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Abstract

Using a novel return-based method to detect allocations of corporate bond offerings, which are underpriced on average, we find that mutual funds most active in the primary market generate significant alpha and outperform those that are less active. Our evidence suggests that underwriters direct underpriced allocations repeatedly to fund families with which they have stronger underwriting relationships. Consistent with the concave performance-flow relationship that describes bond fund investors' behavior, families maximize profitability by strategically distributing allocations to member funds that underperformed their style benchmark over the last year at the expense of those that outperformed.

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1. Introduction

Investors' voracious appetite for mutual funds that hold corporate bonds has reshaped markets. From 2010 to 2020, the value of corporate bonds held by mutual funds more than doubled, growing from \$1.5 trillion to \$3.5 trillion, and their ownership share of the total amount of corporate bonds outstanding increased from 13.5% to 21.6%, making them the fastest growing category of institutional investors in the corporate bond market (see Investment Company Institute 2021).

Figure 1 shows that active investment-grade corporate bond funds enjoyed net inflows from 2010 to 2019, unlike the net outflows from active equity mutual funds. Investor decisions were well founded given the two categories' differential performance. The risk-adjusted returns for active investment-grade corporate bond funds were significantly positive before fees and differed insignificantly from zero after fees over 2010–19 and our longer sample period from 2002–19.[1] In contrast, active equity fund risk-adjusted returns differed insignificantly from zero before fees and were significantly negative after fees over both periods.[2]

In this paper, we examine a potential source of pre-fee alpha generated by active corporate bond funds (hereafter bond funds)—a steady flow of new corporate bond issues, which are underpriced on average (see Table 1). Unlike equities, corporate bonds mature and as a result, corporate bond offerings are far more frequent and much larger in total dollar terms than equity

[1] Results are for an equal-weighted portfolio of our sample of active investment-grade corporate bond funds described in Section 2.1. Risk-adjusted returns are computed using model (4) in Section 3.1. Over 2010–19, the risk-adjusted returns averaged 43.0 bps annually (*t*-statistic of 2.58) before fees and -23.0 bps annually (*t*-statistic of -1.37) after fees.

[2] Results are for an equal-weighted portfolio of US active equity funds (excluding sector funds). Risk-adjusted returns are computed using the Carhart (1997) four-factor model. Over 2010–19, risk-adjusted returns averaged -55.2 bps annually (t-statistic of -1.31) before fees and -166.8 bps annually (t-statistic of -3.92) after fees. Our finding that the risk-adjusted returns of active equity funds are insignificantly different from zero before fees is consistent with prior studies such as Cremers and Petajisto (2009) and Amihud and Goyenko (2013).

offerings.[3] The total money left on the table is economically significant, with primary market investors capturing more than $54 billion of corporate bond underpricing from 2002 to 2019.[4] We expect that funds' substantial presence in the bond market positions them to capture a large fraction of first day underpricing profits, providing funds with an important source of alpha. A back of the envelope calculation, assuming funds received allocations proportional to their share of the corporate bond market over 2002 to 2019, suggests that our sample funds potentially captured an average of 20.0 bps of alpha annually from underpricing profits, nearly two thirds of the 33.0 bps of their average pre-fee alpha over the same period.

A challenge we face is proxying for the primary-market allocations that bond funds receive. Prior work (such as Zhu (2021)) has proxied for allocations by using quarter-end corporate bond holdings. We find evidence, though, consistent with heavy trading in new corporate bond issues by mutual funds shortly after the offering date. Funds receiving allocations frequently liquidate the entire position before the next reporting date; funds shut out in the primary market frequently establish a position in the secondary market before the next reporting date. The use of corporate bond holdings to proxy for primary-market allocations is thus problematic.

To circumvent the limitations of using holdings as a proxy, we introduce a novel return-based method to detect mutual funds' primary-market activities. Our method takes advantage of underpriced new issues trading immediately in the secondary market at higher prices than the primary-market offer price. A fund receiving an allocation will capture underpricing on the issue date regardless of whether the new issue is flipped at the higher secondary-market price or held

[3] Over our 2002 to 2019 sample period, corporate bond offerings averaged $1.2 trillion per year versus $42 billion per year for initial public equity offerings and $153 billion per year for seasoned equity offerings. See https://www.sifma.org/resources/archive/research/statistics/.
[4] Our estimation of total underpricing follows the Nikolova and Wang (2022) approach for all corporate bond—both investment grade and high yield—over our sample period.

and marked at the higher secondary-market price when computing its net asset value. First-day profits from underpricing will therefore be reflected in funds' daily risk-adjusted excess returns.

To compute our primary-market allocation measure, we first construct a daily return series based on a portfolio of all new bond offerings on that day. This portfolio, which we call the new bond offering (NBO) index, captures only the first day returns of bonds issued on that day and is reconstituted every day. We then regress each fund's daily risk-adjusted excess returns on the NBO return series over the prior 24 months while controlling for common risk factors. The NBO regression coefficient estimate, which we call the offering return sensitivity (ORS), serves as our empirical proxy for funds' primary-market allocations. A larger ORS suggests that the fund received performance-contributing allocations to a greater extent than other funds.

For our sample of US actively managed investment-grade bond funds from 2002 to 2019, we find evidence consistent with a subset of funds generating considerable alpha from underpriced allocations. Controlling for fund characteristics that prior research has shown to be important determinants of cross-sectional alpha variation, we regress future (next-month) fund risk-adjusted returns on ORS and find coefficient estimates that prove positive and significant. In economic terms, our multivariate analysis shows that the risk-adjusted return of active bond funds in the highest ORS quintile are about 32.2 bps per year higher than those in the lowest. This difference is economically significant given that the average active corporate bond fund generates an annual alpha of 33.0 bps over the same period.

The pattern of excess returns suggests that the allocations are uneven across funds, raising questions about how underwriters allocate typically oversubscribed and underpriced new issues to fund families, and then how families distribute those allocations across member funds. We find evidence consistent with underwriters directing allocations repeatedly to fund families with which they have stronger underwriting relationships. Offering return sensitivities (ORS) are highly persistent and positively related to the fraction of new issue offerings underwritten by top firms with whom the family has a strong prior underwriting relationship. We do not find evidence, however, consistent with underwriters allocating new issue profits to families as payment for information production. Families that possess industry expertise or that score high on the Cici and Zhang (2021) valuation measure—implying they possess better information that results in bond-picking ability—do not receive an outsized share of profitable new issues.

Drilling down to the fund level, we examine whether families strategically distribute their allocations of underpriced new issues across member funds in a way that increases family profitability. Our results suggest that families directed underpricing profits to member funds that underperformed their style peers over the last year at the expense of those that outperformed. Boosting the returns of poorly performing member funds fits with the Goldstein, Jian, and Ng (2017) finding that for bond funds the flow-performance relationship is concave, unlike the convex relationship for equity funds (see Chevalier and Ellison (1997); Sirri and Tufano (1998)). In other words, bond fund investors are more reactive to underperformance than equity fund investors, providing increased motivation for families to stem outflows by moving member bond funds up from the bottom of peer performance lists.

Our study contributes to the recent literature that examines sources of active bond funds' ability to generate risk-adjusted returns before fees. Cici and Zhang (2022) construct a measure that identifies mispriced bonds based on within-firm variation of individual bond's credit spreads and find that the subset of bond funds that hold the highest fraction of underpriced bonds exhibit positive alpha, consistent with bond-picking ability in the secondary market. Anand, Jotikasthira, and Venkataraman (2021) find that a subset of bond funds earns positive alpha by strategically supplying secondary-market liquidity, building positions when dealers face a selling imbalance and unwinding positions when dealers face a buying imbalance. Our evidence adds a primary-market source of outperformance, capturing first-day profits from underpriced new issues.

We also add to the literature that examines how underwriters allocate underpriced corporate bond offerings. Nikolova, Wang, and Wu (2020) present strong evidence that underwriters direct more profitable offerings to insurers with whom they have a stronger trading relationship and weaker evidence for first-day profits being allocated to insurers' that provide information during the book building process. Our evidence is consistent with bond funds receiving more profitable allocations from underwriters with whom they carry on a stronger prior underwriting relationship.

Finally, we add to the literature that examines whether fund families strategically transfer performance across member funds to favor those most likely to increase overall profitability. Examining families of actively managed equity funds, Gaspar, Massa, and Matos (2006) find that families exploit the convex relation between past performance and investor flows by directing underpriced initial public offerings and the favored side of opposite trades to outperforming member funds at the expense of underperforming funds. We too find evidence of favoritism for actively managed bond funds, but of an opposite pattern that maps to the concave performance-flow relationship that describes bond investors' behavior. Specifically, we find that families direct more allocations of underpriced new bond issues to underperforming member funds at the expense of overperforming funds.

2. Data and Methodology

2.1. Data and Sample Construction

Our corporate bond data comes from two sources: the Mergent Fixed Income Securities Database (FISD) and the enhanced version of the Trade Reporting and Compliance Engine (TRACE) Database. From FISD, we collect bond offering information for all investment-grade (IG), U.S. public, U.S.-dollar-denominated, fixed-rate, non-convertible, non-perpetual, corporate debentures ("CDEB") issued during our sample period from July 2002 to December 2019. We remove bonds with missing coupon, offering price, offering date, interest payment frequency, or maturity date. We also exclude Yankee bonds, bonds that are mortgage-backed or asset-backed, preferred securities, bonds with less than one year maturity, and bonds issued as part of an exchange offer. Moreover, for bonds with no credit rating on the offering date, we use its first available credit rating if it is within the first 30 days after the offering, and we remove the bonds with no credit rating available within this time frame.[5] We limit our sample to investment-grade (IG) bonds, excluding high-yield bonds (HY) due to an insufficient number of new offerings during our sample period.[6] Finally, we clean the TRACE data following Dick-Nielsen (2009) and Dick-Nielsen (2014), and use median and reversal filters as in Edwards, Harris, and Piwowar (2007) and Schestag, Schuster, and Uhrig-Homburg (2016) to remove extreme outliers and apparently erroneous entries.[7]

Table 1 provides information about the resulting sample of 8,576 new issues over July 2002 to December 2019. Panel A shows that underpricing profits spiked upwards during the 2007–09 financial crisis, consistent with added enticement for corporate bond buyers in a difficult credit

[5] For credit ratings, we primarily use Standard & Poor's (S&P) ratings, and only use Moody's or Fitch ratings in case of missing S&P ratings. Specifically, we classify all investment grade bonds into 10 categories by their credit ratings: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-. We then define a CR variable, which takes the value of 1 for the first category, 2 for the second category, and so forth. Higher CR values mean lower credit quality.

[6] New HY offerings for which we could compute first-day returns averaged 54 per year and were as few as 10 in a year. The limited number of offerings was not sufficient for the daily returns-based measure, described later, that we use to detect allocations.

[7] We also correct a small number of erroneous entries with obviously misplaced decimal points.

market. From 2010 onward, the level of new issues and underpricing stayed at an elevated level relative to before 2006. New issues were underpriced by a total of about $31 billion over the sample period. Panel B shows descriptive statistics for our bond sample. Although the total underpricing is economically large, underpricing for individual issues averaged 28 basis points.

Our mutual fund data come from two sources. From Morningstar, we collect fund daily returns and portfolio holdings for both live and dead funds from July 2002 to December 2019. From the CRSP mutual fund (CRSP MF) database, we gather other fund characteristics including fund size, expense ratio, and turnover ratio. We merge the two databases using fund tickers and CUSIPs. We chose to use daily returns from Mornigstar rather than from CRSP MF because CRSP MF treats coupon payments that a bond fund receives during the month as if occurring on its last day for daily return calculations.

Next, we select a comprehensive list of US actively managed investment-grade corporate bond funds using CRSP objective codes and Morningstar categories.[8] To avoid misclassification by CRSP and Morningstar, we require each sample fund to invest, on average, at least 30% of its portfolio in corporate bonds over at least four Morningstar portfolio observations during the sample period (e.g., Anand et al. (2021)). We further exclude funds that invest on average more than 50% of their corporate bond portfolio in HY bonds as in Cici and Gibson (2012) and remove observations with fund flows 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)). Finally, to avoid incubation bias, we exclude observations before a fund's TNA reaches five million dollars and its age reaches 12 months as in Evans (2010).

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

Table 2 provides information about the resulting sample of 338 active investment-grade bond funds. Fund age, net flows, expense ratios, turnover ratios, size, and family size all exhibit considerable variation, underscoring the need for controls in our empirical design. Also showing considerable variation are two measures that prior research has linked to fund performance: the Valuation Accuracy Score of Cici and Zhang (2021), which is higher for funds with better valuation skills, and the Liquidity Score of Anand et al. (2021), which is higher for funds that profit from providing liquidity.

2.2. Methodology

2.2.1. Limitations of Using Holdings to Identify Primary-Market Allocations

Our goal is to identify bond allocations to mutual funds in the primary market. Prior work such as Zhu (2021) uses portfolio quarter-end holdings to proxy for allocations received by individual funds for bonds issued anytime during the quarter. For example, if at quarter-end, a fund holds a certain par value of a bond that was issued sometime during that quarter, a holdings-based approach assumes that the fund received an allocation equal to that par value in the primary market. However, this will be a noisy measure if secondary-market trading takes place between the offering and the quarter-end.

To illustrate just how noisy this holdings-based proxy for bond allocations is, we focus on new issues that occurred on the last day of funds' reporting periods. Funds' reported holdings of these new issues will only differ from their primary-market allocation by the net secondary-market trading on the day of the offering, which we cannot observe, but nonetheless this is the most accurate read on allocations possible given mutual funds' monthly or quarterly reporting of holding snapshots.

We then track the secondary market trading in these new issues using subsequent holdings reports. For example, consider a fund that reports holdings to Morningstar monthly and a new bond issue with a June 30 offering date. Suppose the fund reports that it held $2.4 million par value of the new bond issue on June 30th and $1.4 million on July 31st. We can infer that the fund sold $1 million of the bond in the secondary market during the one-month window. Alternatively suppose the fund reports that it did not hold the bond on June 30th and $1.7 million on July 31st. We can infer that the fund bought $1.7 million of the bond in the secondary market during the one-month window.

Panel A of Table 3 reports results for the subset of 151 funds that reported holdings monthly and the 212 offerings that occurred on the last trading day of the month. We track secondary market trading in the new issues over one-, two-, and three-month widows and categorize it in five ways: buying on the offering day with no subsequent secondary-market trading during the window, buying on the offering day with a partial sale, buying on the offering day with full liquidation, buying on the offering day with additional buying, and no buying on the offering day but establishing a position during the window.

The one-month results in the first column show that among funds that held a new issue either at the beginning or end of the month, only 41.86% held the issue on the offering date and did not engage in secondary market trading during the subsequent month. Presuming no first-day trading, this means that using holdings one month from the offering date to proxy for allocations would have been accurate only 41.86% of the time. The true accurate read on allocations would be even less when first-day trading is accounted for.[9] Funds received an allocation but liquidated

[9] The problem of using holdings to proxy for new issue allocations indicated by the Table 3 results is likely understated because first-day secondary market trading is excluded. Suggesting that such trading is material, Nikolova and Wang (2022), using detailed trade-level data available only for insurance companies, find that insurers collectively sell 6% of allocations within two days.

the position completely at some point during the subsequent month 10.64% of the time. Funds received no allocation and established a position in the secondary market 38.82% of the time. Holdings serve as an even poorer proxy for new issue allocations if we move to longer two- and three-month windows.

Panel B of Table 3 tells a similar story for the 136 funds that reported holdings quarterly and the 42 offerings that occurred on the last trading day of the quarter. The subsequent quarter holdings provided a precise read of the new issue allocation at the beginning of the quarter less than 31% of the time. More than 21% of the time funds received an allocation but liquidated the position completely during the quarter. More than a third of the time funds received no allocation but established a position in the secondary market.

2.3.2 Return-Based Method to Detect Primary Allocations to Mutual Funds

To circumvent the limitations of detecting mutual funds' primary-market allocations of corporate bonds with the holdings-based method, we introduce a novel return-based method. The intuition is straightforward. Consider a fund that actively participates in the primary market for corporate bond offerings and consistently receives allocations. Since corporate bond offerings are systematically underpriced (Cai, Helwege, and Warga (2007) and Nikolova et al. (2020)), the immediate secondary-market price run-up of bonds that the fund acquires in the primary market should be reflected in the fund return on the offering day. This should hold even if the fund chooses to sell the offerings in the secondary market. Thus, the fund return should have a high sensitivity to the secondary-market performance of the corporate bond offerings on offering dates. A stronger sensitivity indicates that the fund receives primary-market allocations to a higher degree.

To implement our idea, we first construct a new bond offering (NBO) index, which tracks the daily secondary-market performance of corporate bond offerings on the offering day. Next, we use the coefficient estimated from regressing fund daily excess returns on the returns of the NBO index as our empirical proxy for funds' primary-market allocations.

The NBO index captures the average first-day return of all corporate bond offerings relative to their primary-market offering prices. To construct its daily return, we first calculate for each sample bond offering its secondary-market clean price as the trading volume-weighted average of intraday TRACE prices after excluding retail-sized trades less than $100,000 as in Bessembinder, Kahle, Maxwell, and Xu (2009). Next, following Cai et al. (2007), for each bond offering *i* issued on day *t*, we calculate its offering-day raw return as the percentage change from the offering price to the secondary-market price using the following:

$$Ret_{i,t} = \frac{P_{i,t} + AI_{i,t} - OP_{i,t}}{OP_{i,t}} \qquad (1)$$

where $P_{i,t}$ is bond *i*'s secondary-market price on the offering day *t*, $AI_{i,t}$ is bond *i*'s accrued interest on day *t*, and $OP_{i,t}$ is the offering price. If a bond has no secondary-market trade on the offering day *t*, then we use its secondary-market price on day *t*+1 for the above calculation. We remove offering observations without any secondary-market trade on day *t* or *t*+1.

Finally, since funds are more likely to get an allocation for large offerings, the return of the NBO index on day *t* is calculated as the market-cap-weighted average of all offerings' first-day raw returns on day *d* minus the risk-free return according to the following:

$$NBO_d = \begin{cases} \frac{\$\sum_{i=1}^{n}(Offering\_Amt_{i,d} \times Ret_{i,d})}{\$\sum_{i=1}^{n} Offering\_Amt_{i,d}} - R_{f,d}, & if\ \$\sum_{i=1}^{n} Offering\_Amt_{i,d} > 0 \\ 0 &, if\ \$\sum_{i=1}^{n} Offering\_Amt_{i,d} = 0 \end{cases} \qquad (2)$$

where $Offering\_Amt_{i,t}$ is bond i's offering amount on day d. The daily return series of the bond offering index tracks the secondary-market performance of all corporate bond offerings relative to their primary-market offering prices on their offering date.

To identify funds that consistently get primary-market allocations for corporate bond offerings, our novel return-based measure exploits the sensitivity of the fund daily return to the NBO index while controlling for other risk factors that can drive fund returns. If a fund consistently receives allocations, its return ought to exhibit a strong sensitivity to the return of the NBO index.

Specifically, at the end of each month t for fund i, we estimate the following time-series regression using daily observations that fall within a 24-month rolling window (a minimum of 18 months with non-missing returns is required) ending on the last day of month t:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_{i,NBO}NBO_d + \beta_{i,STK}STK_d + \beta_{i,BOND}BOND_d + \beta_{i,DEF}DEF_d + \beta_{i,OPTION}OPTION_d + \varepsilon_{i,d} \qquad (3)$$

where $R_{i,d}$ is the fund return during day d, $R_{f,d}$ is the risk-free rate based on the one-month treasury bill rate, STK_d is the excess return of the CRSP value-weighted stock index, $BOND_d$ is the excess return of the Bloomberg Barclays Aggregate Bond Index, DEF_d is the default factor measured as the return difference between the Bloomberg Barclays US Corporate High Yield Index and the Bloomberg Barclays US Intermediate Government Index, and $OPTION_d$ is the option factor calculated as the return spread between the Bloomberg Barclays U.S. GNMA Bond Index and the Bloomberg Barclays US Intermediate Government Index. All the terms in equation (3) are measured at a daily frequency.

We use $\beta_{i,NBO}$, which we refer to as the "offering return sensitivity" (ORS) estimated from a 24-month window that ends at the end of month t, as our empirical measure for funds' primary-market allocations. Intuitively, a high ORS indicates that the fund return is highly sensitive to the immediate secondary-market performance of corporate bond offerings, whereas a low ORS suggests that the fund return is insensitive to the performance of corporate bond offerings. Therefore, funds with a high ORS are more likely to have consistently received meaningful allocations in the primary market compared to funds with a low *ORS*.

3. ***Bond Primary Allocations and Fund Performance***

In this section, we examine whether bond funds that receive more primary allocations exhibit better future fund performance while controlling for fund characteristics that have been previously documented to affect fund performance. We first document our main result and then conduct several robustness tests.

3.1. Main Result

The key dependent variable for our main analysis is an alpha measure for each fund-month pair computed as the actual fund gross return minus its expected return in that month. To estimate the expected return in each month, we first estimate the following monthly four-factor model over the previous 36 months (a minimum of 30 months with non-missing returns is required) to estimate factor betas:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,STK} STK_t + \beta_{i,BOND} BOND_t + \beta_{i,DEF} DEF_t + \beta_{i,OPTION} OPTION_t + \varepsilon_{i,t} \quad (4)$$

where $R_{i,t}$ is the gross return of fund *i* in month *t*, which we base on the fund net-of-fee return plus one-twelfth of the total expense ratio, and $R_{f,t}$ is the one-month treasury bill rate. The construction of the factors is provided in the description of equation (2) except that their returns are at the monthly frequency.

Next, we compute the fund expected return in each month by summing the products of factor realizations in that month and factor betas which we estimate over the previous 36 months.

To examine the relation between fund performance and offering return beta, we estimate the following regression model:

$$\alpha_{i,t+1} = \beta_{ORS} ORS_{i,t} + \gamma' \boldsymbol{X_{i,t}} + \varepsilon_{i,t} \qquad (5)$$

where $\alpha_{i,t+1}$ is fund i 's gross alpha during month *t+1*; $ORS_{i,t}$ is the offering return sensitivity at the end of month t estimated as described in Section 2.3.2; and $X_{i,t}$ is a vector of fund control variables. We control for performance advantages that certain funds have due to previously documented sources of skill. Specifically, we include the Valuation Accuracy Score of Cici and Zhang (2021) (VAS), which is higher for funds with better valuation skills, and the liquidity score of Anand et al. (2021) (LiqScore), which is higher for funds that profit from providing liquidity. The vector of control variables, $X_{i,t}$, includes the natural logarithm of fund total net assets (TNA), natural logarithm of the value of corporate bond holdings held by the fund's family (FmSz), natural logarithm of fund age measured in years (Age), monthly net flow ratio (Flow), expense ratio (Exp), and annual turnover ratio of the prior year (TO). We include style-by-month fixed effects to control for unobservable style-specific effects in each period. Standard errors are clustered by fund.

Table 4 reports results from the estimation of Equation (5). The key independent variable is either ORS or its quintile rank, ORS Quintile, which we use to account for the possibility that ORS is related in a non-linear way to performance and to illustrate economic significance. The results suggest a significant relation between both ORS and ORS Quintile and future fund performance at the 1% significance level. This predictive power is economically significant, as illustrated by the coefficients of the last specification, with funds in the top ORS quintile outperforming funds in the bottom quintile by 2.7 bps (0.67 * 4) over the next month, which translates to 32.2 bps per year (2.7 * 12). This is economically significant since the average annualized gross alpha for our active bond fund sample is 33.0 bps per year.

A comparison of the specifications with and without controls shows little change in the coefficient magnitudes of ORS or ORS Quintile. Thus, controlling for other sources of ability or fund characteristics does not affect our inference that some funds are able to generate alpha by receiving bond allocations in the primary market. This further suggests that enhancing performance through participation in the primary market allocations is orthogonal to other known factors that drive performance.

3.2. Robustness

3.2.1. Bootstrap Analysis

It is possible that our approach for constructing ORS gives rise to a spurious relation between ORS and future fund performance. Perhaps high-ORS funds have persistent outperformance and their returns move coincidentally with the first-day returns of newly issued bonds.

To address this, we perform a bootstrap procedure where we randomly draw with replacement from the actual sample of 4,407 daily returns of the bond offering index during our sample period and assign these values randomly to actual dates that are covered by the bond offering index. This approach creates a simulated bond offering index for each random draw, which we then use to estimate the simulated ORS measure for all fund-months as we do in our original setup and then estimate panel regressions based on the specification of Column (2) or Column (4) of Table 4 to obtain the coefficient of the simulated ORS or ORS Quintile measures. Since this approach assigns timestamps from the bond offering index to actual daily index returns in a random fashion, by construction it imposes the null hypothesis of no performance effect due to primary market allocations.

Figures 2a and 2b, respectively, display the distribution of coefficients of simulated ORS and ORS Quintile. We observe that the actual coefficients from Columns (2) and (4) of Table 4 are located at the right-hand tail of the bootstrap distributions, being significantly greater than the mean of the bootstrap distribution generated under the null of no primary allocation effect on fund performance (respectively, p-values of 0.029 and 0.042). This rejects the null in favor of our hypothesis that funds receiving corporate bond allocations in the primary market benefit and exhibit higher risk-adjusted returns, providing confidence that the results of Table 4 are not spurious.

3.2.2. Robustness Tests

We conduct several tests to confirm that our results do not depend on how we measure our dependent variable or our key independent variable. In the interest of brevity, here and in the rest of the paper, we report results based only on ORS Quintile; however, results are similar when we use the continuous version of ORS. In Columns (1) through (3) of Table 5, we estimate Equation (5) using alternative measures for the dependent variable, i.e., fund performance, while all the independent variables are the same as in Table 4. Specifically, we replace our dependent variable with the alpha estimated based on net-of-fee returns in Column (1), alpha estimated based on a 24-month rolling window in Columns (2), and alpha estimated based on the 4-factor model of Bai, Bali, and Wen (2019) in Column (3).

We also introduce several methodological modifications in terms of how we measure ORS and report estimation results for Equation (5)—based on the resulting alternative measures—in Columns (4) through (6). In Column (4) we replace our original ORS measure with its precision-adjusted version, which is the original ORS divided by its standard error computed from estimating Equation (3). We do this to account for differences in the precision of ORS due to differences in residual variance across funds. In Column (5), ORS is estimated over the prior 12 months instead of the previous 24 months. The ORS version used in Column (6) is based on a modified NBO index that reflects the total dollar amount of underpricing of newly issued bonds on a given day. Thus, in addition to the first-day return, which we use in the original NBO index, we also incorporate the amount of the offering. With this approach we place small offerings with significant underpricing and large offerings with small underpricing on an equal footing. The value of this modified NBO index for a given day is constructed as the total underpricing-related dollar profit of all bonds issued on that day scaled by total TNA of all funds at the beginning of the month. Underpricing-related profit of a bond issue is calculated as the product of the offering amount and first-day return. Finally, to control for unobserved fund heterogeneity, Column (7) includes fund fixed effects to the specification corresponding to Column (2) of Table 4.

The results reported in Table 5 are like those of Table 4, suggesting that our results are robust to the various methodological modifications described above.

3.2.3. Calendar Portfolio Approach

In this section, we check the robustness of our results generated by the approach of Model (5) against a calendar-time portfolio approach. At the end of each month, we rank all funds within each investment style into quintiles based on their ORS measure estimated as of the end of that month. Funds in each quintile are placed into a single portfolio and their returns are measured over the next month. The same ranking procedure and portfolio updating is repeated every month. For each quintile portfolio we construct a monthly return series, which we then evaluate using Model (4). We report results separately based on net-of-fee and gross portfolio returns which have been equal-weighted across all portfolio funds or value-weighted by fund assets at the beginning of the month.

Performance results for the ORS quintile portfolios and corresponding Newey-West (1987) adjusted *t*-statistics are reported in Table 6. Next-month portfolio alphas increase with ORS, and high-ORS (top quintile) funds significantly outperform low-ORS (bottom quintile) funds by 9 to 12 bps per month. These differences between the top and bottom ORS quintile are much greater than those inferred by Table 5; however, the portfolio approach does not account for fund characteristics as Table 5 does. Nonetheless, these results provide additional evidence of robustness.

4. Allocation Channels

Our evidence so far suggests that certain bond funds receive bond allocations in the primary market to a greater extent than other funds and this has a positive effect on their performance. In this section, we investigate the sources of these advantages. Like equity IPOs, bond offerings in the primary market are allocated by the lead underwriter to the family/advisor, who then decides how to allocate the proceeds across member funds. Therefore, we first examine the forces that drive the allocation to the fund family and then from the family to the individual funds.

4.1. Primary Allocations to Fund Families

Our analysis of the primary allocations to fund families draws on previous research from the equity IPO literature. Traditional bookbuilding theories (e.g., Benveniste and Spindt (1989)) argue that underwriters reward regular investors with underpriced equity IPO allocations for truthfully sharing information regarding their demand for the offering and for accepting overpriced allocations. The alternative favoritism/profit sharing view posits that underwriters use underpriced allocations as part of quid pro quo arrangements that reward investors with whom they have strong business relationships (e.g., Loughran and Ritter (2002)). To examine both theories, we introduce proxies for information production by fund families and for prior underwriting relationships between fund families and lead underwriters.

4.1.1. Information Production and Prior Underwriting Relationship Proxies

We introduce two proxies for the information production of fund families. The first information production proxy is based on the idea that fund families with expertise in the industry from which a new bond offering is originating might provide valuable information to the underwriters. To construct this proxy, we proceed as follows. Every quarter we aggregate all the issues from the NBO index that were offered during that quarter and place them in a large portfolio. For each offering we identify its industry based on the first two digits of its SIC code and then use the offering amounts to construct weights for each industry. Similarly, we construct industry weights for the aggregated portfolio of each family at the beginning of the quarter. We then construct the information production proxy as follows:

$$Ind\_Exp_t^f = \sum_{j=1}^{N_t} Weight_{j,t-1}^f \times Weight_{j,t}^{NBO} \quad (6)$$

where $Weight_{j,t}^{NBO}$ is the weight of industry j in the aggregated NBO portfolio for quarter t and $Weight_{j,t-1}^f$ is the weight of industry j in the aggregated portfolio of family f at the end of quarter t-1.[10]

[10] Although our proxy is like that of Nikolova et al. (2020) for insurance companies, which is based on portfolio weights in a single industry, our methodological setup relies on multiple issue offerings and thus we need to consider multiple industries at the same time.

The second information production proxy is the VAS measure of Cici and Zhang (2022), which we compute at the fund level each month or quarter (depending on the frequency of holdings reports). The VAS measure is higher for funds that hold a higher (lower) fraction of undervalued (overvalued) bonds in their portfolio, which implies that they possess bond-picking ability.[11] Cici and Zhang (2022) show that high-VAS funds have general bond-picking ability, thus we deem it a reasonable proxy for information production. To arrive at a family VAS measure, we average the VAS scores of all individual corporate bond funds belonging to a fund family with weights determined by their fund assets lagged by one month. We cannot observe the information that underwriters obtain from fund families regarding specific issue offerings, but whatever private information families with better valuation skills (higher VAS) provide to underwriters, we expect it to be of higher quality and therefore more valuable to the underwriter.

Our proxy for relationships that fund families have with lead underwriters, *Underwriting Relationship*, is constructed following a multi-step procedure: First, we identify the top three lead underwriters of corporate bonds over the last 24 months based on their total dollar amount of new issues underwritten. Next, we determine whether each family had a significant relationship with each of the top three underwriters during the same period. To do so, we first create three alternative versions of the NBO index over the previous 24 months (a minimum of 18 months of non-missing returns are required) based only on the new issues underwritten by each top underwriter. Then, we use these alternative NBO indexes and aggregated daily returns for each family to estimate return-based ORS measures for each family and each index. If a family had an underwriting relation with a given top underwriter, then we expect the family to have a positive and significant ORS with the NBO index of that underwriter. Specifically, we consider an underwriter to have a significant

[11] To identify mispriced bonds, Cici and Zhang (2022) exploit within-firm variation of individual bond's credit spreads.

relationship with family *f* over this period if its ORS with this underwriter's NBO index is significantly positive (p-value ≤ 0.10). Finally, for each fund family *f* we construct *Underwriting Relation* by measuring the fraction of the dollar amount of new offerings in the next 24-month period (a minimum of 18 months of non-missing returns are required) were underwritten by underwriters with which family *f* had a significant relation. For example, if two of the top three underwriters had a significant relationship with family *f* in the previous 24-month period and they underwrite $2B of the new issues in the next 24 months out of a total of $10B new issue offerings, then the *Underwriting Relation* of family *f* in the next 24-month period would be $2B/$10B = 20%. To the extent that a fund family has an underwriting relation with certain top underwriters, then this family should receive more allocations in the subsequent period when those underwriters underwrite a larger fraction of the new issue offerings.

4.1.2. Determinants of Primary Allocations to Fund Families

To examine whether primary allocations to fund families are related to our proxies for information production and prior underwriting relationships with the underwriters, we estimate the following regression equation:

$$ORS\ Quintile^{f}_{[t+1,t+24]} = \beta_I Information\ Production^{f} +$$
$$\beta_R Underwring\ Relation^{f}_{[t+1,t+24]} + ORS^{f}_{[t-23\ ,t]} + \delta' X^{f}_{t} + \varepsilon^{f}_{t} \quad (7)$$

where $ORS\ Quintile^{f}_{[t+1,t+24]}$ is the offering return sensitivity quintile of family *f* estimated using the daily returns of the aggregated family portfolio over the subsequent 24 months; $Information\ Production^{f}$ is either $Ind\_Exp^{f}_{[t]}$, which is the information production proxy constructed for family *f* using equation (6), averaged over the eight quarters over the subsequent

24 months, or VAS_t^f, which is the family VAS described in the previous section, measured based on the most recent holdings records as of time t (no more than 12 months ago); and $Underwring\ Relation_{[t+1,t+24]}^f$ is the underwriting relationship proxy between family *f* and top underwriters constructed as described in the previous section. The vector of control variables, X_t^f, includes family size, computed by aggregating the assets of all corporate bond funds in the family; flows; expense ratios; and turnover ratios averaged across all bond funds in the family and weighted by fund assets in the previous month. We also include time fixed effects and cluster standard errors by family.

Table 7 reports coefficients estimated from equation (7). For comparison, the specification in column (1) includes all independent variables from equation (7) except for the key proxy variables. The positive and significant coefficient on the lagged value of ORS suggests that certain families are favored by underwriters to receive performance-improving primary allocations on a consistent basis. In columns (2) and (3) where we respectively include the two information production proxy variables, we find an insignificant relation between the family ORS and those variables. However, in column (4) we find a significant relation with the *Underwriting Relation* variable, suggesting that families that have an underwriting relationship with the top underwriters are more likely to receive primary allocations.

If business considerations on the part of the underwriters is a cause of these underwriting relationships, then we would expect this effect to be more pronounced for larger families. The idea is that larger families constitute potentially lucrative customers whose larger trading activity could be a major source of commission revenue for underwriters. To examine this possibility, in column (5) we add an additional variable interacting *Underwriting Relation* with family size. The positive and significant coefficient on this interaction term and the insignificant coefficient on

Underwriting Relation suggests that business considerations on the part of the underwriters primarily drive the allocation of primary allocation to fund families. Our evidence is overall consistent with Nikolova et al. (2020) finding that underwriters tend to favor insurance companies with whom they have business relations.

4.2. Primary Allocations to Individual Funds

Having documented how certain families receive primary allocations to a greater extent than other families, we now examine how fund families direct their received share of these primary allocations to individual family funds. Focusing on equity funds, Gaspar et al. (2006) document that families tend to favor "high-value" funds from which they extract more fee revenue with underpriced equity IPOs at the expense of other, "low-value" funds. We examine whether similar patterns of favoritism extend to corporate bond funds when families decide how to allocate their corporate bond allocations received in the primary market.

This investigation hinges on being able to identify which corporate bond funds the family views as "high-value" funds. We consider measures introduced by previous research while at the same time relying on features of corporate bond funds that are different from those of equity funds. Gaspar et al. (2006) show that funds with higher fees, better performance, and younger age have their performance subsidized by their fund families at the expense of other family funds. The argument is that, holding fund assets constant, higher-fee funds will generate even more revenue for the family if their performance, and consequently their assets, are subsidized to a higher level. Regarding the performance dimension, since the flow-performance relation for equity funds is convex (Sirri and Tufano (1998)), fund families will seek to subsidize the performance of their high-performing equity funds to attract more flows, grow assets, and extract higher fees. Along the same lines, since the flow-performance relation for equity funds is more convex for young funds than old funds—based on the idea that investors use past performance of younger funds more heavily to assess ability (Chevalier and Ellison (1997))—then families have an incentive to subsidize the performance of younger funds.

Building upon these ideas, we consider unique features of corporate bond funds that may affect how families think about performance subsidization of these funds. In contrast to the convex flow-performance relation of equity funds, the flow-performance relation for corporate bond funds is concave (Goldstein et al. (2017)). This means that, unlike the favoritism pattern documented for equity funds, fund families would prefer to subsidize corporate bond funds with poor past performance to stem outflows to avoid shrinking assets.[12] Another consideration is that the flow-performance relation of corporate bond funds as a function of fund age is also different for corporate bond funds relative to equity funds. In particular, the flow-performance relation is more concave for younger funds among bond funds (Goldstein et al. (2017)), but more convex for younger funds among equity funds (Chevalier and Ellison (1997)). This suggests that families would prefer to subsidize younger corporate bonds funds to avoid poor performance and control outflows. Thus, although subsidizing younger funds might make sense both for corporate bond and equity funds, the rationale behind the strategy is different. Families would want to capitalize on the more convex flow-performance relation of young equity funds to attract more flows but manage the more concave flow-performance relation of younger corporate bond funds to minimize outflows.

Based on these considerations, we identify a bond fund as high-value along three dimensions if it has: an expense ratio above the median expense ratio of all bond funds in the same

[12] If the family has an outperforming fund and an underperforming fund relative to their style peers, the family gains more by subsidizing the underperforming fund than the outperforming fund because the reduction in outflows of the underperforming fund due to subsidization would surpass the increase in flows of the outperforming fund due to subsidization.

family (*HV_Expense*), past 12-month returns below the median performance of all funds operating in the same investment style (*HV_Performance*) [13]; or age below the median age of all family bond funds (*HV_Age*).

Next, to examine whether favoritism plays a role in how families allocate their share of primary market corporate bond offerings to their member funds, we estimate the following:

$$ORS\ Quintile_{i,[t+1,t+24]} = \beta_{HV} HV\_Dimension_{i,t} + \beta_{HV} ORS\ Quintile^{f}_{i,[t-23,t]} + \gamma' \boldsymbol{X_{i,t}} + \varepsilon^{f}_{t} \quad (8)$$

where $ORS\ Quintile_{i,[t+1,t+24]}$ is the offering return sensitivity of fund *i* estimated based on its daily returns over months *[t+1, t+24]*, $ORS\ Quintile^{f}_{i,[t-23,t]}$ is the offering return sensitivity of family *f* to which fund *i* belongs, $HV\_Dimension_{i,t}$ is one of the measures identifying high-value funds as described above, and $X_{i,t}$ is the vector of fund control variables described in Section 3.1. To ensure sufficient variation for identifying high- and low- corporate bond funds, we estimate equation (8) for the subset of corporate bond funds belonging to fund families with at least two corporate bond funds, which reduces the number of families in the sample by 94 to 83. Again, we include style by fund fixed effects and cluster standard errors by fund.

Results from the estimation of equation (8) are presented in Table 8. The offering return sensitivity at the fund level over the next 24 months is positively related to the offering return sensitivity of its fund family measured over the previous 24 months. As expected, this suggests that, on average, a member fund is more likely to receive primary market allocations when its family received allocations in the past.

[13] Results are robust when we use year-to-date returns as opposed to 12-month returns for the construction of this measure.

When we introduce the three variables proxying for whether a fund is a high-value fund relative to other funds in the family, we find that the coefficient on *HV_Performance* is positive and statistically significant while the coefficients on *HV_Expense* and *HV_Age* are both insignificant. The small number of bond funds offered by the average family (2.74 funds per family) may contribute to diminished power in detecting a relation between *ORS* and *HV_Expense* and *HV_Age*. The reason being that these two variables are constructed by ranking bond funds within each family whereby the small number of funds per family generates little within-family variation.

The positive and significant coefficient on *HV_Performance* is evidence of intra-family favoritism for actively managed bond funds whereby families direct more allocations of underpriced new bond issues to underperforming member funds at the expense of overperforming funds. This is a sensible strategy from the perspective of a profit maximizing family in response to the concavity of the flow-performance relation among such funds and is different from the subsidizing strategy that families pursue for equity funds. The fact that families are subsidizing underperforming bond funds is also encouraging in that it suggests that fund families serve a positive role of mitigating the type of fragility in the corporate bond market analyzed by Goldstein et al. (2017).

5. Conclusion

The growing popularity of active corporate bond funds and their ability to generate positive pre-fee alpha motivates us to study a potential source of this outperformance—the allocation of underpriced new issues. Our study highlights differences between active corporate bond mutual funds and active equity mutual funds that stem from the diverging characteristics of the markets in which they participate. First, unlike equities, corporate bonds mature and often are replaced with new issues. Underpriced new corporate bond offerings are thus far more frequent and much larger in total dollar terms than equity offerings. Using a novel return-based method to detect funds' primary-market activities, we find evidence that points to this steady stream of underpricing profits being a source of the pre-fee alpha that bond funds generate on average, a pre-fee alpha that is absent for equity funds.

Second, the fundamental value of corporate bonds, particularly investment grade bonds, is much less sensitive than equities to differences in firms' pro forma free cash flow projections. Corporate bondholders' claim on free cash flows is fixed whereas stockholders' claim is residual. Bondholder payoffs are invariant in pro forma scenarios where free cash flows are sufficient to meet coupons and par payments at maturity; only payouts in default scenarios are in question. Smart money institutional investors therefore bring relatively little price discovery information to new bond issues vis-à-vis equity initial public offerings. Consistent with this view, we find no evidence of bond funds receiving allocations consistent with traditional bookbuilding theories (e.g., Benveniste and Spindt (1989)) that posit underwriters reward regular investors with underpricing for truthfully sharing price discovery information. We do however find evidence consistent with underwriters using underpriced allocations as part of quid pro quo arrangements that reward investors with whom they have strong business relationships (e.g., Loughran and Ritter (2002)).

Third, active corporate bond and equity fund clienteles react differently to past performance. Prior research suggests that the flow-performance relation for equity funds is convex (e.g., Sirri and Tufano (1998)), and that fund families subsidize the performance of their high-performing equity funds to attract more flows, grow assets, and extract higher fees (e.g., Gaspar et al. (2006)). In contrast, prior research shows that the flow-performance relation for corporate bond funds is concave (e.g., Goldstein et al. (2017)). Consistent with this bond fund investor behavior, our evidence suggests families maximize profitability by strategically distributing allocations to member funds that underperformed their style benchmark over the last year at the expense of those that outperformed.

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Figure 1: Net Investor Flows for Active Equity Funds and Active Corporate Bond Funds

This figure reports cumulative flows aggregated separately for active equity and corporate bond mutual funds during 2010-2019. Fund-level annual flows are obtained from Morningstar.

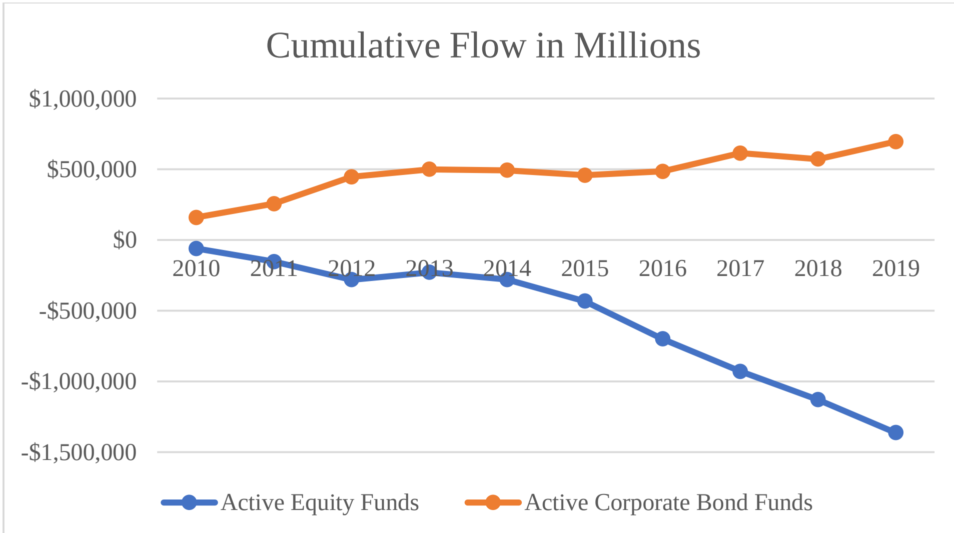

Figure 2: Coefficient of the Bootstrapped ORS Measure in the Panel Regression

This figure illustrates the bootstrapped distribution of regression coefficients of the simulated offering return sensitivity (ORS) from Equation 5 based on 1000 simulated new bond offering (NBO) indices. In each of the 1,000 iterations, we first construct a simulated NBO index by randomly drawing daily returns with replacement from the original NBO index and assigning these simulated values to actual dates that are covered by the original NBO index. Next, we re-estimate each fund's simulated ORS according to the simulated NBO index. Then, we estimate Equation 5, using the same specification as in Column [2] or [4] of Table 4 to obtain the coefficients of the simulated ORS or ORS Quintile measures. Finally, we plot the distribution of the simulated coefficients of ORS and ORS quintile measures in Figure 2a and Figure 2b, respectively.

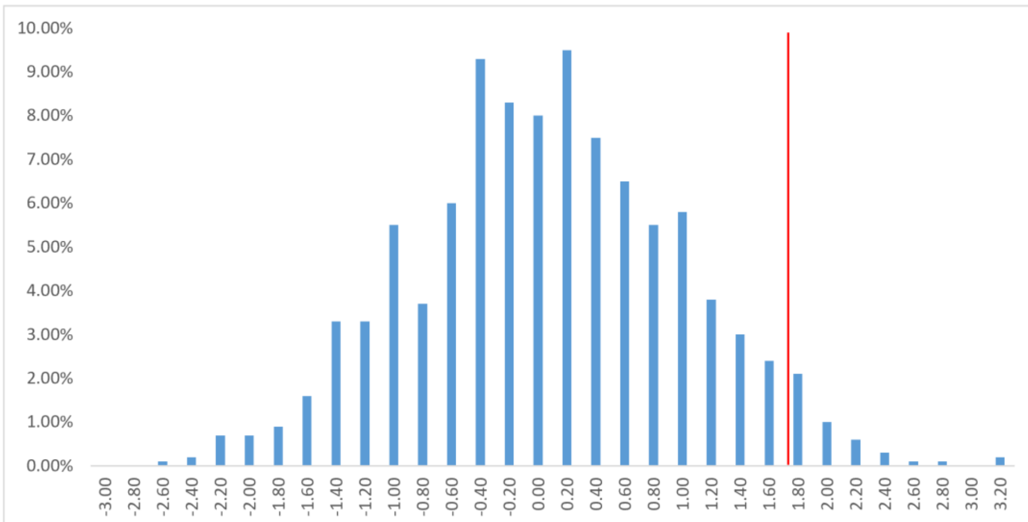

Figure 2a

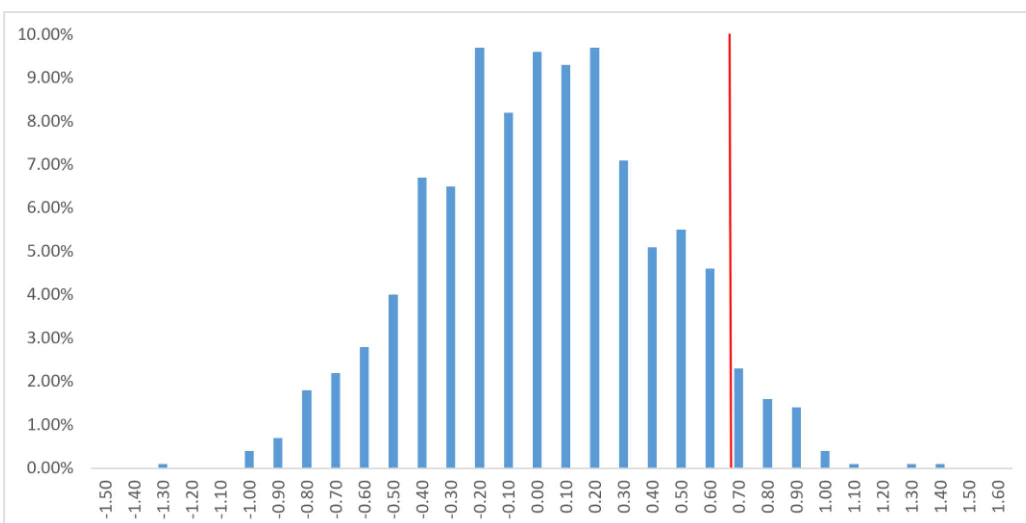

Figure 2b

Table 1: Descriptive Statistics of the Corporate Bond Sample

Panel A reports summary statistics of the sample of 8,576 investment-grade corporate bond offerings during 2002-2019. Profit is calculated as the product of the average underpricing and the total par value of the offerings. If there are secondary market trades on the offering date, then underpricing of a bond is defined as the percentage change from the offering price to the secondary-market price on the offering date; otherwise, underpricing is defined as the percentage change from the offering price to the first available secondary-market price within two days, with accrued interest and market movements adjusted. Daily bond returns with a magnitude > 30% are considered as erroneous and are removed. Bond-days with less than 1 year maturity left are removed. Panel B reports summary statistics of the bond sample used to construct the bond offering index. OfrAmt is the bond offering amount; CR is the bond credit rating ranging from 1-21; TTM is time to maturity at offering in years; UP is the new issue underpricing; and profit is the product of the new issue underpricing and the offering amount.

Panel A: New issue underpricing by year.

	N	Average UP (bps)	Par value ($M)	Profits ($M)
2002	129	20.43	$116,319	$238
2003	369	17.06	$331,365	$565
2004	253	12.40	$281,520	$349
2005	210	9.23	$292,936	$270
2006	301	19.52	$397,815	$777
2007	316	31.23	$455,000	$1,421
2008	307	56.93	$426,310	$2,427
2009	461	74.31	$716,582	$5,325
2010	438	34.82	$516,665	$1,799
2011	477	32.97	$532,730	$1,756
2012	601	39.27	$693,953	$2,725
2013	629	32.21	$671,874	$2,164
2014	687	18.95	$699,529	$1,326
2015	720	26.42	$905,164	$2,391
2016	657	27.60	$920,323	$2,540
2017	751	16.51	$964,417	$1,593
2018	633	18.01	$848,969	$1,529
2019	637	21.80	$835,475	$1,821
2002-2019	8,576	28.31	$10,606,944	$30,778

Panel B: Summary statistics of bond sample for the bond offering index.

	Mean	Std. Dev.	P5	Median	P95
OfrAmt ($M)	727	658	250	500	2,000
CR	7.23	2.15	3.00	8.00	10.00
TTM	12.46	10.33	3.01	10.02	30.06
UP (%)	0.28	0.53	-0.13	0.17	1.16
Profit ($M)	2.31	11.73	-0.38	0.88	8.44

Table 2. Descriptive Statistics of the Corporate Bond Fund Sample

This table reports summary statistics of the sample of 338 investment-grade corporate bond mutual funds. TNA is fund total net asset, TO is fund annual turnover ratio; EXP is fund expense ratio, Age is fund age measured in years, Flow is the monthly net flow ratio, RET is the monthly post-fee fund return, FmSz is the size of corporate bond holdings of the fund's family; VAS is the valuation accuracy score of Cici and Zhang (2021), and LiqScore is the liquidity score of Anand et al. (2021).

	Mean	Std. Dev.	P5	Median	P95
TNA ($ million)	1,743	4,875	20	380	7,453
TO (%)	110.51	124.78	16.79	64.70	356.72
EXP (%)	0.71	0.28	0.27	0.69	1.20
Age	16.76	11.80	3.01	15.83	38.19
Flow (%)	1.01	14.44	-4.70	-0.09	6.79
RET (%)	0.32	0.59	-0.51	0.31	1.17
FmSz ($ billion)	10.02	25.82	0.03	2.49	54.74
VAS	0.52	0.16	0.28	0.52	0.81
LiqScore	-0.04	0.30	-0.56	-0.05	0.47

Table 3. Evidence of Flipping and Secondary Trading of Newly Issued Bonds

This table tracks the secondary-market trading of new bond issues that were offered at month-ends (quarter-ends) by mutual funds that report holdings monthly (quarterly) to Morningstar. Panel A reports results for the subset of 151 funds that reported holdings monthly and the 212 offerings that occurred on the last trading day of the month. Secondary market trading in the new issues is tracked over one-, two-, and three-month widows. Panel B reports results for the 136 funds that reported holdings quarterly and the 42 offerings that occurred on the last trading day of the quarter.

Panel A: Funds that report holdings monthly

	Month *t* to *t*+1	Month *t* to *t*+2	Month *t* to *t*+3
Buy on offering day, no trading during the window	41.86%	36.10%	31.48%
Buy on offering day, partial sale during the window	2.59%	3.61%	4.65%
Buy on offering day, full liquidation during the window	10.64%	15.97%	19.50%
Buy on offering day, buy during the window	6.08%	6.05%	5.55%
No Buy on offering day, buy during the window	38.82%	38.27%	38.82%

Panel B: Funds that report holdings quarterly

	Quarter *t* to *t*+1
Buy on offering day, no trading during the window	30.97%
Buy on offering day, partial sale during the window	5.31%
Buy on offering day, full liquidation during the window	21.57%
Buy on offering day, buy during the window	5.97%
No Buy on offering day, buy during the window	36.17%

Table 4. Multivariate Analysis

The table reports panel regression results based on 338 investment-grade corporate bond mutual funds during July 2002-December 2019. The dependent variable is monthly fund pre-fee abnormal return estimated over the prior 36 months based on the four-factor model. Independent variables include the offering return sensitivity (ORS) or its quintile ranking (ORS Quintile), valuation accuracy score (VAS) of Cici and Zhang (2021), liquidity score (LiqScore) of Anand et al. (2021), natural logarithm of fund total net asset (TNA), natural logarithm of size of corporate bond holdings of the fund's family (FmSz), natural logarithm of fund age measured in years (Age), monthly net flow ratio (Flow), expense ratio (Exp), and annual turnover ratio of the prior year (TO). All independent variables except for Exp are lagged. Month×Style fixed effect are included and standard errors are clustered by fund. All variables are winsorized each month at 1% of both tails. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively.

	ORS		ORS Quintile	
	[1]	[2]	[3]	[4]
Intercept	0.03***	-0.01	0.00	-0.03
	(7.31)	(-0.32)	(0.38)	(-1.22)
ORS	1.80***	1.75***	0.68***	0.67***
	(3.67)	(3.67)	(2.69)	(2.83)
VAS		0.04		0.05*
		(1.63)		(1.68)
LiqScore		-0.01		-0.01
		(-1.37)		(-1.43)
Ln[TNA]		0.00		0.00
		(0.54)		(0.83)
Ln[FmSz]		-0.00		-0.00
		(-1.02)		(-1.41)
Ln[Age]		-0.01		-0.01
		(-1.57)		(-1.50)
Flow		0.12		0.13
		(1.40)		(1.48)
Exp		4.97***		5.28***
		(3.62)		(3.80)
TO		0.01***		0.01**
		(2.59)		(2.53)
R^2	0.316	0.317	0.314	0.316
N	30,720	30,720	30,720	30,720

Table 5. Multivariate Analysis - Robustness Tests

The table reports panel regression results based on 338 investment-grade corporate bond mutual funds during July 2002-December 2019. The regressions relate future fund performance with ORS Quintile. The dependent variable is: the monthly post-fee abnormal return in Column [1], the monthly pre-fee abnormal return estimated over the prior 24 months in Column [2]; and the monthly pre-fee abnormal return estimated over the prior 36 months using the 4-factor bond risk model of Bai, Bali, and Wen (2019) in Column [3]. In Columns [4] through [6], ORS is modified as follows: In Column [4], ORS is replaced by its precision-adjusted version (t-value of the coefficient in Equation 5), while ORS is estimated over the prior 12 months in Column [5]. In Column [6], the ORS is estimated from an alternative new bond offering (NBO) index which is based on the dollar value of profits. The value of this modified NBO index in a given day is constructed as the total underpricing-related dollar profit of all bonds issued on that day scaled by total TNA of all mutual funds at the beginning of the month. Underpricing-related profit of a bond issue is calculated as the product of the offering amount and first-day return. Finally, the specification in Column [7] includes fund fixed effects. All other control variables and month-style fixed effects are as in Table 4. Standard errors are clustered by fund. All variables are winsorized each month at 1% of both tails. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Intercept	-0.03	-0.03	0.04	-0.03	-0.02	-0.03	-0.02
	(-1.27)	(-1.16)	(0.98)	(-1.21)	(-0.82)	(-1.28)	(-0.15)
ORS Quintile	0.66***	0.48**	1.16***	0.67***	0.49**	0.71***	0.90***
	(2.82)	(2.02)	(2.83)	(2.91)	(2.09)	(2.67)	(2.62)
VAS	0.04*	0.04	0.04	0.05*	0.05*	0.05*	0.04
	(1.67)	(1.48)	(1.14)	(1.67)	(1.79)	(1.69)	(1.57)
LiqScore	-0.01	-0.01	0.01	-0.01	-0.01	-0.01	-0.02*
	(-1.44)	(-1.51)	(0.87)	(-1.41)	(-1.49)	(-1.41)	(-1.79)
Ln[TNA]	0.00	0.00	0.01	0.00	0.00	0.00	-0.01
	(0.89)	(1.48)	(1.04)	(0.84)	(0.88)	(0.80)	(-1.39)
Ln[FmSz]	-0.00	-0.00**	-0.01**	-0.00	-0.00	-0.00	-0.01
	(-1.44)	(-2.02)	(-2.17)	(-1.42)	(-1.35)	(-1.31)	(-0.62)
Ln[Age]	-0.01	-0.01*	-0.01	-0.01	-0.01	-0.01	0.01
	(-1.50)	(-1.81)	(-1.06)	(-1.49)	(-1.53)	(-1.53)	(0.23)
Flow	0.13	0.13	0.11	0.13	0.15*	0.14	0.03
	(1.47)	(1.48)	(0.66)	(1.48)	(1.77)	(1.57)	(0.38)
Exp	-2.94**	5.02***	2.29	5.27***	4.96***	5.34***	9.59*
	(-2.08)	(3.91)	(1.04)	(3.77)	(3.40)	(3.85)	(1.82)
TO	0.01**	0.01***	0.01**	0.01**	0.01**	0.01**	0.01**
	(2.57)	(2.81)	(2.44)	(2.52)	(1.99)	(2.54)	(1.99)
R^2	0.316	0.313	0.465	0.316	0.315	0.316	0.330
N	30,793	31,901	26,087	30,720	31,945	30,720	30,720

Table 6. Calendar Portfolio Analysis

The table reports portfolio analysis of 338 investment-grade corporate bond mutual fund performance during July 2002-December 2019. Each month within each style (Lipper objective code), all funds in the sample are sorted into value-weighted (VW) or equal-weighted (EW) quintile portfolios based on the offering return sensitivity estimated over the prior 24 months. Pre-fee and post-fee four-factor alphas of these quintile portfolios as well as the differences in alphas between the highest and lowest quintiles (5-1) are reported. The Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively.

ORS Quintiles	Pre-Fee Returns		Post-Fee Returns	
	VW	EW	VW	EW
	[1]	[2]	[3]	[4]
1 (Low)	-0.08*	-0.02	-0.12***	-0.08***
	(-1.79)	(-0.83)	(-2.92)	(-2.89)
2	0.02	0.02	-0.03	-0.04***
	(0.83)	(1.42)	(-1.65)	(-2.65)
3	0.02	0.02	-0.03	-0.04**
	(1.24)	(1.36)	(-1.30)	(-2.40)
4	0.01	0.04***	-0.04	-0.02
	(0.28)	(3.75)	(-1.18)	(-1.28)
5 (High)	0.04*	0.07***	-0.00	0.01
	(1.80)	(4.38)	(-0.20)	(0.40)
5 - 1	0.12***	0.09***	0.12***	0.09***
	(2.90)	(2.95)	(2.97)	(2.86)

Table 7. Determinants of ORS: Family-Level Analysis

The table reports results from panel regressions at the family level. The dependent variable is the ORS Quintile at the family level estimated over months [t+1, t+24]. Lag (ORS Quintile) is the family level ORS Quintile estimated over months [t-23, t]. Ind_Exp is the industry expertise of a fund family measured as described in Section 4.1. VAS is the valuation accuracy score of Cici and Zhang (2021) aggregated at the family level and measured at *t*. Underwriting is the fraction of the dollar amount of new offerings during [t+1, t+24] underwritten by underwriters with which a family had a significant relation. The control variables include natural logarithm of the size of corporate bond holdings of the fund's family (FmSz); flows (Flow), expense ratios (EXP), and turnover ratios (TO) of the prior year averaged across all bond funds in the family and weighted by fund assets in the previous month. All control variables except for Exp are lagged. Month fixed effects are included and standard errors are clustered by family. All variables are winsorized each month at 1% of both tails. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively.

	[1]	[2]	[3]	[4]	[5]
Intercept	0.32***	0.31***	0.34***	0.31***	0.32***
	(11.45)	(9.06)	(11.97)	(9.08)	(9.17)
Ind_Exp		0.18		0.17	0.19
		(0.59)		(0.57)	(0.65)
VAS			-0.02	-0.01	-0.02
			(-0.87)	(-0.63)	(-0.75)
Underwriting Relation		0.13***	0.13***	0.13***	-0.14
		(2.65)	(2.91)	(2.64)	(-1.13)
Underwriting Relation*Ln[FmSz]					0.04**
					(2.32)
Lag (ORS Quintile)	0.12***	0.09***	0.09***	0.09***	0.09***
	(3.83)	(2.95)	(2.92)	(2.97)	(2.98)
Ln[FmSz]	-0.01**	-0.01**	-0.01***	-0.01**	-0.01***
	(-2.53)	(-2.56)	(-2.67)	(-2.52)	(-2.88)
Flow	0.07	0.07	0.08	0.07	0.07
	(1.40)	(1.34)	(1.49)	(1.33)	(1.37)
Exp	0.10	1.16	-0.41	1.13	1.26
	(0.05)	(0.63)	(-0.22)	(0.61)	(0.67)
TO	-0.01**	-0.01***	-0.01***	-0.01***	-0.01***
	(-2.16)	(-2.95)	(-2.64)	(-2.89)	(-2.83)
R^2	0.042	0.054	0.050	0.054	0.057
N	15,325	14,522	15,270	14,515	14,515

Table 8. Determinants of ORS: Fund-Level Analysis

The table reports panel regression results relating ORS Quintile with fund and family characteristics. The analysis is based on a subset of funds belonging to fund families with at least two corporate bond funds. The dependent variable is ORS Quintile at the fund level estimated over months [t+1, t+24]. Lag (ORS Quintile^f) is the family level ORS Quintile estimated over months [t-23, t]. HV_Expense indicates the top 50% of funds sorted by total fee within the family at time t; HV_Performance indicates bottom 50% of funds sorted by past 12-month return within the respective style (Lipper objective code) at time t; HV_Age indicates the top 50% funds sorted by age within the family at time t. All other control variables and month-style fixed effects are as in Table 4. Standard errors are clustered by fund. All variables are winsorized by month at 1% of both tails. ***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively.

	[1]	[2]	[3]	[4]
Intercept	0.29***	0.27***	0.29***	0.28***
	(9.15)	(8.91)	(9.23)	(8.75)
Lag (ORS Quintile^f)	0.11***	0.11***	0.11***	0.11***
	(4.14)	(4.21)	(4.11)	(4.19)
HV_Expense	-0.00			-0.00
	(-0.28)			(-0.21)
HV_Performance		0.02***		0.02***
		(2.68)		(2.63)
HV_Age			-0.00	-0.00
			(-0.26)	(-0.29)
Ln[TNA]	0.01	0.01	0.01	0.01
	(1.34)	(1.37)	(1.33)	(1.36)
Ln[FmSz]	-0.00	-0.00	-0.00	-0.00
	(-0.58)	(-0.42)	(-0.53)	(-0.37)
Ln[Age]	-0.00	-0.00	-0.00	-0.00
	(-0.43)	(-0.54)	(-0.53)	(-0.62)
Flow	-0.02	-0.00	-0.02	-0.00
	(-0.48)	(-0.00)	(-0.53)	(-0.02)
Exp	-2.82	-3.14	-2.92	-3.01
	(-1.33)	(-1.51)	(-1.39)	(-1.40)
TO	-0.01*	-0.01*	-0.01*	-0.01*
	(-1.73)	(-1.72)	(-1.73)	(-1.72)
R^2	0.156	0.159	0.156	0.159
N	19,225	19,225	19,225	19,225

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