Sitting Bucks: Zero Returns in Fixed Income Funds

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Abstract

Zero returns are highly common in fixed income funds: on over 30% of trading days, NAVs do not change. These extreme occurrences of no price moves are driven by high illiquidity of fund holdings, and further compounded by binding minimum ticks. This is particularly prevalent among municipal bond funds, where more than 85% of holdings do not trade on any given day. We show that for funds with a high prevalence of zero returns, NAVs are extremely stale, and future returns are easy to predict using past fund returns at the daily, weekly, and even monthly horizons. Investors exploit this phenomenon by responding to stale prices and more importantly, by withdrawing capital from overvalued funds holding illiquid securities, which can exacerbate the risk of fund runs, as investors can achieve a first-mover advantage by redeeming at overvalued NAVs. This happens at the expense of buy-and-hold investors, who lose from others opportunistically buying and selling at predictably incorrect prices. Our results reveal shortcomings in existing fair valuation methods that are supposed to solve this problem.

JEL classification: G11, G14, G23.

Keywords: Zero returns; slow-moving prices; portfolio holding illiquidity; return predictability; fund flows; bond funds, municipal bonds

1. Introduction

Since the great recession, the bond mutual fund sector has grown substantially, with total assets under management exceeding $10 trillion as of 2017.[1] This development has introduced new challenges to financial stability. One notable concern among regulators is the increasing liquidity mismatch between underlying bonds and the open-end funds that hold these assets. On the one hand, bond market liquidity has generally worsened,[2] with some bonds not trading at all for weeks at times. On the other hand, funds still have to calculate daily net asset values (NAVs) to redeem liquidating investors, even when market prices are unavailable for a majority of their holdings. Recognizing these concerns, the Securities and Exchange Commission (SEC) places much emphasis on accurate and timely valuation of holdings.[3] Yet, in this paper, we show that the NAVs of bond funds are extremely stale, that is, they do not reflect fair values of holdings, often stretching over periods of weeks. The severity of this problem is thus an order of magnitude greater than for equity funds.

We study the particular pricing challenges facing bond mutual funds and their risks to investors. We show that a surprisingly high number of trading days for bond mutual funds are characterized by "zero returns"; in other words, the fund price does not change by even one cent. We further show that this simple measure is useful for identifying funds that are especially poor at valuing their holdings in a timely manner. We also show that stale fund prices can pose a threat to financial stability, thus contributing to the growing literature that focuses on the fragility of the fixed income fund market (e.g., Goldstein, Jiang, and Ng, 2017).

Stale pricing of fund NAVs has been well-documented in the prior literature, particularly with regards to the nonsynchronous trading of international and illiquid domestic stocks.[4] Note, however, that stale pricing in fixed income presents a new set of challenges. First, the changing landscape of the bond market since the

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[1] See the 2018 Investment Company Fact Book (https://www.ici.org/pdf/2018_factbook.pdf).

[2] Although still debatable, the consensus in the literature is that recent rounds of regulations have led to weaker liquidity provision. See, e.g., Bao, O'Hara, and Zhou (2018), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), and Choi and Huh (2018).

[3] In recent years, the SEC has engaged in a number of high-profile enforcement actions against improper valuation of fund NAVs. For more, refer to the SEC's actions against Calvert Investment Management Inc. (Investment Advisers Act Release No. 4554), or Pacific Investment Management Company LLC (Investment Advisers Act Release No. 4577).

[4] Prominent studies on the topic include Bhargava, Bose, and Dubofsky (1998), Chalmers, Edelen, and Kadlec (2001), Goetzmann, Ivković, and Rouwenhorst (2001), Boudoukh, Richardson, Subrahmanyam, and Whitelaw (2002), and Green and Hodges (2002).

2008 crisis makes the consequences of stale fund prices all the more prominent. The deterioration in bond market liquidity has been particularly problematic, as trading was already thin to begin with in some over-the-counter markets, e.g., the municipal bond market,[5] which can make correct and timely pricing of fixed income funds more difficult. This might explain why fund price staleness persists in fixed income even after the implementation of fair valuation regulations implemented following the stale NAV arbitrage scandals of the early 2000s.[6] Moreover, with further expected tightening of monetary policy, an imminent reversal of the tide in fund flows would greatly exacerbate the problems associated with the liquidity mismatch between mutual funds and their underlying bonds. Since investors' redemption demands incur substantial liquidation costs on a fund's remaining shareholders, investors are subject to payoff complementarity, which creates a first-mover advantage and opens up the possibility of fund runs (Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017). In this instance, any staleness in NAVs would further amplify such complementarity to the extent that fund flows respond to and exploit stale overpricing, further exacerbating financial stability concerns.

Second, the phenomenon through which NAV staleness manifests itself in post-crisis bond funds is distinct from those explored in previous studies. Whereas the existing literature argues that price adjustment may only be *partial* in the face of nonsynchronous trading, we take a step further. We show that many bond mutual funds display excessive price stickiness which manifests itself as many days of simply *no* NAV adjustment at all. One reason for this is that the tick size of open-end funds' NAVs are not continuous but instead have remained at one cent.[7] As Rozeff (1998) notes, fund managers cater to the preferences of their shareholders by targeting conventional price levels, using stock splits if necessary. For our sample of bond funds, NAVs are tightly centered at around $10, implying that a price movement is observed only when changes in estimated holding values are large enough to generate a 10bp NAV movement.

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[5] The SEC (2012) reports that "about 99% of outstanding municipal securities [do] not trade on any given day (p. 113)." Even on the few days when there is a transaction, there is usually only a single trade (Downing and Zhang, 2004).

[6] Bhargava and Dubofsky (2001) and Zitzewitz (2006), e.g., argue that pricing issues have been largely resolved since the scandal and Chalmers, Edelen, and Kadlec (2001) show that returns on trading based on stale pricing are not significant in fixed income funds.

[7] See NASDAQ's minimum price quoting variation rule (Rule 5735). On January 23, 2018, NASDAQ amended this rule, allowing for funds with NAVs below $1 to engage in sub-penny quoting up to $0.0001.

The binding minimum tick, combined with the extreme illiquidity of underlying bonds, motivates us to come up with a new measure of fund staleness, namely the zero return day (ZRD) ratio of fund returns, defined as the ratio of trading days without NAV return movement in a calendar month. We verify that this measure is a stale price measure of fund NAVs; it is driven by the illiquidity of underlying holdings, controlling for other determinants such as the price-to-tick ratio. In other words, when the prices of underlying bonds do not trade, a fund holding these bonds is more likely to stay at its old price, even controlling for the characteristics of the underlying bonds. Using a fund's ZRD ratio as a handy, parsimonious measure of price staleness, we find the striking result that the NAV of a bond fund in our sample remains unchanged on average one-third of trading days in a month, with the corresponding figure being even higher at 39% for municipal funds, using our sample of 2,084 U.S. fixed income mutual funds between 2008 and 2017. This is in stark contrast to domestic equity funds, whose average ZRD ratio is below 4%, which corresponds to less than one trading day per month.

This lack of NAV movements for funds with high holding-level illiquidity should imply strong return predictability, particularly for high-ZRD funds, as the prices of recently-traded assets predict the prices of non-traded assets. As expected, returns become more predictable as a fund's ZRD ratio increases, regardless of whether they are measured at daily, weekly, or monthly levels.[8] This phenomenon is particularly stronger for high-ZRD funds, implying that a persistent lack of movement in NAVs is consistent with greater predictability of fund prices. These results contrast with the existing literature on price staleness of domestic and international equity funds, where the predictability is mostly confined to the daily horizon (e.g., Chalmers, Edelen, and Kadlec, 2001). Moreover, we find the return predictability for these bond funds to be of sizeable magnitude. In a regression of daily fund returns on past returns, the estimated coefficient on the previous-day return is 0.10 for the lowest ZRD tercile, which increases to 0.25 for the highest ZRD tercile, with the latter also yielding substantially higher adjusted R^2 of around 10%.

[8] This is consistent with the literature on the predictability of returns in portfolios consisting of illiquid stocks which has shown that it's possible to predict returns on non-traded assets by using traded assets (e.g., Scholes and Williams, 1977; Dimson, 1979; Lo and MacKinlay, 1990; Boudoukh, Richardson, and Whitelaw, 1994; Kadlec and Patterson, 1999).

To further provide evidence supporting NAV staleness in fixed income funds, we exploit the unique setting offered by ETFs, which have both a traded price set in a competitive market and a NAV set by the fund management company. We find that market prices of bond ETFs are not predictable and thus are not stale, whereas their NAVs are highly predictable, particularly for municipal ETFs. This contrast highlights the shortcomings of existing fair valuation in fixed income funds.[9]

We show that investors respond to fund return predictability, particularly when returns are predicted to be negative, and for funds with high ZRD ratios. This result implies a greater risk of fund runs—in line with Goldstein, Jiang, and Ng (2017)—as well as greater loss to buy-and-hold investors, who are diluted by other investors who trade at advantageous prices. To examine investors' response to stale prices, we construct a "return gap" measure of temporary underpricing, which is defined as the difference between the predicted value of the latest fund return obtained from rolling regressions of past fund returns and the realized fund return. By examining each fund's weekly and monthly flows, we find that investors direct flows into funds with a positive return gap (i.e., predictably underpriced), particularly for high-ZRD funds. Above all, investors are more responsive to a return gap when it is negative, i.e., when we suspect overvaluation, which may stem from two potential channels. First, we find that fund returns are more predictable when their previous-day returns have been negative. This may reflect the incentive to smooth returns to avoid triggering costly outflows, consistent with Cici, Gibson, and Merrick's (2011) findings. Second, investor response to temporary overpricing may be stronger due to heightened payoff complementarity, given the illiquidity of corporate and municipal bonds. If so, stale NAVs should be a cause for concern from financial fragility, increasing the risk of a potential fund run, particularly when future returns are predicted to be negative but not reflected in the current NAVs.

Stale prices may be difficult to exploit in practice, however, due to the imposition of redemption fees and excessive trading policies designed to deter short-term transactions. We also reveal that flows respond less

[9] The SEC has pursued a number of enforcement actions against allegations of inaccurate NAVs resulting from misuse of fair value techniques. In its action against Calvert Investment Management in 2016, (Investment Advisers Act Release No. 4554), the SEC reported that, "at the end of 2009, for example, Calvert fair valued certain Toll Road Bonds at a price that was approximately 65% higher than the price assigned to the same bonds by a major industry participant on that same day."

strongly to return gaps when funds use short-term rear load fees, in line with Zitzewitz (2003). To better assess the economic magnitudes of the returns to investors who exploit stale pricing, we form simple calendar-time portfolios, based on whether a fund's latest monthly return has been positive or negative. To implement such a strategy, we focus on the subset of share classes without load fees and also consider a portfolio strategy that uses relatively infrequent monthly rebalancing.[10] We find that the alpha of a hypothetical portfolio purchasing funds with positive past returns and shorting those with negative past returns is 17 bps per month. Crucially, we find significant results particularly among the funds that display the highest ZRD ratios, suggesting that the alpha likely emanates from stale NAVs.

We contribute to the literature in several ways. First, we extend the rich literature on the staleness of fund NAVs. Whereas the existing literature (e.g., Chalmers, Edelen, and Kadlec, 2001; Goetzmann, Ivković, and Rouwenhorst, 2001; Boudoukh, Richardson, Subrahmanyam, and Whitelaw, 2002; Zitzewitz, 2003) focuses on NAV predictability at a relatively short daily horizon, we find that, over our post-crisis sample period, bond fund returns are predictable at a much longer horizon, up to several weeks for some illiquid market segments. Moreover, we contribute by showing that a fund's price staleness manifests itself through the sheer prevalence of zero return days. Whereas the discussion on stale NAVs in previous studies focuses on partial or incomplete price adjustment, we show that, with the fund managers targeting their NAVs toward a conventional price level of \$10, the minimum tick of one cent may be too large to produce *any* price adjustment at all. This also raises a concern from NASDAQ's perspective, as their recent regulatory change to allow for subpenny quoting only applies to funds with NAVs below \$1.

Moreover, our findings of heightened investor sensitivity to particularly negative predicted returns further contributes to the recent literature on the bond funds' liquidity mismatch (e.g., Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017). Whereas the possibility of a fund run, arising from payoff complementarities induced by liquidation costs of illiquid bond securities, remains even if a fund's NAV

[10] For most fund management firms, excessive trading does not apply if rebalancing occurs at the monthly level. See, for example, Fidelity's policy on short-term excessive trading, which only sets restrictions on roundtrip transactions within 30 calendar days, at: http://personal.fidelity.com/products/trading/Trading_Platforms_Tools/excessive_trading_policies.shtml

accurately reflects all pricing information, as noted in existing studies, we point to a more serious problem; the price itself be stale in the first place. Moreover, investors do appear to be aware of this; they respond more strongly to a temporary overvaluation *in addition to* poor recent performance.[11] If so, NAV staleness could conceivably exacerbate the fragility of bond funds, making it a cause for concern from a regulatory perspective.

2. Data and Variable Construction

To measure the degree of price staleness in bond mutual funds, we combine several datasets, namely: (1) CRSP Survivor-Bias-Free U.S. Mutual Fund database for fund characteristics, (2) Morningstar database for daily fund flow data and fund holdings reported at a monthly or quarterly frequency, (3) Municipal Securities Rulemaking Board (MSRB) database for municipal bond transactions, (4) Trade Reporting and Compliance Engine (TRACE) for corporate bond transactions, and (5) the CRSP stock file for prices of bond ETFs.

2.1. Fund characteristics

We begin with the sample of surviving and dead bond funds reported in the CRSP mutual fund database, with the first letter of CRSP style code "I" (fixed income). We then exclude money market and international bond funds. This restricts our sample funds to domestic general, government, corporate, and municipal bond funds. Then, following Choi and Kronlund (2018), we pool together general and corporate bond funds and divide them into high yield (HY) and investment grade (IG) categories based on their Lipper objective codes.[12] Government and municipal bond funds are defined as those with the first two letters of CRSP style code "IG" and "IU", respectively. We then obtain the funds' daily and monthly returns, monthly total net assets (TNA), and data on turnover ratio, expense ratio, fund age, front and rear loads, and management firm information. We further calculate Wednesday-to-Wednesday weekly returns. Given that we include both active and passive

[11] In this respect, we also contribute to the rich literature on fund flow-performance sensitivity (e.g., Ippolito, 1992; Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lynch and Musto, 2003; Huang, Wei, and Yan, 2007).

[12] As in Choi and Kronlund (2018), we define HY bond funds as those with Lipper objective code "HY", "GB", "FLX", "MSI", or "SFI", while IG bond funds are those coded "A", "BBB", "IID", "SII", "SID", or "USO".

bond funds, we further construct an index fund dummy, which takes the value of one if the fund is flagged as an index fund in the CRSP mutual fund database, or if the fund satisfies the criteria for the definition of index fund as outlined in the data appendix of Berk and van Binsbergen (2015). For ETFs, we further include their daily market returns as reported in the CRSP daily stock file. We run regressions using fund share class as the cross-sectional unit, since the expense and load characteristics of each share class are important in explaining investor flows, our main variable of interest in the later part of the analysis.

2.2. Fund holdings and daily fund flows

As in Cici and Gibson (2012) and Choi and Kronlund (2018), we use the Morningstar Direct holdings data for taxable and municipal bond funds, which report fund holdings of equities, bonds, preferred stocks, futures, options, and cash.[13] During our sample period, the required frequency of disclosure was quarterly, but around 52% of funds in our sample voluntarily reported their holdings at a monthly frequency; following Elton, Gruber, and Blake (2011), we use the highest frequency of disclosed holdings available.

The Morningstar holdings data includes the weight of each security in the portfolio, maturity date in the case of fixed income products, and CUSIP identifiers of all traded securities. In addition, securities are classified according to Morningstar's security type code (*sectype*). We use this code to classify the securities into the following asset categories, as outlined in Appendix A.1: ABS, agency, cash or cash equivalents, corporates, equities, municipals, Treasuries, and others. At every holdings disclosure date, this allows us to calculate the portfolio weight in each respective asset category by summing up the weight of all securities belonging to the security type codes comprising the category.

Morningstar Direct further provides *daily* fund flow and TNA data for municipal and taxable fixed income funds as well as ETFs, but the data coverage is virtually non-existent prior to July 2007. The coverage then gradually increases over the next year, with each broad asset category beginning to contain around 10

[13] Our Morningstar holdings data coverage ends in May 2015, and as holding-level variables enter with a lag, this restricts the sample period of any analysis involving holding-level controls to June 2015.

funds or so from January 2008 onward, and with a final, substantial jump from around 100 funds to over 1,300 funds in July 2008. In light of this varying coverage, we restrict the start of our sample period to January 2008.[14] We then use this daily fund flow data to compute Wednesday-to-Wednesday weekly fund flow.[15]

We merge the CRSP mutual fund and Morningstar databases following most data-cleaning steps in Pástor, Stambaugh, and Taylor (2015). Following Pástor, Stambaugh, and Taylor (2015), we use the CUSIP of each fund share class to join the two databases' respective fund share class identifiers (*fundno* for CRSP and *secid* for Morningstar). Finally, we then exclude all fund share classes with missing daily fund flow and TNA data. This procedure yields our final sample consisting of 6,434 fund share classes of 2,084 funds.

2.3. Price staleness measures

As discussed, we use a fund's zero return day (ZRD) ratio as our headline measure of price staleness. This is the ratio of trading days with zero daily return as reported in the CRSP mutual fund database (identifier *dret*) to the number of possible trading days within the month. While a similar measure has been used as a proxy for liquidity when applied to individual securities (e.g., Lesmond, Ogden, and Trzcinka, 1999; Lee, 2011), we apply the same measure in the context of fund NAV to proxy for the degree of staleness in fund pricing. In the mutual fund setting, observing a zero-return is not a measure of the fund itself being illiquid because changes in NAV don't require that the fund itself is traded; rather, a NAV without a change is an active choice by the fund company not to change the price.

Prior studies such as Lo and MacKinlay (1990), Boudoukh, Richardson, and Whitelaw (1994), and Ahn, Boudoukh, Richardson, and Whitelaw (2002) attribute stale prices at the portfolio level to nonsynchronous trading at the security level. For example, if some but not all securities trade on a given day, yet they share the same value-relevant information, then portfolio pricing based merely on the last sales price of each security will

[14] Setting the beginning of our sample period to July 2008, when the coverage becomes complete, has no qualitative effect on our results.

[15] Monthly flows are calculated from CRSP mutual fund database, but we check whether the monthly flows reported in Morningstar Direct differ significantly; on virtually all instances, we do not find sizeable differences between the two.

essentially be using "mismeasured" prices for non-traded securities; the last price at which the non-traded securities traded do not reflect any information that has arrived since. Fund managers resort to matrix pricing services to tackle this problem, but these services are known to be ambiguous with a degree of subjectivity (e.g., Goldstein, Jiang, and Ng, 2017). If these services thus prove insufficient in eliminating staleness at the NAV level, then we expect to see a positive association between the level of non-trading at the security level and the staleness of fund NAV.

3. Zero Returns in Fixed Income Funds

The first step in our empirical analysis is to document how prevalent stale pricing is among fixed-income funds, both in the time series and cross-section, using the ZRD measure. We further contrast the extent of zero returns in bond funds and that of domestic equity funds.

3.1. Prevalence of zero returns

In Panel A of Table 1, we report average values of the ZRD measure as well as other fund characteristics from January 2008 to December 2017. On average, we find that a bond fund posts zero returns on about one third of trading days in a month, with its median at 30.0%, both roughly corresponding to around 7 (out of 21) days per month. However, ZRD ratio has substantial variation, with its inter-quartile range in excess of 30%. Indeed, as shown in Panel A of Figure 1, some funds have extremely high ZRD ratios; around 4% of our sample observations have ZRD ratios in excess of 80%, which translates to around 17 days in a given month.

TABLE 1 AND FIGURE 1 HERE

The fund NAV levels, in contrast, are tightly centered at around $10, with the inter-quartile range of just over $2. This is not a surprising finding; as Rozeff (1998) notes, fund managers exhibit reluctance to allow their NAVs to deviate significantly from "conventional" prices of other funds, using stock splits to bring the level back to the industry norm. This, in turn, highlights our earlier concern with regards to the binding minimum quote variation of one cent.

An average fund share class in our sample has just under $300 million in assets. 28.6% of our sample observations charge a load fee according to our refined definition, namely the sum of minimum front load fee and rear load fee applicable at the holding period of one month.[16]

For funds with holdings data on Morningstar, we find that the underlying holdings of an average fund have a weighted-average time-to-maturity of around 11.8 years. To measure the illiquidity of the underlying bonds that a fund holds, we next define the zero-trading-day ratio (ZTD), which is calculated as the value-weighted average of a fund's underlying holdings that don't trade on any given day.[17] The average zero trading day (ZTD) ratio of 45.2%, signifying that close to half of the value of a typical fund's holdings are not traded on a given day. Furthermore, the holding-level ZTD ratio has huge variations across funds, with the lowest and highest quartiles at 11.2% and 85.5%, respectively.

3.2. Time series and cross-sectional characteristics of zero returns

In Panel B of Table 1, we document the patterns in the fund-level ZRD ratio for each year across the four bond asset categories: government, high yield, investment grade, and municipal bond funds. In addition, we further report the year-by-year ZRD ratio of domestic equity funds covered by Morningstar Direct daily flow data over the same period.[18] We find that government bond funds have the lowest ZRD ratio at around 25%, with high yield and investment grade bond funds in the middle at around 30% and 31%, respectively. Municipal bond funds have the highest ZRD ratio of around 39%. Above all, we find that the ZRD ratios of bond funds are substantially different from those of equity funds; compared to our sample of bond funds, where the average ZRD ratio ranges from 25% to nearly 40% depending on the asset category, the figure for equity funds is much lower at around 4%, which corresponds to less than one trading day per month. Across all four categories, we find a gradual increase in the ZRD ratio over the first half of our sample period, which

[16] We believe that the holding period of one month is the most relevant from the perspective of a "smart" investor, given excessive trading policies of most management firms. We consider minimum front load fee as many "smart" investors are able to commit large amounts of capital and avoid large front load fees.

[17] Appendix A.1 has a detailed description of the calculation of this measure.

[18] Domestic equity funds are defined as those with the first two characters of CRSP style code "ED".

likely reflects the effect of subdued overall market volatility resulting from the Federal Reserve's zero bound interest rate policy.

Panel C then tabulates the holding-level ZTD ratio for each year and asset category in a similar manner. We find large differences in the ZTD ratio across the four asset categories. Whereas government bond funds have the lowest average ZTD ratio of around 12%, the corresponding figure rises to over 85% for municipal bond funds. Investment grade and high yield bond funds occupy the middle at 20% and 27%, respectively.[19] Over our sample period, we find that the ZTD ratios of government and investment-grade bond funds increase substantially. In particular, average ZTD ratio of government bond funds increases from under 4% in 2008 to over 18% by 2015, which may reflect their tendencies to "reach for yield" in the face of historically low market interest rates (e.g., Choi and Kronlund, 2018). Holding-level ZTD ratio of municipal bond funds, in contrast, remain relatively stable over the years, at around 85%.

FIGURE 2 HERE

In Figure 2, we plot histograms of fund-level ZRD ratio, holding-level ZTD ratio, and holding-level weighted-average-maturity (WAM) for each asset category. In Panel A, it is noticeable that the municipal bond funds' ZRD ratio distribution stands out from the other three categories. Whereas the other categories see a gradual decrease in density as the ZRD ratio increases, albeit with a long tail, the ZRD ratio of municipal bond funds resembles a more bell-shaped pattern, with the density peaking between 40% and 50%.[20]

Panel B of Figure 2, which plots histograms of holding-level ZTD ratio across the asset categories, is staggering. Whereas the ZTD ratio of government bond funds has a huge spike at 0, with the density decreasing rapidly thereafter, less than 5% of municipal bond funds have holding-level ZTD ratio below 75%. The distributions of high yield and investment grade bond funds' holding-level ZTD ratio also differ, with the

[19] The existing literature also documents significant discrepancies in market illiquidity by asset segment. Whereas the municipal bond segment adjusts very slowly over a span of days (Green, Li, and Schürhoff, 2010), Treasury bonds see near-instantaneous adjustments to macroeconomic news (e.g., Fleming and Remolona, 1999; Balduzzi, Elton, and Green, 2001). Corporate bonds lie between these extremes, with high yield corporates on average being slower to react to new information compared to investment grade bonds (e.g., Edwards, Harris, and Piwowar, 2007; Chen, Lesmond, and Wei, 2007; and Bao, Pan, and Wang, 2011).

[20] In all three panels in Figure 2, we trim the variable at the 1% and 99% levels for ease of graphical exposition.

former having a distribution closer to bell shape while the latter's density peaks at around 10% and has a long right tail thereafter. Finally, in Panel C, we plot the holding-level time-to-maturity for each asset category. We find that high yield bond funds have the shortest maturity, peaking at around 7 to 8 years. Municipal bonds have an interesting double-peaked distribution, with two peaks at around 9 and 17 years, respectively.

What drives the high prevalence of zero returns? In addition to the minimum tick effect, the previous figure suggests nontrading in the underlying bonds is likely to be an important contributor: if more of a fund's underlying holdings don't trade, the fund itself is also less likely to update its NAV. To further explore this relationship, we run panel regressions of the fund-level ZRD ratio on the holding-level ZTD ratio and its interaction with the log of the inverse NAV in Table A.1 in the Appendix.[21] We document a strong relationship between fund ZRD ratio and its holding-level ZTD ratio, particularly among funds with low levels of NAV. Although the ZRD ratio could also be driven by other reasons such as lower interest rate risk of short-maturity holdings or overall market volatility, we find that the relationship between fund-level ZRD ratio and the holding-level ZTD ratio remains robust to the inclusion of these additional controls. These results show that the ZRD ratio captures staleness in fund prices driven by nontrading in the underlying holdings.

4. Predictability of Bond Fund Returns

4.1. Return predictability at the daily, weekly, and monthly horizons

In Table 2, we examine the predictability of fixed income fund returns at various horizons as well as the extent to which it is associated with the prevalence of zero returns. At the daily level, we regress fund returns on its lagged values, focusing on the following non-overlapping return horizons that span a total of four weeks: -1, -2, [-5:-3], [-10:-6], and [-20:-11]. Then, at the weekly level, we regress Wednesday-to-Wednesday weekly fund returns on past weekly own-fund returns up to four lags. Finally, we regress fund returns on its previous-month return at the monthly level. Moreover, to gauge the extent to which zero returns affect return predictability, we stratify funds into ZRD ratio terciles and estimate the regressions separately. ZRD terciles are

[21] Log inverse NAV is intended to control for the minimum tick effect, likely to be of greater concern among low-NAV funds.

formed at the end of each month-end, including all fund share classes that belong to the top 30%, middle 40%, or bottom 30% of the sample in terms of the latest one-month ZRD ratio. Table 2 presents our results.

TABLE 2 HERE

Panel A of Table 2 presents our regression results using daily returns. For the full sample, we find that the statistical significance of past fund returns remains strong for two weeks, with the beta coefficient of one- and two-day lagged returns being particularly strong at 0.17 and 0.08, respectively. Moreover, we find that fund returns become more predictable as the funds' ZRD ratios increase; columns (2) through (4) show that both the adjusted R^2 as well as the beta coefficient estimates of the past two day returns monotonically increase across the ZRD terciles. The beta coefficient of the previous-day return for each ZRD tercile is 0.10, 0.20, and 0.25, respectively. This implies that the effect of the previous-day fund return is more than twice as strong among funds with high ZRD ratios compared to low-ZRD funds. In Panel B, we confirm that similar patterns hold at the weekly level. Once again, the statistical significance of past fund returns remains significant for up to two weeks in the full sample. We further report that lag 1 beta coefficient estimates and the adjusted R^2 increase as the ZRD ratios increase.[22] Panel C also reveals that the identical pattern carries over to the monthly level. In other words, regardless of the horizon over which fund returns are measured, we find that return predictability lasts up to several weeks for high ZRD funds.

While the short-term predictability of fund returns has been previously discussed in Chalmers, Edelen, and Kadlec (2001), Goetzmann, Ivković, and Rouwenhorst (2001), and Zitzewitz (2003), among others, our results are unique in a couple of ways. We establish predictability over longer horizons---price staleness persists for many days and weeks as compared to the earlier literature on equity funds, where the return predictability is confined either to the "intra-day" nonsynchronous trading hours or on a short daily horizon.[23] We also show

[22] In Table A.2 in the Appendix, we show that this return predictability is strongest for municipal bond funds, followed by high yield bond funds, both of which are characterized by high holding-level illiquidity. We further confirm in Table A.3 that our qualitative results, particularly with regards to beta coefficient estimates of lagged returns, remain robust to the inclusion of time fixed effect.
[23] To further demonstrate that return predictability of high-ZRD funds primarily emanates from nontrading at the holding level, we interact past daily or weekly fund returns with dummy variables based on funds' ZRD ratios and various explanations for zero returns such as holding-level ZTD ratio, weighted-time-to-maturity, or market volatility in Table A.4. We find that short-maturity funds or

that in the cross-section of bond funds, a fund's frequency of not changing its price implies that its future return is more predictable.

This price staleness could conceivably strengthen the investors' payoff complementarity when funds hold illiquid assets, creating a first-mover advantage in redeeming early before an expected price fall, as noted in Goldstein, Jiang, and Ng (2017). It is therefore worth examining whether the beta coefficients of past returns differ in magnitudes depending on whether the past returns have been negative. Thus, in Table 3, we re-estimate our baseline daily predictive regressions with a piecewise linear specification, separately estimating each past return horizon for its negative vs. non-negative parts, both for the full sample as well as for each ZRD tercile.

TABLE 3 HERE

Table 3 reveals that the previous-day return's beta coefficient increases significantly when it has been negative. More interestingly, the difference in lag 1 beta coefficient between negative and non-negative returns becomes more prominent as we move along the ZRD tercile. Thus, the predictive power of a negative previous-day return appears significantly larger, and especially more so for funds with a high prevalence of zero returns. This could, for example, be consistent with a fund management firm's desire to engage in return smoothing for fear of a significant outflow, preferring to gradually decrease its NAV over a more prolonged period of time instead (e.g., Cici, Gibson, and Merrick, 2011). If so, the increased predictability of a recent negative return would strengthen the first-mover advantage among investors, exacerbating financial fragility of bond funds. However, we do not observe this beta difference to persist beyond lag 1, and in untabulated analysis, we confirm that the difference is not significant at the weekly or monthly level either, suggesting that the phenomenon is short-lived.

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periods of subdued market volatility, both alternative sources of fund-level zero returns, *decrease* return predictability if anything, suggesting that the return predictability of high-ZRD funds likely reflects stale prices arising from nontrading at the holding level.

4.2. Can investors do better? An examination of ETF returns and NAVs

In this subsection, we exploit a unique feature of bond ETFs to provide further evidence of holding-level illiquidity as being a principal driver of return predictability in bond funds. ETFs have both traded exchange prices as well as the NAV prices. Whereas the market prices of ETFs are set in a competitive market, the NAVs are set by the fund management company. It is admittedly difficult to set prices of a fund where the underlying holdings only trade infrequently, which is why we observe such strong predictability of past returns as in the previous subsection. But is the competitive market better at responding to past information?[24] If so, we should observe much lower degrees of return predictability in the market prices of ETFs, even when their future NAVs are predictable.

In Table 4, we investigate this issue by regressing both an ETF's NAV returns as well as its market returns on the past values of ETF market returns. If NAVs are stale, and if the investors believe that the NAV is predicted to increase, then they will capitalize on this opportunity by purchasing the ETF in the exchange. If so, the current market returns of ETFs will predict future NAV movements. However, the same behavior could also be consistent with trend-chasing behavior on the investors' part. If the investors simply chase past returns, or if they underreact to information, then future returns will move in the same direction even when the NAV is correctly priced. In this instance, we ought to observe market returns of ETFs to depend positively on their own past values, according to the predictions of the momentum literature (e.g., Jegadeesh and Titman, 1993; Carhart, 1997). In contrast, in the absence of trend chasing, then there is no reason to expect the ETF market returns to depend positively on their past values; if anything, market returns ought to depend negatively to lag 1 market returns in light of liquidity-driven return reversal (e.g., Pástor and Stambaugh, 2003). We estimate the regressions both for the full sample of ETFs as well as separately for the four broad asset categories.

TABLE 4 HERE

[24] There exists anecdotal evidence of fund NAVs failing to respond even to panic-like events. A Financial Times article in 2009 provides an apt example during the global financial crisis of 2008-09, when panic-stricken investors sold the corporate bond ETFs and "drove down the market price for the ETFs while the net asset value stood still due to the lack of new prices on the underlying securities (The curious case of ETF NAV deviations, March 13)."

Table 4 presents our regression results. We find that the market returns of ETFs predict future NAV returns up to two lags for the full sample. The predictability is most prominent among municipal bond funds, where the market returns predict future NAV movements up to a week, with an adjusted R^2 of over 10%.[25] There is some evidence of predictability among high yield ETFs, though its extent, as measured by adjusted R^2, is much lower. In contrast, there is no evidence of market returns having a significant predictive power on future NAV returns among government or investment grade ETFs, both of which hold more liquid assets. The evidence in columns (1) through (5) is consistent with investors exploiting return predictability arising from high holding-level illiquidity in municipal ETFs. In contrast, columns (6) through (10) yield no evidence of investors engaging in trend-chasing behavior. Apart from return reversal at lag 1, common across all asset categories, there is no noticeable evidence of market returns being dependent on their own past values. This provides us with convincing evidence that existing fair value techniques remain insufficient in eliminating mispricing in NAVs, especially for municipal ETFs. Moreover, investors appear to be aware of these profitable opportunities, and exchange-traded prices of ETFs adjust accordingly as they respond to profit from them.

5. Flow Response to Stale Fund Prices

5.1. Predictable returns and fund flows

If fund returns are predictable and investors are aware of such predictability, they may seek to exploit this phenomenon by opportunistically directing flows into undervalued funds, which are thus predicted to have high returns going forward. In this subsection, we test whether investors' fund flows respond to predictable mispricing of bond funds. If they do, this also implies that buy-and-hold investors lose out from the dilution caused by flows occurring at biased prices. To test whether such smart flows exist, we first establish a proxy for predictable under- and overpricing. Our previous tests have shown that one reliable proxy is simply a fund's own past daily or weekly return. When a fund has positive recent returns, it is significantly more likely to be undervalued and continue having positive returns, which is especially true of stale funds with high ZRD ratios.

[25] We restrict our attention to asset categories rather than ZRD terciles as more than three-quarters of these ETFs have ZRD of 0.

In Table 5, we explore this by regressing fund flows on past returns. However, a positive correlation between fund flow coefficients on past return terms may not necessarily imply that investors are "intentionally smart" because such flow could also be caused by simple return-chasing tendencies. After all, we observe investor flows responding to past returns in equity funds even though past returns may not necessarily be predictive of the future. In other words, it is possible that investors direct flows into funds with favorable recent returns because they chase high-performing funds, and not because they are aware of underpricing.

To better differentiate whether investors are smart or merely trend-chasing, we therefore also create a dedicated measure of undervaluation not confounded by return-chasing, which we refer to as a fund's "return gap." This gap captures how much a fund *should* have predictably moved last week based on its staleness, compared to how much it actually moved. For example, if we predict that a fund should have had a return of 1% last week, but it actually only returned 0.5%, then the return gap is positive. We construct return gaps separately at the weekly and monthly horizons in the following manner. For weekly returns, we run predictive AR(4) rolling-window regressions over a window of [-52:-5] weeks, and for monthly returns, we employ simple AR(1) rolling-window regressions over a window of [-12:-2] months. Then, to construct our "return gap" measure, we calculate the difference between time t predicted return constructed using the information up to $t-1$ and the actual time t return, either at the weekly or monthly horizon. If this is positive, it means the latest realized return was lower than would have been predicted based on the historical level of staleness for the fund. A high return gap thus implies that the fund is likely to be predictably underpriced. The return gap measure is importantly negatively correlated with past returns, and thus not subject to a concern about "return-chasing" flows. Using this return gap measure, we can then study whether flows respond to the relative underpricing or overpricing that the return gap predicts.

TABLE 5 HERE

In Table 5, we present the results of weekly and monthly flow response to our measure of underpricing. The results show that fund flows do respond significantly. First, in column (1), we find that fund flows respond significantly to the fund's own returns last week, which as we reveal in Table 2, strongly predicts future returns.

We find similar patterns at the monthly level in column (3). Specifically, a 1% increase in latest monthly return increases investor flow by 1.35%, even after controlling for Lipper-code-by-time fixed effects as well as a range of other variables such as several lags of past fund flows, fund size, management company size, fund age, an institutional class indicator, index fund indicator, turnover, expense ratio, and rear loads.

As discussed earlier, however, it is possible that investor response to past returns merely reflects "blind" trend-chasing tendencies. Thus, we further examine investor response to the return gap measure. We show in columns (1) and (3) that flows respond significantly to this return gap, both at weekly and monthly horizons, even after controlling for the past return. In other words, a fund receives significant inflows when it is predictably undervalued based on the return gap measure.[26] In our monthly set-up, the return gap measure has a standard deviation of 1.54%. From column (3), this would amount to an extra inflow of around 1.54% × 0.817 = 1.26% over the next month. Given that the monthly flow of our sample of bond funds has a standard deviation of 8.67%, this "smart" flow is estimated to be around 15% of variations in investor flows.

An alternative way of testing whether investors exploit predictable under/over-pricing or whether investors are merely chasing returns is to exploit cross-sectional variation in how well past returns predict future returns. In Table 2, we show that past fund returns are more predictive for future returns among funds with high prevalence of zero returns. If so, we should expect fund flows to respond more strongly to high past fund returns especially for funds with high ZRD ratios. We test this by interacting past return and return gap with the ZRD ratio. The results in columns (2) and (4) of Table 5 show that past returns predict flows more strongly for funds with high ZRD ratios. This cross-sectional relationship is also true for the return gap, where a gap of a given size attracts more flows among high-ZRD funds.

[26] Importantly, in Table A.5 in the Appendix, we further show that the importance of the return gap in predicting returns remains at the weekly level when controlling for the past returns (i.e., longer lags) used in constructing the measure.

5.2. Predictable returns, fund flows, and concavity

We now test whether the relation between fund flows and return predictability is stronger depending on whether our measures of temporary underpricing is positive or negative. On the one hand, there are at least two reasons why we might expect the relation between the return gap, for example, and fund flows to be concave, i.e., stronger on the downside. First, according to Goldstein, Jiang, and Ng (2017), a distinct feature of bond funds is that their flows have a concave relationship with past performance due to investors' strategic complementarity. Investors realize that outflows will result in costly liquidation, providing an incentive to "run" before others. A similar mechanism is likely to exist in our setting, where temporary overpricing due to stale NAVs strengthens investors' concerns with regards to inefficient liquidation. In fact, overpricing resulting from stale NAVs, in this instance, could conceivably amplify the payoff complementarity, increasing the first-mover advantage. Second, we may expect the effect to be stronger upon observing a negative return gap because the return predictability is significantly stronger on the downside at the daily horizon, as shown in Table 3. Given this relationship, we might then expect "smart" flows also to respond more to negative returns.

On the other hand, one reason why we might instead observe a convex relationship is that, for investors to be able to exploit a negative return gap, the investor would already need to be invested in the fund, as it is not possible to short sell mutual funds. In that case, we might expect a stronger reaction of inflows to positive rather than negative return gap. Therefore, whether the flow-return gap relationship is concave or convex is ultimately an empirical question. In Table 6, we thus re-estimate the weekly flow regressions in the first two columns of Table 5 using piecewise linear specifications for lag 1 fund return and the latest return gap.[27]

TABLE 6 HERE

Column (1) reveals that both measures of underpricing, namely the return gap and the lagged fund return, display a strong concave relationship with flows. This is in line with greater predictability of negative fund returns as revealed in Table 3 as well as the payoff complementarity hypothesis of Goldstein, Jiang, and Ng (2017). In column (2), we control for interactions of our underpricing measures with the fund-level staleness

[27] Table A.6 in the Appendix reveals that monthly flow results are broadly consistent.

measure, ZRD ratio. Although we do not find a significant discrepancy in the degree of concavity between high- and low-ZRD funds, given the lack of statistical significance of the negative parts of the interaction terms, column (2) confirms the concavity of the flow-return relationship itself is robust to controlling for interactions with ZRD ratio. This provides further evidence that investors respond to temporary overpricing *as well as* poor recent performance, which in turn implies that stale NAVs may further contribute to the financial fragility of bond funds by increasing the risk of a possible run by investors.

5.3. What inhibits investor flows into stale funds?

What can funds do to prevent smart flows from diluting buy-and-hold investors? One possibility is the use of load fees, particularly holding-period-based rear load fees, which can discourage trading at relatively short horizons over which the return predictability prevails. If load fees are high enough, then they limit the possible profit opportunities from such trading. We might thus expect to see relatively lower sensitivity of flows to our predictors of future return, i.e., past return and the return gap, and especially so for high-ZRD funds.

In Table 7, we thus study whether investor flows are more or less sensitive to these predictors of future returns when the fund share class has load fees that discourage short-term trading, by re-estimating columns (1) and (2) of Table 5 separately for fund share classes with and without a load fee. Because load fees are formulaic and depend on both the amounts invested in a fund and the investment horizon, we calculate a load fee measure that is explicitly constructed to measure the loads relevant for a market timing strategy backed with a significant amount of capital. For this "refined" load measure, we create an indicator for whether a fund share class has a non-zero minimum front load fee, i.e., by assuming that the amount invested is sufficiently high to qualify for the lowest front load, and/or rear load fee applicable to the holding period of one month.[28] Once again, we focus on weekly flow regression results when examining load vs. no-load share class subsamples.[29]

TABLE 7 HERE

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[28] We choose a month as this is roughly the period over which returns tend to be predictable, and because excessive trading policies of many fund management firms prohibit roundtrip transactions within a month.

[29] Table A.7 in the Appendix reveals that monthly flow regression results are consistent.

The results in Table 7 show that the flow sensitivity to both the return gap and the lagged fund return are stronger for the no-load share classes compared to share classes with a load fee. In column (3), we further show that this difference between load and no-load funds is also statistically significant for the lagged fund return, but only marginally significant for the return gap, with a *t*-statistic of 1.64.

However, in Table 5, we reveal that the relationship between flow and our measures of underpricing is significantly stronger when funds have high ZRD ratios. In columns (4) to (6), we further build on this result, and test whether this interaction of return predictability and ZRD ratio depends on the presence of a load fee. The results show that both the interaction between lagged fund return and ZRD ratio as well as between return gap and ZRD are economically and statistically significant for the no-load classes but are indistinguishable from zero for classes with a load fee. This implies that the interaction results in Table 5 are entirely driven by the no-load funds, and that load fees deter investors from trading on potential mispricing created by the staleness in NAV. This issue is also recognized by Zitzewitz (2003), who finds that funds use short-term fees as protection against NAV arbitrage flows as a substitute for improving their pricing methods. Investors thus seem to take advantage of these profit opportunities only when not prohibited by high load fees. In turn, our result suggests that funds use load fees not only to weaken performance-conscious but also staleness-conscious flows.

5.4. Economic magnitude of return predictability: calendar-time portfolios

Given that investors appear to respond substantially to temporary mispricing arising from stale NAVs, a natural question arises: what is the economic magnitude of the profitable opportunities arising from stale prices? To answer this question, we form simple calendar-time portfolios based on past returns. However, it is important to check whether the calendar-time alpha that we obtain can actually be earned in practice, given some obvious difficulties associated with fund transactions. First, fund management firms have strict policies against excessive trading, banning accounts with frequent short-term roundtrip transactions. Nevertheless, in many instances, excessive trading rules apply to roundtrip transactions occurring within 30 calendar days of the initial purchase. Thus, we rebalance our portfolio at a relatively low monthly frequency. Second, as discussed earlier, many fund share classes put prohibitively high load fees for short-term transactions to deter stale price arbitrage. Recognizing this issue, we restrict our attention to no-load share classes, whose returns, in theory, should be easier to exploit from an investor's perspective.

At each month-end, we form equal-weighted portfolios based on whether the latest monthly return has been positive or negative.[30] Then, we hold each past-return-sorted portfolio for the next month. We form these past return portfolios both for the full sample as well as for each ZRD tercile. In addition to the returns of each portfolio, we further examine the statistical significance of the calendar-time return difference between positive and negative past return portfolios, which corresponds to a situation where an investor takes a long position in funds with positive past return and a short position in those with negative past return. Of course, this strategy is not fully implementable in practice as it is not possible to short open-end mutual funds, but this exercise is intended to isolate the economic magnitude associated with price staleness. In each instance, we report excess returns as well as a simple one-factor model, with the return on the Bloomberg Barclays U.S. Aggregate Total Return index as the market benchmark. Table 8 presents our results.[31]

TABLE 8 HERE

Table 8 Panel A reveals that the difference in average returns between positive and negative past return portfolios is significant at the 5% level, at around 19.8 bps per month. The difference in one-factor alpha is also marginally significant at the 10% level, at 17.1 bps per month. These results show that the monthly trading strategy tends to be profitable even after adjusting for benchmark returns.[32]

In Panel B, we re-estimate the calendar-time alphas for each ZRD tercile. Given that stale funds, i.e., funds with greater prevalence of zero returns, exhibit higher return predictability, we expect the difference on

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[30] Fund share classes with monthly return of 0 constitutes less than 0.5% of our sample and are too few in number to be meaningfully aggregated into a separate calendar-time portfolio.

[31] Table A.8 in the Appendix provides the full sample calendar-time portfolio results, including share classes with a load fee. Results are broadly comparable, with statistical significance of the calendar-time difference obtained only among funds belonging to the highest ZRD tercile.

[32] Note, however, that even the negative past return portfolio has a positive alpha in all instances, which may appear puzzling. This is largely because of the biases in alpha and beta estimates due to stale pricing in fixed income portfolios. In untabulated results, we find that the alphas of negative past return portfolios reverse their signs when they are re-estimated using Dimson's (1979) sum beta approach based on past two lags of benchmark returns. However, since our research question focuses precisely on the profitability of trading strategies associated with stale prices, we believe this Dimson approach to be unsuitable for our analysis here.

the positive-negative portfolios to be more prominent among high-ZRD funds. This analysis is additionally intended to separate the impact of price staleness from an alternative explanation for return persistence, namely that the funds with favorable recent returns continue to perform well due to superior skills of their managers. If the observed return persistence is purely attributable to managerial skill, then there is no reason to expect the calendar-time difference between the positive and negative past return portfolios to exhibit a strong relationship with the funds' ZRD ratios. However, Panel B clearly reveals that the statistical significance of this calendar-time difference in one-factor alpha is obtained only for the funds in the highest ZRD tercile. Moreover, *t*-statistics of calendar-time difference in excess returns increase monotonically as we move along the ZRD tercile.

Nevertheless, our analysis may still be confounded by the managerial skill hypothesis if manager skill matters more in more illiquid asset segments such as high yield corporate or municipal securities. To this end, we perform an additional calendar-time analysis in Table A.9 in the Appendix, where we impose a delay between the evaluation of past returns and the actual portfolio formation. Specifically, we impose a time gap of three months, whereby portfolio rebalancing at the end of, for example, June 2013 utilizes the funds' monthly returns in March 2013. If the persistence in calendar-time returns is attributable to superior managerial skill, then this delay in portfolio formation should have little effect on the alpha estimates, as well-performing managers ought to continue to perform well even after one quarter. However, we find that the significance of calendar-time differences in excess returns or alphas all but disappear, both statistically and economically, suggesting that the significantly positive calendar-time differences in alphas obtained in Table 8 more likely reflect short-lived return persistence resulting from the price staleness of high-ZRD funds.

5. Conclusion

In this paper, we document the prevalence of zero returns in fixed income funds. We find that the NAV of a bond fund, on average, remains unchanged on around one-third of trading days, with the corresponding figure reaching closer to 40% for municipal bond funds. The frequency with which a fund posts no change to its NAV is naturally related to the tick-to-price-level ratio, but we show that a fund's holding-level illiquidity—

when interacted with the fund's NAV level—to be a major driver of a fund not changing its price. This is especially true for municipal bond funds, where over 85% of underlying holdings don't trade on any given day.

Consequently, we further document a high degree of short-term return predictability for bond funds, especially those with a high prevalence of zero returns, regardless of whether the returns are measured at daily, weekly, or monthly horizon. This return predictability increases significantly when the previous-day return has been negative, which could exacerbate the payoff complementarity of illiquid funds as documented in Goldstein, Jiang, and Ng (2017). Thus, existing fair value techniques appear insufficient in eliminating the staleness in the NAV, as further indicated by the ability of ETF market returns, i.e., exchange-traded prices, to predict their future NAV returns but *not* future market returns.

Moreover, we find that at least some investors are aware of staleness in fund pricing and seek to exploit it. Indeed, weekly and monthly fund flow sensitivity to measures of predictable underpricing are more sensitive for funds with high ZRD ratios. This trading behavior, stemming from the investors' desire to profit from short-term return predictability, ultimately arises at the expense of long-term investors. We further report evidence of concavity in investor flow response to our measures of temporary mispricing arising from stale NAVs, which, in turn, can amplify the first-mover advantage of investors in funds with illiquid holdings, increasing the risk of a potential fund run.

Funds have tools at their disposal to limit such opportunistic trading. For example, funds can use load fees to dampen the profitability of such short-term trading, as we reveal that the investor flow response to predicted staleness-driven returns is significantly stronger among fund share classes without a load fee. This, however, cannot address the root of the problem, namely the shortcomings of existing matrix pricing services when nearly 90% of a fund's underlying holdings do not trade on any given day, which is the case for many municipal bond funds. Without improvements to pricing techniques, staleness in the prices of these funds will likely persist, contributing to risks of financial fragility and fund runs in bond funds.

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Appendix A.1. Variable Descriptions

The following variables are used in our empirical analysis, with the data source in parentheses.

I. Fund Price Staleness Measure and Price Level

Zero return day ratio (CRSP): The number of days with zero NAV return as reported on CRSP Mutual Funds, divided by the number of possible trading days during the calendar month. Entries with either "R" or "-99" are treated as missing.

Log inverse NAV (CRSP): Negative of the log of previous month-end NAV, which equals log inverse NAV.

II. Proxies for Potential Explanations of Fund Price Staleness

Portfolio weight in ABS, agency, corporates, cash or cash equivalents, munis, or Treasuries (Morningstar): Sum of portfolio weights with the following Morningstar security type codes (*sectype*) – munis (0, 1, 2, 4, 5, 6, 7, 10, 12, 13), ABS (BH, BJ, BM, BY, MF, NB, ND), agency (BD, BG, FE, NC, NE), corporates (B, BF, BI, IP), cash or cash equivalents (C, CD, CH, CP, CR, CT, FM, FV), and Treasuries (BT, TP).

Holding-level zero trading day ratio (ZTDR) (Morningstar/MSRB/TRACE): We calculate zero-trading day ratios at three different levels, in the following order of aggregation: security-level, fund-by-asset-class-level, and fund-level.

> *Security-level ZTDR:* For each security, the zero trading day ratio is defined as the number of zero trading days in a month divided by the number of possible trading days during the month, calculated from its dated date until maturity. For munis, we use the trade entries on MSRB to calculate the security-level zero trading day ratio, while we use TRACE for ABS, agency, and corporate bonds. Prior to calculating the security-level ZTDR, we clean the TRACE entries as proposed in Dick-Nielsen (2014), which has become the standard procedure in recent studies on corporate bonds (e.g., Schestag,

Schuster, and Uhrig-Homburg, 2016). We impose that Treasuries and cash equivalents have zero trading day ratio of 0 given their high liquidity.

Fund-by-asset-class level ZTDR: We calculate the weighted average zero trading day ratio of all securities matched to MSRB or TRACE, using the portfolio weight of each security as reported in the Morningstar portfolio holdings data, to arrive at the asset-class-level zero trading day ratio for each of the following six asset classes: ABS, agency, corporate, and munis, treasuries, and cash.

Fund-level ZTDR: We calculate the holding-level zero trading day ratio at the fund-level by computing the weighted average of the six asset-class-level zero trading day ratio, using the sum of portfolio weights for all securities belonging to the asset class as reported in Morningstar (including all securities not matched to MSRB or TRACE) as the respective weight of each asset class.

Short maturity dummy (Morningstar): We first calculate the weighted average of each security's time to maturity as stated in the Morningstar portfolio holdings data, computed using the security's portfolio weight. If this measure is less than three years, the dummy takes the value of one.

Market volatility (Bloomberg): Annualized volatility of Barclays Bloomberg U.S. Aggregate Total Return daily index return during the [-250:-21] window at each month-end.

III. Other Variables

Daily return (CRSP Mutual Fund/Daily Stock files): Daily NAV return of the fund share class, in percentage terms. For ETFs, we separately construct market return using the CRSP Daily Stock files.

Daily flow (Morningstar): Daily flow of the fund share class, divided by its previous-day total net assets, in percentage terms.

Fund share class size (CRSP): Log of previous month-end total net assets of the fund share class.

Fund share class age (CRSP): Years since the first appearance of the fund share class on the CRSP Mutual Fund file.

Management firm size (CRSP): Log of the management firm's previous month-end total net assets (summed over all fund share classes sharing the same management firm code, *fhmgmt_cd*).

Institutional class dummy (CRSP): A dummy variable that takes the value of 1 if and only if the fund share class is flagged as an institutional class in CRSP (*fhinst_fund*).

ETF fund dummy (CRSP): A dummy variable that takes the value of 1 if and only if the fund share class is flagged as an ETF in CRSP (all funds with the entry "F" for *fhet_flag*).

Index fund dummy (CRSP): A dummy variable that takes the value of 1 if and only if the fund share class is flagged as an index fund in CRSP (*fhindex_fund_flag*), and/or if the fund share class is classified as a passive fund following the methodology as outlined in the Data Appendix of Berk and van Binsbergen (2015). For more information, see pp. 11-15 of their Data Appendix.

Turnover ratio, expense ratio, and actual 12b-1 fees (CRSP): As reported in CRSP, in percentage terms. In the case of actual 12b-1 fees, missing values are replaced with zero.

Front and rear load dummies (CRSP): An indicator variable that equals 1 if and only if the share class has non-zero front and non-zero rear loads, respectively. Missing values are replaced with zero.

(Refined) Load dummy (CRSP): An indicator variable that equals 1 if and only if the share class has non-zero minimum front load, and/or rear load applicable at the holding period of one month. At the fund-month level, we define a fund to be a "load" fund if such share classes constitute more than 75% of the fund's assets.

Table 1. Zero Returns in Fixed Income Funds

Panel A of this table reports summary statistics of the sample of fixed income mutual funds in the CRSP Mutual Funds with non-missing daily flow and total net assets data in Morningstar. Our sample period is from January 2008 to December 2017. We obtain information on the funds' holdings from Morningstar, with the sample period between January 2008 and June 2015. There are 6,434 unique share classes of 2,084 funds in total. All continuous variables are winsorized at the 1% and 99% levels, with the exception of market benchmark returns. We report the summary statistics computed using winsorized values. Panel B of this table reports the average values of zero return day ratio for each asset category and calendar year. We also report the same number for our sample of domestic equity funds with non-missing daily flow data in Morningstar. Then, Panel C reports the average value of holding-level zero trading day ratio, once again by asset category and calendar year. Government bond funds have the first two letters of CRSP style code "IG". High yield and investment grade bonds are defined according to Choi and Kronlund (2018), and muni bond funds have the first two letters of CRSP style code "IU". For a detailed description on the definition of each variable, see Appendix A.1.

Panel A. Summary statistics

	Obs.	Mean	St. Dev.	Q1	Median	Q3
Price staleness measure						
Zero return day (ZRD) ratio (%)	402,040	33.21	21.61	15.79	30.00	47.37
Fund share class characteristics						
Daily return (%)	8,173,401	0.017	0.209	-0.087	0.000	0.102
Weekly return (%)	1,671,869	0.077	0.577	-0.151	0.089	0.347
Monthly return (%)	402,040	0.338	1.370	-0.188	0.300	0.970
Weekly flow (%)	1,671,869	0.092	2.006	-0.313	-0.012	0.332
Monthly flow (%)	402,040	0.464	8.666	-1.721	-0.248	1.385
Month-end NAV ($)	402,040	11.76	9.318	9.29	10.33	11.33
Fund share class size ($ millions)	402,040	295.4	724.0	8.700	48.70	210.4
Front load dummy	402,040	0.198	0.398	0.000	0.000	0.000
Rear load dummy	402,040	0.280	0.449	0.000	0.000	1.000
Refined load dummy	402,040	0.286	0.452	0.000	0.000	1.000
Fund holding characteristics						
Weighted av. maturity (years)	104,211	11.83	5.768	7.249	11.08	16.35
Zero trading day ratio (%)	104,211	45.15	35.86	11.22	33.45	85.45
% held in ABS (%)	104,211	5.152	9.670	0.000	0.000	6.001
% held in agency (%)	104,211	11.85	20.65	0.000	0.000	18.47
% held in cash or equivalents (%)	104,211	3.479	6.209	0.000	1.109	4.139
% held in corporates (%)	104,211	26.58	32.86	0.000	6.704	47.79
% held in munis (%)	104,211	38.45	47.24	0.000	1.282	98.09
% held in Treasuries (%)	104,211	10.79	21.09	0.000	0.000	13.09

Panel B. Zero return day ratio by asset category and year

Year	Bond Funds					Domestic Equity Funds
	Govt.	HY	IG	Muni	Total	
2008	13.50	19.49	16.03	22.42	18.91	1.53
2009	19.96	21.23	20.69	28.88	24.18	3.18
2010	23.85	27.19	25.90	45.99	34.36	4.40
2011	23.50	29.61	26.65	37.44	31.22	3.05
2012	29.96	31.01	34.27	39.84	35.30	4.66
2013	28.58	33.63	35.97	37.70	35.29	4.18
2014	28.23	38.55	38.11	41.62	38.35	4.08
2015	23.57	28.27	32.14	39.42	32.92	3.55
2016	26.94	24.58	34.71	44.46	34.94	4.20
2017	27.23	37.92	36.17	39.81	36.77	5.73
Total	25.22	30.35	31.31	38.67	33.21	3.98

Panel C. Holding-level zero trading day (ZTD) ratio (%)

Year	Govt. Bond Funds	HY Bond Funds	IG Bond Funds	Muni Bond Funds	Total
2008	3.81	30.77	16.67	85.18	47.58
2009	3.44	26.52	13.17	85.92	45.48
2010	6.25	24.53	16.33	85.41	45.05
2011	11.73	28.20	19.65	84.46	46.23
2012	15.86	30.15	22.60	84.92	46.46
2013	15.43	27.08	22.57	83.37	44.61
2014	16.82	25.32	23.57	84.44	44.38
2015	17.55	21.76	24.06	84.59	40.31
Total	11.52	26.72	19.85	84.81	45.15

Table 2. Return Predictability in Bond Funds

This table reports pooled OLS regression results of fund returns on past fund returns. Panels A, B, and C reports the results for daily, weekly, and monthly returns, respectively. We focus on the following non-overlapping daily horizons in Panel A: -1, -2, [-5:-3], [-10:-6], and [-20:-11]. In columns (1)-(4) of each panel, we provide regression results for the full sample and for separately each ZRD ratio tercile, which categorizes fund share classes into bottom 30%, middle 40%, or top 30% of our sample at the latest month-end. Regressions are conducted at the fund share class level. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and time are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Daily predictability regressions

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All Bond Funds	ZRD tercile		
		Low	Mid	High
Fund return [-1] (%)	0.173***	0.103***	0.203***	0.246***
	(11.21)	(6.03)	(12.56)	(12.77)
Fund return [-2] (%)	0.079***	0.052***	0.084***	0.105***
	(6.08)	(3.55)	(6.07)	(6.77)
Fund return [-5:-3] (%)	0.016**	0.011	0.016**	0.016*
	(2.22)	(1.37)	(2.13)	(1.84)
Fund return [-10:-6] (%)	0.012**	0.009	0.012**	0.017***
	(2.46)	(1.52)	(2.36)	(2.73)
Fund return [-20:-11] (%)	0.005	0.008**	0.004	0.003
	(1.56)	(2.16)	(1.10)	(0.81)
Adjusted R^2	0.049	0.018	0.064	0.100
No. of obs.	8,173,401	2,032,526	3,300,035	2,840,840

Panel B. Weekly predictability regressions

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All Bond Funds	ZRD tercile		
		Low	Mid	High
Fund return [-1] (%)	0.125***	0.062*	0.135***	0.208***
	(3.29)	(1.71)	(3.38)	(3.95)
Fund return [-2] (%)	0.082**	0.079**	0.065*	0.105**
	(2.25)	(2.30)	(1.71)	(2.11)
Fund return [-3] (%)	-0.009	0.018	-0.023	-0.041
	(-0.24)	(0.49)	(-0.62)	(-0.85)
Fund return [-4] (%)	0.039	0.018	0.047	0.064
	(1.07)	(0.55)	(1.24)	(1.15)
Adjusted R^2	0.028	0.013	0.027	0.066
No. of obs.	1,671,869	415,993	673,282	582,594

Panel C. Monthly predictability regressions

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All Bond Funds	ZRD tercile		
		Low	Mid	High
Fund return [-1] (%)	0.193**	0.182**	0.173**	0.238**
	(2.59)	(2.47)	(2.25)	(2.54)
Adjusted R^2	0.037	0.036	0.031	0.050
No. of obs.	402,040	99,464	162,365	140,211

Table 3. Return Predictability of Bond Funds: Negative vs. Non-Negative Returns

In this table, we re-estimate Panel A of Table 2 using piecewise linear regressions of fund returns on past fund returns, dividing each respective past fund return into negative and non-negative parts. Regressions are conducted at the fund share class level. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and day are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All Bond Funds	ZRD tercile		
		Low	Mid	High
Fund return [-1] (%)	0.109***	0.050**	0.135***	0.160***
	(5.40)	(2.02)	(6.44)	(7.07)
Fund return [-2] (%)	0.097***	0.078***	0.106***	0.101***
	(5.59)	(3.42)	(5.86)	(5.79)
Fund return [-5:-3] (%)	0.023**	0.013	0.029***	0.021**
	(2.34)	(1.05)	(2.82)	(1.99)
Fund return [-10:-6] (%)	0.020***	0.025***	0.016**	0.022***
	(2.88)	(2.83)	(2.23)	(2.81)
Fund return [-20:-11] (%)	0.009**	0.004	0.009**	0.013***
	(2.21)	(0.76)	(2.37)	(3.09)
Fund return [-1] (%)| Fund return [-1] < 0	**0.134*** **	**0.106*** **	**0.143*** **	**0.184*** **
	(3.80)	**(2.60)**	**(3.76)**	**(4.45)**
Fund return [-2] (%)| Fund return [-2] < 0	-0.042	-0.058	-0.051	-0.003
	(-1.28)	(-1.54)	(-1.40)	(-0.07)
Fund return [-5:-3] (%)| Fund return [-5:-3] < 0	-0.015	-0.004	-0.028	-0.014
	(-0.79)	(-0.20)	(-1.28)	(-0.63)
Fund return [-10:-6] (%)| Fund return [-10:-6] < 0	-0.017	-0.033**	-0.009	-0.011
	(-1.26)	(-2.14)	(-0.66)	(-0.66)
Fund return [-20:-11] (%)| Fund return [-20:-11] < 0	-0.007	0.010	-0.012	-0.020*
	(-0.75)	(0.97)	(-1.36)	(-1.85)
Adjusted R^2	0.051	0.020	0.067	0.105
No. of obs.	8,173,401	2,032,526	3,300,035	2,840,840

Table 4. Price Staleness and Return Predictability of Bond ETFs

This table reports pooled daily OLS regression results of ETF NAV returns (Panel A) and ETF market returns (Panel B), with the former from CRSP Mutual Funds and the latter from CRSP Daily Stock files, on past ETF market returns, for the full sample as well as each asset category. We focus on the following set of non-overlapping horizons as in previous tables: -1, -2, [-5:-3], [-10:-6], and [-20:-11]. Asset categories are defined as in Table 1. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and day are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ETF NAV return [0] (%)					Dependent variable: ETF market return [0] (%)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Bond Funds	Govt. Bond Funds	HY Bond Funds	IG Bond Funds	Muni Bond Funds	All Bond Funds	Govt. Bond Funds	HY Bond Funds	IG Bond Funds	Muni Bond Funds
ETF market return [-1] (%)	0.038***	0.003	0.048**	0.019	0.137***	-0.093***	-0.067***	-0.097***	-0.124***	-0.116**
	(2.99)	(0.22)	(2.54)	(1.09)	(9.31)	(-5.39)	(-2.85)	(-4.41)	(-3.95)	(-2.65)
ETF market return [-2] (%)	0.020**	-0.007	0.032**	0.006	0.081***	-0.003	-0.016	0.004	-0.025	0.034
	(2.04)	(-0.64)	(2.44)	(0.56)	(7.35)	(-0.24)	(-0.99)	(0.24)	(-1.53)	(1.59)
ETF market return [-5:-3] (%)	-0.002	-0.014**	0.001	0.001	0.019**	-0.014*	-0.026**	-0.014	-0.008	0.011
	(-0.25)	(-2.19)	(0.08)	(0.18)	(2.34)	(-1.66)	(-2.65)	(-1.34)	(-0.88)	(0.77)
ETF market return [-10:-6] (%)	-0.001	-0.008	-0.001	0.005	0.004	-0.001	-0.006	-0.003	0.007	0.006
	(-0.24)	(-1.46)	(-0.22)	(0.84)	(0.78)	(-0.21)	(-0.82)	(-0.38)	(0.93)	(0.79)
ETF market return [-20:-11] (%)	0.004	0.004	0.001	0.010**	0.008**	0.006	0.008	0.001	0.012**	0.009
	(1.26)	(0.91)	(0.27)	(2.31)	(2.26)	(1.27)	(1.47)	(0.20)	(2.16)	(1.63)
Adjusted R-squared	0.005	0.002	0.009	0.003	0.104	0.009	0.007	0.010	0.016	0.017
No. of obs.	262,007	64,997	62,263	88,769	45,978	261,962	64,990	62,244	88,754	45,974

Table 5. Price Staleness and Flow Sensitivity to Predicted-Realized Return Gap

In this table, we engage in rolling window regressions to obtain the forecasts of fund return using its own past return data. For weekly returns, we estimate an AR(4) model over a rolling window of [-52:-5], while for monthly returns, we estimate a simple AR(1) model over a rolling window of [-12:-2]. We then construct a return gap measure, namely the difference between predicted return at time t constructed using the information up to $t-1$, and the actual time t return. We then examine weekly or monthly flow sensitivity to the previous period's return gap measure. Columns (1) and (2) report weekly flow regression results using weekly return gap, and columns (3) and (4) report monthly flow regression results using monthly return gap. When examining the flow sensitivity to the return gap measure, we control for lag 1 fund return. Then, in columns (2) and (4), we interact the return gap measure with the ZRD ratio, the latter of which is also interacted with past fund returns. Regressions are conducted at the fund share class level. Controls include the past flow (up to four lags for weekly regressions), log share class size, log management firm size, share class age, institutional class dummy, index fund dummy, turnover ratio, expense ratio, and refined load dummy, whose coefficient estimates we do not report. All specifications include Lipper objective × time fixed effects. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and day are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund flow [0] (%)			
	All bond funds			
	Weekly regressions		Monthly regressions	
	(1)	(2)	(3)	(4)
Return gap [-1] (%)	0.170***	0.100***	0.817***	0.572***
	(7.21)	(3.45)	(8.04)	(5.39)
Fund return [-1] (%)	0.338***	0.273***	1.349***	1.045***
	(11.23)	(7.85)	(10.94)	(8.30)
Return gap [-1] (%) × ZRD ratio (in decimal)		0.387***		1.360***
		(4.34)		(5.46)
Fund return [-1] (%) × ZRD ratio (in decimal)		0.353***		1.706***
		(3.51)		(5.81)
ZRD ratio (in decimal)		0.063**		0.200
		(2.28)		(0.90)
Controls	YES	YES	YES	YES
Lipper obj. × time FE	YES	YES	YES	YES
Adjusted R-squared	0.106	0.106	0.086	0.087
No. of obs.	1,645,958	1,645,958	399,468	399,468

Table 6. Flow-Return Gap Sensitivity: Negative vs. Non-Negative Return Gap

This table re-estimates weekly flow regressions in columns (1) and (2) of Table 5, but with piecewise linear analysis of the return gap and lag 1 fund return for negative vs. non-negative cases. Controls are identical to Table 5. Regressions are conducted at the fund share class level. All specifications include Lipper objective × week fixed effect. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and week are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund flow [0] (%)	
	(1)	(2)
	All bond funds	
Return gap [-1] (%)	0.124***	0.051
	(4.32)	(1.37)
Return gap [-1] (%) │ Return gap [-1] < 0	**0.097*****	**0.094****
	(2.98)	**(2.03)**
Fund return [-1] (%)	0.279***	0.223***
	(8.43)	(5.52)
Fund return [-1] (%) │ Fund return [-1] < 0	**0.133*****	**0.101***
	(3.31)	**(1.87)**
Return gap [-1] (%) × ZRD ratio (in decimal)		0.386***
		(3.75)
Return gap [-1] (%) × ZRD ratio │ Return gap [-1] < 0		0.038
		(0.26)
Fund return [-1] (%) × ZRD ratio		0.341***
		(2.63)
Fund return [-1] (%) × ZRD ratio │ Fund return [-1] < 0		0.089
		(0.59)
ZRD ratio (in decimal)		0.050*
		(1.69)
Controls	YES	YES
Lipper obj. × week FE	YES	YES
Adjusted R-squared	0.106	0.106
No. of obs.	1,645,958	1,645,958

Table 7. Flow-Return Gap Sensitivity: Load vs. No-Load Share Classes

This table re-estimates weekly flow regression results in columns (1) and (2) of Table 5, but separately for fund share classes with and without (refined) load fees. Refined load fee is calculated as the sum of minimum front load fee and the rear load fee applicable at the holding period of one month. Regressions are conducted at the fund share class level. Controls are identical to those in Table 5, except for the omission of the refined load dummy. All specifications include Lipper objective × week fixed effects. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and week are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund flow [0] (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
	All bond funds					
	(Refined) load classes	No load classes	Subsample diff.-in. coeff.	(Refined) load classes	No load classes	Subsample diff.-in. coeff.
Return gap [-1] (%)	0.136***	0.196***	-0.059	0.131***	0.097***	0.034
	(4.72)	(6.82)	(-1.64)	(3.39)	(2.75)	(0.70)
Fund return [-1] (%)	0.262***	0.379***	-0.117**	0.280***	0.276***	0.004
	(6.99)	(10.53)	(-2.55)	(5.62)	(6.60)	(0.06)
Return gap [-1] (%) × ZRD ratio (in decimal)				**0.038**	**0.545*** **	**-0.507*** **
				(0.32)	**(4.91)**	**(-3.29)**
Fund return [-1] (%) × ZRD ratio (in decimal)				**-0.075**	**0.563*** **	**-0.638*** **
				(-0.51)	**(4.51)**	**(-3.49)**
ZRD ratio (in decimal)				0.116***	0.045	0.072
				(2.80)	(1.36)	(1.47)
Controls	YES	YES	-	YES	YES	-
Lipper obj. × week FE	YES	YES	-	YES	YES	-
Adjusted R-squared	0.160	0.091	-	0.161	0.091	-
No. of obs.	471,837	1,173,402	-	471,837	1,173,402	-

Table 8. Calendar-Time Portfolio Analysis

This table presents calendar-time portfolio results. At each month-end, we form equal-weighted portfolios depending on whether a fund share class' latest monthly return has been positive or negative. We restrict our attention to fund share classes without load fees according to our refinement criteria. We form past return portfolios both for the full sample (Panel A) as well as for each ZRD tercile (Panel B). We also construct a calendar-time difference between positive and negative past return portfolios in each instance. In each case, we report excess portfolio returns and then estimate a one-factor calendar-time alpha, using the return on Bloomberg Barclays U.S. Aggregate Total Return index as the market benchmark. Due to the substantially increased coverage of Morningstar daily flow data, our sample begins in August 2008. *t*-statistics based on Newey-West (1987) heteroskedasticity- and autocorrelation-consistent standard errors with three lags are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

A. Full Sample

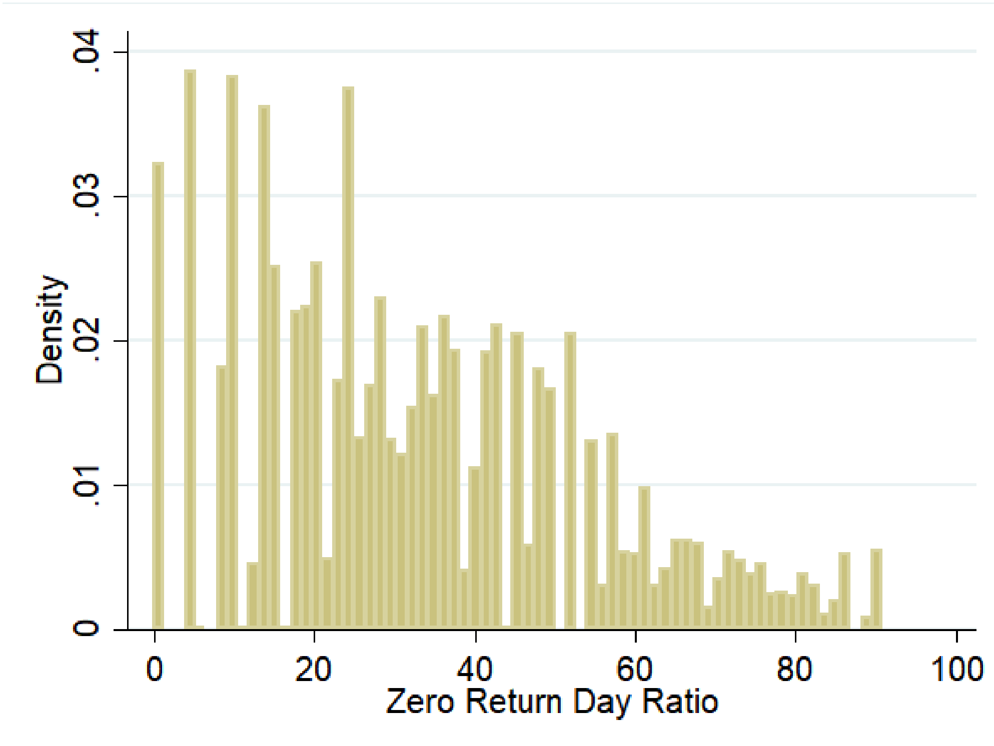
	Dependent variable: monthly portfolio return (%)		
	(1)	(2)	(3)
	Positive lag 1 return	Negative lag 1 return	(1) – (2) difference
Excess Return			
Excess Return (%)	0.425*** (4.96)	0.227** (2.08)	0.198** (2.36)
One-Factor Alpha			
α (%)	**0.230***** **(3.51)**	**0.059** **(0.52)**	**0.171*** **(1.69)**
$\beta_{market\ benchmark}$	0.596*** (7.18)	0.512*** (3.81)	0.083 (0.77)
Adjusted R-squared	0.474	0.191	-0.001
Number of monthly obs.	113	113	113

B. ZRD Tercile

	Dependent variable: monthly portfolio return (%)								
	ZRD tercile								
	Low			Mid			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Positive lag 1 return	Negative lag 1 return	(1) – (2) difference	Positive lag 1 return	Negative lag 1 return	(4) – (5) difference	Positive lag 1 return	Negative lag 1 return	(7) – (8) difference
Excess Return									
Excess Return (%)	0.461*** (4.35)	0.260* (1.90)	0.200* (1.84)	0.468*** (4.85)	0.256** (2.03)	0.212** (2.26)	0.354*** (4.96)	0.129 (1.49)	0.225*** (2.79)
One-Factor Alpha									
α (%)	**0.214** (2.59)**	**0.035 (0.26)**	**0.179 (1.37)**	**0.247*** (3.21)**	**0.071 (0.54)**	**0.176 (1.58)**	**0.211*** (3.46)**	**0.019 (0.19)**	**0.192** (2.18)**
$\beta_{market\ benchmark}$	0.751*** (8.43)	0.686*** (4.86)	0.065 (0.48)	0.673*** (6.91)	0.563*** (3.66)	0.110 (0.96)	0.435*** (5.69)	0.333*** (2.65)	0.101 (0.98)
Adjusted R-squared	0.527	0.211	-0.006	0.470	0.183	0.002	0.318	0.123	0.005
Number of monthly obs.	113	113	113	113	113	113	113	113	113

Figure 1. Distribution of Zero Return Day Ratio and NAV Level

Panel A. Zero return day ratio



Panel B. NAV level

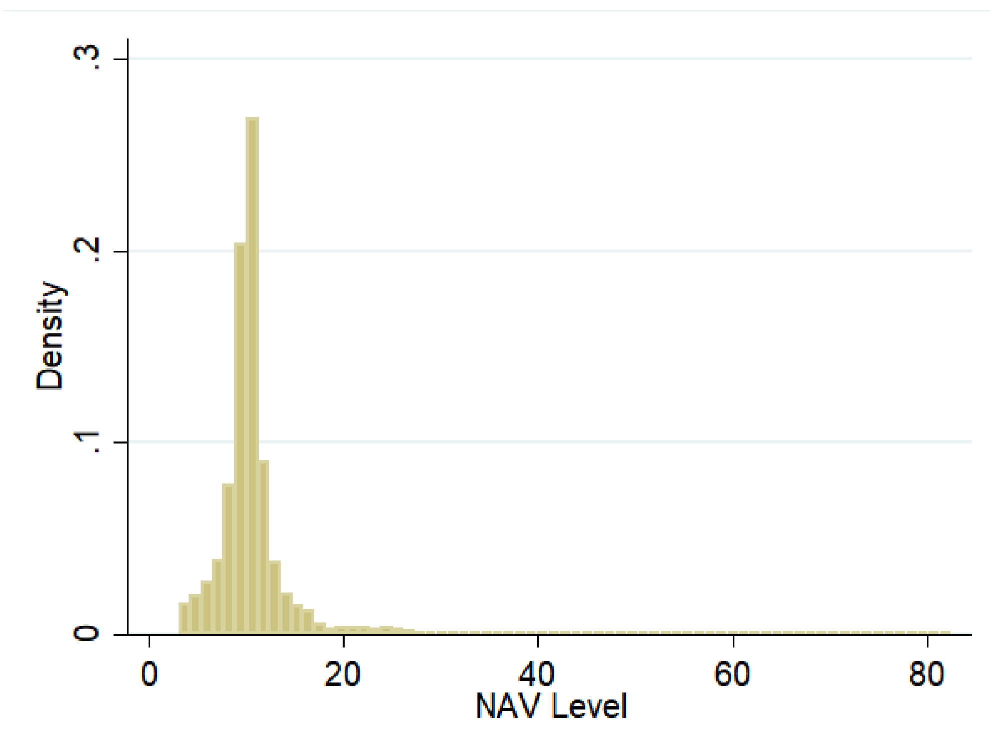
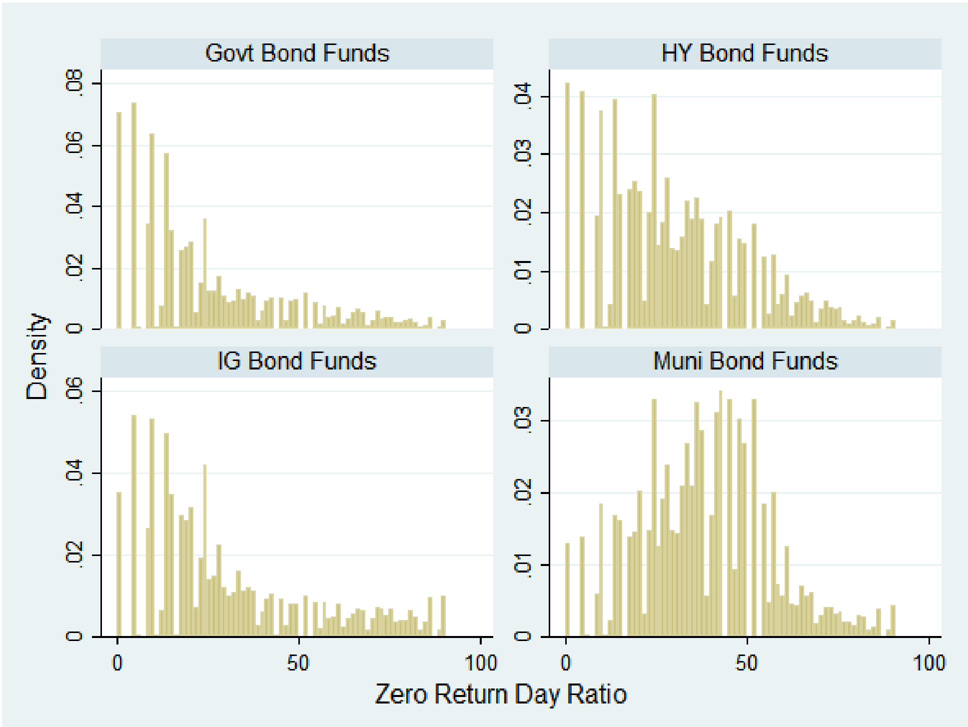
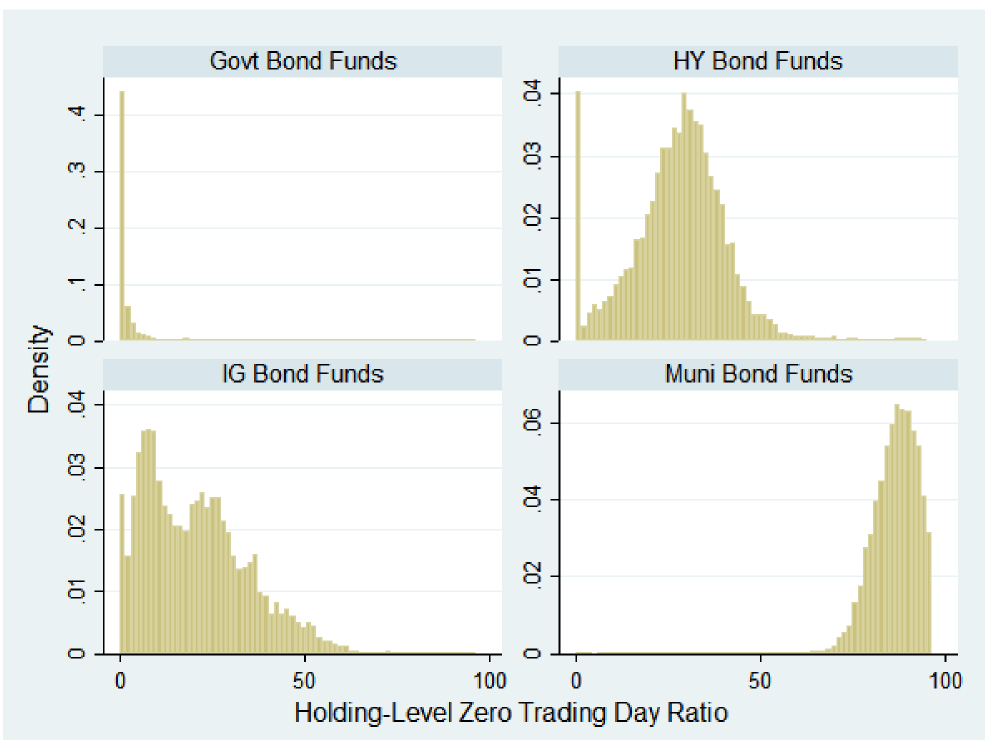


Figure 2. Distribution of Key Fund Characteristics by Asset Category

Panel A. Zero return day ratio



Panel B. Holding-level zero trading day ratio



Panel C. Weighted average maturity

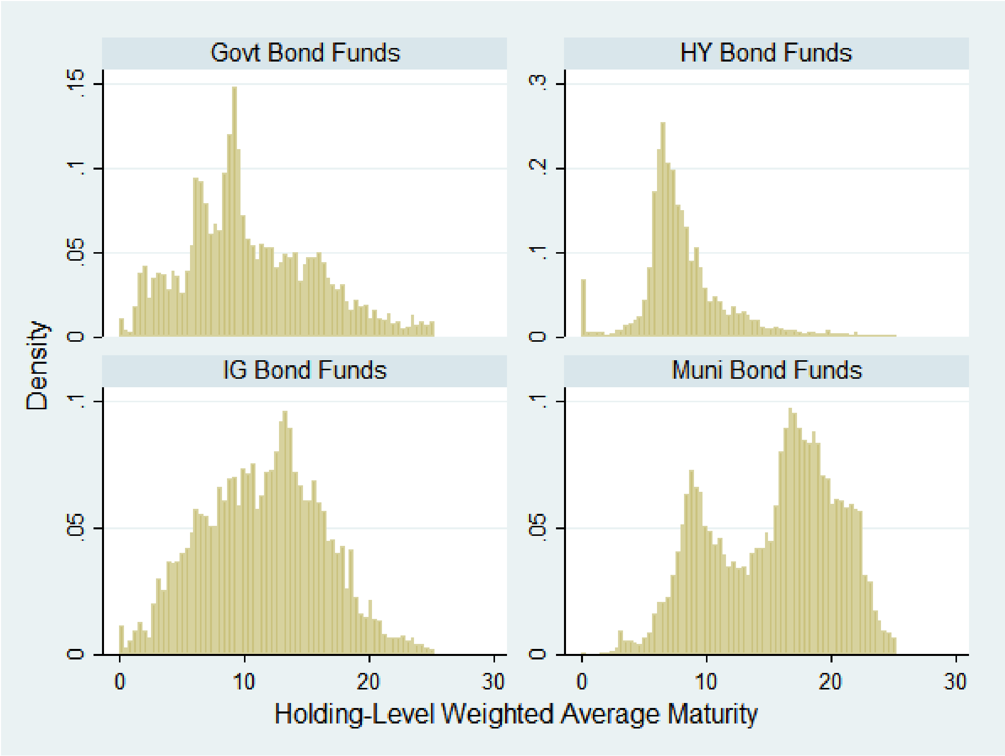


Table A.1. Why Do Funds Have Zero Return Days? Regression Analysis

This table reports the OLS regression results of our headline measure, ZRD ratio, on the interaction of log inverse NAV and the proxies for the explanation of price staleness, namely: holding-level ZTD ratio, short maturity dummy, and market volatility. The market volatility term is excluded in the regression because of the inclusion of month fixed effect. To aggregate across each fund's share classes, share class-level variables that share the same *crsp _cl_grp* are weighted by the previous month-end NAV, except for fund size and fund age. Fund size is the sum of the total net assets of each share class and fund age is the maximum of all classes. Controls are log fund size, log management firm size, fund age, index fund dummy, turnover ratio, expense ratio, and load dummy, whose coefficient estimates are omitted. All controls are lagged by one month. All specifications include Lipper objective × month fixed effects. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: Zero return day ratio (%)			
	(1)	(2)	(3)	(4)
	All Bond Funds			
Log inverse NAV	10.261***	13.331***	18.608***	15.148***
	(9.43)	(17.14)	(9.42)	(7.18)
Holding-level ZTD ratio (%)	**0.276*** **			**0.285*** **
	(5.18)			**(5.33)**
Log inverse NAV × Holding-level ZTD ratio (%)	**0.088*** **			**0.088*** **
	(4.72)			**(4.69)**
Short maturity dummy		10.996*		15.563**
		(1.77)		(2.42)
Log inverse NAV × Short maturity dummy		1.579		3.317
		(0.68)		(1.36)
Log inverse NAV × Market volatility (%)			-1.432***	-1.325***
			(-3.03)	(-2.86)
Controls	YES	YES	YES	YES
Lipper obj. × month FE	YES	YES	YES	YES
Adjusted R^2	0.726	0.726	0.723	0.730
No. of obs.	92,836	92,836	92,836	92,836

Table A.2. Return Predictability in Bond Funds: Asset Category Subsamples

This table re-estimates the daily predictability regression result in Panel A of Table 2, albeit separately each asset category (following the asset class definitions in Table 1). Weekly and monthly regression results are broadly consistent. Regressions are conducted at the fund share class level. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and day are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	By Asset Category			
	Govt. Bond Funds	HY Bond Funds	IG Bond Funds	Muni Bond Funds
Fund return [-1] (%)	-0.009	0.246***	-0.003	0.375***
	(-0.46)	(12.72)	(-0.16)	(15.41)
Fund return [-2] (%)	-0.022	0.096***	0.006	0.095***
	(-1.27)	(5.34)	(0.32)	(4.19)
Fund return [-5:-3] (%)	-0.018*	0.020**	0.006	0.003
	(-1.77)	(2.18)	(0.54)	(0.26)
Fund return [-10:-6] (%)	-0.008	0.012**	0.014*	0.012*
	(-1.11)	(2.06)	(1.68)	(1.71)
Fund return [-20:-11] (%)	0.009*	0.001	0.016***	0.003
	(1.71)	(0.40)	(2.68)	(0.60)
Adjusted R^2	0.003	0.095	0.005	0.187
No. of obs.	954,511	1,522,288	2,583,474	3,113,128

Table A.3. Return Predictability in Bond Funds: Time Fixed Effect

This table re-estimates Table 2 with time fixed effect. In columns (1)-(4) of each panel, we provide regression results for the full sample and for separately each ZRD tercile. Regressions are conducted at the fund share class level. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and time are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Daily predictability regressions

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All Bond Funds	ZRD tercile		
		Low	Mid	High
Fund return [-1] (%)	0.115***	0.087***	0.131***	0.158***
	(8.71)	(5.85)	(9.39)	(9.82)
Fund return [-2] (%)	0.059***	0.044***	0.062***	0.093***
	(4.88)	(3.22)	(4.81)	(6.97)
Fund return [-5:-3] (%)	0.019***	0.011	0.021***	0.023***
	(2.92)	(1.41)	(3.07)	(3.21)
Fund return [-10:-6] (%)	0.009*	0.008	0.008	0.010*
	(1.88)	(1.60)	(1.61)	(1.89)
Fund return [-20:-11] (%)	0.004	0.005	0.003	0.005*
	(1.28)	(1.60)	(0.88)	(1.71)
Trading day fixed effect	YES	YES	YES	YES
Adjusted R^2	0.367	0.452	0.432	0.400
No. of obs.	8,173,401	2,032,526	3,300,035	2,840,840

Panel B. Weekly predictability regressions

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All Bond Funds	ZRD tercile		
		Low	Mid	High
Fund return [-1] (%)	0.086***	0.043	0.098***	0.166***
	(2.73)	(1.30)	(2.68)	(4.38)
Fund return [-2] (%)	0.036	0.045	0.023	0.044
	(1.20)	(1.43)	(0.64)	(1.18)
Fund return [-3] (%)	0.024	0.052*	0.015	0.005
	(0.84)	(1.69)	(0.49)	(0.16)
Fund return [-4] (%)	0.012	-0.000	0.013	0.050
	(0.41)	(-0.01)	(0.41)	(1.20)
Week fixed effect	YES	YES	YES	YES
Adjusted R^2	0.430	0.475	0.495	0.479
No. of obs.	1,671,869	415,993	673,282	582,594

Panel C. Monthly predictability regressions

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All Bond Funds	ZRD tercile		
		Low	Mid	High
Fund return [-1] (%)	0.124*	0.159**	0.085	0.214***
	(1.89)	(2.50)	(1.11)	(3.14)
Month fixed effect	YES	YES	YES	YES
Adjusted R^2	0.473	0.473	0.514	0.550
No. of obs.	402,040	99,464	162,365	140,211

Table A.4. What Drives the Return Predictability of Bond Funds?

This table reports pooled daily (Panel A) or weekly (Panel B) OLS regression results of fund returns on the interaction of past fund returns with one of the following fund characteristic-based indicator variables: high ZRD dummy, which takes the value of one if the latest monthly ZRD of the fund share class is above or equal to the median of the full sample or each respective asset category at the same month-end; high holding-level ZTD dummy, constructed in the analogous manner; short maturity dummy, which equals one if the weighted average time-to-maturity of the latest fund holdings is less than 3 years, or low market volatility dummy, which takes the value of one if the latest market volatility (standard deviation of daily Bloomberg Barclays U.S. Aggregate Total Return index return over the [-250:-21] window at each month-end) is below the median during our sample period. Columns (2) and (3) have shorter sample period ending in June 2015 due to the availability of Morningstar holdings data. Regressions are conducted at the fund share class level. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and time are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Daily predictive regressions

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All bond funds			
Variable of interest	High ZRD dummy	High ZTD dummy	Short maturity dummy	Low market vol. dummy
Fund return [-1] (%)	0.126***	0.104***	0.205***	0.194***
	(7.76)	(5.24)	(11.32)	(9.85)
Fund return [-2] (%)	0.061***	0.048***	0.086***	0.092***
	(4.35)	(2.78)	(5.70)	(5.45)
Fund return [-5:-3] (%)	0.015**	0.016	0.016*	0.017*
	(1.98)	(1.65)	(1.92)	(1.85)
Fund return [-10:-6] (%)	0.010**	0.017**	0.016***	0.020***
	(1.98)	(2.42)	(2.75)	(3.02)
Fund return [-20:-11] (%)	0.005	0.007	0.004	0.002
	(1.63)	(1.42)	(1.02)	(0.50)
Variable of interest	-0.005**	-0.003	-0.007**	-0.013**
	(-2.01)	(-0.80)	(-2.39)	(-2.32)
Fund return [-1] (%)	**0.121*** **	**0.237*** **	**-0.147*** **	**-0.060** **
× variable of interest	**(7.74)**	**(9.69)**	**(-7.06)**	**(-2.09)**
Fund return [-2] (%)	**0.040*** **	**0.057** **	**-0.061*** **	**-0.039**
× variable of interest	**(3.07)**	**(2.57)**	**(-3.95)**	**(-1.45)**
Fund return [-5:-3] (%)	-0.001	-0.009	0.001	-0.009
× variable of interest	(-0.18)	(-0.78)	(0.11)	(-0.58)
Fund return [-10:-6] (%)	0.004	-0.003	0.011	-0.025**
× variable of interest	(0.84)	(-0.39)	(1.29)	(-2.50)
Fund return [-20:-11] (%)	-0.001	-0.005	0.008	0.005
× variable of interest	(-0.33)	(-0.94)	(1.38)	(0.68)
Adjusted R^2	0.054	0.083	0.067	0.053
No. of obs.	8,173,401	5,442,326	5,442,326	8,173,401

Panel B. Weekly predictive regressions

	Dependent variable: fund return [0] (%)			
	(1)	(2)	(3)	(4)
	All bond funds			
Variable of interest	High ZRD dummy	High ZTD dummy	Short maturity dummy	Low market vol. dummy
Fund return [-1] (%)	0.078**	0.065	0.144***	0.151***
	(2.27)	(1.48)	(3.19)	(3.13)
Fund return [-2] (%)	0.074**	0.154***	0.112**	0.126***
	(2.20)	(3.43)	(2.56)	(2.69)
Fund return [-3] (%)	0.003	0.005	-0.023	-0.015
	(0.08)	(0.10)	(-0.53)	(-0.32)
Fund return [-4] (%)	0.022	0.010	0.020	-0.017
	(0.68)	(0.25)	(0.46)	(-0.38)
Variable of interest	-0.025*	-0.004	-0.046**	-0.078**
	(-1.79)	(-0.15)	(-2.20)	(-2.01)
Fund return [-1] (%)	**0.110*** **	**0.160*** **	**-0.044**	**-0.094**
× Variable of interest	**(3.03)**	**(2.66)**	**(-0.91)**	**(-1.26)**
Fund return [-2] (%)	0.012	-0.093	0.021	-0.133*
× Variable of interest	(0.38)	(-1.64)	(0.44)	(-1.91)
Fund return [-3] (%)	-0.036	-0.041	0.072*	0.002
× Variable of interest	(-1.16)	(-0.71)	(1.80)	(0.03)
Fund return [-4] (%)	0.045	0.023	0.019	0.148**
× Variable of interest	(1.17)	(0.38)	(0.41)	(2.06)
Adjusted R^2	0.031	0.047	0.040	0.043
No. of obs.	1,671,869	1,101,340	1,101,340	1,671,869

Table A.5. Weekly Flow Regressions: Controlling for Longer Lags

In this table, we re-estimate weekly flow regressions in columns (1) and (2) of Table 5, controlling for past fund return up to four lags. Controls are identical to those in Table 5. All specifications include Lipper objective × week fixed effects. Regressions are conducted at the fund share class level. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and week are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund flow [0] (%)	
	(1)	(2)
	All bond funds	
Return gap [-1] (%)	**0.149*** (6.30)**	**0.079*** (2.70)**
Fund return [-1] (%)	**0.311*** (10.48)**	**0.243*** (6.94)**
Fund return [-2] (%)	0.089*** (6.54)	0.097*** (6.22)
Fund return [-3] (%)	0.046*** (3.76)	0.054*** (3.95)
Fund return [-4] (%)	0.114*** (8.88)	0.082*** (5.73)
Return gap [-1] (%) × ZRD ratio (in decimal)		**0.409*** (4.53)**
Fund return [-1] (%) × ZRD ratio		**0.404*** (3.98)**
Fund return [-2] (%) × ZRD ratio		-0.059 (-1.54)
Fund return [-3] (%) × ZRD ratio		-0.039 (-1.14)
Fund return [-4] (%) × ZRD ratio		0.204*** (5.02)
ZRD ratio		0.057** (2.12)
Controls	YES	YES
Lipper obj. × week FE	YES	YES
Adjusted R-squared	0.107	0.107
No. of obs.	1,645,958	1,645,958

Table A.6. Monthly Flow Regressions: Negative vs. Non-Negative Return Gap

This table re-estimates Table 6 at monthly horizon. Controls are identical to those in Table 6. Regressions are conducted at the fund share class level. All specifications include Lipper objective × month fixed effect. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund flow [0] (%)	
	(1)	(2)
	All bond funds	
Return gap [-1] (%)	0.679***	0.428***
	(5.75)	(3.20)
Return gap [-1] (%) | Return gap [-1] < 0	0.262*	0.259*
	(1.84)	(1.68)
Fund return [-1] (%)	1.275***	1.034***
	(8.83)	(6.60)
Fund return [-1] (%) | Fund return [-1] < 0	0.169	0.002
	(0.94)	(0.01)
Return gap [-1] (%) × ZRD ratio (in decimal)		1.514***
		(4.29)
Return gap [-1] (%) × ZRD ratio | Return gap [-1] < 0		-0.207
		(-0.49)
Fund return [-1] (%) × ZRD ratio		1.379***
		(4.26)
Fund return [-1] (%) × ZRD ratio | Fund return [-1] < 0		0.895*
		(1.84)
ZRD ratio (in decimal)		0.301
		(1.17)
Controls	YES	YES
Lipper obj. × month FE	YES	YES
Adjusted R-squared	0.087	0.087
No. of obs.	399,468	399,468

Table A.7. Monthly Flow Regressions: Load vs. No-Load Share Classes

This table re-estimates Table 7 at monthly horizon. Controls are identical to Table 7. Regressions are conducted at the fund share class level. All specifications include Lipper objective × month fixed effects. *t*-statistics based on standard errors robust to heteroskedasticity and two-way clustered by fund and month are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: fund flow [0] (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
	All bond funds					
	(Refined) load classes	No load classes	Subsample diff.-in. coeff.	(Refined) load classes	No load classes	Subsample diff.-in. coeff.
Return gap [-1] (%)	0.632***	0.909***	-0.277**	0.578***	0.594***	-0.017
	(5.59)	(8.02)	(-2.47)	(4.37)	(5.22)	(-0.13)
Fund return [-1] (%)	1.070***	1.493***	-0.423***	1.012***	1.089***	-0.076
	(7.34)	(11.26)	(-3.13)	(5.99)	(8.33)	(-0.50)
Return gap [-1] (%) × ZRD ratio (in decimal)				0.344	1.751***	-1.407***
				(1.03)	(5.60)	(-3.37)
Fund return [-1] (%) × ZRD ratio (in decimal)				0.379	2.270***	-0.484**
				(0.99)	(6.31)	(-2.29)
ZRD ratio (in decimal)				0.772**	0.007	0.765**
				(2.20)	(0.03)	(1.99)
Controls	YES	YES	-	YES	YES	-
Lipper obj. × month FE	YES	YES	-	YES	YES	-
Adjusted R-squared	0.138	0.071	-	0.139	0.072	-
No. of obs.	114,384	284,932	-	114,384	284,932	-

Table A.8. Calendar-Time Portfolio Analysis: Full Sample

This table re-estimates the calendar-time portfolio analysis in Table 8, albeit for the full sample, i.e., including fund share classes with load fees. *t*-statistics based on Newey-West (1987) heteroskedasticity- and autocorrelation-consistent standard errors with three lags are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

A. Full Sample

	Dependent variable: monthly portfolio return (%)		
	(1)	(2)	(3)
	Positive lag 1 return	Negative lag 1 return	(1) – (2) difference
Excess Return			
Excess Return (%)	0.428*** (4.73)	0.228** (2.00)	0.200** (2.30)
One-Factor Alpha			
α (%)	**0.231*** (3.18)**	**0.061 (0.51)**	**0.170 (1.64)**
$\beta_{market\ benchmark}$	0.599*** (6.50)	0.509*** (3.51)	0.090 (0.81)
Adjusted R-squared	0.433	0.177	-0.001
Number of monthly obs.	113	113	113

B. ZRD Tercile

	Dependent variable: monthly portfolio return (%)								
	ZRD tercile								
	Low			Mid			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Positive lag 1 return	Negative lag 1 return	(1) – (2) difference	Positive lag 1 return	Negative lag 1 return	(4) – (5) difference	Positive lag 1 return	Negative lag 1 return	(7) – (8) difference
Excess Return									
Excess Return (%)	0.458*** (4.19)	0.250* (1.84)	0.208* (1.97)	0.468*** (4.70)	0.281** (2.18)	0.187* (1.97)	0.363*** (4.76)	0.137 (1.48)	0.226*** (2.75)
One-Factor Alpha									
α (%)	**0.219**** **(2.45)**	**0.040** **(0.30)**	**0.179** **(1.41)**	**0.253***** **(3.07)**	**0.091** **(0.68)**	**0.162** **(1.42)**	**0.214***** **(3.20)**	**0.018** **(0.17)**	**0.196**** **(2.15)**
$\beta_{market\ benchmark}$	0.728*** (7.54)	0.640*** (4.33)	0.088 (0.67)	0.652*** (6.19)	0.577*** (3.47)	0.076 (0.63)	0.454*** (5.25)	0.363*** (2.68)	0.091 (0.86)
Adjusted R-squared	0.477	0.185	-0.004	0.416	0.186	-0.004	0.299	0.133	0.001
Number of monthly obs.	113	113	113	113	113	113	113	113	113

Table A.9. Calendar-Time Portfolio Analysis: Full Sample

This table re-estimates the calendar-time portfolio analysis in Table 8, albeit with three months of time delay between monthly return evaluation and portfolio formation. This, for example, implies that rebalancing at the end of June 2013, is based on the funds' monthly returns for March 2013. *t*-statistics based on Newey-West (1987) heteroskedasticity- and autocorrelation-consistent standard errors with three lags are reported in parentheses below the coefficient estimates. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

A. Full Sample

	Dependent variable: monthly portfolio return (%)		
	(1)	(2)	(3)
	Positive lag 1 return	Negative lag 1 return	(1) – (2) difference
Excess Return			
Excess Return (%)	0.377*** (4.18)	0.308*** (3.05)	0.069 (0.90)
One-Factor Alpha			
α (%)	**0.136**** **(2.35)**	**0.121** **(1.21)**	**0.016** **(0.17)**
$\beta_{market\ benchmark}$	0.659*** (7.43)	0.514*** (3.91)	0.146 (1.59)
Adjusted R-squared	0.556	0.217	0.014
Number of monthly obs.	110	110	110

B. ZRD Tercile

	Dependent variable: monthly portfolio return (%)								
	ZRD tercile								
	Low			Mid			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Positive lag 1 return	Negative lag 1 return	(1) – (2) difference	Positive lag 1 return	Negative lag 1 return	(4) – (5) difference	Positive lag 1 return	Negative lag 1 return	(7) – (8) difference
Excess Return									
Excess Return (%)	0.475*** (4.58)	0.397*** (3.04)	0.077 (0.74)	0.449*** (4.43)	0.298** (2.58)	0.151* (1.82)	0.279*** (3.46)	0.189** (2.40)	0.090 (1.04)
One-Factor Alpha									
α (%)	**0.143*** (2.65)**	**0.168 (1.23)**	**-0.025 (-0.21)**	**0.180*** (2.64)**	**0.074 (0.66)**	**0.106 (1.03)**	**0.115* (1.82)**	**0.104 (1.09)**	**0.011 (0.11)**
$\beta_{market\ benchmark}$	0.908*** (17.53)	0.626*** (4.14)	0.281** (2.19)	0.736*** (6.90)	0.614*** (4.27)	0.122 (1.29)	0.449*** (4.46)	0.233 (1.62)	0.217** (2.06)
Adjusted R-squared	0.709	0.177	0.039	0.521	0.232	0.004	0.363	0.064	0.047
Number of monthly obs.	110	110	110	110	110	110	110	110	110