Baskets Full of Cash: Primary Market Frictions and the Performance of Active Bond ETFs*

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Abstract

We find that active corporate bond ETFs earn lower net-of-fee alpha than comparable mutual funds, particularly among high-yield funds and even when comparing same-manager funds. We trace this performance gap to a friction inherent in the ETF structure: misaligned incentives between active managers and authorized participants (APs). Bonds received in kind from APs reflect dealer inventory pressures and subsequently earn lower long-horizon returns than bonds purchased directly by the same ETFs. Knowing this, active ETFs—unlike passive ETFs—rely *predominantly* on cash to settle creation and redemption, and trade directly in the bond market, much like mutual funds. We investigate the determinants of cash settlement and build a model that rationalizes the performance gap despite managers' flexibility to use cash. Overall, these results suggest that the ETF structure introduces frictions to active bond funds, to which managers respond by using cash settlement as a partial remedy.

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1 Introduction

The U.S. corporate bond market has seen rapid growth in actively managed exchange-traded funds (active ETFs) in recent years. As of 2024, their assets under management (AUM) exceeded 160 billions—a 200% increase from less than 75 billion in 2020 (Figure 1). In contrast, actively managed bond mutual funds (active MFs) grew by only about 8% over the same period. Providers of active ETFs emphasize their lower management fees, higher tax efficiency via in-kind redemption, and greater trading flexibility of exchange-traded shares, relative to active mutual funds.

In this paper, we first ask an important yet little explored question: Does the active bond ETF structure translate into better performance? Our answer is no: Net of fees, active ETFs do not outperform comparable active mutual funds. In fact, high-yield ETFs *underperform* their mutual fund counterparts by approximately 1.3% annually. The performance gap remains robust in fund-level regressions with various fund characteristic controls and a rich set of fixed effects, in matched samples, and in same-manager ETF–mutual fund comparisons. Our results, together with additional analyses and anecdotal evidence, suggest that the usual suspects—differences in manager skill, information, portfolio transparency, or the costs of managing investor flows—are unlikely to explain the performance gap.[1]

What then explains this performance gap? We argue that a friction intrinsic to the ETF structure could negatively impact active ETF performance: authorized participants (APs) have no obligation to deliver the managers' desired bonds during in-kind transfers. APs have inherent bargaining power over ETFs because they effectively control the timing of creations and redemptions and can steer custom baskets toward bonds they wish, for example to offload from their inventories, rather than those desired by the managers. Realized baskets therefore reflect not only managers' discretion but also APs' incentives and bargaining power during the negotiation of custom (non-pro-rata) baskets.

Knowing this, active ETFs settle creations and redemptions *predominantly* in cash, often *entirely* so, after which managers trade directly in the secondary bond market, much like mutual funds. N-CEN regulatory filing data show that more than 60% of investment-grade and 40% of high-yield active ETFs settle creations and redemptions almost *entirely* in cash, rather than via in-kind transfers (Figures 2 and 3). In sharp contrast, roughly 60% of passive ETFs settle almost entirely in kind. At

[1] We discuss these potential explanations in Section 4.1.1.

the same time, we observe changes in holdings on 14 days in a typical month among which only 3 days show primary market creation or redemption, suggesting that they frequently trade directly in the bond market (Figures 4 and 5).

Cash creations and redemptions allow ETFs to bypass AP–manager negotiation over in-kind basket composition, preserving managers' discretion over portfolio choices.[2] However, APs might prefer in-kind basket over cash because they could offload the bonds to alleviate their balance-sheet frictions and because they have to pay an additional cash fee to the ETFs. This gives rise to a form of conflict of interests in which the ETFs and the APs bargain over the cash proportion in the custom basket. We formalize these intuitions in a simple bargaining model (in Section 5), derive testable predictions, and present evidence supporting the mechanism. The model predicts that the equilibrium cash fraction (i) increases with the ETF's relative bargaining power, (ii) decreases with trading costs, and (iii) decreases with the AP's balance-sheet frictions. Moreover, the ETFs underperform comparable mutual funds less when the cash fraction is higher.[3]

Our empirical investigation provides evidence in support of the mechanism and model predictions. If such primary market frictions exist in active ETFs, they should leave a footprint in what these funds buy. Following the approach in studies on passive ETFs (Pan and Zeng 2017, Reilly 2022, Dannhauser and Karmaziene 2023, Du 2023), we test whether APs' inventory management incentives—proxied by changes in dealers' bond inventories, reflecting APs' dual role as bond market dealers—tilt active ETFs' purchases. We find that they do: bonds accumulated in dealer inventory during the past two weeks are purchased about 37% more often than bonds on average in our sample. These results echo recent findings for passive ETFs (e.g., Dannhauser and Karmaziene 2023), yet the persistence of this effect among active ETFs is noteworthy—alpha-oriented managers should, in principle, negotiate custom baskets and use cash transactions to avoid AP-driven, potentially alpha-diluting influences on realized baskets.

The effect of dealer inventory is no longer significant, both economically and statistically, when ETFs use cash creation or trade on days without primary market activity. These results again point to primary market frictions as the most plausible driver of the dealer-inventory effect. Importantly, the results suggest that managers regain full discretion over bond selection when they sidestep in-kind

[2] See, for example, this article from Vanguard.

[3] In the model, the ETF could even outperform mutual funds for highly liquid securities because it receives a cash fee, whereas mutual funds do not.

basket negotiations. Combined with the unconditional results above, the evidence indicates that cash transactions and direct trading preserve discretion if used, but do not eliminate primary market frictions on average.

We then test whether primary market frictions steer active ETFs toward lower-performing bonds relative to the bonds they could otherwise purchase. Maybe, those bonds managers accept in kind from APs do not hurt the performance. However, we find that these bonds, especially those purchased by high-yield ETFs, underperform bonds purchased on days without primary market activity. For example, bonds acquired by in-kind-settling high-yield ETFs on days with primary market activity subsequently underperform by an average 0.7% over the next year, relative to bonds the same ETFs purchase on days without primary market activity. Consistent with our prior, we find no such pattern for ETFs that settle primarily in cash. These results suggest that primary market frictions constrain fund performance.

Last but not least, we test the model predictions regarding cash proportion in the custom basket. As guided by the model, we collect information about the relevant variables. First, we include the cash-transaction fee, inferred from Form N-CEN and prospectus, that ETFs charge APs on top of standard creation/redemption fees. We also account for the number of APs trading with each ETF (from Form N-CEN) to proxy for ETF–AP bargaining power, along with fund characteristics, as well as bond-holding attributes that capture APs' inventory costs and ETFs' direct-trading costs. Consistent with the predictions, we find that active ETF's cash use is more likely when cash-transaction fees are low, more APs transact with the ETF in the primary market, expense ratio is high, and portfolio tilts toward better rated and shorter maturity bonds (proxies for lower trading costs and primary market frictions).

Overall, our paper contributes to understanding active management in corporate bond markets by documenting frictions that the ETF structure imposes on active strategies. Because these implementation frictions are largely invisible, investors may underappreciate them and only focus instead on the appealing narrative that active ETFs deliver the same active strategies as active mutual funds, but at lower cost with ample secondary-market liquidity. At the same time, alpha is only one of many components of investor welfare. Investors also benefit from the ETF structure's tax advantages and from low secondary market trading costs relative to comparable mutual funds, and these benefits can exceed the implementation costs we document. For example, Moussawi et al. (2025) document that active equity ETFs can enhance long-term investor returns by about 1.05% per year through tax efficiency.

That said, our main message is not that active ETFs deliver lower returns to the end investors, but that—amid their rapid growth—investors should evaluate them with appropriate caution, recognizing the structural limits to implementing active strategies in ETF form.

Our paper also provides practical takeaways and policy-relevant implications. Practically, ETF–AP relationship, fee design on the cash component, and operational choices that decouple portfolio trades from the cadence of primary market activity emerge as levers for ETF sponsors and managers to facilitate the implementation of active strategies. For researchers and regulators, how custom-basket negotiation interact with AP incentives in bond markets—and the widespread resort to cash transactions, against the ETF structure's intended design—deserves further study, including unified welfare accounting that incorporates taxes and liquidity for end investors, as well as evaluation of institutional counterfactuals (e.g., alternative cash-fee design and primary market parameters such as basket unit sizes) under which active strategies can be implemented more effectively in ETFs.

Related literature This paper contributes to the growing literature of active ETFs, which has largely focused on equity ETFs. Du et al. (2023) show that active ETFs cloned from mutual funds (ETF-mutual fund twins) are not cannibalizing the mutual funds' flows. Luo and Schumacher (2023) show that mutual fund managers are likely take dual roles by managing ETFs side-by-side to retain their institutional clients in response to the ETF competition. Huang and Martinez (2024) study ETF–mutual fund twins and find mutual-fund flows costly. Chau et al. (2025) show that investors discipline bad active equity ETF managers via short selling. We extend this literature by focusing on actively-managed corporate bond ETFs, where interactions between active managers and APs—within relatively illiquid markets in which APs often serve as both ETF arbitrageurs and bond dealers—create distinct frictions absent in equity settings.

We also contribute to the growing literature of bond ETFs. Most existing studies on bond ETFs focus on passive index-trackers.[4] This is likely because active bond ETFs have gained the traction only recently. Existing studies of passive ETFs often focus on the liquidity transformation that passive

[4]See, for example, Dannhauser (2017), Pan and Zeng (2017), Dannhauser and Hoseinzade (2022), Reilly (2022), Dannhauser and Dathan (2023), Dannhauser and Karmaziene (2023), Du (2023), Koont et al. (2023), Shim and Todorov (2023), Holden and Nam (2024), Dannhauser and Karmaziene (2025).

bond ETFs offer in relation to the illiquid bond market and APs' dual role as bond market dealer (e.g., Pan and Zeng 2017, Dannhauser and Hoseinzade 2022, Koont et al. 2023, Shim and Todorov 2023), and their effects on underlying bonds' price and liquidity (e.g., Dannhauser 2017, Holden and Nam 2024). This paper fills a gap in the literature by examining the rapidly expanding market for active bond ETFs and highlighting the implementation costs inherent in running active strategies within the ETF structure.

Our paper complements evidence from passive ETFs showing APs' influence on realized baskets. For example, Koont et al. (2023) show that passive ETFs actively include cash into baskets to promote the liquidity transformation by APs. Reilly (2022) document that APs choose to deliver bonds with negative outlooks into the creation baskets. Dannhauser and Karmaziene (2023) show that APs use ETFs as "warehouse", offloading inventory to ETFs; later rises in ETF ownership predict more downgrades and weaker earnings surprises. Also, Du (2023) show that adverse selection is mitigated if APs when APs have the relevant bonds on hand. Our paper departs from these prior works by focusing on active ETFs. For active ETFs, both question and empirical patterns differ fundamentally. Pursuit of alpha often requires timely trades of specific bonds. This reduces the substitutability of managers' desired bonds, which in turn weakens alignment with APs who face higher sourcing costs for specific securities. Reflecting these distinct features, we observe that active ETFs exploit the operational flexibility of cash creations/redemptions and direct bond market trading substantially more than passive ones. Whether active ETFs can eliminate effects of primary market frictions on their performance remains an open empirical question, which we address in this paper. It makes our finding striking that, at least in principle, active managers could use cash transactions and direct trading to avoid AP-influenced trades that could dilute alpha.

Our theoretical model also relates to recent studies emphasizing the role of primary market frictions in ETF mispricing and performance (Pan and Zeng 2017, Koont et al. 2023, Du 2023, Shim and Todorov 2023). Unlike these papers, which focus primarily on passive ETFs, our analysis shows how primary market frictions constrain the portfolio choices of active bond ETFs. The model further demonstrates that the composition of cash and securities in custom baskets arises endogenously from bargaining between ETFs and APs, generating novel empirical predictions.

Finally, our paper contributes to the broad literature on active management. The seminal works by Sharpe (1991) and Carhart (1997) demonstrated the inherent difficulties in consistently outperforming the market after accounting for fees and transaction costs. This motivated numerous studies that ask whether active managers have "skills" to consistently outperform passive strategies.[5] At the same time, studies have pointed out several challenges in active management[6] and issues more specific to corporate bond mutual funds.[7] While we do not take a stance on whether active ETF managers possess persistent skill to outperform the market or passive funds, we contribute to the literature by highlighting the constraint on active management that is inherent in the ETF wrapper.

2 Institutional background

This section provides institutional background on the ETF structure with particular emphasis on active bond ETFs.

2.1 Rise of active ETFs

ETFs were introduced in the early 1990s as passive index-tracking vehicles. For decades, the ETF market was dominated by passive strategies, with actively managed funds representing only a small fraction of total assets. This began to change in the late 2010s.

[Figure 1 here]

Figure 1 illustrates the dramatic growth of actively managed fixed-income ETFs in the United States. Panel A shows that total net assets (TNA) of active fixed income ETFs grew from less than USD 1 billion in 2010 to over USD 160 billion by 2024; the number of active fixed income ETFs increased from fewer than 10 to over 220 during the same period. Panel B shows that the number of new active ETF launches jumped following the SEC's September 2019 adoption of the ETF Rule. This regulatory change streamlined the launch process for new ETFs and explicitly permitted the use

[5] See, for example, Blake et al. (1993), Elton et al. (1995), Chevalier and Ellison (1999), Elton et al. (1996), Berk and Green (2004), Kosowski et al. (2006), Huij and Derwall (2008), Chen et al. (2010), Cici and Gibson (2012), Kacperczyk et al. (2014), Berk and Van Binsbergen (2015), Jordan and Riley (2015), Hoberg et al. (2018), Ibert et al. (2018a), among many others.

[6] For example, diseconomies of scale (Pástor et al. 2015), incentive structures (Ibert et al. 2018b), fire sales (Coval and Stafford 2007, Chernenko and Sunderam 2020), search costs (Roussanov et al. 2021)

[7] For example, flow-performance sensitivity (Chen and Qin 2017, Goldstein et al. 2017), reaching-for-yields behavior (Choi and Kronlund 2018), fire sales and liquidity management (Choi et al. 2020, Jiang et al. 2021, Ma et al. 2022, Giannetti and Jotikasthira 2024), outperformance against passive funds (Choi et al. 2021), liquidity provision (Giannetti et al. 2024), valuation skills (Cici and Zhang 2024)

of custom, non-pro-rata creation and redemption baskets without requiring individualized exemptive relief.

Another noticeable pattern in Panel B is the contrast between active bond ETFs and active bond mutual funds. While the number of new active mutual fund launches has declined in recent years, new active ETF launches surged post-2019, overtaking mutual funds by 2021. This shift reflects both regulatory facilitation and growing investor demand for actively managed strategies delivered through the ETF wrapper, which promises the benefits of professional bond selection combined with intraday liquidity and potential tax advantages.

2.2 Overview of the ETF structure

A distinguishing feature of the ETF structure is that ETF shares trade on exchanges throughout the day at market-determined prices. Unlike mutual funds, which transact only at end-of-day NAV, ETF prices may deviate from their NAV during intraday trading. To keep market prices aligned with NAV, the ETF structure relies on APs—typically large broker-dealers—and the creation/redemption mechanism.

When an ETF trades at a premium to NAV, APs can profit by creating new shares: they deliver an agreed-upon basket of securities (the “creation basket”) to the ETF issuer in exchange for new ETF shares, which they then sell in the secondary market. The increased supply of shares pushes the ETF price back toward NAV. Conversely, when an ETF trades at a discount, APs can redeem shares by returning them to the issuer in exchange for the underlying securities (the “redemption basket”), reducing share supply and raising the price.

AP participation is voluntary, not mandatory. APs engage in this arbitrage when the profit opportunity is enticing given their transaction costs and balance sheet constraints; the baskets exchanged in these transactions can be customized instead of pro-rata slices of the fund’s holdings. Each business day, ETFs disclose an announced basket composition, but the realized baskets used in actual creations and redemptions are negotiated between the ETF manager and APs and often differ from what was announced.

A key feature of this mechanism is that exchanges of securities for ETF shares are generally treated as in-kind transfers rather than cash transactions. This allows ETFs to offload low-cost-basis securities during redemptions without realizing taxable capital gains, providing a tax advantage over mutual funds where redemptions are generally settled in cash.[8]

3 Data and stylized facts on active ETFs

In this section, we describe our data and present key stylized facts that motivate our subsequent analyses.

3.1 Data

Our sample consists of active corporate bond ETFs and mutual funds from 2016 to 2023. We classify ETFs and mutual funds as corporate bond funds if they fall under the CRSP style categories I, ICQH, ICQM, ICQY, ICDI, ICDS, or IC and hold at least 15% of their portfolio in corporate bonds, following Choi and Kronlund (2018). We further classify funds as investment-grade if their Lipper Objective code is A, BBB, IID, SII, SID, or USO and as high-yield if the code is HY, GB, FLX, MSI, or SFI.

We classify an ETF as active if the actively-managed ETF flag obtained from the ETF Global is "yes" and the fund's prospectus explicitly states that it follows an active management strategy. We exclude leveraged, inverse, and smart-beta ETFs. We classify a mutual fund as an active mutual fund if it is not classified as an index fund based on the index-fund flag from the CRSP Survivor-Bias-Free Mutual Fund Database following Goldstein et al. (2017) and its Pástor et al. (2020) activeness measure is above the sample median.

We obtain fund characteristics, returns, manager names, and quarterly holdings from the CRSP Survivor-Bias-Free Mutual Fund Database. When we examine daily portfolio changes of ETFs, we use daily holdings and shares outstanding of ETFs obtained from the ETF Global. Our ETF Global coverage ends at March 2023. We merge holdings data with the London Stock Exchange Group (LSEG) Mergent Fixed Income Securities Database (FISD) to obtain bond-level characteristics such as, amount outstanding, coupon information, offering dates and maturity dates. We obtain corporate bond prices and trading volumes, from the Enhanced Trade Reporting and Compliance Engine (TRACE). We apply standard filters to clean the TRACE data following Dick-Nielsen (2014). We

[8] Mutual funds may reserve the right to meet redemptions in kind and sometimes use it (see, Agarwal et al. 2023).

calculate the bond illiquidity measure following Bao et al. (2011).[9].

We use Form N-CEN filing data to obtain information on ETFs' creation/redemption baskets and their APs. Form N-CEN is a mandatory annual filing that U.S.-based registered investment companies (RICs) have been required to submit to the U.S. Securities and Exchange Commission (SEC) as part of the modernization of investment company reporting since 2018.[10] This filing contains detailed information on RICs' operational relationships with counterparties, including the names of all registered APs and the primary market activities (creations and redemptions) between each AP and the ETF. Notably, the data also include the average cash share of creation and redemption baskets as well as the average actual basket fees.

Our final sample funds consist of 164 active ETFs and 484 active mutual funds. Our sample period runs from 2016 to 2023. We exclude first two quarters of 2020 to make sure the ETF-mutual fund return comparison results are not driven by the COVID crisis and the subsequent Fed intervention.[11] Table 1 reports descriptive statistics of fund characteristics as well as average credit ratings and time to maturity of their corporate bond holdings.

3.2 Stylized facts on active ETFs

We find three notable empirical patterns for active ETFs. First, cash transactions, rather than in-kind transfers, are prevalent. Second, primary market activity (creations and redemptions) is infrequent. Third, portfolio compositions often change even without primary market activity, suggesting that fund managers trade directly in secondary markets.

3.2.1 Prevalence of cash transactions

Using Form N-CEN regulatory data, we first show a striking pattern that active ETFs settle creations and redemptions predominantly in cash rather than in kind. We often observe 100% cash transactions.

[Figure 2 and Figure 3]

[9] In calculating the illiquidity measure, we use the code sourced from the Open Source Bond Asset Pricing website. We thank Alex Dickerson for sharing the code (Dickerson et al. 2023).

[10] We downloaded the data from the SEC website.

[11] For example, prior studies document significant dislocations in corporate bonds and corporate bond ETFs during the COVID episode (Haddad et al. 2021, Shim and Todorov 2023). Our results remain intact without excluding the two quarters.

Figure 2 shows the histogram of the cash percentage for creation baskets and Figure 3 shows the histogram for redemption baskets. The figure shows that active ETFs settle creations and redemptions *mainly* in cash rather than through securities exchanges.

Consider investment-grade funds first. Approximately 65% of active investment-grade ETFs settle creations mostly in cash (cash more than 90%) and 40% of creations use 100% cash, with an average cash creation percentage of 77%. By contrast, passive investment-grade ETFs settle predominantly in kind, with around 60% relying on mostly in-kind settlements (cash <10%), with an average cash percentage of 28%.

For high-yield funds, the pattern persists with lesser magnitudes. More than 40% of active high-yield ETFs settle creations mostly in cash, with an average cash percentage of 62%. Passive high-yield ETFs again favor in-kind transfers, with about 60% settling mostly in kind and an average cash percentage of 27%.

As shown in Panel B, active ETFs prefer cash settlement relative to passive ETFs for redemption baskets as well. Cash transaction is relatively less common for redemptions than for creations, potentially due to the tax-efficiency advantages of in-kind redemptions and the role of APs in buffering against fire sales (Shim and Todorov 2023). During our sample periods, 22% of active ETFs pay out on average 0.7% of TNA as capital gain. The fraction is smaller than that in active mutual funds where 32% of funds distribute about 1.3% capital gain, but larger than that in passive ETFs where 15% of funds distribute about 0.04% capital gain.

Cash transactions are not costless for ETFs. They entail direct trading in the bond market, which can dilute existing shareholders due to transaction costs from direct trading (e.g., bid-ask spreads, brokerage expenses) and may reduce tax efficiency as it avoids in-kind transfers. To offset these costs, ETFs may impose an additional fee on the cash portion of the basket when settlements occur fully or partially in cash, on top of the standard creation and redemption fees. This cash transaction fee can discourage unnecessary use of cash by pricing the convenience APs gain from avoiding the need to source specific bonds, thereby preserving the ETF wrapper's intended functioning—in-kind transfers.

We infer the cash transaction fee using data from N-CEN filings and fund prospectuses, and describe the process in Appendix A. On average, the cash transaction fee amounts to 3 basis points for investment-grade funds and 10 basis points for high-yield funds.

3.2.2 Infrequent primary market activity

We next show that active ETFs' primary market activity is far less frequent than one might expect. The frequent cash transaction, in principle, may correspond to frequent primary market activity, as APs benefit from the convenience of not having to source specific bonds. In practice, however, this is not the case.

Figure 4 shows the proportion of trading days with primary market activity for our sample ETFs, separately for high-yield and investment-grade funds. For each fund, we calculate this proportion as number of days on which the fund's shares outstanding change, divided by number of all trading days. It is worth noting that days with primary market activity correspond to when investor flows enter or exit the ETF portfolio.

[Figure 4 here]

For both panels in Figure 4, we see that days with primary market activity are relatively sparse, with the majority of funds experiencing changes in shares outstanding on less than 13% of all trading days. This fraction corresponds to average 3 days in a month for average ETFs. This is surprising under the casual impression that ETFs' trades occur through in-kind transfers.

3.2.3 Frequent portfolio changes without primary market activity

How, then, do active ETFs trade "actively"? Lastly, we document that active ETFs frequently exhibit changes in portfolio holdings on days without primary market activity—suggestive evidence of their direct trading.

To show this, we begin with fund-day observations from ETF Global's daily holdings data. We define a "day with trades" as any day on which a fund's corporate bond holdings change. Then, for each fund-month, we calculate the proportion of (i) days with primary market activity (i.e., changes in shares outstanding), (ii) days with portfolio trades but no primary market activity, and (iii) days without any portfolio changes.[12]. Finally, we plot the cross-sectional monthly averages of these proportions.

[Figure 5 here]

[12]We exclude portfolio changes due to calls and maturities of the bonds.

Figure 5 presents the resulting plot. The most noticeable pattern is the prevalence of days with portfolio changes but no primary market activity, shown by the red area. These days account for an average of 60% of the trading days in a month.[13] This pattern suggests that active ETF managers frequently trade directly in the secondary bond market without in-kind transfers. The proportion of days with primary market activity (shown by the dark gray area) is rather small. These days account for around 9% of the trading days for high-yield ETFs and 13% for investment-grade ETFs.

The proportion of days with trades but no primary market activity is substantial, yet these trades might simply reflect small amounts of minor portfolio adjustments. We next examine the magnitude of these changes by calculating the gross change in bond holdings as well.

For a given fund, we compute the daily changes in bond holdings for all bonds in its portfolio in terms of par value, then normalize by the fund's lagged total net assets. Positive changes are considered purchases and negative changes are considered sales. Then, for each fund-month, we sum all portfolio changes associated with purchases across all bond-day observations within that fund-month. We then separately sum purchases that occur on days without primary market activity. Dividing the latter by the former yields the proportion of gross purchases made on days without primary market activity. We compute the proportion for days with primary market activity analogously. Finally, we repeat this procedure for sales (negative changes in holdings).

[Figure 6]

Figure 5 shows the results. The average proportion of portfolio changes made during days without primary market activity is shown in red. We compute the average proportions among high-yield funds and investment-grade funds separately.[14] In all cases, portfolio changes on days without primary market activity account for more than half of total portfolio changes. This pattern echoes Figure 5.

[13] While not shown in this figure, passive ETFs exhibit portfolio changes without primary market activity on approximately 45% of trading days.

[14] We also compute averages within different subsamples of ETFs split along two dimensions: (i) high-yield versus investment-grade funds, and (ii) cash funds versus in-kind funds. For the latter, we classify funds as cash funds if the proportion of cash in creation/redemption baskets exceeds 75%, hypothesizing that cash funds make a larger proportion of portfolio changes on days without primary market activity. The results are shown in Figure A1.

4 Empirical results

In this section, we compare the performance of active ETFs with that of their active mutual fund counterparts. We then examine the role of (i) AP-dealer bond inventory and (ii) cash transaction vs. in-kind transfer in explaining this performance gap.

4.1 Performance of active ETFs vs. mutual funds

We examine fund returns in Section 4.1.1, then turn to the returns of corporate bonds traded by ETFs and mutual funds in Section 4.1.2.

4.1.1 Fund alpha

We begin with a portfolio analysis. We first construct two equally-weighted portfolios that include all active corporate bond ETFs and active mutual funds, respectively. We then track the returns of a long–mutual-fund, short–ETF portfolio. The portfolio is rebalanced monthly. One interpretation of this exercise, under equal weighting, is that it reflects the performance gap faced by an end investor who randomly chooses between ETFs and mutual funds.

We estimate the following regression of monthly long–short portfolio returns on standard risk factors:

$$R_{\mathrm{MF},t} - R_{\mathrm{ETF},t} = \alpha + \beta_1 \mathrm{STOCK}_t + \beta_2 \mathrm{BOND}_t + \beta_3 \mathrm{DEF}_t + \beta_4 \mathrm{OPTION}_t + \varepsilon_t \tag{1}$$

where the dependent variable is the monthly return of the long–mutual-fund, short–ETF portfolio. We use two standard multi-factor models: (i) the two-factor model with bond and stock market factors following Goldstein et al. (2017), and (ii) the four-factor model that adds default and option factors following Elton et al. (1995).[15] Specifically, the stock market factor (STOCK) is the excess return on the CRSP value-weighted stock index. The bond market factor (BOND) is the excess return on the Bloomberg U.S. Aggregate Bond Index. The default factor (DEF) is the return difference of the Markit iBoxx USD Liquid High Yield Index and Bloomberg U.S. Intermediate Government/Credit Bond Index. The option factor (OPTION) is the return difference of the Bloomberg U.S. GNMA Bond Index and Bloomberg U.S. Intermediate Government/Credit Bond Index.

[15] These factor models are widely used to measure bond fund alphas, for example, in Cici and Gibson (2012) and Giannetti et al. (2024)

[Table 2 here]

Table 2 reports alphas from estimating the regression model in Equation (1). We find that active ETFs underperform active mutual funds. For high-yield funds, the two-factor alpha is 5.41 basis points per month and the four-factor alpha is 4.56 basis points per month. The four-factor alpha of 4.56 basis points per month translates to approximately 0.55% per year. For investment-grade funds, the intercepts are smaller in magnitude—1.35 basis points per month for the two-factor model and 0.85 basis points per month for the four-factor model—and statistically insignificant. These results suggest that the ETF–mutual fund performance gap is concentrated in high-yield funds, where the annualized underperformance of approximately 0.55% per year is economically meaningful given that the annualized returns is 3.7% for high-yield funds.[16]

We next examine fund-level performance using panel regressions. This setting allows us to directly control for any differences between ETFs and mutual funds that may drive the performance gap. Specifically, we estimate the following regression:

$$\alpha_{i,t} = \beta \mathbf{1}(\text{ETF})_i + \Gamma \mathbf{X}_{i,t} + \alpha_m + \delta_s + \theta_t + \varepsilon_{i,t} \tag{2}$$

where the dependent variable is the month t four-factor alpha for fund i. We calculate fund alpha based on loadings on risk factors estimated using past returns in a 12-month rolling basis. The regressor of interest is $\mathbf{1}(\text{ETF})_i$, an indicator equal to one for active ETFs and zero for active mutual funds. We use a comprehensive set of control variables, $\mathbf{X}_{i,t}$, and fixed effects to account for observable and unobservable differences between ETFs and mutual funds that could explain the performance gap. Specifically, we include fund characteristics (log TNA, log fund age, expense ratio, turnover ratio, past fund flow, past return, and cash holding ratio) and average corporate bond holding characteristics (average credit rating and log time to maturity) to control for observed differences between ETF and mutual fund characteristics. We also include fixed effects for management company (α_m), investment style (δ_s), and month (θ_t) allowing us to control for unobservable factors that are common to a management company, style, and month. The investment style is obtained from the CRSP style code, which is defined based on each fund's prospectus description of how it intends

[16]Untabulated TNA-weighted long–short portfolio results are similar both quantitatively and qualitatively, confirming that the ETF underperformance is not driven solely by small new funds.

to invest. In addition, we use style-month and manager-month interacted fixed effects to capture unobservable time-varying variables specific to investment style and fund manager—for example, shifts in investment opportunities within a given style and changes in managers' information sets, as well as managers' skills.

[Table 3 here]

Table 3 reports the regression results. The results suggest that ETFs underperform comparable mutual funds in the high-yield segment. The coefficients on $\mathbf{1}$(ETF) for high-yield funds are negative and statistically significant across all specifications. For example, the point estimate is −10.90 basis points in Column (1), suggesting that ETFs underperform mutual funds by −10.90bp per month (about 1.3% per year). In Column (3), the coefficient estimate is larger in magnitude (−20.15) after including the manager-month fixed effect, suggesting that ETFs underperform mutual funds share a same management.

In Column (4), we repeat the regression in Column (3) using a matched ETF-mutual fund sample to further improve the comparability between ETFs and mutual funds. We run propensity-score matching based on the fund characteristics. Figure 7 displays the match quality: after matching, the standardized mean differences for these characteristics are all below 20% of their sample standard deviations, and t-tests indicate that the differences are not statistically significant at the conventional level.[17] The results from the matched sample (Column 4) are similar to those from the full sample (Column 3), confirming the underperformance of ETFs.

For investment-grade funds, we do not find any performance differences between ETFs and mutual funds after controlling for the various characteristics and fixed effects. The coefficients on $\mathbf{1}$(ETF) are statistically insignificant in most specifications (Columns 5–8). We conjecture that this result is related to the stylized fact we observe in Section 3.2.1 that these funds predominantly use cash transactions. Later, we discuss this point further in Section 4.2.

What drives the performance gap? A few explanations are possible: (i) manager-specific skill or information, (ii) greater transparency of ETFs, (iii) the cost of accommodating investor flows and managing liquidity, and (iv) primary market frictions specific to the ETF structure. Our preferred

[17] The mean difference test results are omitted for brevity and are available upon request.

explanation is primary market frictions, which we examine in detail in Section 4.2. Here, we briefly discuss the alternative explanations.

The first possibility that mutual fund managers, on average, have better skill than ETF managers. However, the results in Columns (3) and (4), which control for manager-month interacted fixed effects, indicate that this explanation is unlikely to account for the performance gap. Notably, the coefficient estimates on **1**(ETF) are larger in Columns (3)–(4) than in Columns (1)–(2), suggesting again that differences in manager skill and information sets are unlikely to be the main source of the ETF–mutual fund performance gap. We acknowledge, however, that the smaller sample of same-manager ETF-mutual fund pairs warrants caution.

Another possibility is the greater transparency of ETFs. Because ETFs are required to report their holdings daily, whereas mutual funds report only quarterly, ETFs may be more exposed to front-running and strategy leakage, which can hurt their performance. Mutual funds, by contrast, can keep positions undisclosed between quarterly filings and may therefore implement more sophisticated strategies that benefit from temporary opacity. Anecdotal evidence suggests that daily portfolio disclosure concerns bond fund managers less than equity managers because the fragmented over-the-counter market protects managers from copy trading and front-running.[18]

To further assess whether portfolio disclosure contributes to the performance gap, we re-estimate the regression model in Equation (2) with manager–month fixed effects, comparing ETFs (i) with mutual funds that voluntarily disclose their holdings monthly and (ii) with those that disclose only quarterly, as required by regulation. While this empirical setup is not perfect—since no mutual funds disclose their holdings on a daily basis—if differences in disclosure frequency were the main driver of the performance gap, the gap would be larger between ETFs and mutual funds that disclose less frequently.

Table 4 reports the regression results. The estimated gap, captured by the coefficient on **1**(ETF), is nearly identical when ETFs are compared with monthly- and quarterly-disclosing mutual funds. Together with the aforementioned anecdotal evidence, this pattern suggests that differences in portfolio disclosure are unlikely to explain the ETF-mutual fund performance gap.

The next potential explanation is the cost of accommodating investor flows and managing liquidity. Corporate bond funds perform liquidity transformation for their investors, standing between illiquid

[18]For example, see these articles from Bloomberg and ETF Stream.

underlying bonds and liquid fund shares. As shown by the concave flow–performance relation, bond funds are more vulnerable to outflows (Goldstein et al. 2017). As a result, they tend to manage liquidity more proactively by holding cash and cash-like securities as buffers against investor redemptions,[19] which is costly. This flow-related cost, however, is typically greater for mutual funds than for ETFs (Huang and Martinez 2024). APs can buffer investor outflows from imposing direct costs on portfolio values through fire sales (Shim and Todorov 2023). Hence, liquidity-transformation costs are unlikely to account for the underperformance of ETFs relative to mutual funds.

The remaining possibility—primary market friction—is our preferred interpretation of the data. The mechanism is that APs' incentives (e.g., inventory management) can distort ETFs' bond selection during negotiations over in-kind baskets. We therefore proceed to examine evidence of this mechanism in the data.

4.1.2 Bond selection

We now turn to the bond-level analysis and examine the bond-selection decisions of active ETFs and mutual funds. Specifically, we compare bonds more commonly selected by ETFs with those more commonly selected by mutual funds within the same quarter, analyzing purchases and sales separately. Under the AP-friction view, weaker bond selection by ETFs arises from a systematic constraint induced by AP-side economic forces (e.g., dealer inventory pressures), not from idiosyncratic misjudgment by individual managers. Accordingly, if ETF-specific frictions like those from APs distort security choice, bonds purchased by disproportionately many ETFs should subsequently underperform those favored by mutual funds. An analogous prediction applies to sales.

Specifically, we estimate the following regression separately for bonds purchased and sold by funds:

$$R_{b,t}^{1\text{yr}} = \beta\mathbf{1}(\text{ETF-favored})_{b,t} + \Gamma\mathbf{X}_{b,t} + \alpha_b + \delta_r + \theta_t + \varepsilon_{b,t} \tag{3}$$

where the dependent variable $R_{b,t}^{1\text{yr}}$ is the forward 1-year return of bond i measured from the end of quarter t.[20] The main independent variable $\mathbf{1}(\text{ETF-favored})_{b,t}$ is an indicator for bonds that are traded by relatively more ETFs, which we construct as follows. We first count the number of active

[19] See, for example, Choi et al. (2020) and Jiang et al. (2021).

[20] We focus on the 1-year horizon given that Table 1 reports an average annual portfolio turnover of 120%, which translates to an approximately 1-year holding horizon.

ETFs and mutual funds that increase (decrease) their holdings of bond b during quarter t.[21] We then rank bonds separately by these ETF and mutual-fund counts. Bonds in the top quintile of either ranking—but not both—are retained to isolate bonds purchased primarily by ETFs or by mutual funds, but not by both. This step excludes bonds that are widely selected across funds, likely due to liquidity or information reasons. Finally, we set $\mathbf{1}(\text{ETF-favored})_{b,t}$ equals to one for bonds in the top quintile of ETF counts in quarter t and zero otherwise. The control variables, $\mathbf{X}_{b,t}$, include the log of time to maturity and the illiquidity measure of Bao et al. (2011). We also include bond, credit rating, and quarter fixed effects.

[Table 5 here]

Table 5 Panel A reports the regression results. For bonds purchased by more high-yield ETFs, the coefficient on $\mathbf{1}(\text{ETF})$ is -1.213 (Panel A, Column 1), indicating that they underperform bonds purchased by more mutual funds by approximately 1.21% over the subsequent 12 months. Conversely, for bonds sold by more high-yield ETFs, the estimated coefficient of 1.310 (Panel A, Column 2) implies roughly 1.31% higher returns over the subsequent 12 months. These return differences are economically large, roughly 25% of average yield on those bonds.Results for investment-grade funds exhibit the same pattern but with smaller—roughly half—magnitudes.

In Panel B, we repeat the same exercise using the subsample of funds matched on their characteristics as explained in the previous section.[22] Panel B presents results that are qualitatively consistent with those in Panel A, especially for high-yield funds.

In sum, ETFs' purchases subsequently underperform while their sales subsequently outperform, relative to mutual funds' bond selection. These patterns align with our fund-level evidence of ETF underperformance. While consistent with the view that primary market frictions systematically distort ETF bond choice, this analysis does not yet provide direct evidence on the AP channel. In the next section, we further investigate the mechanism using data on bond dealer inventories and Form N-CEN filings.

[21] Quarterly observations are used due to the availability of mutual fund holdings.

[22] See the description for Table 3 Columns (4) and (8).

4.2 Evidence of AP influence on active ETFs

We now examine whether primary market frictions affect active ETFs' bond selection and subsequent performance, and whether cash transaction mitigates these effects.

4.2.1 Cash transactions and AP influence on bond selection

If primary market frictions influence active ETFs' bond selection, we should observe the footprint of APs' incentives in the bonds these funds buy. Recent studies on passive ETFs show that APs' inventory-management incentives—arising from their dual role as bond dealers—can shape these ETFs' realized baskets (Reilly 2022, Dannhauser and Karmaziene 2023, Du 2023). Motivated by this evidence, we test whether a buildup of bonds in dealer inventories increases the likelihood that active ETFs purchase a given bond, and whether the use of cash transactions mitigates this effect.[23] We examine this effect separately for days with and without primary market activity, as primary market frictions should matter only when ETFs involve primary market activity via in-kind transfers.

Specifically, we estimate the following regression:

$$\begin{aligned} 100 \times \mathbf{1}(\text{ETF buy})_{b,i,t} = {} & \beta_1 \mathbf{1}(\Delta\text{dealer inventory} > 0)_{b,t-1} + \beta_2 \mathbf{1}(\text{cash fund})_{i,t} \\ & + \beta_3 \mathbf{1}(\Delta\text{dealer inventory} > 0)_{b,t-1} \times \mathbf{1}(\text{cash fund})_{i,t} \\ & + \Gamma \mathbf{X}_{b,t} + \alpha_r + \gamma_b + \delta_i + \theta_t + \varepsilon_{b,i,t} \end{aligned} \tag{4}$$

where the dependent variable $\mathbf{1}(\text{ETF buy})_{b,i,t}$ is a dummy variable that equals to one if the fund i buys bond b on day t, and zero otherwise. We scale this variable by 100. The dummy variable $\mathbf{1}(\Delta\text{dealer inventory} > 0)_{b,t-1}$ equals to one if dealer have net purchased bond b over the past two weeks. The dummy variable $\mathbf{1}(\text{cash fund})_{i,t}$ equals one if the fund i's average cash proportion in creations exceeds 75% in the most recent reporting year. Control variables $\mathbf{X}_{b,t}$ include the logged time to maturity and Bao et al. (2011) illiquidity measure of bond b on day t. In addition, we include credit rating, bond, fund, and day fixed effects.

[Table 6 here]

[23]We focus on purchases because sales provide a less clean testing ground, being more constrained by tax considerations, liquidity needs, and existing portfolio holdings.

Columns (1) and (2) of Table 6 presents the regression results for days when primary market activity occurs. For high-yield funds (Column 1), bonds with positive dealer inventory flows are 1.1 percentage points more likely to be purchased. This magnitude is economically meaningful as the the unconditional purchase probability is only 3%, and suggests that dealer inventory pressures tilt ETF portfolios toward bonds dealers wish to offload.

Strikingly, this effect vanishes for funds that predominantly settle in cash. The coefficient on the interaction term is -1.327, leaving a net effect near zero for cash-settling funds. This pattern indicates that when managers retain discretion by settling in cash, and thus trading directly in the bond market, they are no longer subject to dealer inventory pressures. Investment-grade funds exhibit similar patterns, but the coefficients are statistically insignificant and are smaller in magnitudes (Column 2), consistent with weaker primary market frictions in more liquid segments.

Columns (3) and (4) shows the results from a placebo test: we repeat the regression for days *without* primary market activity, when managers trade directly and do not interact with APs. The coefficients on positive inventory flow are statistically indistinguishable from zero across all specifications. This confirms that dealer inventory affects purchases only through the in-kind creation channel, not through broader market dynamics or managers' own trading strategies.

Taken together, these results suggest three takeaways. First, dealer inventory pressures influence active ETFs' bond selection on in-kind settlement days, echoing findings for passive funds despite active managers' alpha-maximizing goal. Second, cash transaction and direct trading fully mute this effect, restoring manager discretion. Third, the dealer inventory effect operates exclusively through the AP–ETF interactions—when managers bypass APs, it becomes irrelevant.

4.2.2 Performance of AP-influenced purchases

Having established that dealer inventory pressures influence which bonds active ETFs purchase in kind, we now test whether these purchases harm subsequent performance. If primary market frictions steer managers toward bonds that serve dealers' inventory management needs rather than managers' investment performance objectives, bonds acquired via in-kind creations should underperform bonds acquired through direct trading where managers retain full discretion.

We estimate bond-level regressions of forward 1-year returns on an indicator for whether the purchase occurred on a day with share creations, controlling for bond characteristics and fixed effects. Specifically, we estimate:

$$R^{1\text{yr}}_{b,i,t} = \beta \mathbf{1}(\text{shares created})_{i,t} + \Gamma \mathbf{X}_{b,t} + \alpha_r + \gamma_b + \delta_i + \theta_t + \varepsilon_{b,i,t} \tag{5}$$

where $R^{1\text{yr}}_{b,i,t}$ is the forward 1-year return of bond b purchased by fund i on day t. The indicator $\mathbf{1}(\text{shares created})_{i,t}$ equals one if the purchase occurred on a day when the fund created shares, capturing purchases that likely involve in-kind transfers. Controls $\mathbf{X}_{b,t}$ include the natural logarithm of time to maturity and illiquidity. We include credit rating, bond, fund, and day fixed effects.

[Table 7 here]

Table 7 reveals the performance gap. For high-yield bonds purchased by all active ETFs (Column 1), the coefficient on shares created is −0.716, indicating that in-kind purchases underperform direct purchases by 72 basis points over the subsequent year, which is about 20% of average annual return on high-yield bonds in our sample.

The source of this underperformance becomes clearer when we split funds by settlement method. Column (3) shows that in-kind funds drive the entire effect: their in-kind purchases underperform by approximately 72 basis points. In contrast, Column (2) shows that cash-settling funds exhibit no significant underperformance: the coefficient is −0.017 and statistically insignificant. Cash settlement fully eliminates the performance drag associated with in-kind purchases, consistent with managers retaining discretion over bond selection when they bypass in-kind transfers and trade directly. In further (untabulated) analysis, we find that the average holding periods of bonds acquired in kind are similar to those of bonds purchased directly. Potentially due to the high transaction costs of corporate bonds, managers do not sell these positions quickly to rebalance their portfolios via direct trading.

For investment-grade funds (Columns 4–6), coefficients are smaller and statistically insignificant across all specifications. This weaker pattern aligns with two features of investment-grade funds discussed above. First, bonds are more homogeneous and liquid. Second, as shown in Table 6, dealer inventory pressures are weaker in investment-grade segments.

These results provide evidence that primary market frictions harm active bond selection.[24] Bonds acquired through in-kind transfers on days with primary market activity, when dealer inventory

[24] An alternative explanation is that these returns reflect reversals of fire-sale price pressures that led dealers to accumulate

pressures are strongest, subsequently underperform bonds purchased through direct trading. Cash settlement eliminates this pattern by preserving manager discretion, but the persistence of in-kind settlement among certain high-yield funds indicates that frictions or costs constrain managers' ability to always settle in cash. We explore the determinants of cash settlement in Section 4.3.

4.3 Determinants of cash transaction

Having established that cash transaction preserves manager discretion and mitigates primary market frictions, we now examine what economic forces determine funds' use of cash versus in-kind transfers.

Specifically, we estimate the following regression:

$$\text{Cash proportion}_{i,t} = \beta\,\mathbf{X}_{i,t} + \theta_t + \varepsilon_{i,t} \tag{6}$$

where the dependent variable is the percentage of cash in creation or redemption baskets for fund i in year t. We include year fixed effects θ_t. The set of variables $\mathbf{X}_{i,t}$ represent potential determinants of cash transaction. We consider several variables that may affect the trade-off between operational flexibility and costs.

First, we incorporate the cash transaction fee. This fee is directly related to the ETF's costs of cash transactions (e.g., liquidity costs in directly trading the underlying bonds) and APs' convenience of avoiding the need to source specific bonds (see Section 3.2.1 for further discussion). Holding other factors constant, higher fees should discourage cash settlement. We also add the standard creation/redemption fee to control for APs' fixed costs for trading in the primary market, and average basket value (the dollar size of a creation or redemption unit) which is related to the scale of direct trading costs managers incur when settling in cash.

Second, we include the number of APs trading with the fund as a proxy for competition among APs. Greater competition can either strengthen the ETF's bargaining position (e.g., vis-à-vis APs seeking to manage inventory through in-kind transfers) and facilitate cash usage or improve APs' ability to deliver the specific bonds the ETF wishes to trade, so the net effect is ambiguous ex ante.

Third, we add various fund characteristics: log TNA, log fund age, expense ratio, turnover ratio,

these bonds. Although it is unlikely that our long-horizon return results are primarily driven by such price pressure, which is typically expected to unwind over short windows, we also examine same-quarter returns (rather than forward returns) and find largely insignificant effects (untabulated but available upon request).

and cash holdings. Larger funds may have greater bargaining power in negotiations with APs, which could increase cash usage, but they may also face larger price impact when trading directly, which could reduce it. Younger funds may favor cash transactions because they provide more discretion in building portfolios. The expense ratio reflects operational costs, including management and brokerage fees, which are likely higher when funds trade directly in the secondary bond market; hence we expect a positive relation with cash usage. The turnover ratio may capture both strategic orientation—short-horizon trading that benefits from the flexibility of cash—and the liquidity of underlying assets, implying an ambiguous relation with cash transactions. Finally, the cash holdings ratio may matter if ETFs prefer or avoid building cash buffers depending on their current cash levels.

Finally, we include portfolio characteristics: the average credit rating and time to maturity of corporate bond holdings. These variables capture the underlying bonds' credit and term risk and, more broadly, how difficult they are to trade and warehouse. Lower-rated and longer-maturity bonds are harder to move in the secondary market. For creations, in-kind transfers allow APs to offload such positions from their inventories into the ETF rather than selling them outright. For redemptions, in-kind transfers allow the ETF to remove illiquid positions without trading, shifting them back to APs, who are compensated for warehousing and redistributing these bonds.

Importantly, the regression is not causal; we interpret the coefficients as correlations rather than causal effects.

[Table 8 here]

Table 8 reports the results. Column (1) examines creation baskets. The coefficient on additional cash fee for creations is −0.543 and statistically significant at the 1% level, consistent with our premises. The result indicates that a one-basis-point increase in the additional cash fee is associated with the lower cash fraction in creation baskets by 54 basis points.

The number of APs is positively correlated with cash proportion, with a coefficient of 4.446 and statistically significant at the conventional level. Funds with more APs use more cash settlement, consistent with greater competition among APs strengthening the ETF's bargaining position against APs who wish to use in-kind transfers for warehousing. Basket value is negatively correlated with cash proportion, with a coefficient of −9.942. A potential explanation for the negative coefficient is that larger creation amounts entail higher costs and price impact of direct trading following cash settlements.

Expense ratio shows a positive association with cash proportion (62.57), statistically significant at the 1% level, consistent with the higher operational costs from cash settlements and direct trading.

Among portfolio characteristics, the coefficient on average bond rating is negative and significant (-5.426) at the conventional level, as is the coefficient on average time to maturity (-6.711), in line with the notion that lower credit quality and longer maturities entail higher trading and inventory costs.

For redemption baskets (Column 2), we find similar patterns, but with weaker statistical significance. The weaker relation for redemptions likely reflect that ETFs want to offload low-cost-basis bonds without realizing capital gains via in-kind redemption, so cash usage is mainly governed by the tax advantage rather than fund characteristics.

Taken together, these results suggest that the cash transaction fee, ETF–AP bargaining power, and the costs of direct trading and inventory management (e.g., basket size, expense ratio, and bond characteristics) are the main economic forces shaping the decision to settle in cash, especially for creations. Guided by this intuition, we develop a model of cash transactions in the next section.

5 A model of cash proportion in custom baskets

In this section, we present a stylized model to illustrate the economic forces behind the bargaining problem between an active ETF and its APs. The model formalizes the trade-offs we documented empirically: cash settlement grants managers discretion over bond selection but imposes direct trading costs, while in-kind settlement allows APs to offload inventory but may steer portfolios toward bonds that serve dealers' needs rather than the fund's investment objectives.

We model a single creation event in which the ETF receives a custom basket with normalized value \$1, composed of cash (fraction $x \in [0, 1]$) and securities (fraction $1 - x$), in exchange for newly issued ETF shares. The cash fraction x emerges from Nash bargaining between the ETF and the AP, each of whom has distinct preferences over the basket composition. The model delivers predictions about how the equilibrium cash fraction varies with the ETF's bargaining power, asset illiquidity, and the AP's balance-sheet frictions—predictions we test in Section 4.3.

Model setup The ETF's and the AP's utilities before the creation event are normalized to zero. Upon creation, and irrespective of the cash fraction x, the ETF and the AP enjoy some benefits $b \geq 0$ and $b_{APs} \geq 0$ respectively. These baseline benefits capture the direct gains from the creation itself—for example, increased assets under management for the ETF and arbitrage profits for the AP.

The cash fraction x affects the ETF's and AP's payoffs through three channels. First, the ETF prefers cash because it provides full discretion over which bonds to purchase in the secondary market. This flexibility allows the manager to generate risk-adjusted excess returns $\alpha \geq 0$ net of trading costs $\lambda \geq 0$, where λ captures the effects of asset illiquidity such as bid-ask spreads and price impact. Second, to compensate the ETF for incurring these trading costs, the AP pays a cash fee $f \geq 0$ on the cash portion of the basket. Third, from the AP's perspective, delivering securities helps reduce its inventory position and hence saves balance-sheet cost $\psi \geq 0$. All of these costs and benefits are proportional to the value of cash or securities.

Payoffs under cash and in-kind settlement

	Cash basket ($x = 1$)	In-kind basket ($x = 0$)
ETF	$b + \alpha - \lambda + f$	b
AP	$b_{AP} - f$	$b_{AP} + \psi$
MF	$b + \alpha - \lambda$	N/A

The table above summarizes the payoffs to each party under pure cash and pure in-kind settlement. When the basket consists entirely of cash ($x = 1$), the ETF's payoff is $b + \alpha - \lambda + f$: it receives the baseline benefit b, generates alpha α through discretionary bond selection, incurs trading costs λ, and collects the cash fee f from the AP. The AP's payoff under full cash settlement is $b_{AP} - f$: it earns the baseline arbitrage profit but pays the cash fee. When the basket consists entirely of securities ($x = 0$), the ETF simply receives b as it gains no alpha and pays no trading costs, but also collects no cash fee. The AP's payoff under full in-kind settlement is $b_{AP} + \psi$: it earns the baseline profit plus the benefit ψ from reducing its inventory position. For comparison, the table also shows a mutual fund's payoff under cash inflows, which is $b + \alpha - \lambda$—identical to the ETF's cash payoff except the mutual fund receives no cash fee since it transacts directly with investors rather than through APs.

We model the negotiation between the ETF and the AP as a Nash-bargaining problem, with

$\theta \in (0, 1)$ representing the bargaining power of the ETF. The ETF and the AP splits the surplus from the basket creation by jointly choosing the cash fraction x to maximize the Nash product of their gains:

$$\max_{x \in [0,1]} \underbrace{[b + x(\alpha - \lambda + f)]}_{U^{ETF}}^{\theta} \underbrace{[b_{AP} - xf + (1 - x)\psi]}_{U^{AP}}^{1-\theta}. \tag{7}$$

We assume $\alpha - \lambda + f \geq 0$ so that the ETF prefers cash over securities, and $f \leq b_{AP}$ so that the AP is willing to participate even under full cash settlement. Without these conditions, the solution would be trivial: if cash were value-destroying for the ETF, it would never accept cash; if the cash fee exceeded the AP's baseline profit, the AP would refuse to create shares.

Remarks Our analysis focuses on the economically interesting case in which the ETF and the AP have conflicting preferences over basket composition: the ETF prefers cash ($\alpha - \lambda + f > 0$) while the AP prefers to deliver securities ($\psi > 0$). The other cases yield corner solutions. If $\alpha - \lambda + f < 0$, the ETF gains nothing from the flexibility cash provides, even after receiving the cash fee, and the bargaining solution is a pure in-kind basket ($x^* = 0$). Conversely, if the AP holds no inventory and must source securities at a cost, then $\psi < 0$ and the solution is a pure cash basket ($x^* = 1$), provided the cash fee is not too large ($\psi + f < 0$). In both cases, one party's preference dominates and no meaningful bargaining occurs.

Solving the model As the objective function is concave in $x \in (0, 1)$, the solution x^* is characterized by the first-order condition. The following proposition characterizes the equilibrium cash fraction.

Proposition 1. *The equilibrium cash fraction in the custom basket x^* solves Equation (7). There exists $\bar{\theta}$ and $\underline{\theta}$ where $1 > \bar{\theta} > \underline{\theta} > 0$ such that*

$$x^* = \begin{cases} 0 & \text{for } \theta \leq \underline{\theta} \\ \theta \dfrac{b_{AP} + \psi}{f + \psi} - (1 - \theta) \dfrac{b}{\alpha - \lambda + f} & \text{for } \theta \in (\underline{\theta}, \bar{\theta}) \\ 1 & \text{for } \theta \geq \bar{\theta} \end{cases} \tag{8}$$

Proof. Define $G(\theta) \equiv \theta \frac{b_{AP}+\psi}{f+\psi} - (1 - \theta) \frac{b}{\alpha-\lambda+f}$ as the expression for x^* in the intermediate case, which comes directly from the first-order condition of Equation (7). It is immediate that $G(1) > 1$ and $G(0) < 0$. Since $G(0) < 0$ and $G(1) > 1$, and $G(\theta)$ is strictly increasing in θ, there exist unique values $\underline{\theta}$ and $\bar{\theta}$ satisfying $0 < \underline{\theta} < \bar{\theta} < 1$ such that $G(\underline{\theta}) = 0$ and $G(\bar{\theta}) = 1$. As x is bounded between 0 and 1, the x^* in the other cases follow immediately. □

Proposition 1 shows that the equilibrium cash fraction is 100% if the ETF has sufficiently strong bargaining power ($\theta \geq \bar{\theta}$) and 0% if the ETF has sufficiently weak bargaining power ($\theta \leq \underline{\theta}$). In the intermediate case with $\theta \in (\underline{\theta}, \bar{\theta})$, which we view as the most empirically relevant regime, the cash fraction varies with the ETF's bargaining power (θ), asset illiquidity (λ), and the AP's balance-sheet costs (ψ), as well as the baseline benefits (b and b_{AP}), alpha (α), and cash fee (f). Comparative statics with respect to these parameters yield testable predictions that we examine in Section 4.3.

Empirical predictions The model generates predictions consistent with the empirical patterns documented in Section 4.3 and Section 4.1.1.

1. *Cash fraction increases in the ETF's bargaining power* $\frac{dx^*}{d\theta} > 0$.
2. *Cash fraction decreases in the asset illiquidity* $\frac{dx^*}{d\lambda} < 0$.
3. *Cash fraction decreases in the AP balance-sheet cost* $\frac{dx^*}{d\psi} < 0$.
4. *The ETF–MF performance difference increases in* x^*.

Linking to empirical findings Greater bargaining power allows the ETF to negotiate its preferred settlement method. In Section 4.3, we proxy for bargaining power using the number of APs transacting with each fund, under the assumption that more APs increase competition in the primary market and shift bargaining power toward the ETF. Consistent with this prediction, Table 8 shows that the number of APs is positively correlated with cash usage in creation baskets.

Higher trading costs reduce the net benefit the ETF derives from cash settlement, making in-kind transfers relatively more attractive. We measure illiquidity at the portfolio level using average bond characteristics. Table 8 shows that funds holding bonds with worse ratings and longer maturities, which are typically less liquid, use less cash settlement, consistent with this prediction. This empirical pattern is also consistent with the model's prediction about the AP's balance sheet costs.

Our stylized model also provides an explanation of why ETFs underperform comparable mutual funds. Mutual funds have no APs and hence they receive flow directly in cash. In the context of our model, mutual funds are equivalent to ETFs with only cash basket $x^* = 1$ and no cash fees from APs $f = 0$. Therefore, relative to mutual funds, the ETF performance difference is $x^* f - (1 - x^*)(\alpha - \lambda)$. The ETF underperforms if $x^* f < (1 - x^*)(\alpha - \lambda)$, which occurs when the cash fee the ETF receives does not fully compensate for the alpha it forgoes on the in-kind portion of the basket. The performance gap is largest when x^* is small: ETFs that rely heavily on in-kind transfers forgo alpha on a large fraction of the basket while receiving minimal cash fee compensation.

This prediction is consistent with our empirical findings as well. Table 3 shows that high-yield ETFs, which use less cash settlement, underperform comparable mutual funds, while investment-grade ETFs, which settle predominantly in cash, show no significant performance difference. Table 7 further shows that bonds purchased on flow (primary market activity) days via in-kind transfers subsequently underperform, directly documenting the alpha forgone through AP-influenced basket composition.

6 Conclusion

The evidence in this paper points to economically meaningful implementation frictions in active ETFs, stemming from the ETF–AP structure. Comparable active mutual funds outperform active ETFs with the performance gap concentrated among high-yield funds. Active ETFs respond to this friction: creations and redemptions settle predominantly in cash and they often trade directly in the secondary bond market. Tracing the mechanism, we find that purchases associated with in-kind transfers tilt toward bonds recently accumulated in dealer inventory, whereas this footprint is absent for ETFs predominantly use cash transactions or when trading takes place on days without primary market activity. A simple framework with ETF–AP bargaining rationalizes these facts.

Our findings carry practical and policy implications. For corporate bond ETF investors, the well-known tax benefits and on-exchange trading flexibility of ETF shares should be weighed against the structural limits to active bond investment within the ETF structure. For sponsors and managers, our results highlight that the operational flexibility of cash transactions and fee design can be used to mitigate primary market frictions. For researchers and regulators, the widespread use of cash transactions, contrary to the ETF wrapper's intended design, warrants further study. This may include a unified welfare accounting that incorporates taxes and liquidity benefits for end-investors and potential improvement of institutional designs (e.g., alternative cash-fee design and basket unit sizes) that facilitate the implementation of active strategies within the ETF structure.

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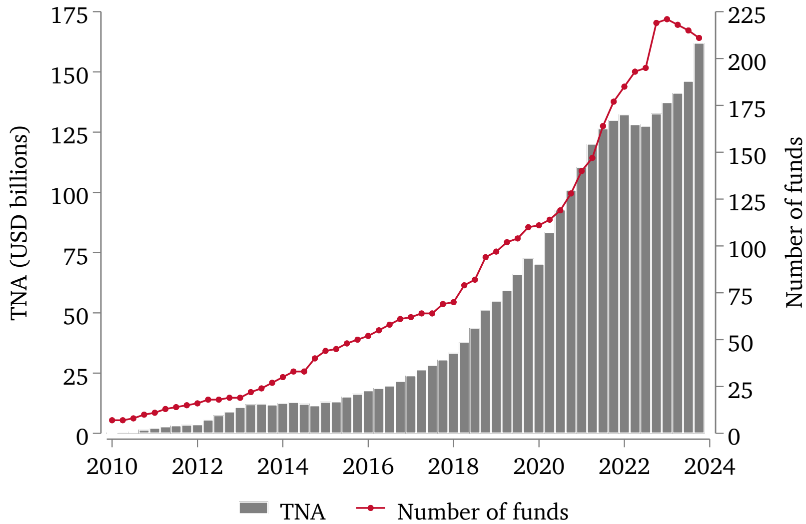
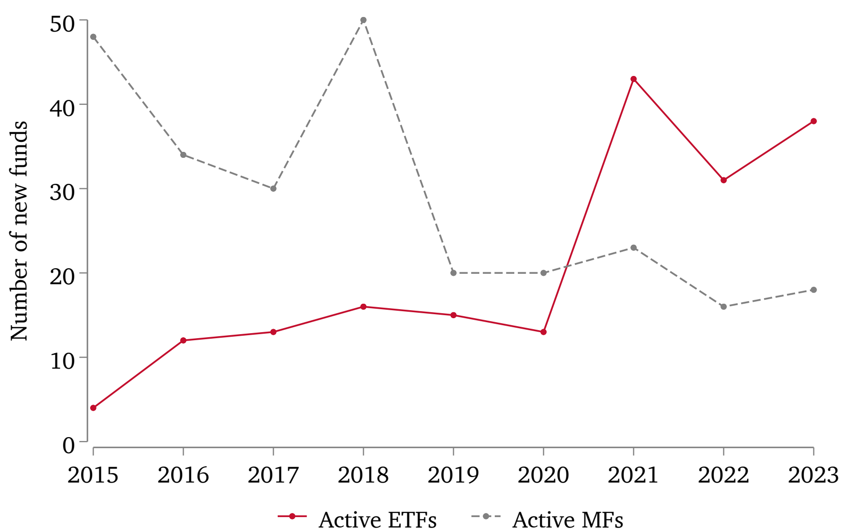


(a) Panel A: TNA and number of active fixed income ETFs



(b) Panel B: Number of new active funds

Figure 1. Growth of active fixed income ETFs

This figure shows the growth of active fixed income ETFs in the United States. Panel A reports the total net assets (gray bars, left axis) and the number of active fixed income ETFs (red line, right axis). Panel B plots the number of new active fixed income mutual funds and ETFs.

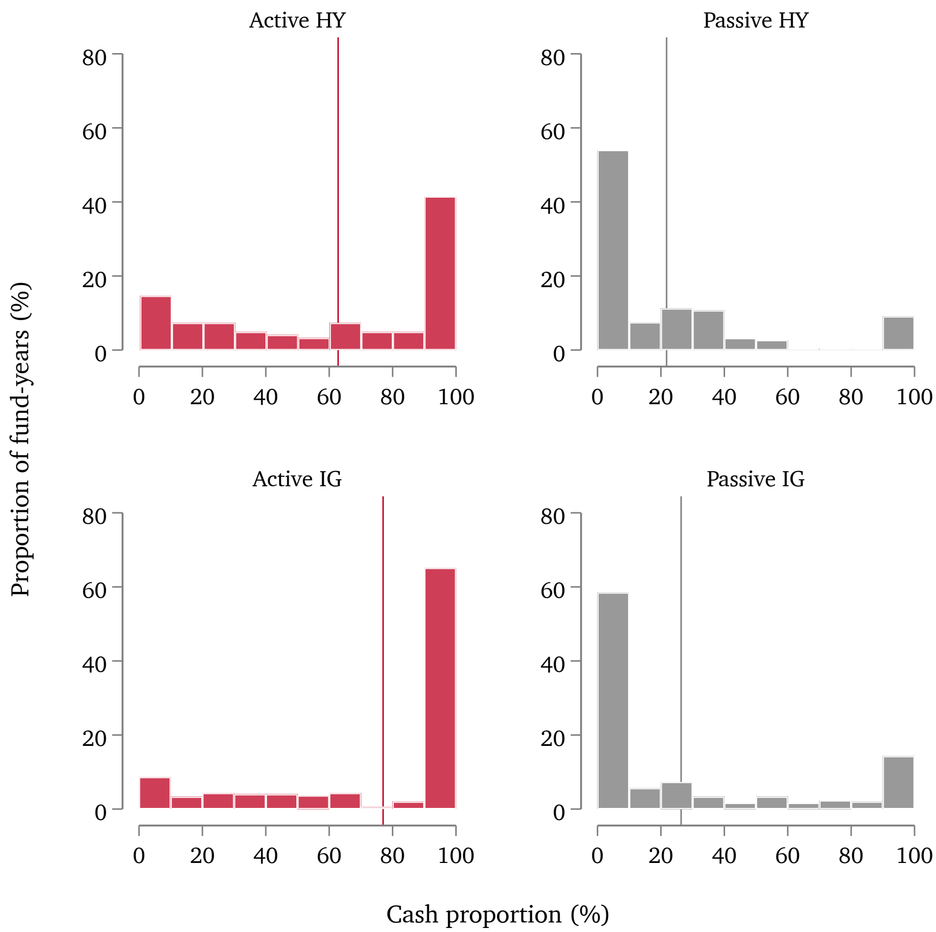


Figure 2. Proportion of cash in creation baskets

This figure shows the histograms of the average proportion of cash in creation baskets for active and passive corporate bond ETFs. The data is obtained from annual N-CEN filings from 2018 to 2023. The figure displays creation basket cash percentages for four ETF categories: active high-yield, passive high-yield, active investment-grade, and passive investment-grade. The unit of observation is fund-year.

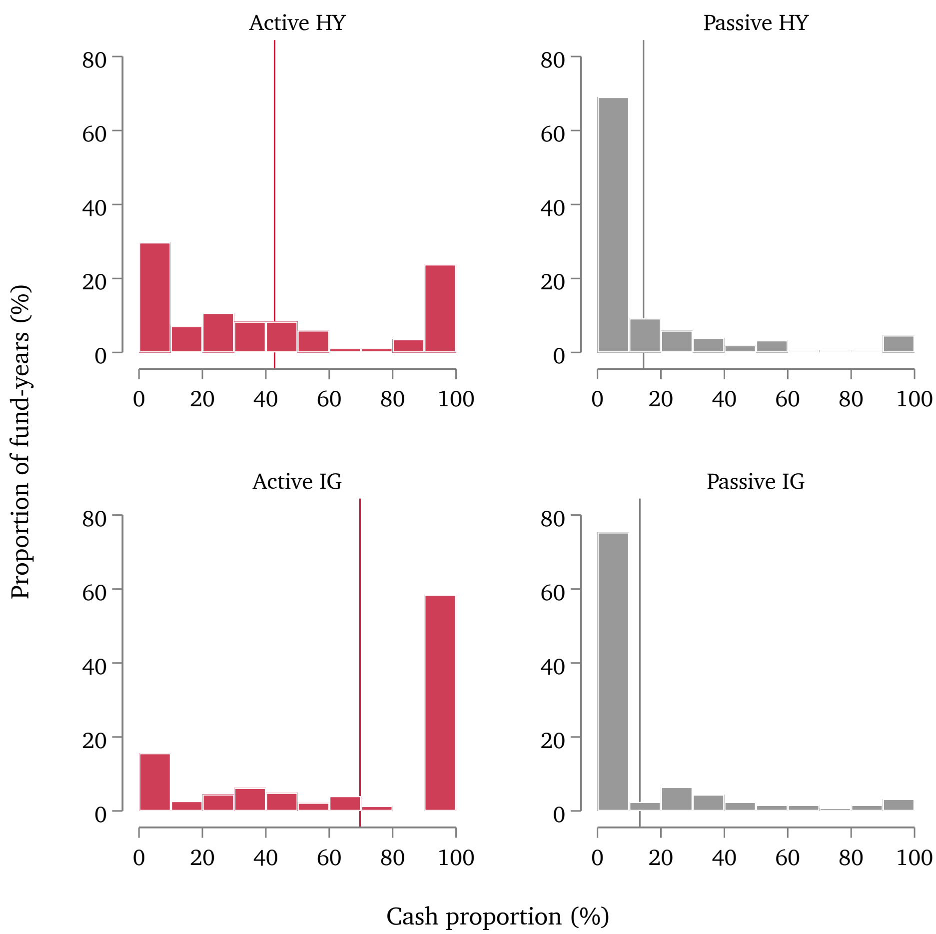


Figure 3. Proportion of cash in redemption baskets

This figure shows the histograms of the average proportion of cash in redemption baskets for active and passive corporate bond ETFs. We repeat the exercise described in Figure 2, but for redemption baskets.

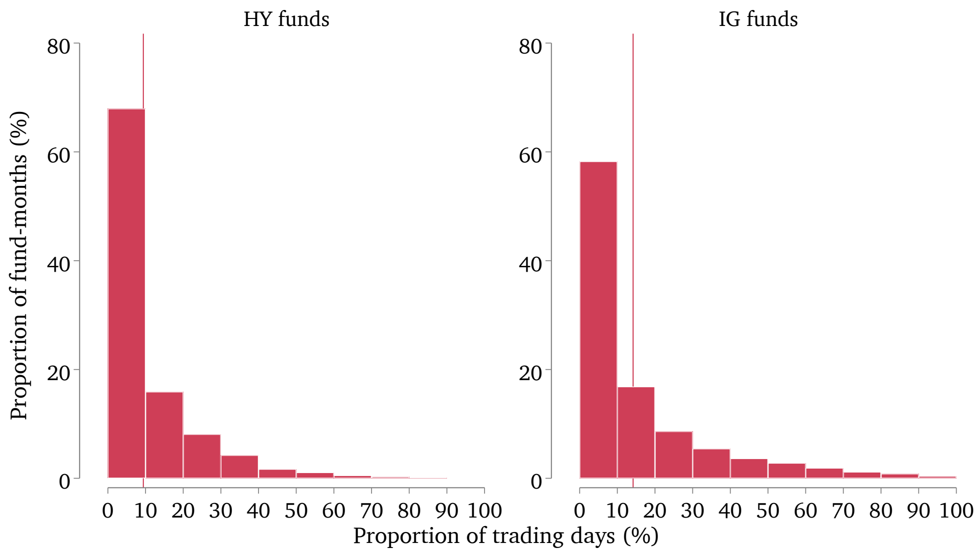


Figure 4. Proportion of days with primary market activity

This figure shows the histograms for the proportion of trading days with primary market activity within each fund-month for active ETFs. For each fund-month, we count the number of trading days with primary, defined as a day with a non-zero change in shares outstanding, and divide it by the number of all trading days for that month. The left panel shows the histogram for high-yield funds and the right panel shows the histogram for investment-grade funds. The vertical red line marks the mean.

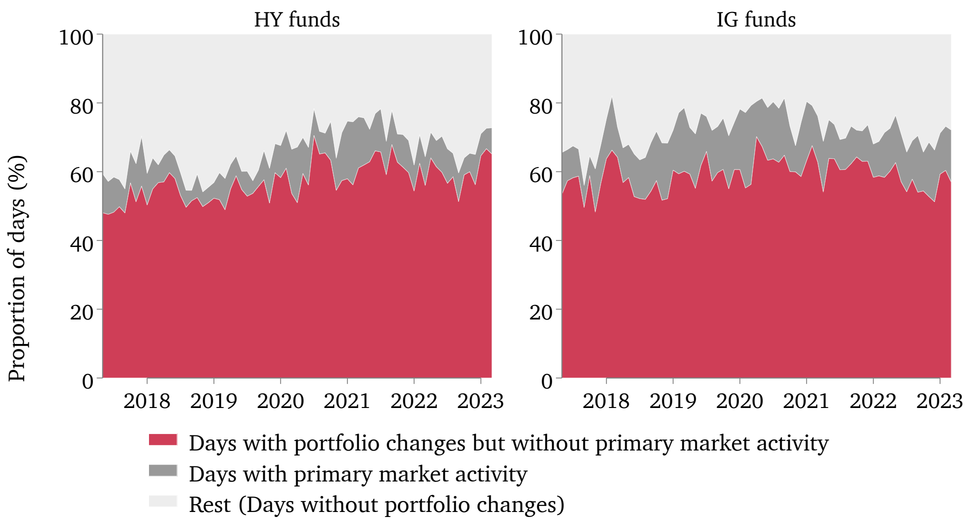


Figure 5. Frequency of portfolio changes versus primary market activity

This figure shows the composition of trading days for active ETFs. Trading days are classified into three categories: (i) days with portfolio changes but no primary market activity (red), (ii) days with primary market activity (dark gray), and (iii) days without portfolio changes (light gray). Primary market activity is defined as a non-zero change in shares outstanding; portfolio changes are defined as non-zero changes in corporate bond holdings. For each fund-month, we calculate the proportion of days in each category, then average across funds. The left panel shows the resulting time-series for high-yield funds and the right panel for investment-grade funds.

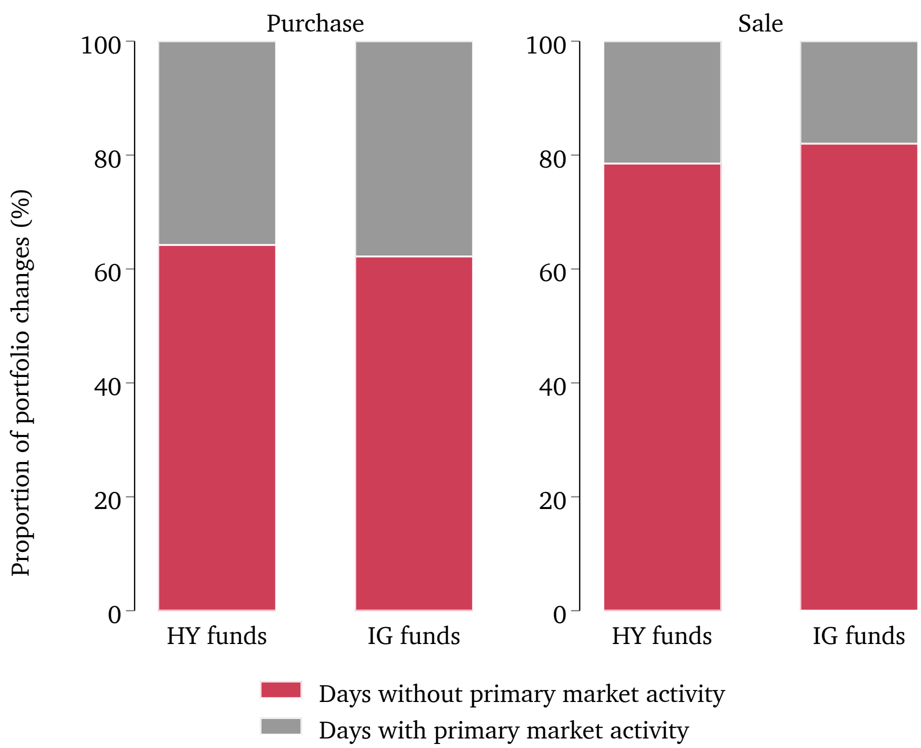


Figure 6. Portfolio changes on days with and without primary market activity

This figure shows the proportion of portfolio changes that occurs on days with and without primary market activity for active ETFs. Portfolio change is measured as the following: for each fund-bond-day, we compute the absolute daily change in corporate bond holdings in terms of face value and normalize this by lagged total net assets. For each fund-month, we add the changes that occur on days with primary market activity and divide by the sum of all changes for that fund-month. These quantities are aggregated by averaging across fund-months. The left panel shows the proportions for purchases (positive portfolio changes) and the right panel for sales (negative portfolio changes). Within each panel, the left bar shows the proportions for high-yield funds and the right bar for investment-grade funds. Red bars represent the proportion of changes during days without primary market activity and gray bars the proportion during days with primary market activity.

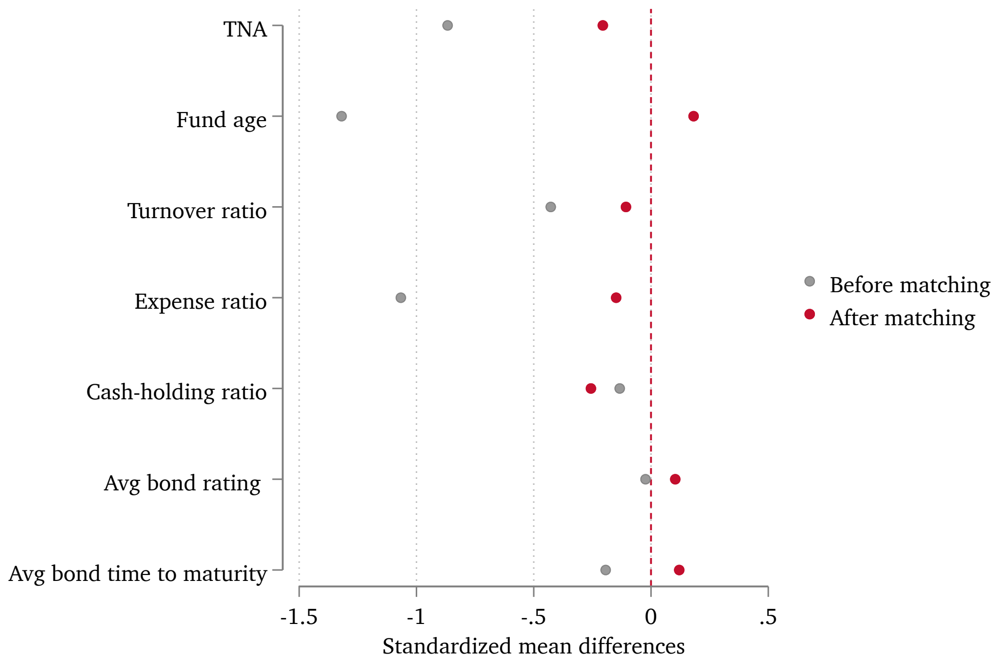


Figure 7. Quality of propensity score matching

This figure shows the quality of the propensity score matching used to construct a control group of active mutual funds. The vertical axis lists the matching variables. Fund characteristics (TNA, fund age, turnover ratio, expense ratio, cash-holding ratio) and characteristics of corporate bond holdings (average credit rating and time to maturity, value-weighted by par amounts held) are used. The graph plots the standardized mean difference (SMD) between the ETF and mutual fund groups for each variable, calculated as:

$$\text{SMD} = \frac{\bar{X}_{\text{ETF}} - \bar{X}_{\text{MF}}}{\sqrt{\frac{s^2_{\text{ETF}} + s^2_{\text{MF}}}{2}}}.$$

Gray dots represent SMDs before matching; red dots represent SMDs after matching. The dashed red line at zero indicates perfect balance.

Table 1. Descriptive statistics on active ETFs and mutual funds

This table reports summary statistics for the sample of active ETFs and active mutual funds. Panel A presents fund characteristics, returns, and flows; Panel B reports bond characteristics aggregated at the fund level. For each group, the table shows time-series averages of cross-sectional means, along with standard deviations (SD) and medians (p50). *TNA* is total net assets in USD millions. *Fund age* is measured in years. *Expense ratio* is the annual expense ratio expressed in percentage points. *Turnover ratio* is the annual portfolio turnover ratio. *Return* is the monthly gross return. *Return net of fees* is the monthly return after deducting management fees. *Fund flow* is the net inflow as a percentage of total net assets. TNA, returns, and flows are measured at monthly frequencies and other characteristics are measured at quarterly frequencies. Portfolio characteristics are calculated at the fund-quarter level by weighted-averaging bond characteristics using face value of bond holdings as weights. *Rating* is the credit rating expressed in integers where AAA = 1 and C or below = 21. *Time to maturity* is measured in years. The sample period is January 2016 to December 2023. There are 164 active ETFs and 484 active mutual funds in the sample.

	Active ETFs			Active mutual funds		
	Mean	SD	p50	Mean	SD	p50
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fund characteristics, returns and flow						
TNA (USD millions)	647	1903	104	4172	16057	593
Fund age (year)	3.4	2.8	2.8	16	13	14
Expense ratio (%)	0.35	0.22	0.32	0.63	0.28	0.6
Turnover ratio	1.2	1.4	0.74	1.7	1.7	1.2
Return	0.17	1.8	0.2	0.28	2.2	0.25
Return net of fees	0.15	1.8	0.17	0.22	2.2	0.2
Fund flow (%)	6.8	111	-0.053	1.4	61	-0.088
Panel B: Bond characteristics						
Rating	9.4	2.3	8.6	9.6	2.3	8.8
Time to maturity (years)	6.3	4.8	5.1	7.3	4.5	6.9
Number of funds		164			484	

Table 2. Long-short portfolio alphas

This table reports results from ordinary least squares regressions of long-short portfolio returns on common risk factors. The dependent variable is the monthly return of an equally weighted portfolio that is long active mutual funds and short active ETFs. Columns (1) and (2) report the results for high-yield funds, and Columns (3) and (4) for investment-grade funds. Odd-numbered columns report results according to the CAPM, where the aggregate bond market return (BOND) and the aggregate stock market excess return (MKTRF) are included as risk factors. Even-numbered columns report results according to the Elton four-factor model, which includes two additional bond market factors: the default spread (DEF) and the term spread (OPTION). All returns are expressed in basis points. Standard errors are Newey-West adjusted with three lags and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 2016 to December 2023.

	HY Funds		IG Funds	
	(1)	(2)	(3)	(4)
Intercept	5.406**	4.562**	1.347	0.848
	(2.510)	(2.271)	(2.775)	(2.228)
MKTRF	-0.028***	0.007	-0.009	-0.014
	(0.009)	(0.012)	(0.008)	(0.015)
BOND	0.015	0.042*	0.036	0.047***
	(0.019)	(0.022)	(0.029)	(0.014)
DEF		-0.086***		0.020
		(0.032)		(0.031)
OPTION		-0.165***		-0.041
		(0.046)		(0.068)
N	90	90	90	90
R^2	0.189	0.436	0.059	0.076

Table 3. Fund alphas: Active ETFs versus active mutual funds

This table reports results from ordinary least squares regressions comparing the performance of active ETFs and mutual funds. The dependent variable is the alpha, expressed in basis points, from the four-factor model in Equation (1), calculated using factor loadings estimated over the past 12 months in a rolling window. The variable **1**(ETF) is an indicator equal to one for an ETF and zero for a mutual fund. *ln(TNA)* is the natural logarithm of the fund's total net asset value. *ln(Fund age)* is the natural logarithm of the fund's age in years. *Expense ratio* is the annual fee charged by the fund, expressed in percentage points. *Turnover ratio* is the annual portfolio turnover ratio. *Past fund flow* is the fund's net monthly flow expressed as a percentage of total net assets. *Past return* is the fund's monthly return net of fees. *Cash-holding ratio* is the reported cash holding of the fund. *Avg bond rating* is the average credit rating of the fund's corporate bond holdings as in Table 1. *ln(Avg bond time to maturity)* is the natural logarithm of the average time to maturity of the fund's corporate bond holdings. Both average rating and time to maturity are weighted by the par amounts of the bonds held. All monthly (quarterly) control variables are included with a one-month (one-quarter) lag. Continuous variables are winsorized at the 1st and 99th percentiles at each cross section. Columns (1)–(4) report results for high-yield funds, while Columns (5)–(8) report results for investment-grade funds. Columns (4) and (8) use the ETF–mutual fund matched subsample. The regressions include various combinations of fixed effects, as indicated in the table: management company, style, month, style-month, and manager-month. Standard errors are clustered at the fund and month levels and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The unit of observation is fund-month. The sample period is January 2016 to December 2023.

	Dependent variable: Alpha (basis point)							
	HY funds				IG funds			
				Matched				Matched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(ETF)	-10.90***	-10.70***	-20.15**	-26.72**	1.93	3.29*	4.56	2.47
	(3.57)	(3.61)	(9.50)	(12.25)	(2.48)	(1.71)	(2.77)	(2.06)
ln(TNA)	-1.85***	-1.64***	-2.66***	-8.19*	-0.10	-0.36	-0.32	-0.05
	(0.49)	(0.61)	(1.00)	(4.11)	(1.46)	(1.21)	(0.38)	(0.89)
ln(Fund age)	-1.59	-1.37	-0.65	14.38	1.28	2.21	0.44	-0.89
	(1.47)	(1.62)	(2.15)	(11.21)	(1.75)	(2.05)	(0.66)	(1.93)
Past fund return	2.03	2.49	-0.55	-4.61	-30.05***	-31.92***	4.19*	4.81**
	(3.27)	(3.57)	(4.03)	(5.71)	(4.12)	(2.19)	(2.14)	(2.33)
Past fund flow	-20.14	-20.17	14.22	14.15	7.50	0.49	-4.02	-3.41
	(13.57)	(13.75)	(13.49)	(17.66)	(6.49)	(3.79)	(3.58)	(3.27)
Turnover ratio	-0.05	0.27	-0.66	0.91	-0.36	-1.01	-0.70	-0.64
	(0.95)	(1.13)	(2.03)	(4.05)	(0.52)	(0.65)	(0.64)	(1.05)
Expense ratio	-12.06**	-15.11***	-12.62*	-44.97	-14.81	-15.24*	-5.92	-2.48
	(5.44)	(5.59)	(6.88)	(28.56)	(9.11)	(7.70)	(4.01)	(12.01)
Cash-holding ratio	-0.01	-0.04	-0.00	0.37	-0.07	-0.12***	-0.01	-0.02
	(0.06)	(0.06)	(0.26)	(0.49)	(0.06)	(0.04)	(0.03)	(0.04)
Avg bond rating	0.67	0.96	-3.25	-1.02	0.12	-0.41	0.76	2.09
	(1.22)	(1.19)	(2.37)	(2.73)	(2.62)	(3.19)	(0.90)	(1.33)
ln(Avg bond time to maturity)	5.18*	4.14	6.71	13.38	8.39	9.64*	3.14	3.14
	(2.61)	(2.62)	(5.55)	(11.80)	(5.12)	(5.19)	(1.91)	(2.77)
N	7,798	7,604	1,386	861	17,337	17,218	6,558	3,334
R^2	0.44	0.53	0.80	0.80	0.07	0.15	1.00	0.72
Management company FE	✓	✓	✓	✓	✓	✓	✓	✓
Style FE	✓		✓	✓	✓		✓	✓
Month FE	✓				✓			
Style-Month FE		✓				✓		
Manager-Month FE			✓	✓			✓	✓

Table 4. Fund alphas: Active ETFs versus active mutual funds by disclosure frequency

This table replicate results in Columns (3) and (8) of 3 across differing mutual-fund disclosure frequencies. Mutual funds are classified as as monthly reporters if their holdings are available more frequently than quarterly, and quarterly reporters if their portfolio holdings are available only at a quarterly frequency, based on CRSP holdings data. We include control variables as in Table 3. Standard errors are clustered at the fund and month levels and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The unit of observation is fund-month. The sample period is January 2016 to December 2023.

	Dependent variable: Alpha (basis point)			
	HY funds		IG funds	
Mutual fund disclosure:	Monthly (1)	Quarterly (2)	Monthly (3)	Quarterly (4)
1(ETF)	-23.77**	-24.03***	2.22	2.21
	(11.13)	(8.08)	(2.01)	(4.94)
N	938	539	2,871	2,089
R^2	0.74	0.87	0.74	0.71
Controls	✓	✓	✓	✓
Management company FE	✓	✓	✓	✓
Style FE	✓	✓	✓	✓
Manager-Month FE	✓	✓	✓	✓

Table 5. Bond performance: ETF versus mutual fund trades

This table presents results from ordinary least squares regressions comparing the performance of bond selection of active ETFs and mutual funds. The dependent variable is the forward 12-month return of bond b, computed from the month following the trade. The indicator **1**(ETF) equals one for bonds traded by active ETFs and zero for bonds traded by active mutual funds. We count, for each quarter, the number of active ETFs and mutual funds that purchase bond b, rank bonds separately by these ETF and mutual fund counts, and retain bonds in the top quintile of either ranking but not both. Panel A reports the baseline regressions for all actively managed funds and Panel B restricts the sample to matched fund–bond trades between active ETFs and active mutual funds. *Purchase* and *Sale* indicate whether the fund increased or decreased its holdings of the bond during the quarter. The natural logarithm of time to maturity and the Bao et al. (2011) illiquidity measure are included to control for bond characteristics. Credit rating, bond, and quarter fixed effects are also included. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the bond and quarter levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The unit of observation is bond-quarter. The sample period is January 2016 to December 2023.

Panel A: Full sample of active ETFs and mutual funds

	Dependent variable: Forward 12-month bond return (%)			
	HY ETFs		IG ETFs	
	Purchase	Sale	Purchase	Sale
	(1)	(2)	(3)	(4)
1(ETF-favored)	-1.213***	1.310**	-0.677***	0.706***
	(0.417)	(0.530)	(0.242)	(0.239)
N	4,726	4,497	11,153	11,058
R^2	0.698	0.660	0.766	0.806
Controls	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Bond FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓

Panel B: Matched subsample of active ETFs and mutual funds

	Dependent variable: Forward 12-month bond return (%)			
	HY ETFs		IG ETFs	
	Purchase	Sale	Purchase	Sale
	(1)	(2)	(3)	(4)
1(ETF-favored)	-1.056**	0.982*	-0.180	0.588***
	(0.484)	(0.483)	(0.216)	(0.210)
N	4,140	3,765	10,155	9,429
R^2	0.679	0.671	0.787	0.773
Controls	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Bond FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓

Table 6. Dealer inventory and active ETF purchases

This table reports results from ordinary least squares regressions analyzing the relationship of an active ETF's portfolio choice and the dealers' recent net order flow. The dependent variable is 100 times an indicator for a bond purchase, $\mathbf{1}$(ETF buy), which equals one if the fund increases its holding of bond b on day t, and zero otherwise. The independent variables of interest are defined as follow: $\mathbf{1}(\Delta\text{dealer inventory} > 0)$ is an indicator that equals one if the dealer order imbalance over the past two weeks for bond b was positive, and zero otherwise; $\mathbf{1}$(cash fund) is an indicator that equals one if the ETF's average cash percentage in the creation basket is at least 75% in the last reporting year, and zero otherwise. The interaction term captures the differential purchase propensity for cash funds when a bond has positive prior order flow. The natural logarithm of time to maturity and the Bao et al. (2011) illiquidity measure are included to control for bond characteristics. Credit rating, bond, fund, and day fixed effects are also included. We estimate the regression among two subsamples: days with large primary market activity and other days. Columns (1) and (2) report results for the former and Columns (3) and (4) for the latter. Large primary market activity is defined as changes in shares outstanding that fall in the top tercile in terms of magnitude within a given fund. Standard errors are clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The unit of observation is fund-bond-day. The sample period is May 2017 to March 2023.

	Dependent variable: $100 \times \mathbf{1}$(ETF buy)			
	Large primary market activity		Other days	
	HY ETFs	IG ETFs	HY ETFs	IG ETFs
	(1)	(2)	(3)	(4)
$\mathbf{1}(\Delta\text{dealer inventory} > 0)$	1.103**	0.034	0.041	0.004
	(0.497)	(0.175)	(0.057)	(0.054)
$\mathbf{1}(\Delta\text{dealer inventory} > 0) \times \mathbf{1}(\text{cash fund})$	-1.327**	-0.058	-0.060	-0.048
	(0.634)	(0.182)	(0.077)	(0.057)
$\mathbf{1}$(cash fund)	18.119	0.349	0.102	-0.148
	(12.626)	(0.770)	(0.296)	(0.274)
N	39,658	254,109	279,892	1,149,254
R^2	0.771	0.137	0.093	0.054
Controls	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Bond FE	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓

Table 7. Performance of bonds purchased on days with primary market activity

This table reports results from ordinary least squares regressions comparing the performance of bond selection within active ETFs on days when ETF shares are created. The dependent variable is the forward 12-month return of bond b, computed from the month following the trade. The indicator variable $\mathbf{1}$(shares created) equals one if the bond was purchased on a day when ETF shares were created, and zero otherwise. Columns (1)–(3) report results for high-yield funds and Columns (4)–(6) report results for investment-grade funds. Within each fund group, the results are reported for all funds, cash funds, and in-kind funds. A fund is classified as a cash fund if its average cash proportion in creation baskets exceeds 75% in the most recent reporting year, and as an in-kind fund otherwise. The natural logarithm of time to maturity and the Bao et al. (2011) illiquidity measure are included to control for bond characteristics. Credit rating, bond, fund, and day fixed effects are also included. Standard errors are clustered at the bond and day levels and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The unit of observation is fund-bond-day. The sample period runs from January 2019 through March 2023.

	Dependent variable: Forward 12-month bond return (%)					
	HY ETFs			IG ETFs		
	All	Cash	In-kind	All	Cash	In-kind
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}$(shares created)	-0.686***	-0.017	-0.717***	0.030	-0.210	-0.126
	(0.265)	(0.333)	(0.264)	(0.191)	(0.280)	(0.323)
N	9,697	2,632	7,065	29,963	9,799	20,164
R^2	0.865	0.891	0.912	0.870	0.897	0.882
Controls	✓	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Bond FE	✓	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓

Table 8. Determinants of cash transaction

This table reports results from ordinary least squares regressions of the cash proportion in ETF baskets on various fund characteristics. Cash transaction fee is defined as the additional fee applied to the cash component of the respective basket. Number of APs is the number of authorized participants associated with the fund during the year. *ln(TNA)* is the natural logarithm of the fund's total net assets. *ln(Fund age)* is the natural logarithm of the fund's age in years. *Rating* is the fund-level, face value–weighted average credit rating of the corporate bond portfolio. *ln(Time to maturity)* is the natural logarithm of the fund-level, face value–weighted average time to maturity of the corporate bond portfolio. *Expense ratio* is the annual fee charged by the fund, expressed in percentage points. *Turnover ratio* is the annual portfolio turnover ratio. *ln(Basket value)* is the natural logarithm of the annual average basket value (average NAV × basket size). *Cash-holding ratio* is the reported cash holding of the fund. All control variables are constructed at the fund-year level and included with a one-year lag. Continuous variables are winsorized at the 1st and 99th percentiles. The regressions include year fixed effects. Standard errors are obtained via a bootstrap clustered at both the fund and year levels and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The unit of observation is the fund-year over the sample period from 2019 to 2023.

	Dependent variable: Cash fraction in basket (%)	
	Creation basket	Redemption basket
	(1)	(2)
Cash transaction fee	-0.543***	-0.279
	(0.136)	(0.227)
Creation/redemption fee	0.503	-1.050
	(1.185)	(3.009)
Number of APs	4.446**	3.505
	(2.057)	(2.182)
ln(basket value)	-9.942*	-8.036
	(5.808)	(7.215)
ln(TNA)	-0.287	2.165
	(1.821)	(2.020)
ln(fund age)	-4.854	-9.024**
	(3.520)	(4.053)
Turnover ratio	-2.249	2.583
	(3.079)	(2.517)
Expense ratio	62.57***	45.48*
	(13.34)	(23.51)
Cash-holding ratio	-0.0787	-0.198
	(0.116)	(0.146)
Avg bond rating	-5.426***	-5.226***
	(1.470)	(1.937)
ln(avg bond time to maturity)	-6.711**	-9.093***
	(2.721)	(2.792)
N	179	149
R^2	0.361	0.265
Year FE	Yes	Yes

Appendix A Cash transaction fee estimation

We estimate the cash transaction fee for each fund and year as follows:

$$\text{cash transaction fee} = \frac{(\text{average total fee} - \text{standard fee})}{\text{cash proportion} \times \text{basket value}} \tag{A1}$$

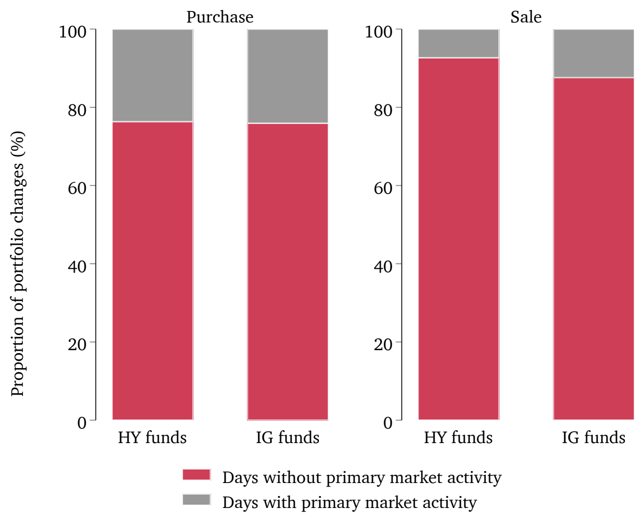
where the total fee (\$) is the average fee per basket inferred from the N-CEN filing; the standard fee (\$) is the fixed fee per a creation or redemption basket, obtained from the prospectus; the cash proportion is average cash proportion per a basket, sourced from the N-CEN filing; and the basket value is estimated as average ETF share price (\$) during the year times creation/redemption unit size specified in the prospectus. The ETF share price is obtained from the CRSP.

We now describe the details of how we infer total fees from Form N-CEN. The filing reports the fees—separately for creations and redemptions—that an ETF charges APs in three fields (Items E.3.d.i.1–E.3.d.i.3), reflecting how fees are actually levied (e.g., a dollar amount per creation unit or a percentage of the unit's value). Following Gorbatikov and Sikorskaya (2022), we convert all reported fees to a percentage of the value of each creation (redemption) unit. This percentage corresponds to $\frac{\text{Average total fee}}{\text{Basket value}}$ in equation (A1). If an ETF reports fees in multiple fields, we use the average across those fields. The remaining steps of the calculation are then straightforward.

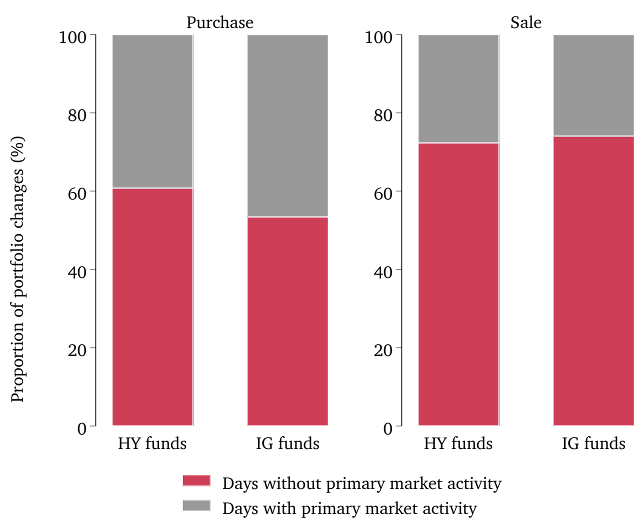
[Table A1 here]

Table A1 reports summary statistics of standard transaction fees for creation and redemption as well as additional fees charged on the cash portion used in creation and redemption. On average, cash transaction fees are about three times higher for high-yield ETFs (around 0.12–0.09%) than investment-grade ETFs (around 0.03%), yet there is a significant variation across fund-year: for example, standard deviation of cash fees ranges from 0.26–0.38 for creation and redemption by high-yield ETFs.

Appendix B Additional figures and tables



(a) Panel A: Cash funds



(b) Panel B: In-kind funds

Figure A1. Portfolio changes on days with and without primary market activity for cash funds vs. in-kind funds

This figure repeats the exercise in Figure 6 for subsamples of ETFs. ETFs are divided into cash funds and in-kind funds based on the average cash proportion in their creation and redemption baskets. A 75% cutoff is used.

Table A1. Descriptive statistics on average basket transaction fees

This table reports descriptive statistics for transaction fees charged by active ETFs from authorized participants (APs) for primary market activities. *Standard transaction fee* is the fixed fee per a creation or redemption basket, obtained from the prospectus. *Cash creation fee* and *Cash redemption fee* are additional fees charged on the cash portion used in the creation and redemption basket, respectively. These additional fees are calculated using equation A1. All fees are scaled by the average basket value estimated as average ETF share price ($) during the year times creation/redemption unit size specified in the prospectus. The unit of observations is the fund-year level over sample period from 2019 to 2023.

	HY ETFs			IG ETFs		
	Mean	SD	p50	Mean	SD	p50
	(1)	(2)	(3)	(4)	(5)	(6)
Standard transaction fee (% of basket value)	0.037	0.044	0.023	0.023	0.026	0.019
Additional fees charged on the cash portion:						
Cash creation fee (%)	0.12	0.26	0.0049	0.032	0.13	0
Cash redemption fee (%)	0.093	0.38	0	0.03	0.13	0
Number of fund-year		125			287	