bonds, Mispriced Bond Holdings, and Other Bond Holdings

This table reports average monthly alphas of buy-and-hold strategies with overlapping holding periods according to Jegadeesh and Titman (1993) from July 2002 to December 2019. In Columns 1 and 2, at the end of each month *t*, buy-and-hold strategies are the average return of *K* value-weighted portfolios formed by bonds with a positive residual spread (*Pos-RS*) and a negative residual spread (*Neg-RS*) identified in the current month *t* as well as in the previous *K* - 1 months, where *K* is the holding period. In Columns 3 and 4, at the end of each month *t*, buy-and-hold strategies are the average return of *K* value-weighted portfolios formed by mispriced bonds held by high-VAS (quintile 5) and low-VAS (quintile 1) funds in the current month *t* as well as in the previous *K* - 1 months, where *K* is the holding period. In Columns 5 and 6, at the end of each month *t*, buy-and-hold strategies are the average return of *K* value-weighted portfolios formed by IG bonds (excluding mispriced bonds) held by high-VAS (quintile 5) and low-VAS (quintile 1) funds in the current month *t* as well as in the previous *K* - 1 months, where *K* is the holding period. Buy-and-hold strategy 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.

# Months Holding Periods (K)	Mispriced Bonds		Mispriced Bond Holdings		Corporate Bond Holdings Excluding Mispriced Bonds	
	(1) Pos-RS	(2) Neg-RS	(3) VAS Q5	(4) VAS Q1	(5) VAS Q5	(6) VAS Q1
1	0.0027***	-0.0021***	0.0020***	-0.0002	0.0015**	0.0005
	(4.40)	(-4.29)	(3.32)	(-0.47)	(2.02)	(0.95)
2	0.0017***	-0.0011**	0.0016***	0.0001	0.0012**	0.0007
	(3.09)	(-2.31)	(2.86)	(0.17)	(2.19)	(1.29)
3	0.0014***	-0.0008	0.0015***	0.0002	0.0010**	0.0005
	(2.62)	(-1.59)	(2.66)	(0.43)	(2.15)	(1.09)
4	0.0012**	-0.0005	0.0014**	0.0003	0.0010**	0.0006
	(2.20)	(-1.11)	(2.44)	(0.51)	(2.21)	(1.20)
5	0.0010*	-0.0004	0.0011**	0.0002	0.0012**	0.0007
	(1.94)	(-0.88)	(2.01)	(0.44)	(2.59)	(1.31)
6	0.0009*	-0.0004	0.0011*	0.0001	0.0014***	0.0008
	(1.75)	(-0.74)	(1.86)	(0.27)	(2.99)	(1.57)
7	0.0009	-0.0003	0.0010*	0.0001	0.0014***	0.0008
	(1.61)	(-0.60)	(1.77)	(0.26)	(2.94)	(1.58)
8	0.0008	-0.0002	0.0010*	0.0001	0.0013***	0.0007
	(1.49)	(-0.47)	(1.72)	(0.24)	(2.72)	(1.46)
9	0.0008	-0.0002	0.0010	0.0001	0.0012***	0.0007
	(1.43)	(-0.42)	(1.61)	(0.23)	(2.63)	(1.38)
10	0.0007	-0.0002	0.0009	0.0002	0.0012**	0.0007
	(1.37)	(-0.35)	(1.54)	(0.36)	(2.54)	(1.38)
11	0.0007	-0.0001	0.0008	0.0002	0.0011**	0.0007
	(1.29)	(-0.27)	(1.43)	(0.44)	(2.43)	(1.35)
12	0.0007	-0.0001	0.0008	0.0003	0.0011**	0.0007
	(1.20)	(-0.18)	(1.37)	(0.52)	(2.34)	(1.38)

Table 7: Valuation Accuracy Measures and Future Fund Performance Over Longer Horizons

This table reports results from regressions relating future fund performance, measured over longer horizons, 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 in Columns 1 and 2 is the average gross alpha between *t+1* and *t+6* in basis points. The dependent variable in Columns 3 and 4 is the average gross alpha between *t+1* and *t+9* in basis points. The dependent variable in Columns 5 and 6 is the average gross alpha between *t+1* and *t+12* 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+1, t+6)		Avg Gross Alpha (t+1, t+9)		Avg Gross Alpha (t+1, t+12)	
	(1)	(2)	(3)	(4)	(5)	(6)
VAS Quintile	0.46**		0.32**		0.27*	
	(2.48)		(2.06)		(1.84)	
VAS		5.41**		3.35*		2.58
		(2.49)		(1.81)		(1.49)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,151	24,151	23,571	23,571	22,782	22,782
Adjusted R^2	0.23	0.23	0.23	0.23	0.22	0.22

Table 8: 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***		0.60**		0.65***		0.75***	
	(3.51)		(3.71)		(3.44)		(3.14)		(2.60)		(2.86)		(3.35)	
VAS		8.03***		7.50***		7.27***		6.72**		5.69**		6.60***		6.94***
		(3.18)		(3.30)		(3.04)		(2.61)		(1.99)		(2.75)		(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	0.18	0.18	0.20	0.20	0.07	0.07

Table 9: Transition Matrix for Valuation Accuracy Score

This table reports a transition matrix reporting the fraction of funds with rankings based on average VAS in months [t-11, t] that stay in the same or different rankings of average VAS in months [t+1, t+12]. Funds are first sorted into quintiles by their average VAS in months [t-11, t]. Then, they are sorted into quintiles based on average VAS in months [t+1, t+12]. The first column reports the sorting variable. The next five columns report the likelihood of a fund in a VAS quintile during [t-11, t] falling into each VAS quintile formed in the subsequent period [t+1, t+12]. The reported chi-square statistics are for the test of null hypothesis that the probability for being in each VAS quintile in the next 12 months is independent of the fund's VAS quintile in the previous 12 months. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Quintile of	Percentage in Quintile of AVAS (t +1, t +12)				
AVAS (t-11, t)	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 10: Determinants of Valuation Accuracy Score

This table examines the determinants of VAS. Observations are based on each fund's reporting period. The dependent variable is the first available VAS within 3 months after month t in percent. *AVAS (t-11, t)* is the fund's average VAS over the last 12 months in percent. *LS_scoreQ* is the fund's quintile rank of average liquidity supply score over the last 12 months. *Return GAP* is the fund's average return gap over the last 12 months. *Bond Selection* is the fund's average bond-selection return over the last 12 months. *Characteristic Timing* is the fund's average characteristic-timing return over the last 12 months. *Issuer Active Share* is the fund's latest issuer active share. 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.

	Dependent variable: VAS (t+1)		
	(1)	(2)	(3)
AVAS (t-11, t)	0.72***	0.72***	0.72***
	(33.98)	(35.58)	(35.52)
LS_scoreQ	0.09	0.12	0.12
	(1.05)	(1.32)	(1.32)
Past Alpha	-0.01	-0.01	-0.01
	(-1.13)	(-1.08)	(-1.06)
log(Fund Size)	0.01	0.02	0.03
	(0.13)	(0.28)	(0.35)
Log(Fund Age)	0.22	0.21	0.21
	(1.10)	(1.03)	(1.01)
CRSP Turnover	0.35***	0.38***	0.38***
	(3.23)	(3.12)	(3.16)
Corp Bond Turnover	0.20	0.19	0.18
	(1.54)	(1.27)	(1.24)
Expense Ratio	-0.00	-0.00	-0.00
	(-0.93)	(-0.75)	(-0.96)
log(Family Size)	0.03	0.07	0.08
	(0.35)	(0.91)	(1.01)
Past Flow	0.11**	0.10*	0.10*
	(2.10)	(1.87)	(1.88)
Flow Volatility	-0.03	-0.01	-0.02
	(-0.59)	(-0.32)	(-0.34)
Return Volatility	0.00	0.00	0.00
	(0.60)	(1.10)	(1.11)
Return Gap	0.00	0.00	0.00
	(0.28)	(0.49)	(0.47)
Bond Selection		-0.01	-0.01
		(-1.25)	(-1.26)
Characteristic Timing		-0.00	-0.00
		(-0.29)	(-0.28)
Issuer Active Share			3.41
			(1.00)
Month FE:	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes
Observations	24,525	23,283	23,283
Adjusted R^2	0.30	0.30	0.30

Table 11: Liquidity Characteristics of Bonds Held by High- and Low- VAS Funds

This table reports average liquidity characteristics of bonds held by high- and low-VAS funds, i.e., funds in the top and bottom VAS quintiles. First, for each fund and report date we value-weight each liquidity 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 and the difference between the two. Standard errors corresponding to the t-statics reported for the difference are Newey-West adjusted. T-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Liquidity Characteristic	VAS Q5 Mean	VAS Q1 Mean	Avg Difference
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

Table 12: Valuation Accuracy Score and Return Decomposition

This table reports results from regressions relating future fund bond-selection and characteristic-timing 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 Bond Selection between *t+1* and *t+3* in basis points. In Panel B, the dependent variable is the average Characteristic Timing between *t+1* and *t+3* in basis points. Bond Selection and Characteristic Timing are calculated, respectively, according to Equations 5 and 6 with benchmark portfolios sorted by bonds' duration quintile, rating group, and illiquidity quintile. Illiquidity is the autocovariance of the daily TRACE price changes within each month, multiplied by -1 (Bao, Pan, and Wang 2011). *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 Bond Selection (t+1, t+3)			
	(1)	(2)	(3)	(4)
VAS Quintile	0.97***		0.99***	
	(3.48)		(3.52)	
VAS		8.93**		9.32***
		(2.64)		(2.72)
Control	No	No	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	22,877	22,877	22,877	22,877
Adjusted R^2	0.03	0.03	0.04	0.04

Panel B: Characteristic Timing

	Dependent variable: Avg Characteristic Timing (t+1, t+3)			
	(1)	(2)	(3)	(4)
VAS Quintile	0.15		0.12	
	(0.80)		(0.62)	
VAS		1.30		1.09
		(0.53)		(0.43)
Control	No	No	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes
Observations	22,877	22,877	22,877	22,877
Adjusted R^2	0.07	0.07	0.08	0.08

Table 13: Valuation Accuracy Score and Future Fund Flow

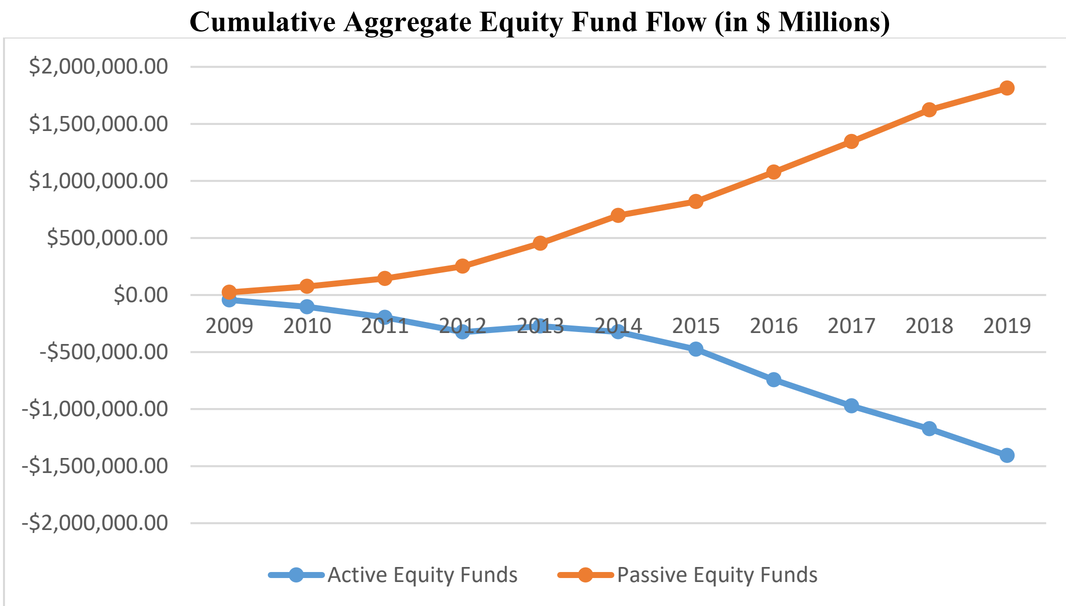
This table reports results from regressions relating future fund flow with the fund valuation accuracy score (*VAS*) for IG bond funds from July 2002 to December 2019. Observations are based on each fund's reporting period. The dependent variable is the average fund flow between t+1 and t+3 in percent. *VAS* is the fund's continuous *VAS* at time *t*. *Neg* is an indicator variable equal to one if the *Past Alpha* is negative and zero otherwise. All control variables in Columns 1 to 6 are the same as Table 4 and measured at time *t.* In Column 7 and 8, we add four additional controls including *Load*, *12b-1 Fee*, *Tax Burden*, and *Return Gap*. *Load* is computed by summing the maximum front-end load and the maximum rear-load of each share class and then taking an asset-weighted average of this sum across all share classes of the same fund. *12b-1* Fee is the fund's 12b-1 fee, asset-weighted across all share classes of the same fund. *Tax Burden* is the sum of the product of the fund's dividend, short-term, and long-term capital gains distribution yields with the respective average marginal tax rates (Sialm and Stark 2012). *Return Gap* is the fund's average return gap computed as in Kacperczyk et al. (2008) and averaged over the last 12 months. In Column 8, we replace all alpha-related variables with alphas estimated from fund net returns. 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.

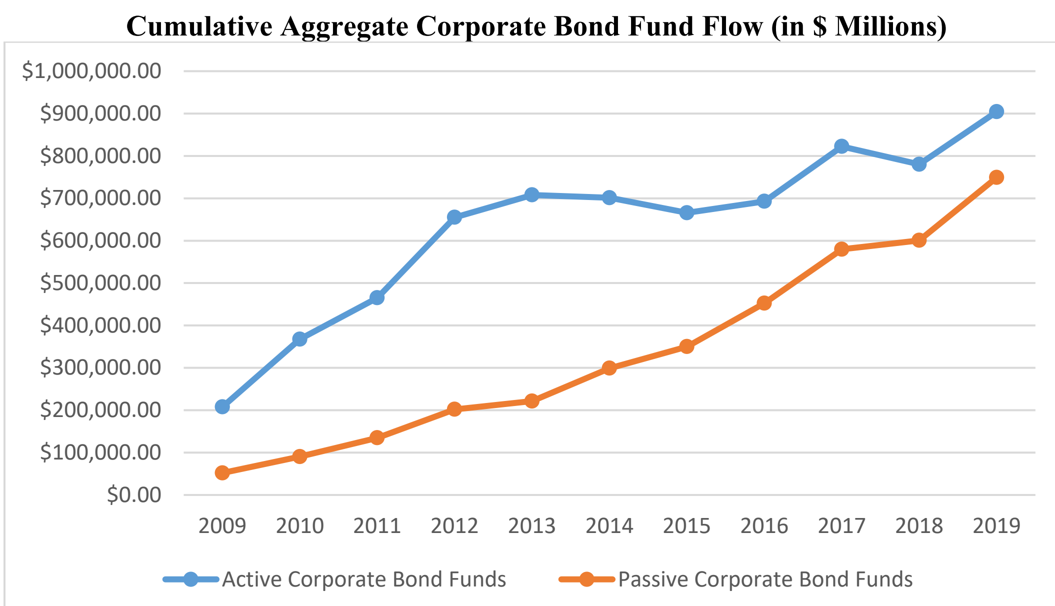
Table 13.-continued

	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	(7) Additional Control	(8) Net Alpha
VAS		-0.01	-0.43				-0.45*	-0.32
		(-0.03)	(-1.61)				(-1.67)	(-0.86)
VAS * Past Alpha		0.02**	0.05***				0.04***	0.05**
		(2.05)	(3.03)				(2.72)	(2.29)
Past Alpha	0.02***	0.01**	-0.00	0.03***	0.02**	0.02**	0.01	-0.01
	(7.73)	(2.14)	(-0.24)	(5.05)	(2.87)	(2.59)	(1.02)	(-1.21)
Past Alpha * Neg			0.02	-0.02**	0.00	-0.00	0.02	0.02*
			(1.46)	(-2.27)	(0.54)	(-0.56)	(1.41)	(1.65)
VAS * Past Alpha * Neg			-0.05**				-0.05**	-0.05**
			(-2.59)				(-2.13)	(-2.13)
Neg			-0.29	-0.08	-0.21*	-0.15	-0.31	-0.36
			(-1.09)	(-0.59)	(-1.71)	(-1.28)	(-1.13)	(-1.43)
VAS * Neg			0.25				0.22	0.08
			(0.52)				(0.44)	(0.16)
Load							-0.01	-0.01
							(-0.36)	(-0.39)
12b-1 Fee							0.19	0.27
							(1.03)	(1.43)
Tax Burden							-0.18***	-0.18***
							(-2.69)	(-2.74)
Return Gap							0.01***	0.01***
							(5.28)	(5.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,735	24,735	24,735	7,190	9,906	7,639	24,735	24,735
Adjusted R^2	0.23	0.23	0.23	0.23	0.24	0.22	0.23	0.23

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.





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