Beyond Creation and Redemption: Principal Trading by Bond ETFs*

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Abstract

We investigate principal trading in corporate bond ETFs. While rare in equity ETFs, we show that principal trading by bond ETF managers is widespread, occurring on 35% of trading days, more often than either creations or redemptions. Adjusted for ETF size, volumes of principal trading and creation/redemption are comparable. Because bond ETFs hold more issues and face maturities, redemptions, and credit migrations, we show how principal trading allows passive bond ETF managers to more effectively align bond holdings and reduce tracking error. Principal trading also increases portfolio alpha for active ETFs by 25 basis points.

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Beyond Creation and Redemption: Principal Trading by Bond ETFs

Exchange-traded funds (ETFs) have revolutionized asset management. Starting with equities, ETFs are now a mainstay investment product in asset classes as diverse as fixed income, REITs, banks loans, commodities, and TIPS. This ubiquity is largely due to ETF's innovative structure. Unlike traditional mutual funds, whose portfolios are managed primarily through direct trading of underlying securities, ETFs adjust their holdings largely through an in-kind creation and redemption mechanism. This process allows authorized participants (APs) to exchange baskets of underlying securities for ETF shares, thereby altering the composition of the ETF's portfolio. The mechanism not only determines how ETFs manage inflows and outflows but also underpins the arbitrage process that keeps ETF prices closely aligned with the value of their underlying holdings. Consequently, a large literature has examined how creations and redemptions shape ETF behavior, influence arbitrage dynamics, and affect the liquidity and efficiency of the underlying markets.

However, in-kind flows are not the only way ETFs manage their portfolios. ETFs can also engage in principal trading, directly buying and selling securities in the secondary market. This activity has received far less attention, partly because for equity ETFs it is relatively infrequent and operationally secondary. Equity ETFs typically track highly liquid benchmarks and rely on full replication, which minimizes the need for active rebalancing beyond creations and redemptions. In contrast, the fixed-income setting is fundamentally different. Bond ETFs track indices containing thousands of often illiquid securities, many of which mature, roll off, or are replaced by new issues. Constituent turnover in bond indices is substantially higher than in equity indices (Figure 1).[1] In-kind baskets are therefore imperfect, and APs often deliver custom baskets that do not precisely match the benchmark. To manage duration, credit exposures, and tracking error, bond ETF managers can step into the bond market themselves. Moreover, principal trading offers managers flexibility not only to maintain index alignment but also to potentially improve portfolio performance by selectively trading bonds.

[1] Using data from S&P Dow Jones Indices, we examine the monthly rebalancing of the iBoxx iShares $ Corporate Bond Index (investment-grade and high-yield segments, which underlie the largest corporate bond ETFs LQD and HYG) and the S&P 500 over the period 2015–2023. On average, 35 (24) bonds are added to (deleted from) the investment-grade index each month and 30 (27) are added to (deleted from) the high-yield index, compared with only about two stocks replaced per month in the S&P 500. Measured as a share of index constituents, 2.2% (1.5%) of the bonds in the investment-grade index and 2.6% (2.0%) in the high-yield index are added (deleted) each month, versus about 0.4% of S&P 500 constituents. Figure 1 summarizes these patterns.

In this paper we investigate principal trading in corporate bond ETFs. Our focus is on answering three questions: To what extent do bond ETFs engage in principal trading, what drives this behavior, and how, if at all, does it affect ETF performance? To address these issues, we first need to solve a basic problem: how do we identify principal trades? While the literature has developed methods to infer daily creations and redemptions, this is not the case for principal trades. One contribution of our research is providing a methodology for discerning these principal trades. Our approach infers ETF trading activities indirectly by combining information on daily ETF holdings and ETF primary market flows. Unlike traditional mutual funds, which typically disclose their holdings monthly or quarterly, ETFs report their portfolio holdings daily, reflecting a unique feature of their structure designed to facilitate transparency and the creation and redemption process. Matching this high-frequency holdings data with daily changes in ETF shares outstanding makes it possible to infer when trading activity reflects principal transactions conducted by the ETF itself rather than flows with APs.[2]

Our research demonstrates a remarkable breadth to bond ETF principal trading. Looking across trading days, 35% of days have principal trading compared to 16% of days with creations, 7% with redemptions, and 42% with no principal trading or in-kind flows. Across all bond ETFs, the dollar volume of creation/redemptions is larger than principal trading, but this difference disappears once scaled by fund size. We show how fund characteristics affect the intensity of principal trading usage, finding, for example, significant differences in its importance for smaller funds and for more active ETFs.

We also examine how ETFs implement principal trading by investigating which bonds ETFs purchase and sell, and the timing of these trades. We find that bond ETFs often use principal trades to both buy and sell different bond issues on a given day. Moreover, ETF principal trades are concentrated in particular issues and are closely linked to recent creation and redemption activity, consistent with their use in adjusting the composition of the portfolio. Unlike creations and redemptions, which are relatively constant across the month, we find that principal trading shows a distinct increase at month's end. These results reveal a large and pervasive role played by principal trades in fine-tuning the portfolios of bond ETFs.

[2] As we discuss in more detail in Section 3, this methodology is conservative, so our results on principal trading potentially understate the extent of such trading.

Of equal importance is the impact of these actions. We conjecture that principal trading may play a role in affecting ETF performance metrics such as tracking error and fund performance. Using panel regressions, we show that a 1% increase in principal trading is associated with a 1.7% reduction in tracking error over the subsequent three-day window. This effect does not arise from creation/redemption activity, nor is it found in active bond ETFs. Turning to ETF performance, if funds use principal trades to enhance performance, we should find that bonds more heavily traded in month t should have excess returns in month t+1. Our finding that for active ETFs a 1 standard deviation increase in principal trading leads to an increase of 0.12 basis points in daily returns (or, 30.91 annualized) confirms this conjecture. To investigate aggregate fund performance, we decompose each bond ETF's alpha into components associated with creations and redemptions and with portfolio trades. For active ETFs, we find that annual alpha is 19 basis points, with principal trades adding 25 basis points while creation and redemptions subtract 6 basis points. For passive ETFs, alpha is -9 basis points, with principal trading contributing 1 basis point and creation and redemption reducing alpha by 11 basis points.[3]

Overall, our research highlights the important role principal trading plays in explaining the operation and performance of both active and passive bond ETFs. For passive ETFs, principal trading can reduce tracking error by more effectively aligning the composition of holdings due to the underlying turnover of bond issues. For active bond ETFs, principal trading contributes to higher alpha by allowing greater flexibility in portfolio composition. For bond ETFs, principal trading enhances the effectiveness of the creation and redemption process, extending the benefits of the ETF structure to fixed income assets.

Our paper, the first to our knowledge to examine ETF principal trading, contributes to the growing literature on ETFs. The existing literature has primarily focused on the unique structural feature of ETFs, the primary market mechanism of creation and redemption by APs,[4] and its implications for both ETFs and their underlying assets. One major strand of this literature investigates the impact of ETFs on underlying markets through the creation/redemption process, documenting effects on volatility (Ben-David, Franzoni, and Moussawi (2018)), return comovement (Da and Shive (2018)), liquidity (Sağlam, Tuzun, and Wermers (2025)), returns and

[3] Other factors contribute to a small rounding error.

[4] For example, Huang and Martinez (2024) show that ETF creation and redemption mechanisms reduce the liquidity-motivated trading typically driven by fund flows in bond mutual funds, resulting in lower costs associated with investor flows.

trading activity (Box, Davis, Evans, and Lynch (2021)), and informational efficiency (Israeli, Lee, and Sridharan (2017); Bhattacharya and O'Hara (2018); Glosten, Nallareddy, and Zou (2020); Huang, O'Hara, and Zhong (2021)). Similar analyses in the context of bond ETFs include Dannhauser (2017), Dannhauser and Hoseinzade (2022), Holden and Nam (2024), Finnerty, Reisel, and Zhong (2025), and Brogaard, Heath, and Huang (2025).

A second line of research emphasizes the dual role of APs as both ETF intermediaries and market makers in the underlying markets. These studies analyze how APs' participation in both arenas shapes their incentives and the linkage between ETF and underlying markets (e.g., Pan and Zeng (2019); Dannhauser and Karmaziene (2023); Du (2023); Shim and Todorov (2023); Koont et al. (2025); Moussawi, Shen, and Velthuis (2025)). A related literature highlights the strategic behavior of APs in the creation and redemption process and its consequences for ETF performance (Reilly (2022); Huang, Wermers, Xue, and Zhou (2025)).

In contrast to the predominant focus on the primary market activity initiated by APs, our paper shifts attention to ETF managers and their secondary-market trading activities. We document that principal trading by bond ETFs is widespread and economically significant. We further show that principal trading serves dual purposes within the ETF ecosystem. For passive bond ETFs, it functions as an operational tool that facilitates index maintenance and mitigates tracking error. For active bond ETFs, it operates as a performance-enhancing mechanism. Our findings thus reveal principal trading as an essential complement to the creation and redemption mechanism, extending the ETF literature's understanding of how these funds manage portfolios and generate performance.

Our paper also contributes to the literature on how fund managers' trading activities affect portfolio performance. A large body of work documents that securities purchased by mutual funds subsequently outperform those they sell (e.g., Wermers 2000; Chen, Jegadeesh, and Wermers 2000; Alexander, Cici, and Gibson 2007; Yan and Zhang 2009). Other studies link trading activity itself to future fund performance. Wermers (2000), for example, uses portfolio turnover as a proxy for active trading and finds that funds with higher trading intensity modestly outperform passive benchmarks net of costs. Kacperczyk, Sialm, and Zheng (2008) introduce the "return gap", the difference between a fund's reported return and the return implied by its publicly disclosed holdings, and show that this gap predicts subsequent fund performance, suggesting that trading decisions not visible in holdings data are an important driver of returns.

A key challenge in this literature is the lack of high-frequency observations of managers' trades. Researchers typically only observe monthly or quarterly holdings, which obscures the timing, purpose, and performance implications of actual trades. While Puckett and Yan (2011) provide valuable evidence using institutional trade-level data, their sample is limited to the subset of institutions covered by a single consulting firm and therefore does not offer broad, generalizable insight into fund trading behavior.

Our paper overcomes these limitations by leveraging the unique availability of daily ETF holdings and by developing a methodology to infer principal trades executed by bond ETFs. This setting allows us to directly observe how ETF managers adjust positions in underlying bonds on a day-to-day basis, something that is infeasible in traditional mutual fund data. By linking inferred principal trades to subsequent performance, we provide clean evidence on the trading-based component of ETF returns and identify how fund managers' trading decisions translate into investor outcomes.

Moreover, our inferred trades allow us to analyze, for the first time, how funds trade to minimize tracking error. This dimension of manager behavior is largely unobservable in low-frequency holdings data, particularly given that many fixed-income indices rebalance only monthly. Our approach therefore yields new insights into the microstructure of ETF management and opens the door to studying questions about active trading and benchmark replication that could not previously be addressed in the literature.

The remainder of the paper is organized as follows. Section 1 presents the institutional background. Section 2 describes the data and outlines the sample construction. Section 3 identifies principal trading by bond ETFs and characterizes the nature of these trades. Section 4 investigates the drivers and implications of principal trading for the ETF industry, focusing on tracking errors and fund performance. Section 5 concludes.

1. Institutional Background

ETFs are open-end vehicles whose share count adjusts through an in-kind creation and redemption process, which allows ETF shares to be exchanged for baskets of the underlying securities. This process is intermediated by a small set of institutional counterparties known as APs, typically large broker-dealers capable of transacting directly with ETFs. Investors trade ETFs in the secondary market, where prices fluctuate with demand and supply. When ETF shares trade

at a premium to the net asset value (NAV) of their underlying holdings, APs can deliver the underlying securities to the ETF in exchange for newly created shares, which they sell in the secondary market, thereby narrowing the premium. Conversely, when ETF shares trade at a discount, APs redeem ETF shares for the underlying securities, which they can sell, eliminating the discount. This mechanism forms the basis of the ETF arbitrage process that anchors secondary-market prices to the value of the underlying portfolio.

Historically, the composition of in-kind creation and redemption baskets closely mirrored the ETF's portfolio on a pro-rata basis. In early ETF structures, primarily equity ETFs, regulators required that the securities exchanged during the in-kind process represent proportionate slices of the ETF's holdings to prevent selective disclosure and ensure equal treatment across investors. Because these early ETFs pursued full replication of liquid equity benchmarks, the pro-rata basket design effectively aligned the creation and redemption process with the ETF's underlying portfolio, leaving little scope for discretion. This structure also reduced the need for ETF managers to engage in direct, or principal, trading activity. Equity benchmarks are composed of liquid, continuously traded securities that do not mature, and ETFs can usually achieve near-perfect replication with minimal tracking error. As a result, the creation and redemption mechanism efficiently accommodates investor flows, while principal trading remains limited to routine cash management, minor index rebalancing trades, or dividend reinvestments. Consequently, for most equity ETFs, principal trading is operationally secondary and economically marginal.

The pro-rata framework, while promoting transparency and consistency, also imposed operational rigidity. It constrained ETF sponsors' flexibility to manage liquidity, handle restricted or illiquid securities, and accommodate cash or substitute instruments in the baskets. As ETF markets evolved and expanded into less liquid asset classes, particularly fixed income securities, these limitations became increasingly problematic.

Unlike equity ETFs, bond ETFs operate in a fundamentally different environment. Fixed-income markets are decentralized, less transparent, and often characterized by infrequent trading. Bond indices typically contain thousands of securities spanning diverse maturities, credit qualities, and issuers, many of which rarely trade or are unavailable in sufficient quantities. As a result, full replication of bond benchmarks is costly and sometimes infeasible, and most bond ETFs rely on representative sampling or optimization-based strategies to approximate index exposures.

To address the need for greater flexibility, in 2019 the SEC adopted Rule 6c-11 under the Investment Company Act of 1940. Commonly known as the ETF Rule, Rule 6c-11 codified prior exemptive relief and established a uniform framework for ETF operations. A central feature of the rule was its explicit recognition of custom baskets, which allow ETF sponsors, under written policies and procedures, to deviate from strictly pro-rata compositions when doing so serves investors' best interests. By enabling custom baskets, Rule 6c-11 reduced frictions in the arbitrage mechanism and facilitated more efficient portfolio management, particularly for funds tracking complex or illiquid benchmarks, where representative sampling rather than full replication is necessary.

Custom baskets play an important role in managing bond ETF portfolios. Shim and Todorov (2021) show that bond ETFs employ custom baskets to reduce tracking error as fixed-income indices continuously rebalance due to maturities, new issuance, and credit migration. Custom baskets allow ETF managers to substitute toward bonds that improve benchmark alignment and liquidity. However, this flexibility is limited. Because APs negotiate basket compositions, especially during creations, ETF managers retain only partial discretion over portfolio alignment. Even during redemptions, regulatory and operational constraints restrict issuers from selectively offloading less desirable securities, often leading to redemption baskets whose characteristics diverge from the fund's intended factor exposures (Cohen, Laipply, Madhavan, and Mauro (2022)). Moreover, when investor flows are muted, opportunities to adjust holdings through in-kind exchanges are effectively absent. In such cases, principal trading becomes indispensable. By directly participating in the bond market, ETF managers can fine-tune exposures, manage duration drift, replace maturing issues, and ensure that the representative sample remains aligned with the index's evolving risk and liquidity characteristics. In this sense, principal trading functions as an essential extension of the in-kind mechanism, particularly in asset classes where representative sampling and custom basket limitations make ongoing active adjustments necessary.

Beyond its role in maintaining index alignment, principal trading also provides ETF managers with strategic flexibility to enhance portfolio performance. By selectively trading bonds, managers can exploit temporary mispricing, adjust credit or sector exposures, and improve portfolio liquidity without materially increasing tracking error. This discretion is particularly valuable in fixed-income markets, where heterogeneity in security characteristics and episodic liquidity create opportunities for incremental value generation.

2. Data and Sample Construction

We examine the corporate bond market to study principal trading by bond ETFs. Our primary dataset combines daily ETF flows from Bloomberg and security-level holdings from Morningstar. The sample period spans 2017–2023. We start with all U.S.-domiciled ETFs and identify corporate bond ETFs from Morningstar's U.S. Fixed Income category, restricting attention to funds that invest substantially in corporate bonds.[5]

Several exclusions refine our sample. First, we remove target-date ETFs, as these funds increase cash allocations as they approach maturity (Koont et al., 2025). Second, following Huang, Wermers, Xue, and Zhou (2025), we exclude Vanguard ETFs, which do not report daily holdings to Morningstar and often operate under a dual-share structure (where the ETF shares a portfolio with an underlying mutual fund). Third, we drop ultra-small and non–corporate bond–focused ETFs. Specifically, we include ETFs that reached total net assets (TNA) of at least $50 million prior to 2023, to avoid distortions from micro funds and to ensure a sufficiently long time series for each ETF. Fourth, we remove nine ETFs that do not specify the indices they track. Our final sample contains 90 corporate bond ETFs, encompassing 29,417 unique bonds and 162,654,069 fund–bond–day observations.

We supplement the fund flow and holdings data by merging information from three additional sources. First, we obtain each ETF's prospectus index from Morningstar and its corresponding daily index returns from Morningstar and Bloomberg. We also collect daily ETF shares outstanding from Bloomberg. Second, from CRSP, we collect trading volume, closing prices, bid-ask spreads, along with ETF-level characteristics such as index-tracking status and expense ratios. Finally, for bond-level characteristics, we draw from the Mergent Fixed Income Securities Database (FISD), which provides issuance, maturity, and full credit-rating histories from

[5] Specifically, we choose the following seven categories of corporate bond funds: "US Fund Corporate Bond," "US Fund High Yield Bond," "US Fund Long-Term Bond," "US Fund Intermediate Core Bond," "US Fund Intermediate Core-Plus Bond," "US Fund Multisector Bond," and "US Fund Short-Term Bond." Because many ETFs in these categories may also invest in other fixed income securities, we exclude ETFs that, over their lifetime, hold fewer than 50 distinct corporate bonds. This restriction removes funds whose portfolios consist primarily of non-corporate fixed income instruments.

S&P, Moody's, and Fitch. For each bond-day observation, we construct a composite credit rating that consolidates ratings across agencies.[6]

We measure ETF characteristics at the ETF–year level by averaging daily observations within each calendar year. This aggregation reduces short-term noise and aligns our analysis with fund-level attributes that evolve gradually over time. Table 1 reports summary statistics based on these ETF–year averages. On average, bond ETFs in our sample hold $3 billion in total net assets, with roughly $2 billion invested in corporate bonds. The distribution is highly skewed: the median TNA and corporate-bond TNA are only $250 million and $164 million, respectively, highlighting the dominance of several very large ETFs. This skewness underscores the importance of controlling for fund size when examining ETF trading behavior. Consistent with size dispersion, ETF trading volume is also skewed. The mean daily trading volume is approximately $74 million, compared with a median of $2 million. Scaling by fund size substantially mitigates this skewness: the mean and median daily turnover (trading volume / TNA) are 1.5% and 0.9%, respectively. Liquidity and cost measures are more balanced. The average bid-ask spread is 39 bps, and the average expense ratio is 26 bps, both only slightly above their median values. Roughly 23% of the ETFs are classified as actively managed.[7]

The median ETF holds bonds with an average credit rating of 4 (corresponding to BBB), an average remaining maturity of 7 years, and an average bond age of 4 years. The median fund owns 512 bonds, compared with a mean of 1,146, again reflecting significant heterogeneity in ETF size and scope.

3. The Prevalence of ETF Principal Trading in Corporate Bonds

In this section, we examine the extent to which bond ETFs engage in secondary market principal trading and the characteristics of these activities. We begin by outlining our empirical methodology for identifying ETF principal trading from available data. We then document the prevalence of such trading and explore its relationship with ETF primary market activities, specifically, share creations and redemptions. Finally, we analyze which ETFs are more likely to

[6] Numerically, we map each rating to an integer scale (AAA = 1, AA = 2, A = 3, BBB = 4, and so on). If a bond has only one rating, that value defines its composite. For two ratings, we take the lower (more conservative) rating, and for three, the median. This approach ensures comparability across rating agencies and over time.

[7] An ETF is classified as active if it is not identified as index-tracking by either CRSP or Morningstar. We manually verified classifications using fund prospectuses.

engage in principal trading and which corporate bonds are more frequently involved in these transactions.

3.1 Identifying Principal Trading by Bond ETFs

A key empirical challenge in studying principal trading by bond ETFs lies in the limitations of available data. The standard dataset for corporate bond market research, the TRACE (Trade Reporting and Compliance Engine) corporate bond transaction data, provides detailed information on nearly all secondary market trades, including trade prices, sizes, and timestamps. However, it does not contain the identities of the buy-side investors involved in each transaction, which are required to distinguish trades involving ETFs from those by other investors.[8]

Further, unlike insurance companies that disclose detailed, security-level bond transaction information in their Schedule D filings to the National Association of Insurance Commissioners (NAIC), ETFs only report aggregate annual principal trading in their Form N-CEN filings with the Securities and Exchange Commission (SEC). These filings provide total principal trading activity across all portfolio bonds and all trading days, without any information on the timing, direction, or security composition of these trades. This aggregation makes it difficult to study how ETF principal trading operates in practice or to assess its implications for ETF portfolio management.

To address these data limitations, we infer ETF trading activities indirectly by combining information on daily ETF holdings and ETF primary market flows. Unlike traditional mutual funds, which typically disclose their holdings monthly or quarterly, ETFs report their portfolio holdings daily, reflecting a unique feature of their structure designed to facilitate transparency and the creation and redemption process. When this high-frequency holdings data is matched with information on ETF flows (i.e., changes in ETF shares outstanding), it becomes possible to infer when trading activity reflects principal transactions conducted by the ETF itself rather than flows with APs.

Specifically, we define principal trading as changes in an ETF's corporate bond holdings that occur on days when the fund experiences no net primary market flows, that is, when there is

[8] The regulatory version of TRACE data includes the identities of sell-side dealers behind each trade. See, for example, O'Hara and Zhou (2021a, 2021b).

no change in shares outstanding.[9] In principle, zero-flow days could still involve offsetting creations and redemptions, which would result in no net change in shares outstanding despite significant underlying trading activity with APs. However, in practice, such exact offsetting is highly unlikely. To produce a net flow of zero, the volume of share creations would have to match redemptions precisely, an outcome that is improbable, especially given the small number of APs active in the fixed income ETF market. [10]

Figure 2 illustrates our identification strategy using the holdings of an Oracle corporate bond (CUSIP: 68389XBJ3) by the SPDR® Portfolio Long Term Corporate Bond ETF (Ticker: SPLB). The figure plots daily changes in SPLB's holdings of this bond together with the ETF's daily net flows over the period November 1–15, 2021. During this sample period, SPLB experienced zero net flows on five trading days: November 2, 4, 10, 11, and 12. On two of these days, November 4 and November 10, SPLB's holdings of the Oracle bond declined by $40,000 and $120,000 in par amount, respectively, corresponding to principal sales. On November 12, the ETF's holdings increased by $100,000 in par amount, reflecting a principal purchase. These trades occurred on days with zero net flows, thus meeting our definition of principal trading. In contrast, when SPLB experienced positive or negative net flows, changes in its Oracle bond holdings are attributed to creations or redemptions. For instance, the increase in holdings on November 1 and November 5 corresponds to bond acquisitions through creation activity, whereas the decline on November 3 represents a redemption. For the remaining days in this sample period, SPLB's holdings of the Oracle bond did not change. This could be because SPLB experienced no net flows (as on November 2 and 11) or because custom baskets were used in the creation or redemption process, such that SPLB's inflows on November 8, 9, and 15 involved adjustments in other bonds rather than in this Oracle issue.

It is important to note that principal trading can also occur on days with nonzero net flows. However, data limitations prevent us from cleanly distinguishing between bond holding changes

[9] Some ETFs report end-of-day holdings prior to that day's creation and redemption activity, while others report after such activity. To ensure accurate inference of principal trading, we follow the adjustment procedure in Huang, Wermers, Xue, and Zhou (2025, Appendix C), which aligns the timing between Morningstar holdings data and Bloomberg shares outstanding data.

[10] In our N-CEN sample, there are 21 APs, with the top three accounting for 81% of total creation and redemption activity. The largest APs are JPMorgan (38% market share), Goldman Sachs (22%), and Bank of America Merrill Lynch (21%). The next largest are Virtu (4%), Morgan Stanley (4%), and RBC Capital Markets (4%). The high concentration of fixed-income ETF activities among a small number of APs is consistent with findings in Arora et al. (2020), Gorbatikov and Sikorskaya (2022), and Du (2023).

arising from creations and redemptions and those resulting from principal trades on such days. Consequently, our identification strategy captures only a subset of actual principal trading activity. The estimates we report should therefore be interpreted as conservative measures, representing a lower bound on the true incidence of bond ETF principal trading.

3.2 Principal Trading Characteristics

We apply the identification strategy described above to our full sample of ETF–bond–day observations, which are then aggregated to the ETF–day level and classified into one of four mutually exclusive categories: Principal Trade, Creation, Redemption, or No Principal Trade No Flow. Specifically, an ETF–day is classified as a Principal Trade if an ETF experiences zero net flows, that is, no change in ETF shares outstanding, but adjusts the holdings of at least one of its portfolio bonds. On such days, both principal purchases and principal sales may occur concurrently if the ETF increases its positions in some bonds while reducing holdings in others. ETF–days with net inflows (i.e., positive changes in ETF shares outstanding) are classified as Creations, while those with net outflows (i.e., reductions in ETF shares outstanding) are classified as Redemptions. The remaining observations, i.e., days with zero net flows and no change in any bond holdings, are categorized as No Principal Trade No Flow days.

Figure 3 shows that principal trading constitutes a frequent and economically meaningful component of bond ETF activity, occurring at a rate comparable to, and even exceeding, primary market transactions. Specifically, 35% of ETF–day observations are classified as Principal Trades, compared with 16% classified as Creations and 7% as Redemptions. The remaining 42% of observations correspond to No Principal Trade No Flow days. Taken together, these statistics indicate that ETFs engage in principal trading nearly as often as they transact with the primary market through creations and redemptions, underscoring the importance of principal trading as a mechanism in bond ETF portfolio management.

To further characterize ETF principal trading and compare it with creation and redemption activities, we analyze trade frequency, number of trades, and trade volume at the ETF–year level.[11] Consistent with Figure 3, Panel A of Table 2 shows that, on average, an ETF engages in principal trading on 34% of trading days in a year. Within these days, 25% involve principal purchases and

[11] Individual trades are inferred from changes in ETF holdings at the ETF-bond–day level; these trade-level observations are subsequently aggregated to the ETF–day and ETF–year levels for summary analysis.

25% involve principal sales, indicating that both can occur concurrently. By comparison, 16% of ETF–year days are associated with Creations and 7% with Redemptions, while the remaining 43% of days shows No Principal Trade No Flow activity.

Although principal trading occurs more frequently than creations or redemptions, the size of principal trades, measured by both the number of bond transactions and total dollar volume, is considerably smaller. Panel B reports that the average ETF–year includes 1,070 principal trades (532 purchases and 538 sales), compared with 7,475 bond-day transactions associated with creations and 6,041 with redemptions. The distribution of trades is highly skewed, particularly for creations and redemptions: the median number of trades for creation (830) and redemption (315) is far below their respective means, implying that a small number of large bond ETFs account for the bulk of primary-market activity. While the median number of principal trades is lower than that for creations and redemptions, the difference is notably smaller than when comparing means, indicating that principal trading is more evenly distributed across funds.

Panel C reveals a similar pattern in annual trading volume. The mean principal-trade volume per ETF–year ($258 million) is well below the mean for creations ($1.44 billion) and redemptions ($1.04 billion). However, the median principal-trade volume ($123 million) exceeds that of both creations ($78 million) and redemptions ($31 million), suggesting that while large primary-market transactions dominate in a few large funds, principal trading constitutes a meaningful share of trading activity for the typical ETF.

Finally, to control for fund-size effects, we scale the aggregate annual trading volume by each ETF's TNA in corporate bonds.[12] Panel D shows that the average annual normalized trading volume for principal trades (77% of corporate-bond TNA) is comparable to that for creations (66%) and exceeds that for redemptions (36%). Median values display a similar pattern. Overall, these results demonstrate that principal trading is not only frequent but also economically significant relative to primary-market activity, raising the possibility that it plays an important role in the portfolio management of bond ETFs.

3.3 Principal Trading and ETF Characteristics

[12] We scale volume in corporate bonds by each ETF's TNA invested in corporate bonds, rather than by total fund TNA, to make the ratio comparable across ETFs. Many ETFs also hold other fixed income instruments such as Treasuries, agencies, or securitized products that are outside the scope of our analysis.

Which ETFs are more likely to engage in principal trading? To address this question, we measure an ETF's principal trading intensity using its annual principal trade volume scaled by TNA in corporate bonds and divide the ETF–year sample into two groups: High Principal Trading Intensity and Low Principal Trading Intensity. We then compare their fund characteristics, summarized in Table 3.

Panel A shows that the two groups exhibit broadly similar frequencies of principal trading activity. Both the High and Low Intensity ETFs engage in principal trades on a comparable proportion of trading days, roughly one-third of the year, and the differences between them for either principal purchases or principal sales are not statistically significant. However, the groups differ sharply in their primary market activity and No Principal Trade No Flow incidence. High-intensity ETFs show substantially fewer creation and redemption days, averaging 6% and 2% of trading days, respectively, compared with 26% and 12% for the low-intensity group. Conversely, the high-intensity ETFs spend a significantly larger fraction of time in No Principal Trade No Flow status (54% versus 32%).

Panel B provides corroborating evidence from trading volumes. Among high-intensity ETFs, the average scaled principal trading volume equals 126% of corporate-bond TNA, far exceeding the corresponding figures for creations (55%) and redemptions (27%). In contrast, low-intensity ETFs exhibit an average principal trading volume of only 27%, markedly lower than their scaled creation (76%) and redemption (45%) volumes. These differences confirm that ETFs with high principal trading intensity rely more heavily on secondary-market adjustments through principal trades and less on primary-market creations and redemptions.

Panel C compares the two groups across additional ETF characteristics. High-intensity ETFs are generally smaller, with lower total net assets (mean = $316 million vs. $5.6 billion) and smaller corporate-bond holdings (mean = $191 million vs. $3.7 billion). They also hold fewer individual bonds (mean = 437 vs. 1,870), consistent with a more concentrated portfolio structure. High-intensity ETFs are also more likely to be actively managed (37% vs. 10%) and tend to charge higher expense ratios. In terms of market liquidity, high-intensity ETFs exhibit lower total ETF trading volume in absolute terms; however, once scaled by TNA, the difference in trading intensity is modest and not statistically significant. Likewise, the two groups show no significant difference in liquidity as measured by average bid–ask spreads.

Regarding the characteristics of the bonds held, high-intensity ETFs tend to invest in lower-rated and younger bonds, though the difference in average time to maturity is not statistically significant. Overall, these patterns suggest that ETFs with higher principal trading intensity are typically smaller, more active, and more flexible in portfolio management, relying more on secondary-market trading than on primary-market creations and redemptions to adjust their bond holdings.

3.4 Principal Trading and Bond Characteristics

We next examine how principal trading intensity varies with the characteristics of the bonds traded by ETFs. The analysis is conducted at the ETF–bond–day level, restricted to observations with zero net ETF flows. This restriction ensures that we isolate trading activity unrelated to primary market transactions and focus on secondary-market principal trades. We then estimate the following panel regression:

$$\begin{aligned} &\textit{Principal Trading Intensity}_{b,f,t+1} \\ &\quad = \beta_1 \times Log(\textit{Remaining Maturity})_{b,t} + \beta_2 \times Log(\textit{Bond Age})_{b,t} \\ &\quad + \beta_3 \times Log(\textit{Issue Size})_{b,t} + \beta_4 \times \textit{Bond Turnover}_{b,t} + \beta_5 \times \textit{High Yield}_{b,t} + \mu_t \\ &\quad + \mu_f + \varepsilon_{b,f,t} \quad , (1) \end{aligned}$$

where $\textit{Principal Trading Intensity}_{b,f,t+1}$ is defined as an ETF f's principal trade amount in bond b on day $t + 1$, scaled by its TNA in corporate bonds on day t. The explanatory variables capture key bond characteristics measured on day t: the logarithm of remaining maturity, the logarithm of bond age, the logarithm of issue size, bond turnover (total trade volume scaled by amount outstanding), and an indicator for whether the bond is high yield. We include day fixed effects (μ_t) to control for time trends and macroeconomic factors and ETF fixed effects (μ_f) to account for unobservable fund characteristics. Because the analysis is conducted at the ETF–bond–day level, ETF fixed effects also absorb fund-specific portfolio characteristics in interpreting bond

characteristics.[13] The regression is estimated separately for principal purchases and principal sales, with standard errors double-clustered by fund and day.

Table 4 presents the estimation results. The findings indicate that bond characteristics significantly influence principal trading intensity, and the effects differ between purchases and sales. ETFs tend to buy bonds with longer remaining maturities and sell bonds with shorter maturities, consistent with the idea that funds divest bonds approaching maturity that will soon exit benchmark indices. In addition, ETFs appear to buy younger bonds and sell older ones, suggesting active portfolio rebalancing toward recently issued, more liquid securities.

Liquidity considerations also play an important role. Because ETFs incur transaction costs in secondary-market trading, they are more likely to trade bonds that are easier to transact. Consistent with this hypothesis, principal trading intensity increases with issue size, a common proxy for bond liquidity. This relationship is statistically significant for both purchases and sales. Moreover, bond turnover is positively associated with principal trading, though the effect is statistically significant only for sales. This pattern implies that ETFs are more likely to dispose of holdings in bonds that are actively traded and thus easier to sell in the secondary market.

Finally, principal trading intensity shows little systematic relation to credit quality. The High Yield indicator is insignificant for both purchases and sales, suggesting that ETFs' principal trading decisions are not driven primarily by a bond's credit risk. As a robustness check, we re-estimate model (1) including ETF–day fixed effects, thereby comparing bonds traded by the same ETF on the same day. The results remain virtually unchanged, reinforcing the conclusion that bond-level characteristics, particularly maturity, age, and liquidity, are the dominant determinants of ETF principal trading behavior.

3.5 Principal Trading and Creation/Redemption

[13] For example, a bond with eight years of remaining maturity may be considered short for a long-term bond ETF with a portfolio average effective maturity greater than 10 years but long for an intermediate-term ETF of effective maturity between four to 10 years. See Morningstar's definitions of Long-Term Bond Category and Intermediate-Term Bond Category, available at https://awgmain.morningstar.com/webhelp/glossary_definitions/categories/Long_Term_Bond_Category.html and https://awgmain.morningstar.com/webhelp/glossary_definitions/categories/Intermediate_Term_Bond_Category.html .

We next examine how an ETF's principal trading intensity relates to a bond's recent involvement in the ETF's primary-market activity, specifically, its inclusion in creation and redemption baskets. Principal trades allow ETF managers to fine-tune portfolio positions established through the primary market and therefore may complement creations and redemptions in the rebalancing process. For example, an ETF may sell additional quantities of a bond it recently delivered through redemptions or acquire more of a bond it recently received through creations. Because bonds placed into redemption (creation) baskets are typically those the ETF seeks to decrease (increase) in its portfolio,[14] their subsequent secondary-market trading is likely to reflect these prior primary-market decisions.

To evaluate this mechanism, we link an ETF's principal trading in a given bond to the bond's prior participation in the ETF's creation and redemption baskets. Specifically, we estimate the following panel regression at the ETF–bond–day level, restricted to observations with zero net ETF flows at $t + 1$:

$$\textit{Principal Trading Intensity}_{b,f,t+1} = \beta_1 \times \textit{Redemption/Creation}_{b,f,(t-2,t)} + \mu_{f,t} + \mu_{b,t} + \mu_{f,b} + \varepsilon_{b,f,t}, \quad (2)$$

where $\textit{Principal Trading Intensity}_{b,f,t+1}$ is ETF f's principal purchase (sale) amount of bond b on day $t + 1$, scaled by the ETF's TNA in corporate bonds. $\textit{Redemption}_{b,f,(t-2,t)}$ and $\textit{Creation}_{b,f,(t-2,t)}$ represent, respectively, the cumulative inclusion of bond b in ETF f's redemption and creation baskets over the previous three trading days, scaled by TNA in corporate bonds. The model includes ETF-day fixed effects ($\mu_{f,t}$) to absorb time-varying fund-specific factors, bond–day fixed effects ($\mu_{b,t}$) to account for daily changes in bond-specific conditions, and ETF–bond fixed effects ($\mu_{f,b}$) to control for persistent ETF preferences toward particular bonds. Standard errors are clustered by fund and day.

The results, reported in Table 5, reveal a strong and systematic link between an ETF's principal trading activity and its recent primary-market transactions. Columns (1) and (2) show that when a bond has been heavily included in recent redemption baskets, ETFs tend to sell more

[14] For example, Shim and Todorov (2021) document that ETF use creation and redemption to maintain a relatively constant duration by receiving longer-duration bonds in creation baskets and delivering shorter duration bonds in redemption baskets.

and buy less of that bond in the secondary market. This pattern indicates that ETFs use principal trades to further reduce their exposure to securities that have already been removed through redemptions. In other words, following redemptions, ETFs continue to unwind their positions in the affected bonds, using secondary-market transactions to complete the adjustment process associated with the primary market.

Columns (3) and (4) provide a parallel set of results for creation activity. Consistent with the patterns observed for redemptions, these estimates show that creation activity alone may not fully establish an ETF's desired exposure to newly added bonds. Instead, ETFs tend to continue adjusting their positions through principal trades: following periods in which a bond is heavily included in creation baskets, ETFs subsequently purchase more, and sell less, of that bond in the secondary market. This behavior indicates that principal trading serves to reinforce and complete the portfolio adjustments initiated through creations, just as it does following redemptions.

When both creation and redemption measures are included jointly in Columns (5)–(6), the estimates remain stable, confirming that the relationship between primary- and secondary-market activity is robust to controlling for both flows simultaneously. Collectively, the evidence indicates that ETFs rely on principal trading as a complementary tool to fine-tune portfolio exposures. Although custom baskets provide flexibility in adjusting holdings through creations and redemptions, they do not fully resolve portfolio imbalances. Principal trades therefore play an important role in completing these adjustments and achieving more precise control over portfolio composition.

4. The Implications of Principal Trading for Bond ETFs

The widespread use of principal trading by bond ETFs, and its close connection to creation and redemption activity, raises important questions about the underlying drivers of these transactions and their broader implications for the ETF industry. In this section, we develop and empirically test two sets of hypotheses. Specifically, we examine the role of principal trading in (i) helping ETFs reduce their tracking errors and (ii) enhancing their performance relative to benchmark indices.

4.1 Principal Trading and ETF Tracking Errors

A core fiduciary obligation of ETF sponsors is to maintain close alignment between the fund's portfolio and its benchmark index. The standard metric for assessing this alignment is tracking error, defined as the deviation between ETF and index returns. Tracking error is a key risk measure for passive investment products (Bollen and Busse (2001)), as it reflects the effectiveness of the ETF's replication strategy and directly affects investors seeking index-like returns. Regulatory requirements reinforce the importance of managing tracking error. Under SEC Rule 6c-11, ETFs must disclose their full portfolio holdings daily, making deviations from benchmark exposures transparent and creating strong incentives for managers to actively control tracking error.

Tracking error is especially challenging for bond ETFs due to the structural features of fixed-income markets and index construction. Bond indices contain thousands of securities spanning diverse maturities, credit qualities, and liquidity levels. Many constituents trade infrequently or are unavailable in sufficient size for full replication. Index membership also changes mechanically as bonds mature, roll off the index, or experience rating changes. As a result, full replication is generally infeasible, and most bond ETFs rely on representative sampling to approximate benchmark exposures.

Although custom baskets used in creations and redemptions provide ETF managers with some flexibility to shape portfolio composition, they cannot fully resolve tracking frictions. Custom baskets often differ from the benchmark and are negotiated with APs, meaning that securities exchanged in the primary market may not match the index constituents or target weights. Moreover, creations and redemptions occur only when initiated by APs in response to investor flows, which do not necessarily align with the timing of needed portfolio adjustments. As a result, ETF managers may not rely exclusively on in-kind activity to maintain benchmark alignment, making principal trading a necessary tool for keeping portfolios synchronized with index changes.

To investigate whether tracking-error mitigation motivates principal trading, we first examine trading behavior around month-end, when bond indices commonly rebalance. During these periods, constituent lists and weights are updated to reflect new issuance, maturities, and credit migrations, creating predictable pressures for ETFs to realign their portfolios. Figure 4 shows a pronounced increase in principal trading at month-end. The share of ETF-days with principal trades rises from roughly 30–35% on average to nearly 50% on the final trading day of the month. This spike is consistent with managers using secondary-market transactions to adjust holdings in response to index rebalancing. By contrast, the incidence of creations and redemptions

remains remarkably flat throughout the month, including around month-end. This stability highlights a key operational constraint: because primary-market activity depends on AP-initiated flows, ETF managers cannot rely on it to execute timely rebalancing precisely when benchmark changes occur.

If tracking-error mitigation is indeed a motive for principal trading, the month-end increase should be more pronounced for passive funds, whose mandate is to replicate the benchmark closely, than for active funds, which have discretion to deviate from index weights. To test this prediction, we divide the full sample of 90 ETFs into 67 passive and 23 active ETFs and compare their characteristics and trading behavior. Panel A of Table 6 shows that passive ETFs are substantially larger, both in total net assets and in corporate bond holdings, and hold more bonds on average. They also feature lower expense ratios, consistent with passive management. Liquidity characteristics, such as trading volume relative to TNA and bid–ask spreads, are broadly similar across the two groups. Panel B reveals sharp differences in trading behavior. Passive ETFs use principal trading less frequently than active ETFs, particularly on the buy side, and depend more heavily on creations and redemptions for adjusting their portfolios. Active ETFs, by contrast, engage in principal trades much more intensively. Panel C confirms this pattern in trading volume: passive ETFs exhibit significantly lower principal trading volume relative to TNA than active funds but higher primary-market activity, especially through redemptions.

Figure 5 further contrasts month-end behavior across passive and active ETFs. Panel A shows that the month-end spike in principal trading is almost entirely driven by passive ETFs. Active ETFs show no corresponding increase, reinforcing the interpretation that principal trading at month-end is primarily tied to index-tracking considerations rather than liquidity management or discretionary portfolio decisions. Panel B confirms that neither passive nor active ETFs exhibit a systematic increase in creations or redemptions around month-end.

The evidence in Figures 4 and 5 documents a strong link between principal trading and periods of heightened tracking-error pressure. When benchmark indices rebalance, passive ETFs markedly increase their use of principal trading, while primary-market activity remains unchanged. Active ETFs, which do not face strict tracking constraints, do not exhibit similar behavior. This pattern suggests that principal trading serves as an important mechanism through which passive ETFs maintain benchmark alignment. This naturally leads to the question: does principal trading, in fact, reduce tracking error? Formally, we test the following hypotheses:

H1 (Tracking-error mitigation): Greater principal trading activity should lead to a larger subsequent reduction in ETF tracking error, as direct secondary-market transactions enable managers to realign their portfolios more precisely with benchmark indices.

H2 (Passive-fund dominance): The impact of principal trading on reducing tracking error should be concentrated in passive ETFs, with little or no effect for active ETFs.

To test these hypotheses, we examine how changes in tracking error evolve around days with principal trading. Tracking error is inherently dynamic, reflecting both shifts in an ETF's portfolio composition and fluctuations in its benchmark index. These dynamics are especially pronounced for bond ETFs, whose underlying securities are often illiquid and infrequently priced, introducing idiosyncratic noise into daily estimates. Because principal trading occurs frequently, the horizon used to measure tracking-error changes must be short enough to isolate the effects of individual trading episodes. At the same time, a purely daily measure would be overly sensitive to pricing noise. To strike this balance, we adopt a short multi-day event-study approach that compares tracking error in the days before and after principal trading events.

Following the extant literature (e.g., Bae and Kim, 2020), we measure tracking error as the square root of the average squared difference between daily fund returns from its daily NAV and the prospectus benchmark index returns, computed over a three-day window. We then calculate changes in tracking error around day t by taking the difference in this measure ($\Delta\ Tracking\ Error_{f,\,(t+1,\,t+3)}$) between the three-day post-event ($t + 1$ to $t + 3$) and pre-event windows ($t - 2$ to t).

We construct a sample at ETF-day level and estimate the following panel regression:

$$\Delta\ Tracking\ Error_{f,\,(t+1,\,t+3)} = \beta_1 \times Fund\ Principal\ Trading\ Intensity_{f,\,t} + \mu_t + \mu_f + \varepsilon_{f,t}, \quad (3)$$

where $Fund\ Principal\ Trading\ Intensity_{f,\,t}$ equals an ETF f's aggregate principal trade amount on day t, scaled by its TNA in corporate bonds. The regression includes day fixed effects (μ_t) to capture market-wide factors that may influence tracking errors across all ETFs on a given day, and ETF fixed effects (μ_f) to control for time-invariant fund characteristics, such as persistent differences in principal trading intensity. Standard errors are double-clustered by fund and day.

Results reported in Table 7 support our hypothesis H1. Column (1) shows that the coefficient of principal trading intensity is negatively and highly significant, indicating that greater principal

trading on day *t* predicts a subsequent decline in tracking error. Column (2) adds total creations and redemptions, which are economically small and statistically insignificant, suggesting that in-kind activity does not contribute meaningfully to tracking-error reduction. Column (3) restricts the sample to days with zero ETF flows, and the coefficient on principal trading remains negative and highly significant, confirming that the effect is not simply an artifact of primary-market transactions. Quantitatively, given an average three-day tracking error of 3.76 basis points, the coefficient of −6.56 ($t = -3.41$) implies that a one-percentage-point increase in daily principal trading (scaled by TNA) is associated with a roughly 1.7% reduction in tracking error over the subsequent three-day window. ETF managers could achieve greater reductions in tracking error by increasing the scale of principal trading on a given day or by sustaining such trading over consecutive days, thereby compounding its effect on benchmark alignment.

We next test H2 by splitting the sample into passive and active ETFs and re-estimating model (3) for each subsample. Results reported in Table 8 confirm H2. The relationship between principal trading and tracking-error reduction is evident only for passive ETFs. For passive funds, the coefficients are −5.42 (t = −2.91) in the full sample and −6.11 (t = −3.09) on zero-flow days. By contrast, for active funds the coefficients are muted and statistically insignificant (-0.99 and -1.98, respectively). These findings imply that principal trading primarily serves to minimize benchmark deviations for passive ETFs but not for active ETFs.

To assess robustness, we vary the time windows used to compute future tracking-error changes, employing both two-day and four-day horizons. As reported in Table 9, the results remain qualitatively unchanged, indicating that the negative relationship between principal trading and subsequent tracking error is not sensitive to the specific measurement window. Collectively, these findings provide strong evidence in support of H1 and H2, demonstrating that principal trading plays a central role in enabling ETFs to realign with their benchmarks and mitigate short-term tracking deviations.

Taken together, these results strengthen the interpretation that principal trading serves as a strategic complement to the in-kind mechanism. When predictable benchmark shifts occur, such as the monthly reconstitution of fixed-income indices, ETF managers rely on direct secondary-market trades to correct residual misalignments that cannot be addressed through creations or redemptions. This behavior not only illustrates the operational flexibility afforded by principal

trading but also emphasizes its essential role in maintaining the integrity of index tracking in the bond ETF market.

4.2 Principal Trading and ETF Performance

Beyond minimizing tracking error, principal trading may also serve as a mechanism for performance enhancement, particularly for actively managed ETFs that possess discretion to deviate from benchmark compositions. Active ETFs are often explicitly designed to pursue excess returns relative to a benchmark, commonly referred to as alpha. The pursuit of alpha is a defining characteristic of active management and has been extensively documented as a central objective of actively managed investment vehicles (e.g., Cremers and Petajisto (2009)). Recent studies further highlight that many ETFs, despite their passive origins, increasingly function as active investment instruments, either in organizational form or in portfolio construction (Easley, Michayluk, O'Hara, and Putniņš (2021)). The rapid growth of active ETFs also reflects investor demand for differentiated strategies capable of outperforming traditional index-based products, particularly in volatile or segmented fixed-income markets (BlackRock (2025)).

In the bond-ETF setting, principal trading offers a natural channel through which active managers can translate skill and information into performance. Fixed-income markets are decentralized, opaque, and often characterized by episodic liquidity and pricing inefficiencies. Within this environment, active ETFs can employ principal trading to selectively acquire undervalued securities or unwind positions in overvalued ones, exploiting transient mispricing in credit spreads or liquidity premia. By contrast, passive ETFs, whose mandate is strict index replication, engage in principal trading primarily for portfolio maintenance, adjusting holdings to manage duration, liquidity, or credit exposures, rather than seeking excess returns. This reasoning leads to our third hypothesis:

H3 (Performance-enhancing trading): If active ETFs use principal trading to enhance returns, then bonds more heavily purchased on net by active ETFs should exhibit higher future returns. In contrast, this relation should be absent for passive ETFs.

A related implication is that, if principal trading reflects informed or skill-based trading decisions, it should contribute positively to fund-level alpha for active ETFs, while having little or no impact for passive ETFs whose trades are operational rather than strategic.

H4 (Alpha contribution): For active ETFs, but not passive ETFs, principal trading contributes positively to portfolio alpha.

To test these hypotheses, we begin by estimating daily raw returns for each corporate bond as follows:

$$r_{b,t} = \frac{\left(P_{b,t}+AI_{b,t}+Coupon_{b,t}\right)-\left(P_{b,t-1}+AI_{b,t-1}\right)}{\left(P_{b,t-1}+AI_{b,t-1}\right)}, \quad (4)$$

where $r_{b,t}$ denotes bond b's return on day t, $P_{b,t}$ is the bond's price on that day, and $AI_{b,t}$ and $Coupon_{b,t}$ represent accrued interest and coupon payment (if any) at the end of day t, respectively. Because many corporate bonds do not trade every day, return calculations based solely on TRACE transaction data may be stale or missing. Moreover, the majority of TRACE-reported trades are of retail size, and transaction costs vary substantially across trade sizes, introducing additional noise into return estimates. To address these limitations, we infer end-of-day bond prices from daily ETF holdings by dividing the reported market value of each bond by its par amount held by the ETF. These inferred prices reflect valuations used by ETF managers and are economically meaningful, as funds can transact at these levels through creations and redemptions. When multiple ETFs report holdings of the same bond on a given day, we take the median inferred price across funds, following Huang, Wermers, Xue, and Zhou (2025).

We then compute excess daily returns by subtracting duration-matched government bond returns following van Binsbergen, Nozawa, and Schwert (2025). Specifically, we construct zero-coupon Treasury bond returns using the Bloomberg zero-coupon yield curve and calculate each corporate bond's benchmark return as the weighted average of the corresponding zero-coupon Treasury returns, where each weight equals the present value of a given cash flow divided by the bond's price. A bond's excess return is then defined as the difference between its raw return and its benchmark Treasury return. To link ETF trading activity to subsequent bond performance, we evaluate excess returns over the next month, providing a forward-looking measure of how principal trading relates to future bond returns. The one-month horizon balances the need to capture meaningful price adjustments following ETF trading against the risk of excessive short-term return noise.

We estimate the following panel regression at bond-month level to test H3:

$$\textit{Excess Return}_{b,m+1} = \beta_1 \times \textit{Net Principal Trade}_{b,m} + \mu_m + \mu_b + \varepsilon_{b,m}\,, (5)$$

where $\textit{Excess Return}_{b,m+1}$ denotes bond b 's average daily excess return for month $m+1$, and $\textit{Net Principal Trade}_{b,m}$ refers to the aggregate principal buy volume of bond b by ETFs minus the aggregate principal sale volume of bond b by ETFs in month m, scaled by the bond's total amount outstanding. We estimate the measure separately for active ETFs and passive ETFs. The regression includes day fixed effects (μ_t) to capture market-wide conditions and bond fixed effects (μ_b) to account for bond characteristics. Standard errors are double-clustered by bond and month.

The results in Table 10 provide strong support for hypothesis H3. Column (1) shows that for active ETFs, the coefficient on $\textit{Net Principal Trade}_{b,m}$ is positive and highly significant, indicating that bonds more heavily traded by active ETFs in month *m* earn higher excess returns in month *m + 1*. The effect is also economically meaningful: a one–standard deviation increase in active-ETF principal trading (0.012% of amount outstanding) is associated with approximately 0.12 daily (or, 30.91 annualized) basis points higher subsequent excess return. The results remain robust after controlling for primary-market activity, lagged excess returns, and time-varying bond characteristics, including bond age, time to maturity, and rating-by-month fixed effects (Column (2)). Specifically, the coefficient on $\textit{Net Creation}_{b,m}$, defined as the difference between a bond's aggregate creation and redemption volumes within month *m*, is also positive and significant, suggesting that active ETFs use custom baskets to build desired exposures in certain corporate bonds. However, the magnitude of the $\textit{Net Creation}_{b,m}$ coefficient is substantially smaller than that of $\textit{Net Principal Trade}_{b,m}$, highlighting that the predictive power for future returns is concentrated in secondary-market principal trading rather than in primary-market flows.

In contrast, for passive ETFs, the coefficient on $\textit{Net Principal Trade}_{b,m}$ is economically small and only marginally significant, offering little evidence that principal trading predicts subsequent bond performance (Columns (3) and (4)). The coefficient on $\textit{Net Creation}_{b,m}$ is negative and significant, consistent with the interpretation that passive ETFs primarily use principal trading to reduce tracking errors and might receive underperforming bonds from APs during creations (Reilly (2022)).

To further explore the information content of principal trading by active ETFs, we decompose aggregate principal trading into purchases and sales. Column (1) of Table 11 shows that aggregate principal purchases by active ETFs strongly predict higher future bond returns, consistent with informed or skill-based purchases. By contrast, the coefficient on principal sales is economically small and statistically insignificant, indicating little evidence that sales convey information about future bond performance. When we control for time-varying bond characteristics and lagged excess returns, the positive association between principal purchases and future bond performance remains robust, whereas principal sales continue to show no meaningful relation to future returns (Column (2)).

We also examine primary market activities separately. Columns (3) and (4) show that the link between a bond's participation in ETF primary market flows and its future performance is driven primarily by creations, rather than redemptions. Finally, when both primary and secondary market activity variables are included simultaneously (Column (5)), our results remain qualitatively unchanged. Overall, these findings reinforce the conclusion that active ETFs use principal purchases to selectively accumulate bonds with superior expected performance, consistent with information-based trading motives.

We next evaluate hypothesis H4 by examining the contribution of principal trading to fund-level performance. At the ETF–year level, we estimate each fund's holding-based alpha and decompose it into three components associated with (i) creations and redemptions, (ii) principal trading, and (iii) other portfolio activities. To do so, we implement the Daniel, Grinblatt, Titman, and Wermers (1997; hereafter, DGTW) performance attribution methodology at the daily frequency. Specifically, for each bond, we compute a credit risk–adjusted excess return by first subtracting the duration-matched Treasury return and then applying an additional credit adjustment, defined as the average Treasury-adjusted return of all bonds within the same credit rating category on day t ($CR\ Adjust\ Excess\ Return_{b,t}$). This approach allows us to evaluate the return contribution from bond selection within principal trading, rather than from market-timing of broad duration or credit exposures.[15] The fund's holding-based alpha is then expressed as:

[15] For bond mutual funds specifically, Chen, Ferson, and Peters (2010) show that after controlling for non-timing-related nonlinearities, market-timing ability is generally neutral while performance is driven primarily by security selection rather than factor timing.

$$\alpha_{f,t} = \sum w_{f,b,t-1} \times CR\ Adjust\ Excess\ Return_{b,t}\,. (6)$$

By leveraging daily ETF holdings, our analysis is not subject to the unobserved action bias identified by Kacperczyk, Sialm, and Zheng (2008). Furthermore, because we track the evolution of each bond position within an ETF and attribute changes in holdings to either primary-market activity or secondary-market principal trading, we decompose the bond weight $w_{f,b,t-1}$ into three components:

$$w_{f,b,t-1} = w^{C}_{f,b,t-1} + w^{P}_{f,b,t-1} + w^{O}_{f,b,t-1}, (7)$$

where $w^{C}_{f,b,t-1}$denotes the fraction of weight due to past creation activity, $w^{P}_{f,b,t-1}$ the fraction due to past principal purchases, and $w^{O}_{f,b,t-1}$ the residual weight attributable to unclassified holdings, such as bonds already present in the ETF portfolio at the start of our sample in 2017. To implement this decomposition, we track the evolution of each bond position within an ETF using a first-in, first-out (FIFO) approach. Under FIFO, changes in a fund's holdings are attributed to the earliest remaining units of a bond in the portfolio, allowing us to map each share of a position back to the specific channel through which it entered the fund: creation activity, principal purchases, or pre-existing holdings. Accordingly, the fund's holding-based alpha can be decomposed as:

$$\begin{aligned}\alpha_{f,t} &= \alpha^{C}_{f,t} + \alpha^{P}_{f,t} + \alpha^{O}_{f,t} \\ &= \sum w^{C}_{f,b,t-1} CR\ Adjust\ Excess\ Return_{b,t} + \sum w^{P}_{f,b,t-1} CR\ Adjust\ Excess\ Return_{b,t} \\ &\quad + \sum w^{O}_{f,b,t-1} CR\ Adjust\ Excess\ Return_{b,t}\,. (8)\end{aligned}$$

We estimate these αs at the ETF-day level and then aggregate them to the ETF-year level. Table 12 reports the summary statistics for the annual α components separately for active and passive ETFs. For active ETFs, the average annual alpha is 19 basis points, with principal trading contributing +25 bps, partially offset by −6 bps from creations and redemptions. This pattern indicates that principal trading is the dominant source of excess performance among active ETFs. In contrast, passive ETFs exhibit an average alpha of −9 bps, driven largely by −11 bps from creations and redemptions, while principal trading contributes only +1 bp on average. The

negligible effect for passive funds reinforces that their principal trades are primarily maintenance-oriented rather than return-seeking.

5. Conclusion

From its first issuance in July 2002, bond ETFs have experienced almost exponential growth, reaching over $2.2 trillion in total assets in 2025. This popularity reflects the underlying appeal of the ETF structure which relies on the revolutionary creation and redemption process to provide greater liquidity and enhanced tax efficiency relative to more traditional mutual fund structures. As shown in this paper, this innovative structure has also had to evolve over time to accommodate the distinctive features of different asset classes. Regulatory changes such as SEC Rule 6c-11, although designed to enhance operational efficiency and tracking precision, have expanded the strategic scope of ETFs. For bond ETFs, our analysis demonstrated how the flexibility to conduct secondary-market principal trades enables active ETFs to engage in selective, alpha-driven trading that mirrors traditional active management. This dual role, facilitating both benchmark tracking and informed trading, underscores the important role that principal trading plays in allowing bond ETFs to flourish.

While our research here has focused on corporate bond ETFs, we conjecture that principal trading may hold a broader significance for the many other asset classes in the evolving ETF industry. Understanding how the underlying ETF structure has, or can, adapt to different asset classes seems an important area for future research.

References

Arora, R., Betermier, S., Ouellet Leblanc, G., Palumbo, A., and Shotlander, R., 2020. Concentration in the market of authorized participants of US fixed-income exchange-traded funds. Staff Analytical Note No. 2020-27. Bank of Canada.

Bae, K. and Kim, D., 2020. Liquidity risk and exchange-traded fund returns, variances, and tracking errors. *Journal of Financial Economics*, 138(1), 222–253.

Ben-David, I., Franzoni, F., and Moussawi, R., 2018. Do ETFs increase volatility? *Journal of Finance*, 73(6), 2471–2535.

Bhattacharya, A. and O'Hara, M., 2018. Can ETFs increase market fragility? Effect of information linkages in ETF markets. Available at SSRN 2740699.

BlackRock, 2025. Decoding active ETFs: How the growth of active ETFs is unlocking innovation and opportunity for investors. iShares. Retrieved from https://www.ishares.com/us/literature/whitepaper/decoding-active-etfs.pdf

Bollen, N.P. and Busse, J.A., 2001. On the timing ability of mutual fund managers. *Journal of Finance*, 56(3), 1075–1094.

Box, T., Davis, R., Evans, R., and Lynch, A., 2021. Intraday arbitrage between ETFs and their underlying portfolios. *Journal of Financial Economics*, 141, 1078–1095.

Brogaard, J., Heath, D., and Huang, D., 2025. ETF sampling and index arbitrage. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Carhart, M.M., Kaniel, R., Musto, D.K., and Reed, A.V., 2002. Leaning for the tape: Evidence of gaming behavior in equity mutual funds. *Journal of Finance*, 57(2), 661–693.

Chen, Y., Ferson, W.E., and Peters, H., 2010. Measuring the timing ability and performance of bond mutual funds. *Journal of Financial Economics*, 98(1), 72–89.

Choi, J. and Kronlund, M., 2018. Reaching for yield in corporate bond mutual funds. *Review of Financial Studies*, 31(5), 1930–1965.

Cohen, S., Laipply, S., Madhavan, A., and Mauro, J., 2022. The primary market process for fixed income exchange-traded funds under market stress. *Journal of Fixed Income*, 31(3), 66–78.

Cremers, K.M. and Petajisto, A., 2009. How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*, 22(9), 3329–3365.

Da, Z. and Shive, S., 2018. Exchange traded funds and asset return correlations. *European Financial Management*, 24, 136–168.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, 52(3), 1035–1058.

Dannhauser, C.D., 2017. The impact of innovation: Evidence from corporate bond exchange-traded funds (ETFs). *Journal of Financial Economics*, 125, 537–560.

Dannhauser, C.D. and Hoseinzade, S., 2022. The unintended consequences of corporate bond ETFs: Evidence from the taper tantrum. *Review of Financial Studies*, 35, 51–90.

Dannhauser, C.D. and Karmaziene, E., 2023. The dealer warehouse–corporate bond ETFs. Available at SSRN 4676850.

Du, L., 2023. Inventory in liquidity transformation: Evidence from corporate bond ETF creations. Available at SSRN 4653799.

Easley, D., Michayluk, D., O'Hara, M., and Putniņš, T., 2021. The active world of passive investing. *Review of Finance*, 25(5), 1433–1471.

Finnerty, J.D., Reisel, N., and Zhong, X., 2025. ETFs, creation and redemption processes, and bond liquidity. *Journal of Financial and Quantitative Analysis*, 60, 1891–1924.

Glosten, L., Nallareddy, S., and Zou, Y., 2021. ETF activity and informational efficiency of underlying securities. *Management Science*, 67, 22–47.

Gorbatikov, E., & Sikorskaya, T., 2022. Two APs are better than one: ETF mispricing and primary market participation. Available at SSRN 3923503.

Grinblatt, M., Titman, S., and Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review*, 85(5), 1088–1105.

Holden, C.W. and Nam, J., 2024. Market accessibility, corporate bond ETFs, and liquidity. *Review of Finance*, 18–1.

Huang, S., O'Hara, M., and Zhong, Z., 2021. Innovation and informed trading: Evidence from industry ETFs. *Review of Financial Studies*, 34(3), 1280–1316.

Huang, X. and Martinez, J.V., 2024. Mutual funds, ETFs, and the impact of investor flows on fund performance. ETFs, and the impact of investor flows on fund performance. Available at SSRN 5019820.

Huang, A.G., Wermers, R., Xue, J., and Zhou, X.A., 2025. Underlying valuation uncertainty, strategic ETF creation and pricing efficiency. Available at SSRN 5046012.

Israeli, D., Lee, C.M., and Sridharan, S.A., 2017. Is there a dark side to exchange traded funds? An information perspective. *Review of Accounting Studies*, 22(3), 1048–1083.

Kacperczyk, M., Sialm, C., and Zheng, L., 2008. Unobserved actions of mutual funds. *Review of Financial Studies*, 21(6), 2379–2416.

Koont, N., Ma, Y., Pastor, L., and Zeng, Y., 2025. Steering a ship in illiquid waters: Active management of passive funds. *Review of Financial Studies*, 38(10), 2887–2935.

Moussawi, R., Shen, K. and Velthuis, R., 2025. The role of taxes in the rise of ETFs. *Review of Financial Studies*, 38(10), 2988–3039.

O'Hara, M., and X. Zhou, 2021a. The electronic evolution of corporate bond dealers. *Journal of Financial Economics*. 140, 368–390.

O'Hara, M., and X. Zhou, 2021b. Anatomy of a Liquidity Crisis: Corporate Bonds in the Covid-19 Crisis. *Journal of Financial Economics*, 142(1), 46-68.

Pan, K. and Zeng, Y., 2019. ETF arbitrage under liquidity mismatch. Available at SSRN 3723406.

Reilly, C., 2022. The hidden cost of corporate bond ETFs. Available at SSRN 4147882.

Sağlam, M., Tuzun, T., and Wermers, R., 2025. Do ETFs increase liquidity? Available at SSRN 3142081.

Shim, J.J. and Todorov, K., 2021. ETFs, illiquid assets, and fire sales. *BIS Working Papers*, No. 975.

Shim, J.J. and Todorov, K., 2023. ETFs, illiquid assets, and fire sales. Available at SSRN 3886881.

van Binsbergen, J.H., Nozawa, Y., and Schwert, M., 2025. Duration-based valuation of corporate bonds. *Review of Financial Studies*, 38(1), 158–191.

Wermers, R., 1999. Mutual fund herding and the impact on stock prices. *Journal of Finance*, 54(2), 581–622.

Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses. *Journal of Finance*, 55(4), 1655–1695.

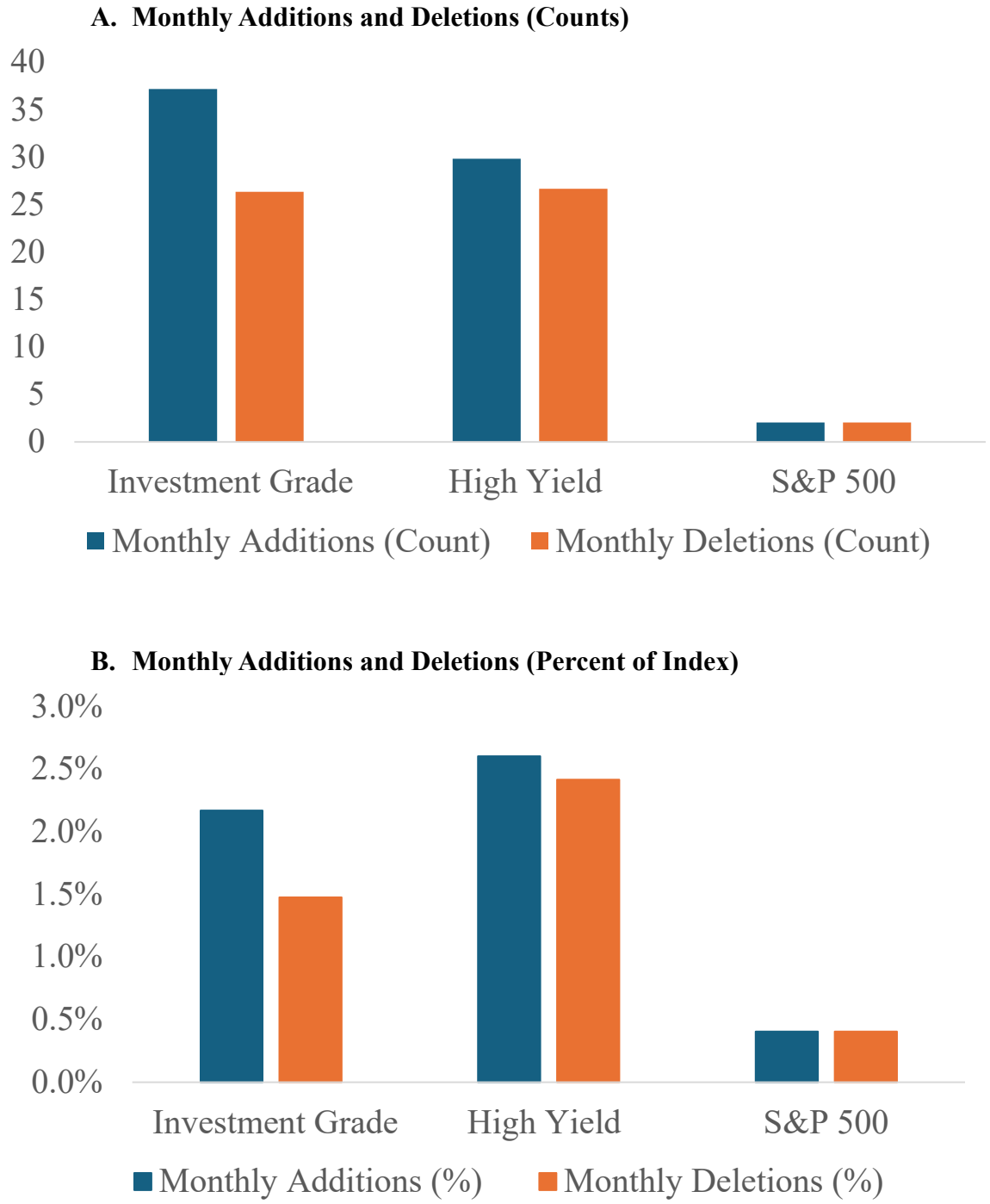


Figure 1 Monthly Additions and Deletions Across Indices. This figure summarizes monthly index turnover for the iBoxx iShares $ Investment Grade Corporate Bond Index, the iBoxx iShares $ High Yield Corporate Bond Index, and the S&P 500 from January 2015 to July 2023. Panel A reports the average number of bonds added to and deleted from each index each month, while Panel B presents the same additions and deletions scaled by the total number of constituents, expressed as monthly percentages.

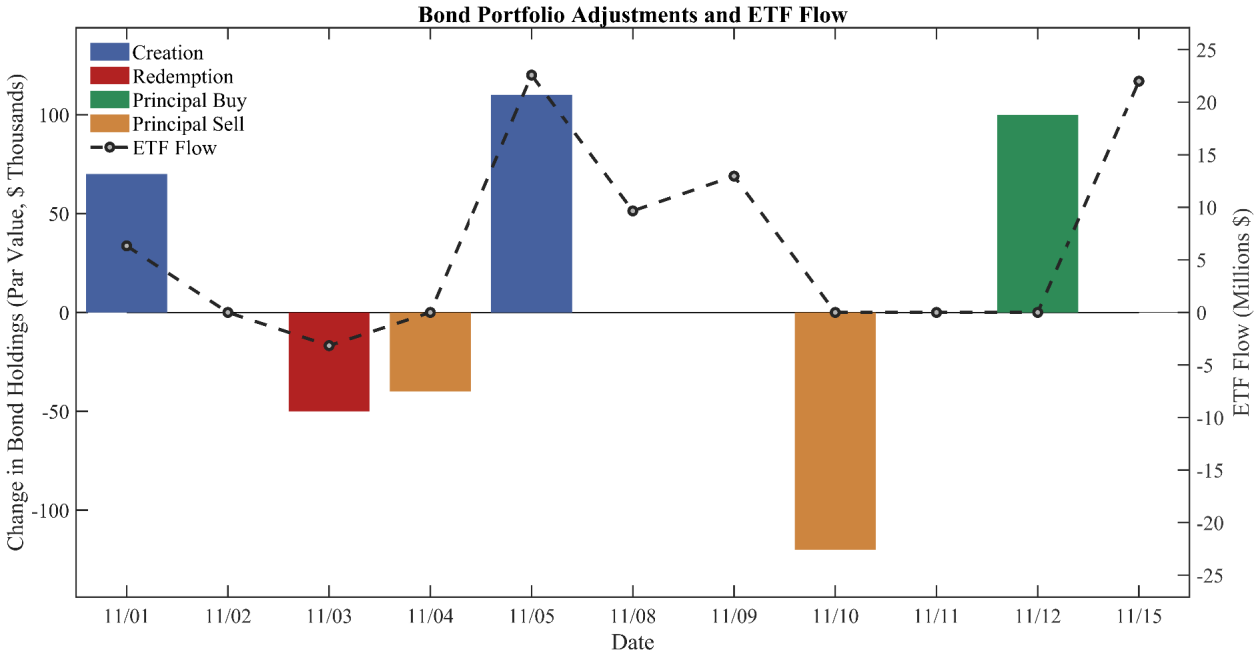


Figure 2 Bond Portfolio Adjustments and ETF Flow. This figure illustrates how changes in ETF bond holdings are decomposed into primary-market activities (creations and redemptions) and secondary-market principal trading (purchases and sales) for a representative ETF-bond pair. The bars show the daily changes in bond holdings of an Oracle corporate bond (CUSIP 68389XBJ3) by the SPDR Portfolio Long Term Corporate Bond ETF (SPLB) from November 1 to 15, 2021. Blue and red bars denote bond acquisitions and disposals through share creations and redemptions, respectively. Green (brown) bars indicate principal purchases (sales) conducted by the ETF itself on days with zero net share flows. The dashed line plots the ETF's daily net flow, measured in millions of dollars (right axis).

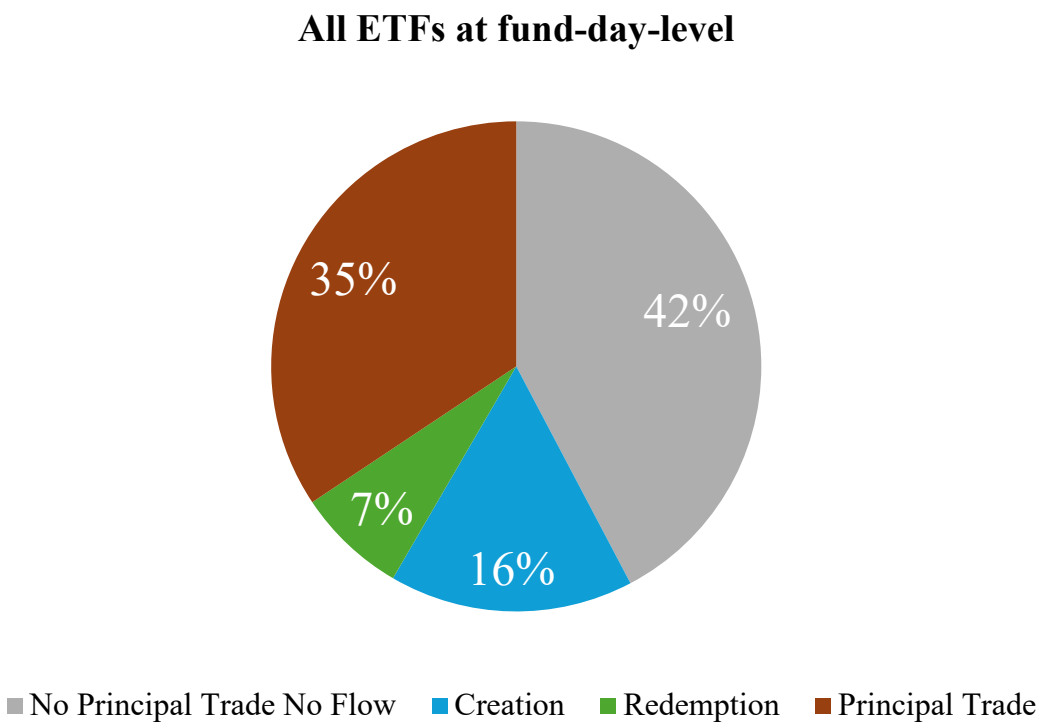


Figure 3 Composition of ETF Trading Days. This figure shows the fraction of ETF-day observations classified by trading activity over the 2017-2023 sample period. Each ETF-day falls into one of four categories: net creation days, net redemption days, principal trading days with no creations or redemptions ("Principal Trade" days), and days with neither principal trading nor in-kind flows ("No Principal Trade No Flow" days).

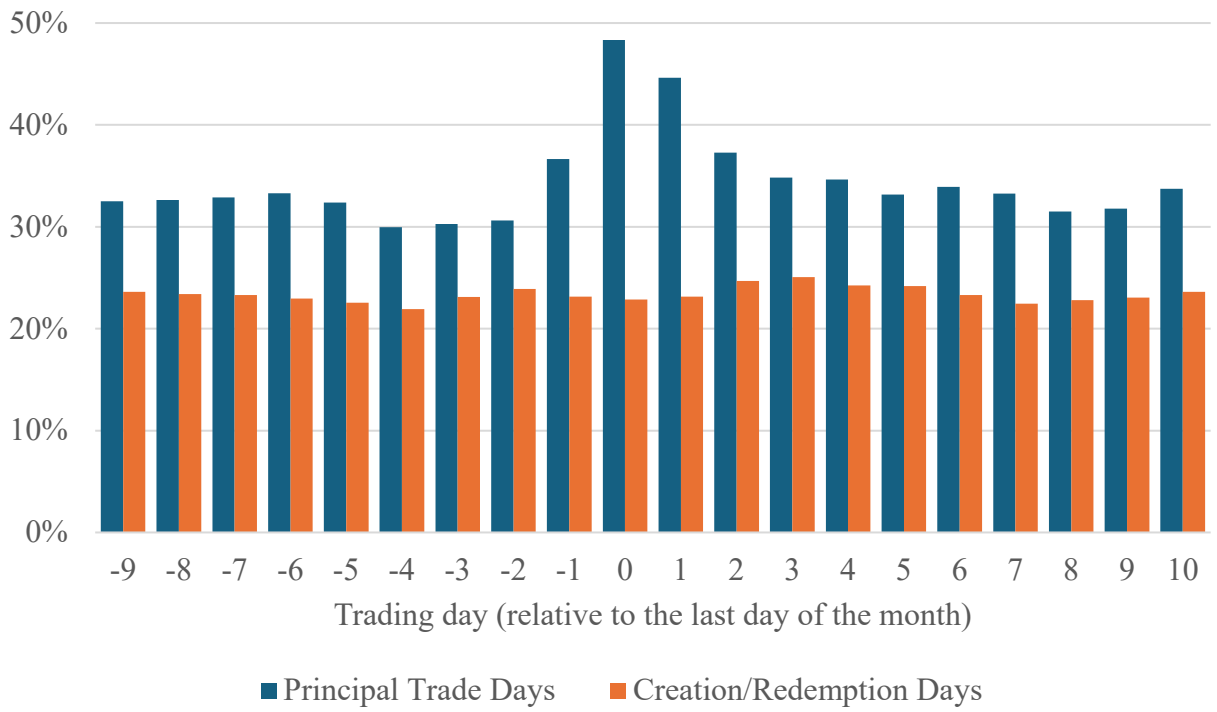


Figure 4 Principal Trading and Creation/Redemption Activity Around Month-End. This figure plots the fraction of ETF–day observations with principal trading (blue bars) and with creation/redemption activity (orange bars) relative to trading days surrounding month-end. Days are indexed from the ninth trading day before month-end (–9) through the tenth trading day after month-end (+10). Principal trading spikes sharply on the final trading day of the month and remains elevated in the surrounding days, consistent with ETFs adjusting holdings in response to benchmark rebalancing. By contrast, creation and redemption activity remains relatively stable throughout the month, exhibiting no systematic month-end pattern.



Figure 5 Principal Trading and Creation/Redemption Activity Around Month-End: Passive vs. Active ETFs. This figure shows how the incidence of principal trading and primary-market flow activity varies around month-end for passive and active corporate bond ETFs. Days are indexed from the ninth trading day before month-end (–9) through the tenth trading day after month-end (+10). Panel A reports the fraction of ETF–day observations with principal trading. Panel B reports the fraction of ETF–day observations with creation or redemption activity.

Table 1: Summary Statistics of Bond ETFs

This table reports summary statistics for 90 U.S. corporate bond ETFs, corresponding to 591 ETF-year observations, over the 2017-2023 sample period. All variables are measured as daily averages within each ETF–year. Total net assets (TNA) are computed as shares outstanding multiplied by net asset value (NAV) from CRSP. Fund TNA in corporate bonds is obtained from Morningstar and reflects the total market value of corporate bond holdings. Expense ratios, bid–ask spreads, and trading volumes are obtained from CRSP. Credit ratings, remaining maturities, and the number of bond holdings are calculated from daily Morningstar holdings data. The table presents the mean, standard deviation (SD), first quartile (Q1), median, and third quartile (Q3) across ETF-year observations.

	Mean	SD	Q1	Median	Q3
TNA ($Million)	2,956	9,323	88	250	1,585
TNA in Corporate Bonds ($Million)	1,920	5,213	55	164	977
ETF Trading Volume ($1,000)	73,531	318,331	639	2,141	14,226
ETF Trading Volume / TNA (%)	1.5	2.6	0.6	0.9	1.4
Bid-ask Spread (bps)	39	24	21	33	49
Expense Ratio (bps)	26	19	12	22	38
Active Fund	0.23	0.42	0	0	0
Average Credit Rating (AAA=1, AA=2, A=3,…)	4.2	0.9	3.5	3.8	5.3
Remaining to Maturity (Year)	8.8	8.1	4.8	6.5	11.7
Bond Age (Year)	3.8	1.4	2.9	3.7	4.3
Number of Bonds in the Portfolio	1,146	1,553	249	512	1,413

Table 2. Principal Trading and Primary-Market Activity of Bond ETFs

This table summarizes the frequency and magnitude of trading activities for 90 U.S. corporate bond ETFs (591 ETF–year observations, 2017–2023). All statistics are measured at the ETF–year level. Panel A classifies each trading day by activity type. Creation and Redemption days reflect net inflows and outflows, respectively. Principal Trading days are those with zero net ETF flows but changes in bond holdings, indicating secondary-market transactions executed directly by the ETF. The remaining days with neither net flows nor holding changes are labeled No Principal Trade No Flow. Panel B reports the total number of bond transactions over the year, inferred from daily holding changes. Panel C presents the total annual dollar volume of these trades (in $1,000s), and Panel D scales total trading volume by the ETF's average corporate-bond TNA (in %). The table reports the mean, standard deviation (SD), and the 25th, 50th (median), and 75th percentiles (Q1, Median, Q3) across ETF–year observations.

	Mean	SD	Q1	Median	Q3
Panel A. Number of days / Total days in a year (%)					
Principal Trade	34	22	17	30	48
Principal Buy	25	19	10	19	35
Principal Sell	25	17	12	20	33
Creation	16	18	2	7	26
Redemption	7	11	0	2	7
No Principal Trade No Flow	43	30	13	45	70
Panel B. Number of trades					
Principal Trade	1,070	1,679	287	603	1,138
Principal Buy	532	776	156	302	614
Principal Sell	538	1,058	110	251	513
Creation	7,475	16,128	168	830	5,643
Redemption	6,041	16,916	16	315	2,436
Panel C. Annual volume ($1,000)					
Principal Trade	258,072	358,973	49,352	123,780	323,503
Principal Buy	127,689	175,020	25,207	63,570	164,771
Principal Sell	114,486	157,133	19,128	57,948	151,779
Creation	1,442,591	3,881,011	16,183	77,785	615,139
Redemption	1,044,639	3,128,451	2,436	30,975	242,886
Panel D. Aggregate Volume / TNA in Corp (%)					
Principal Trade	77	79	26	57	101
Principal Buy	40	43	13	29	54
Principal Sell	32	32	11	24	45
Creation	66	76	21	45	88
Redemption	36	50	2	19	47

Table 3. Fund Characteristics by Principal Trading Intensity

This table compares trading activity and fund characteristics for 90 U.S. corporate bond ETFs (591 ETF–year observations, 2017–2023). ETFs are sorted each year into high and low principal trading intensity groups based on aggregate principal trading volume scaled by total net assets in corporate bonds (TNA in Corp). Panel A reports the share of trading days in a year associated with principal trading, creations, and redemptions. Panel B presents aggregate annual trading volumes scaled by the ETF's corporate-bond TNA. Panel C summarizes fund characteristics, including size, liquidity, expenses, and portfolio composition, measured as daily averages over the year. The Wald test in the last column evaluates whether mean differences between the two groups are statistically significant, with *p*-values based on regressions clustered by fund and year.

	Groups by Trading Intensity (Agg. Principal Trade / TNA in Corp)				Wald Test H0:
	High		Low		High=Low
	Mean	SD	Mean	SD	P-val
Panel A. Number of days / Total days in a year (%)					
Principal Trade	39	24	30	19	0.08
Principal Buy	28	21	23	17	0.17
Principal Sell	27	19	22	15	0.12
Creation	6	8	26	20	0.00
Redemption	2	3	12	14	0.00
No Principal Trade No Flow	54	27	32	29	0.00
Panel B. Aggregate Volume / TNA in Corp (%)					
Principal Trade	126	85	27	17	0.00
Principal Buy	66	46	14	10	0.00
Principal Sell	52	34	12	8	0.00
Creation	55	86	76	62	0.07
Redemption	27	42	45	56	0.06
Panel C. Other ETF Characteristics (Daily Average over the Year)					
TNA ($Million)	316	764	5,633	12,667	0.03
TNA in Corporate Bonds ($Million)	191	417	3,678	6,970	0.01
ETF Trading Volume ($1,000)	2,601	6,264	145,429	440,523	0.06
ETF Trading Volume / TNA (%)	1.1	2.0	1.8	3.0	0.10
Bid-ask Spread (bps)	36	22	41	25	0.21
Expense Ratio (bps)	33	19	20	17	0.00
Active Fund	0.37	0.48	0.10	0.29	0.00
Average Credit Rating	4.4	0.9	4.1	0.9	0.08
Remaining Maturity (Year)	7.9	7.0	9.7	9.0	0.12
Bond Age (Year)	3.5	1.3	4.1	1.4	0.03
Number of Bonds in the Portfolio	437	370	1,870	1,923	0.00

Table 4. Bond Characteristics and Principal Trading Intensity

This table examines how bond characteristics relate to ETFs' principal trading activity. The analysis is conducted at the ETF–bond–day level, restricted to observations with zero net ETF flows at day *t+1* to isolate secondary-market transactions. The dependent variable is *Principal Trading Intensity*, defined as an ETF *f*'s principal trade amount in bond *b* on day *t + 1*, scaled by its TNA in corporate bonds on day *t*. Columns (1) and (2) report results for principal purchase and sale, respectively, using ETF fixed effects and day fixed effects. Columns (3) and (4) include ETF × day fixed effects to control for time-varying fund-specific factors. The explanatory variables include the logarithm of remaining maturity, bond age, and issue size, bond turnover (measured as total trading volume scaled by amount outstanding), and an indicator for high-yield bonds. Standard errors are double-clustered by ETF and day, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep Var.	(1)	(2)	(3)	(4)
	Principal Trading Intensity$_{b, f, t+1}$			
	Purchase	*Sale*	*Purchase*	*Sale*
Log(Remaining Maturity)$_{b, t}$	1.98**	-6.54***	0.68*	-6.68***
	(2.59)	(-5.26)	(1.94)	(-5.32)
Log(Bond Age)$_{b, t}$	-1.34***	0.94**	-1.07***	1.13***
	(-2.83)	(2.52)	(-3.52)	(2.95)
Log(Issue Size)$_{b, t}$	4.89***	7.52***	4.64***	7.47***
	(4.78)	(6.49)	(5.12)	(6.38)
Bond Turnover$_{b, t}$	0.27	1.32*	-0.48	1.09*
	(0.24)	(1.89)	(-1.11)	(1.68)
High Yield$_{b, t}$	-0.01	-3.36	1.21	-3.17
	(-0.01)	(-1.53)	(1.22)	(-1.55)
Fund FE	Yes	Yes		
Day FE	Yes	Yes		
Fund × Day FE			Yes	Yes
Observations	87,166,162	87,166,162	87,166,162	87,166,162
Adj R-squared	0.01	0.00	0.44	0.09

Table 5. Principal Trading and Recent Creation and Redemption Activity

This table examines the relationship between ETFs' principal trading activity and their recent primary-market transactions. The analysis is conducted at the ETF–bond–day level, restricted to observations with zero net ETF flows at day *t+1* to isolate secondary-market transactions. The dependent variable is *Principal Trading Intensity*, defined as an ETF *f*'s principal trade amount (purchase and sale, respectively) in bond *b* on day *t + 1* (to isolate secondary-market transactions), scaled by its TNA in corporate bonds on day *t*. The key explanatory variables are the cumulative redemption amount and creation amount over the previous three trading days (*t*, *t–2*), each scaled by the ETF's TNA in corporate bonds. Columns (1)–(2) include only redemption variables; Columns (3)–(4) include only creation variables; and Columns (5)–(6) include both simultaneously. All regressions include fund × day, bond × day, and fund × bond fixed effects. Standard errors are double-clustered by fund and day, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var.	*Principal Trading Intensity*$_{b, f, t+1}$					
	Sale	*Purchase*	*Sale*	*Purchase*	*Sale*	*Purchase*
Redemption$_{b, f, (t-2, t)}$	175.57*	-49.47***			175.58*	-49.60***
	(1.96)	(-3.04)			(1.96)	(-3.07)
Creation$_{b, f, (t-2, t)}$			-15.57*	282.37***	-15.59*	282.37***
			(-1.74)	(2.64)	(-1.75)	(2.64)
Fund × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund × Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87,166,162	87,166,162	87,166,162	87,166,162	87,166,162	87,166,162
Adj R-squared	0.16	0.44	0.16	0.44	0.16	0.44

Table 6. Principal Trading and Fund Characteristics by ETF Style

This table compares trading activity and fund characteristics for 90 U.S. corporate bond ETFs (591 ETF–year observations, 2017–2023), including 67 passive and 23 active funds. Panel A summarizes ETF characteristics, including fund size, liquidity, expenses, and portfolio composition, measured as daily averages over the year. Panel B reports the share of trading days in a year associated with each activity type. Principal Trade days are those with zero net ETF flows but with changes in bond holdings, indicating secondary-market transactions. Creation and Redemption days correspond to net inflows and outflows, respectively. Panel C presents aggregate annual trading volumes scaled by total net assets in corporate bonds (TNA in Corporate Bond). The Wald test in the last column evaluates whether the mean differences between passive and active ETFs are statistically significant, with *p*-values based on regressions clustered by fund and year.

	Group by ETF Style				**Wald Test H0:**
	Passive		**Active**		**Passive=Active**
	Mean	SD	Mean	SD	P-val
Panel A. Characteristics (Daily Average over the Year)					
TNA ($Million)	3,735	10,513	382	643	0.04
TNA in Corp. Bonds ($Million)	2,438	5,848	202	334	0.02
ETF Trading Volume ($1,000)	94,852	360,663	3,033	5,377	0.07
ETF Trading Volume / TNA (%)	1.5	2.3	1.4	3	0.73
Bid-ask Spread (bps)	39	24	36	22	0.48
Expense Ratio (bps)	21	14	43	22.26	0.00
Average Credit Rating	4.2	1.0	4.2	0.7	0.99
Remaining Maturity (Year)	9.3	9.0	7.1	3.7	0.10
Bond Age (Year)	4.0	1.4	3.1	1.2	0.02
Number of Bonds in the Portfolio	1,406	1,684	289	254	0.00
Panel B. Number of days / Total days in a year (%)					
Principal Trade	31	21	44	23	0.02
Principal Buy	23	18	34	22	0.03
Principal Sell	23	16	29	20	0.19
Creation	18	19	8	12	0.03
Redemption	9	13	1	2	0.00
No Principal Trade No Flow	42	31	46	27	0.74
Panel C. Aggregate Volume / TNA in Corp (%)					
Principal Trade	60	57	130	113	0.00
Principal Buy	30	28	73	62	0.00
Principal Sell	27	25	49	45	0.02
Creation	69	63	56	108	0.36
Redemption	42	54	17	27	0.01

Table 7. Principal Trading and Subsequent Reductions in Tracking Error

This table examines how ETFs' principal trading relates to subsequent changes in tracking error. The analysis is conducted at the ETF–day level. Tracking error is defined as the square root of the average squared difference between an ETF's daily NAV return and its benchmark index return, computed over a three-day window. The dependent variable is the change in tracking error, measured as the difference between the post-event window and the pre-event window ($Tracking\ Error_{f,\,(t+1,\,t+3)} - Tracking\ Error_{f,\,(t-2,\,t)}$). *Fund Principal Trading Intensity* is the ETF's aggregate principal trade volume (purchases plus sales) on day *t* scaled by TNA in corporate bonds, and *Fund C/R Intensity* is the combined in-kind flow volume (creations plus redemptions) on day *t* scaled by TNA in corporate bonds. Columns (1)–(2) use all ETF–day observations, and Column (3) restricts the sample to zero-flow days to isolate secondary-market activity. All regressions include fund and day fixed effects. Standard errors are double-clustered by fund and day, and t-statistics are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)
	All days		Zero flow days
Dep Var.	$\Delta\ Tracking\ Error_{f,\,(t+1,\,t+3)}$		
$Fund\ Principal\ Trading\ Intensity_{f,\,t}$	-5.73***	-5.85***	-6.56***
	(-3.33)	(-3.34)	(-3.41)
$Fund\ C/R\ Intensity_{f,t}$		-0.62	
		(-0.48)	
Fund FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	123,541	123,541	91,061
Adj R-squared	0.129	0.129	0.125

Table 8. Principal Trading, ETF Style, and Tracking Error

This table compares the relationship between principal trading and tracking error for passive and active bond ETFs. The analysis is conducted at the ETF–day level. Tracking error is defined as the square root of the average squared difference between an ETF's daily NAV return and its benchmark index return, computed over a three-day window. The dependent variable is the change in tracking error, measured as the difference between the post-event window and the pre-event window ($Tracking\ Error_{f,(t+1,\ t+3)} - Tracking\ Error_{f,\ (t-2,\ t)}$). *Fund Principal Trading Intensity* is the ETF's aggregate principal trade volume on day *t* scaled by TNA in corporate bonds, and *Fund C/R Intensity* is the combined in-kind flow volume (creations plus redemptions) on day *t* scaled by TNA in corporate bonds. Columns (1)–(2) use all ETF–day observations, while Columns (3)–(4) restrict the sample to zero-flow days to isolate secondary-market activity. Columns (1) and (3) report results for passive ETFs, and Columns (2) and (4) for active ETFs. All regressions include fund and day fixed effects. t-statistics, shown in parentheses, are based on standard errors double-clustered by fund and day. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	All days		Zero flow days	
ETFs	Passive	Active	Passive	Active
Dep Var.	$\Delta\ Tracking\ Error_{f,(t+1,\ t+3)}$			
Fund Principal Trading Intensity$_{f,\ t}$	-5.42***	-0.99	-6.11***	-1.98
	(-2.91)	(-0.33)	(-3.09)	(-0.60)
Fund C/R Intensity$_{f,t}$	-0.91	1.73		
	(-0.79)	(0.37)		
Fund FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	96,921	26,620	67,865	23,196
Adj R-squared	0.14	0.23	0.13	0.22

Table 9. Robustness: Alternative Tracking-Error Windows

This table tests the robustness of the relationship between principal trading and tracking error using alternative measurement windows. The analysis is conducted at the ETF–day level. Tracking error is defined as the square root of the average squared difference between an ETF's daily NAV return and its benchmark index return. The dependent variable is the change in tracking error, measured as the difference between the post-event and pre-event windows. Panel A uses a two-day window ($Tracking\ Error_{f,\,(t+1,\,t+2)} - Tracking\ Error_{f,(t-1,\,t)}$); Panel B uses a four-day window ($Tracking\ Error_{f,\,(t+1,\,t+4)}$-$Tracking\ Error_{f,\,(t-3,\,t)}$). *Fund Principal Trading Intensity* is the ETF's aggregate principal trade volume on day *t* scaled by TNA in corporate bonds, and *Fund C/R Intensity* is the combined in-kind flow volume (creations plus redemptions) on day *t* scaled by TNA in corporate bonds. Columns (1)–(4) include all ETF–day observations; Columns (5)–(7) restrict to zero-flow days. All regressions include fund and day fixed effects. Standard errors are two-way clustered by fund and day. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A: Two-day window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All days				Zero flow days		
ETFs	All	All	Passive	Active	All	Passive	Active
Dep Var.	$\Delta\ Tracking\ Error_{f,(t+1,\,t+2)}$						
$Fund\ Principal\ Trading\ Intensity_{f,\,t}$	-4.70***	-4.74***	-5.34**	1.61	-5.06**	-5.76**	1.07
	(-2.75)	(-2.70)	(-2.45)	(0.56)	(-2.60)	(-2.46)	(0.34)
$Fund\ C/R\ Intensity_{f,t}$		-0.22	-1.06	3.00			
		(-0.17)	(-0.90)	(0.57)			
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123,805	123,805	97,148	26,657	91,277	68,047	23,230
Adj R-squared	0.10	0.10	0.13	0.18	0.10	0.11	0.17

Table 9, cont'd

Panel B: Four-day window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All days				Zero flow days		
ETFs	All	All	Passive	Active	All	Passive	Active
Dep Var.	*Δ Tracking Error*$_{f,t+1:t+4}$						
Fund Principal Trading Intensity$_{f,t}$	-4.70***	-4.78***	-4.04**	1.39	-5.34***	-4.71**	0.74
	(-3.12)	(-3.12)	(-2.50)	(0.57)	(-3.15)	(-2.60)	(0.28)
Fund C/R Intensity$_{f,t}$		-0.41	-0.36	1.83			
		(-0.35)	(-0.32)	(0.48)			
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123,266	123,266	96,686	26,580	90,831	67,668	23,163
Adj R-squared	0.15	0.15	0.16	0.27	0.15	0.15	0.26

Table 10: ETF Trading Activity and Subsequent Bond Returns

This table examines whether ETF trading and flow activity predict subsequent bond performance. For each bond–month, we aggregate principal trading and creation/redemption volumes across all ETFs and scale them by the bond's total par value. *Net Principal Trade* is defined as principal bond purchases minus sales by ETFs during month m, while Net Creation equals creations minus redemptions over the same period. The dependent variable, Excess Return, is the next month's Treasury duration–adjusted return following van Binsbergen, Nozawa, and Schwert (2025). Net Principal Trade and Net Creation are expressed in percentage points, and Excess Return is measured in basis points. All regressions are estimated separately for active and passive ETFs and include bond fixed effects, and either year–month or year–month × rating fixed effects. Standard errors are two-way clustered by bond and month, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dep Var.	(1)	(2)	(3)	(4)
	Excess Return$_{b,m+1}$			
	Active ETFs		Passive ETFs	
Net Principal Trade$_{b,m}$	9.12***	7.10***	2.49	1.74*
	(3.21)	(3.56)	(1.39)	(1.73)
Net Creation$_{b,m}$		3.97***		-0.81**
		(3.50)		(-1.99)
Excess Return$_{b,m}$		-0.12***		-0.08***
		(-3.90)		(-2.99)
Log(Bond Age)$_{b,m}$		-0.31***		-0.30***
		(-3.70)		(-3.98)
Log(Remaining Maturity)$_{b,m}$		0.57		0.29
		(1.27)		(0.76)
Year-Month FE	Yes		Yes	
Year-Month × Rating FE		Yes		Yes
Bond FE	Yes	Yes	Yes	Yes
Observations	270,615	270,615	828,892	828,892
Adj R-squared	0.38	0.45	0.35	0.40

Table 11: Principal Purchase and Sale, Flow Activity and Subsequent Bond Returns
This table focuses on active ETFs and examines whether their principal buying and selling activity, as well as in-kind creation and redemption operations, predict subsequent bond performance. For each bond–month, we aggregate principal transactions and creation/redemption volumes across active ETFs and scale them by the bond's total par value. *Principal Purchase* and *Principal Sale* measure the value of bonds purchased and sold by active ETFs during month *m*, respectively. *Gross Creation* and *Gross Redemption* capture the total value of all in-kind creations and redemptions during the same period. The dependent variable, *Excess Return*, is the next month's Treasury duration–adjusted return following van Binsbergen, Nozawa, and Schwert (2025). *Principal Buy (Sell)* and *Gross Creation (Redemption)* are expressed in percentage points, and *Excess Return* is measured in basis points. All regressions include bond fixed effects and either year–month or year–month × rating fixed effects. Standard errors are two-way clustered by bond and month, and t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep Var.	*Excess Return*$_{b,m+1}$				
Principal Purchase$_{b,m}$	10.41***	10.95***			8.92***
	(2.77)	(3.22)			(3.25)
Principal Sale$_{b,m}$	-3.35	-1.07			-0.79
	(-0.97)	(-0.38)			(-0.28)
Gross Creation$_{b,m}$			4.38***	3.88***	3.31***
			(3.71)	(4.00)	(4.16)
Gross Redemption$_{b,m}$			-1.84	-0.36	-0.32
			(-0.52)	(-0.21)	(-0.19)
Excess Return$_{b,m}$		-0.12***		-0.11***	-0.12***
		(-3.91)		(-3.89)	(-3.91)
Log(Bond Age)$_{b,m}$		-0.29***		-0.36***	-0.30***
		(-3.34)		(-4.30)	(-3.48)
Log(Remaining Maturity)$_{b,m}$		0.57		0.58	0.56
		(1.27)		(1.29)	(1.26)
Year-Month FE	Yes		Yes		
Year-Month × Rating FE		Yes		Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Observations	270,615	270,615	270,615	270,615	270,615
Adj R-squared	0.375	0.446	0.375	0.446	0.446

Table 12: Holding-Based Alpha and Its Decomposition by ETF Style

This table reports holding-based alpha ($\alpha_{f,t}$ in bps) and its decomposition for U.S. corporate bond ETFs, distinguishing active and passive funds. For each ETF–year, daily alphas are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method adapted to corporate bonds, based on credit risk–adjusted excess returns relative to duration-matched Treasuries and credit-rating peers. Fund-level alpha is the holdings-weighted sum of these adjusted returns. We decompose total alpha into contributions from creation/redemption activity ($\alpha^{C}_{f,t}$), principal trading ($\alpha^{P}_{f,t}$), and other portfolio holdings ($\alpha^{O}_{f,t}$), tracked using a first-in, first-out (FIFO) approach. The table reports the mean, standard deviation, and 25th (Q1), 50th (median), and 75th (Q3) percentiles across ETF–year observations.

Active (23 ETFs, 137 ETF-year)	Mean	SD	Q1	Median	Q3
Holding based alpha ($\alpha_{f,t}$, bps)	19.1	194.4	-79.4	19.7	118.4
Decomposition:					
Creation/Redemption ($\alpha^{C}_{f,t}$)	-5.5	73.8	-27.5	-4.7	21.5
Principal Trade ($\alpha^{P}_{f,t}$)	24.9	124.9	-12.1	16.6	73.0
Other ($\alpha^{O}_{f,t}$)	0.3	49.0	-6.1	0.1	6.1

Passive (67 ETFs, 454 ETF-year)	Mean	SD	Q1	Median	Q3
Holding based alpha ($\alpha_{f,t}$, bps)	-9.3	157.0	-95.2	-25.9	83.7
Decomposition:					
Creation/Redemption ($\alpha^{C}_{f,t}$)	-11.1	91.4	-57.3	-9.3	35.4
Principal Trade ($\alpha^{P}_{f,t}$)	1.1	71.1	-19.5	0.0	21.8
Other ($\alpha^{O}_{f,t}$)	1.0	37.2	-7.0	0.0	7.0