Should Passive Investors Actively Manage Their Trades?

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Abstract

Using novel daily holding data for exchange-traded funds (ETFs), I identify three types of ETFs that adopt distinct approaches to rebalancing their portfolios, which generates meaningful return heterogeneity. First, 56% of ETFs track public indices that pre-announce their rebalances, and they trade entirely on reconstitution days *at* closing prices. Their large, uninformed trades pay 67 bps in execution costs, a figure that is three times higher than what is paid in similar-sized institutional trades. Second, 7% of ETFs spread out their trades across 10 days and save 34 bps per trade or 7.3 bps per year. Third, 37% of ETFs use self-designed indices to avoid pre-announcements of rebalancing stocks and save 30 bps per trade. The alternative rebalance schedule leads to a tracking error of 10.6 bps per year and an information ratio of 0.69. For a $2 million retirement account that accrues over 30 years, the transaction cost savings rise to $29 thousand at retirement.

Keywords: Exchange-Traded Funds (ETFs), index investing, execution costs, self-indexing, sunshine trading

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I. Introduction

Passive investing, including the use of index mutual funds and exchange-traded funds (ETFs), has expanded greatly in the past two decades. Total assets under management (AUM) of index-tracking funds has reached $7 trillion, or 33% of the aggregate U.S. stock market capitalization as of 2020. One of the most powerful insights that supports passive investing is provided by Sharpe (1991), who finds that one active investor's gain is another active investor's loss, leading to a zero-sum game for all active investors. Thus, accounting for the hefty costs and fees associated with active investing, passive funds will outperform the average active fund.

Passive investment strategies still require the funds to perform significant amount of trading in response to index constituent changes, initial public offerings, mergers, and delistings. Due to these factors, in 2020 the median portfolio turnover rate of U.S.-listed ETFs that track U.S. equity indexes was 16%. Therefore, even if an investor chooses to buy and hold an ETF, the ETF manager needs to trade on behalf of the investor. This paper first identifies three trading patterns of passive funds, and then evaluates the trading costs of the different strategies. How *do* passive funds trade? How *should* they trade? I contribute to the literature by providing the first analysis of the trading decisions of passive funds.

Using a novel dataset of daily ETF holdings, I identify three types of ETF trading strategies: a "sunshine trading" strategy; camouflaging *when* to trade; and camouflaging *what* to trade. Most ETFs (56%) employ the "sunshine trading" strategy suggested by Admati and Pfleiderer (1991). These ETFs track publicly available indices that announce stock lists to be added or removed at least 5 days prior to rebalance dates. Moreover, these ETFs trade by adding and dropping the announced stocks only on index rebalancing days. For added/removed stocks, the number of shares traded by the ETFs represents, on average, 1.14% of the daily trading volume associated with these stocks. Using daily reported portfolios, I calculate the hypothetical net asset value (NAV) returns on the ETFs had they rebalanced at the opening, intraday, or closing prices. Comparing the hypothetical NAVs with the realized NAVs, I find that the sunshine ETFs trade exactly at the 4:00 p.m. closing prices, which are determined in the closing auction.[1] Therefore, those ETFs' trades are (1) large, (2) abrupt, (3) not driven by informational advantages, and (4) fully predictable.

[1] The underlying indices rebalance at the close prices, too. Thus, the ETFs' trades incur no tracking errors.

[Insert Figure 1 about here]

Figure 1 plots the average returns on the stocks being rebalanced, adjusted for trade direction. As Figure 1 shows, the stock prices rise, on average, 67 bps during the 5 days prior to the index rebalance date. A price reversal of 20 bps then occurs within 20 days following the rebalance date. However, 67 bps is a large execution shortfall for orders representing 1.14% of Average Daily Volume (ADV). As a comparison, Anand et al. (2012) document an execution shortfall of 24 bps for institutional orders that averaged 2.4% of ADV, Di Maggio et al. (2019) document the price impact of 10.52 bps for 0.5% ADV orders, and Frazzini, Israel, and Moskowitz (2012) document a 13.00 bps execution shortfall for 1.2% ADV orders. Furthermore, the ETFs' trades are not driven by private information related to the underlying stocks, so the adverse-selection issue for liquidity providers is limited. Therefore, it is especially intriguing that there exists considerable room for sunshine ETFs to optimize their transaction costs.

Two types of ETFs deviate from public-indexing ETFs that use sunshine-trading strategies, and I find that they both achieve lower transaction costs. One type camouflages *when* it trades; and I call these "Opaque ETFs." These ETFs report only their month-end portfolios, while other ETFs report their portfolio holdings on a daily basis. As a result, the pace at which Opaque ETFs trade is unknown to other investors, nor does the daily portfolio of Opaque ETFs appear in my data. Nevertheless, Opaque ETFs report their NAVs on a daily basis, enabling me to compare their rebalance pace and performance with those of Sunshine ETFs. Specifically, I exploit the fact that 16 Opaque ETFs track an identical index with 16 corresponding Sunshine ETFs. These ETFs' pairwise NAV correlation outside index rebalance windows is about 0.9999, as they track the same index, and their portfolios are almost identical. During quarterly index reconstitution periods, however, their NAV correlation falls to 0.97. Thus, while the portfolios for the ETF pairs are largely identical outside the index rebalance windows, Opaque ETFs diverge from the index during the rebalance periods.[2]

[2] The paired sunshine ETFs' portfolios are disclosed daily, and I find that the disclosed portfolio fully replicates the index and strictly follows the index rebalance schedule.

[Insert Figure 2 about here]

To further identify Opaque ETFs' trading schedules, in Figure 2 I plot the average pairwise NAV difference between Opaque and Sunshine ETFs during the rebalance and placebo periods (one calendar month following the rebalance dates). Figure 2 shows that Opaque ETFs outperform Sunshine ETFs during the [T-5, T+5] period of quarterly index rebalancing dates, while the NAV difference remains zero during other periods.[3] Therefore, because the returns in the [T-5, T] period differ, it is evident that Opaque ETFs rebalance their portfolios before the index rebalancing date. Additionally, because the returns continue to diverge in the [T, T+5] period, it is evident that the Opaque ETFs also delay some rebalancing trades as well. On average, the Opaque ETFs outperform Sunshine ETFs by 1.8 basis points (bps) per quarter or 7.3 bps per year.

Another type of ETF that deviates from sunshine trading camouflages *what* it trades. Instead of using public indices, these ETFs invent their own indices to track ("Self-indexing" ETFs). For example, the Schwab 1000 ETF tracks the Schwab 1000 Index, which is 99% correlated with the S&P 500 index. Unlike S&P indices—or any other index from index companies such as FTSE Russell, MSCI, etc.—the Schwab 1000 Index does not offer subscriptions to external investors nor does it announce the stocks to be rebalanced before a rebalance is executed. As a result, this ETF's rebalancing trades are less transparent and less crowded. Indeed, I find that what I call Self-indexing ETFs' rebalance cost is 30 bps-per-trade lower than the cost paid by ETFs that track publicly available indices. Considering the 16% average ETF turnover rate, the annual rebalance cost savings for these ETFs is $16\% \times 2 \times 30 = 9.6$ bps.[4] The results are robust to controlling for rebalancing sizes and various fixed effects. Therefore, camouflaging *what* to trade also helps to reduce execution costs for ETFs.

My paper contributes to the literature on trade transparency. On the one hand, Admati and Pfleiderer (1991) suggest that uninformed traders can pre-announce their trades to reduce the price impact. In their

[3] I added the management fees back to the NAVs to ensure the NAV divergences are due to the differences in the portfolios.

[4] The turnover rates of self-indexing ETFs are similar to those of public-indexing ETFs. Thus, the savings in execution costs reflect lower transaction costs per trade, not heterogeneity in turnover rates.

model, uninformed traders can credibly signal their type to market makers. When they pre-announce and commit to their trading schedule, they help the liquidity providers better estimate the informed order flow, so they incur lower price impacts and the market becomes more liquid. Since the model has only one period, no "front-running" or "predatory trading" strategies are present. On the other hand, Brunnermeier and Pedersen's (2005) continuous-time model suggests that strategic traders ("predators") can front-run liquidity traders, i.e., sell before liquidity traders and buy back later at a lower price. Thus, it becomes an empirical question as to which effect is stronger.

The paper related most closely to mine is Bessembinder et al. (2016), who find that crude oil futures traders supply liquidity to the U.S. Oil Fund's predictable trades, and they document transaction costs of 24 bps for the fund. I contribute to the literature by establishing identification strategies that can be used to test these models: given a transparent trade, it is hard to predict what would have happened *if* the trader had conducted the trade in a camouflaged manner. I examine ETF pairs that track the same index and therefore face the same trading problem. Because ETF managers do not make investment decisions, this trading problem occurs independently of underlying investment decisions. Therefore, the differing trading approaches of Sunshine and Opaque ETFs provide a clean head-to-head comparison that sheds light on the comparative effects of transparent and camouflaged trades. Insofar as the NAVs of Sunshine and Opaque ETFs diverge only around index rebalancing periods, the opaque ETF approach of camouflaging their trading schedules appears to involve a lower trading cost than is incurred by Sunshine ETFs.

In view of traditional academic theories, the price of a stock is an unbiased estimate of the stock's fundamental value, so it is perfectly elastic to uninformed supply and demand shocks. Yet there is a longstanding strand of literature on the inelastic demand curve of stocks.[5] For example, Shleifer (1986) finds that stock additions to the S&P 500 Index earn significant positive abnormal returns at inclusion *announcements*. Koijen and Gabaix (2021) find that investing exogenously in the stock market *per se* can increase the market's aggregate value. My paper represents the first exhaustive study that finds an inelastic

[5] See Shleifer (1986), Harris and Gurel (1986), Beneish and Whaley (1996), Lynch and Mendenhall (1997), Wurgler and Zhuravskaya (2002), Duffie (2010), Petajisto (2011), and many others. In a related strand of literature, Grossman and Miller (1988) and Hendershott and Menkveld (2014) show that large order imbalances can push prices to deviate from fair values if liquidity providers are risk-averse.

demand curve for hundreds of benchmark indices. Because I can see daily portfolio holdings of index funds, I find that abnormal returns peak around trade *execution* dates. Also, my results indicate that asset price shocks caused by heavy demand is partially permanent and partially transitory: As Figure 1 shows, prices moved 67 bps before the execution date and a reversal of 20 bps occurred afterward (trading volume weighted). Also, I document three distinct approaches to rebalancing that can generate meaningful heterogeneity in returns.

My paper also contributes to the literature that measures traders' execution costs and analyzes the relationship between information and liquidity. Collin-Dufresne and Fos (2015) identify activists as informed traders, and they find that these informed traders pay lower execution costs because they spread out the trades, time the liquidity, and rush to trade before announcing their trades (13D filings). My paper echoes their paper by finding that index reconstitutions, which are generally not driven by private information possessed by index compilers, are associated with execution costs as high as 67 bps. In other words, uninformed traders pay higher execution costs than informed traders because they are transparent in their trades and do not time liquidity.

This paper also adds to the literature on the impact of passive investment flows on the cross-section of equity prices, including studies by Frazzini and Lamont (2008), Lou (2012), Ben-David et al. (2018), Chinco and Fos (2021), Jiang and Yao (2021) and Bogousslavsky and Muravyev (2021). Ben-David et al. (2018) find that higher ETF holdings of a given stock will lead to higher return volatilities. The authors conjecture that liquidity shocks to ETFs caused by short-horizon liquidity traders can propagate to the underlying stocks, so ETFs may increase the nonfundamental volatility of the securities in their baskets. Jiang and Yao (2021) and Bogousslavsky and Muravyev (2021) find that stocks associated with higher ETF ownership exhibit greater distortion in closing prices. My paper provides a micro-foundation for their findings, as I find that the trading behaviors of most ETF managers are both mechanical and abrupt. Whether they do so intentionally or not, 93% of ETFs fully add/dump a stock within 1 day *at* the closing auction price. Therefore, sub-optimal execution of passive fund trades not only costs their own investors but also significantly affects the underlying stocks.

The trading cost of mechanical rebalancing is large in many senses. First, it is comparable to total management fees charged by ETF managers. Deploying mechanical, predictable rebalance strategies costs ETFs about 30 bps per trade above what ETFs that camouflage their trades pay. The 30 bps of one-way savings combined with a 16% average turnover rate for passive funds translate to 9.6 bps of round-trip savings per year. Assuming that 56% of funds operating in the $7 trillion passive investment business are not rebalancing optimally, $3.9 billion in rebalancing costs could be saved with smarter rebalancing strategies. Remarkably, the AUM weighted-average expense ratio of U.S. equity ETFs is only 15.1 bps per year, so the 9.6 bps execution cost reflects a hidden cost of 60% in management fees. Another comparable number is that the cost to the indexing companies for developing indices is only ~1 bps per year. [6] The index-licensing fee is about 3 bps, while the hidden cost of using publicly available indices is three times higher. Finally, for a $2 million retirement account accrued over 30 years, failing to save 9.6 bps per year translates to $29,000 in losses at retirement.

The paper proceeds as follows. Section II describes the data and the procedure that identifies three types of ETFs. Section III reverse-engineers the trading paces of sunshine ETFs and calculate the execution costs. Section IV compares the trading paces and execution costs of Self-indexing ETFs and Sunshine ETFs. Section V compares Opaque ETFs and Sunshine ETFs. I conclude in Section VI.

II. Identifying Three Types of ETFs and Summary Statistics

A. Data Description

My data cover all ETFs listed in the U.S. and Canada with no survivorship biases. For non-opaque ETFs, the data provide daily holdings of each ETF for 2012–2020. For Opaque ETFs, the data provide monthly holdings. The data also provide, for each ETF, the full name, issuer, inception date, benchmark index, AUM, leverage ratio, listing exchange, sector exposures, investment region, fund focus, asset class, active management dummy, currency and sector exposure, put and call options volume, short interest, management fee, and total/net expenses.

[6] Source: S&P Dow Jones Indices LLC annual report 2020.

I focus on unlevered passive ETFs that list on and invest in the U.S. equity market. Specifically, to exclude leveraged ETFs, I require an ETF to have a leverage ratio that equals one. [7] To exclude fixed income and commodity ETFs, I require that ETF's fall into the "Equity" asset class. To select funds that invest mainly in U.S. equity markets, I require an ETF's investment region to be "North America" and its currency exposure to USD to be greater than 0.8.[8] To exclude funds that focus on Canada and Mexico, when a fund's currency exposure is missing, I drop ETFs that include "Canada", "Mexico", or "ex-US" in the fund name. To exclude active funds, I require that an ETF's active management dummy equals zero and the fund's focus not be "alpha-seeking." These criteria leave me with 732 U.S. equity ETFs. Table 1 presents summary statistics describing their characteristics.

[Insert Table 1 about here]

B. Three Types of ETFs

I categorize the ETFs in my data into three types: Sunshine ETFs, Self-indexing ETFs, and Opaque ETFs.

Sunshine ETFs and Self-Indexing ETFs

Sunshine ETFs are daily-reporting ETFs that track indices from large index companies such as S&P, FTSE, Russell, Dow Jones, MSCI, Wilshire, CRSP, STOXX, Morningstar, CBOE, NYSE, and NASDAQ. Self-indexing ETFs are ETFs that choose not to track indices from large index companies. Instead, these ETFs track private indices that are typically compiled by the ETF issuer itself. For example, the Schwab 1000 ETF (SCHK) tracks the Schwab 1000 Index, which is essentially a float market cap–weighted index for

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[7] Leveraged ETFs often choose not to hold or trade underlying stocks. Instead, they use swaps and other derivatives to achieve the intended market exposure. The derivatives usually directly track the underlying index. As is the case with public-indexed ETFs, here the indices *per se* also use publicly announced and abrupt rebalance schedules. Thus, public-indexed leverage ETFs also suffer from costly rebalances. Nevertheless, leveraged ETFs involve much lower AUMs than unlevered ones, and I exclude them from my sample.

[8] My data contain all U.S.-listed ETFs, including those that invest mainly on international markets. However, I focus my research on those ETFs that invest in U.S. equity markets because the CRSP and TAQ data cover only U.S. markets. In unreported results, I find that the international-investing ETFs in my sample also largely use the 1-day rebalance schedule on international equity markets.

roughly the largest 1000 stocks listed on the U.S. market. Its return series is 99%+ correlated with both the S&P 500 ETF (SPY) and the Russell 1000 ETF (IWB). However, the Schwab 1000 Index is not open to subscriptions, so external traders can only guess what stocks will be added and deleted in an index reconstitution.[9] Therefore, self-indexing ETFs disguise their trading intentions from other traders.

Self-indexing is made possible by a series of exemptive orders from the SEC,[10] which allowed ETFs to use affiliated index providers to compile their benchmark indices. Such exemptive orders allowed ETFs to remain secretive about underlying index methodologies and index components. Therefore, self-indexers are able to camouflage *what* they will trade. However, to provide some transparency, the SEC requires all self-indexing ETFs to disclose their daily portfolios. Thus, it is impossible for self-indexers to simultaneously camouflage *what* and *when* they trade.[11]

Both Sunshine and Self-indexing ETFs disclose their portfolios daily. Therefore, for these ETFs, I can simply compare their portfolios on two consecutive business days to infer trades on a daily basis. To distinguish self-indexing ETFs from daily reporting ETFs, I parse the "benchmark index" columns of the ETFs. First, I label all ETFs whose benchmark indices include the following strings as non-affiliated index users: S&P, FTSE, Russell, Dow Jones, MSCI, Wilshire, CRSP, STOXX, Morningstar, CBOE, NYSE, and NASDAQ. Second, I label all ETFs whose benchmark indexes include their own investment advisers' names, e.g., Schwab, WisdomTree, Fidelity, John Hancock, Nuveen (=TIAA), SoFi, Syntax, Cushing, and Victory Capital Management (=CEMP), as self-indexers. I manually label the remainder of the sample by searching for benchmark index compilers. Eventually I identify 265 Self-indexing ETFs. The remaining ETFs are included among the Sunshine ETFs. Panels A and B of Table 2 summarizes statistics for the

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[9] Certainly, other traders *can* guess what stocks will be added and deleted, based either on an ETF's (potentially outdated) self-indexing methodology or the ETF's historical rebalance patterns. Such guesses are arguably less accurate and much less transparent than guesses of the rebalances of public indices.

[10] See, e.g., WisdomTree Investments, Inc., et al., Investment Company Act Release Nos. 27324 (May 18, 2006) (notice) and 27391 (June 12, 2006) (order); Van Eck Associates Corp., et al., Investment Company Act Release Nos. 29455 (Oct. 1, 2010) (notice) and 29490 (Oct. 26, 2010) (order); Fidelity Commonwealth Trust, et al., Investment Company Act Release Nos. 30341 (Jan. 7, 2013) (notice) and 30375 (Feb. 1, 2013) (order).

[11] ETFs that use unaffiliated public index compilers are not required to disclose their daily holdings. Although most ETFs (sunshine traders) disclose daily holdings anyway, Opaque ETFs choose to be secretive on their daily holdings, and I analyze Opaque ETFs' strategy in Section V.

Sunshine ETFs and Self-indexing ETFs, respectively. In Section III and Section IV, I merge the daily holding data with CRSP and millisecond Trade and Quote (TAQ) data to infer the intraday trading times for Sunshine and Self-indexing ETFs. I also compare their transaction costs at the stock-day level and report the results in Section IV.

[Insert Table 2 about here]

Opaque ETFs

ETFs that report the holdings at only monthly frequency are Opaque ETFs. With monthly holdings, it is impossible to identify the daily or intraday trades. Fortunately, there exist Opaque ETFs that track the same benchmark indexes that Sunshine ETFs track. On most days, the daily NAV returns of the sunshine and opaque ETFs based on the same indexes are almost perfectly correlated, because they hold the same portfolios. Around index rebalance dates the returns differ, which reveals the dates when the portfolios are not identical and thus the dates when the opaque ETFs traded. Therefore, I obtain the daily NAVs of Opaque ETFs from CRSP mutual fund data and compare them with data on Sunshine ETFs. Insofar as index rebalance dates can be inferred from Sunshine ETFs, I can calculate NAV divergences between Opaque and Sunshine ETFs around the rebalance dates. Thus, I analyze the Opaque ETFs' transaction costs at the fund level in Section V. Panel C of Table 2 summarizes the statistics for Opaque ETFs.

C. Summary Statistics for Rebalance Trades by Non-Opaque ETFs

In this subsection I describe the summary statistics for the sample of ETF trades from the daily holdings data. For each trading day in my sample, I compare each ETF's stock holdings with those of the day before. Specifically, I record a stock's first appearance date as the day a stock is added to an ETF. If a stock was in the portfolio on date T-1 but not date T, I record date T as the deletion day. To avoid data irregularities, I require the stock that is added or deleted to have appeared in the dataset continuously for at least 60 days.[12] I end up with 122,492 addition/deletion events for 9 years. Note that I focus on the cleanest

[12] I select the number 60 because index rebalances could be as frequent as quarterly.

addition/deletion events for my analysis and exclude constituent weight changes. This very likely leads to an underestimation of ETF turnover (and their annual trading costs in dollar terms), as the index weight of a stock can partially change through share buy-backs, SEOs, etc.

I then merge the addition/deletion events with the CRSP for stock prices and stock characteristics. In addition, I merge the data with millisecond TAQ data for stock intraday prices and liquidity measures. I exclude observations for which I cannot find matches based on tickers or CUSIPs, and then winsorize the data at the 1% level on both sides. Table 3 presents the summary statistics for the addition/deletion events. The median rebalance represents 0.01% of a stock's market cap or 1.14% of the stock's trading volume on the rebalance day.

[Insert Table 3 about here]

III. Trading Paces and Costs Associated with Sunshine ETFs

This section documents the rebalance patterns and transaction costs for sunshine ETFs. For these ETFs, my data provide daily portfolio holdings and I compare holdings for two consecutive days to calculate the daily trades for each ticker. In subsection III.A I summarize the rebalancing paces of ETFs at the daily level and the abnormal trading volumes around rebalancing dates. The detailed daily holdings data also provide a unique opportunity to detect *intraday* ETF trading patterns. Although the ETFs do not disclose when they trade within a rebalance day, variations in trade timing would lead to varying end-of-day NAVs. Thus, in Subsection III.B I reverse-engineer the intraday trading patterns of Sunshine ETFs.[13] I find that public ETFs systematically choose to trade at closing prices. In Subsection III.C I use closing prices on the rebalance dates as the trading prices of the ETFs and evaluate their trading costs.

A. Rebalance Trade Paces for Sunshine ETFs

[13] Kacperczyk, Sialm, and Zheng (2008) use quarterly reported holding data for mutual funds to calculate the difference between buy-and-hold NAVs and actual NAVs. They find remarkable "unobserved actions of mutual funds" between the quarter-ends.

In this subsection, I evaluate the rebalance paces of Sunshine ETFs' trades.[14] The rebalance date is called date T. For stock-addition events, the first day that a stock appears in the portfolio of an ETF is date T. For deletion events, the day following the last day that a stock appears in the ETF's portfolio is date T, i.e., the actual trading day that the ETF sold the stock. For each addition/deletion event, I calculate the trading volume from the rebalancing ETF as well as the general abnormal trading volume around date T.

The methodology is as follows:

1. Denote the holdings by ETF i of stock j on day t as $H_{i,j,t}$ shares. If a stock split happens, all impacted $H_{i,j,t}$ are adjusted to be comparable to date T. The ETF traded $\left|H_{i,j,T+k} - H_{i,j,T+k-1}\right|$ shares of the stock on date $T+k$, where $|\cdot|$ is the absolute value function. Then, for each k in $-15, -14, \ldots, 14, 15$, I calculate the ETF-driven stock turnover rate as:
$$ETF\_Trade_{i,j,k} = \frac{\left|H_{i,j,T+k} - H_{i,j,T+k-1}\right|}{SHROUT_{j,T}},$$
where $SHROUT_{j,T}$ is the shares outstanding of stock j on date T from the CRSP.
2. Denote the stock's total trading volume recorded on CRSP as $VOL_{j,T+k}$. I select the benchmark trading volume window as $[T-60, T-30]$, and the regular trading volume is $\overline{VOL} = \sum_{k=-60}^{-30} \frac{VOL_{j,T+k}}{31}$. I calculate the abnormal turnover rate on date $T+k$ as:
$$Abnormal\_Turnover_{i,j,k} = \frac{VOL_{j,T+k} - \overline{VOL}}{SHROUT_{j,T}}.$$

Figure 3 compares the time series of the average abnormal turnover rate with the turnover rate traded directly by the ETF.

[Insert Figure 3 about here]

Figure 3 reveals several interesting empirical findings. First, the shaded green bar(s) plot the turnover rates that stem directly from the ETFs' trades, yet the only visible green

[14] The methodology for Self-indexing ETFs will be similar, as I note in Section 4.

bar corresponds to date T. In other words, the ETFs almost always use one-day trade schedules, and they do not spread their trades across multiple trading days. This finding echoes Bogousslavsky and Muravyev (2021), who find that higher ETF ownership is associated with higher trading volumes in closing auctions. Second, the unshaded yellow bars plot the general abnormal turnover rates around date T. In contrast to the ETFs' abrupt 1-day trading schedules, there is a remarkable abnormal trading volume *not* conducted by ETFs around date T.[15] Third, the ETFs' trade sizes account for only about one-tenth of the abnormal trading volume on date T, indicating the strong market impact of ETF reconstitution trades.

B. Intraday Trade Timing for Sunshine ETFs

Daily portfolio-holdings reports allow me to reverse-engineer the intraday trading patterns of ETFs. Performing this task is econometrically challenging because the action space of ETFs is massive: they could have traded any stock at any moment within a given day. On the other hand, I can observe only day-end portfolios and NAVs at $0.01 accuracy. In other words, the ETFs' action space involves more dimensions than the number of known variables.

Although the exact trading time and price of a specific ETF-stock-day is indeterminable, I have ample numbers of rebalance events with which to infer the average timings of the ETF trades. Specifically, I hypothesize an ETF's trading times (e.g. open, intraday time-weighted average price, 1 PM, and close) and calculate the hypothetical day-end NAV. The best hypothesis should lead to the best guess of the true NAV. Therefore, I measure the prediction accuracy of hypothetical NAVs and draw statistical inferences regarding the intraday trading patterns of ETFs.

The first step is to build true NAV returns excluding management fees. For each ETF i and date t where at least one stock has been traded, I pull the true NAV from the CRSP mutual fund database as $True\ NAV_{i,t}$. The gross-fee NAV return of the ETF is:

$$GrossRet_{i,t} = \frac{True\ NAV_{i,t}}{True\ NAV_{i,t-1}} - 1 + ManagementFee_{i,t}.$$

[15] These market participants might include other traders who also follow the same index or traders pre-positioned to the index reconstitution.

I then build the hypothetical returns based on distinct trade-timing hypotheses. The correct hypothesis regarding the trading time should lead to a precise estimation of the gross-fee return. Denote the day-end holdings by ETF i of stock j on day t as $H_{i,j,t}$ shares. I denote the price of stock j on day t at time τ as $P_{j,t,\tau}$, where τ can be OPEN, VWAP, or CLOSE.[16] Therefore, if stock j on day t was rebalanced at time τ, it contributed a dollar Profit and Loss of:

$$PnL_{i,j,t,\tau} = H_{i,j,t-1}\left(P_{j,t,\tau} - P_{j,t-1,CLOSE}\right) + H_{i,j,t}\left(P_{j,t,CLOSE} - P_{j,t,\tau}\right).$$

For stock j that has not been traded on day t, $H_{i,j,t} = H_{i,j,t-1}$ and its dollar Profit and Loss is independent of τ:

$$PnL_{i,j,t,NoTrade} = H_{i,j,t-1}\left(P_{j,t,CLOSE} - P_{j,t-1,CLOSE}\right).$$

Then, conditional on the hypothesis that all trades happen at τ, the total NAV return on the ETF is:

$$HypRet_{i,t,\tau} = \frac{\sum_j PnL_{i,j,t,\tau}}{\sum_j H_{i,j,t-1} \times P_{j,t-1,CLOSE}}.$$

The numerator is the ETF's hypothetical total dollar PnL on all stocks j. The denominator is the AUM of the ETF on date $t-1$. Thus, $HypRet_{i,t,\tau}$ is the reverse-engineered gross-fee return of the ETF.

Suppose that on date t ETF i chooses to trade an α portion of its rebalance trades at the open auction, β at the intraday VWAP price, and γ at the closing auction; its gross-fee NAV return should be:

$$GrossRet_{i,t} = \alpha \cdot HypRet_{i,t,OPEN} + \beta \cdot HypRet_{i,t,VWAP} + \gamma \cdot HypRet_{i,t,CLOSE}.$$

For each individual ETF i and rebalance date t, rounding errors in NAVs, fund-flows, and data errors can make the prediction very noisy. Taking all observations together, though, the prediction errors should be asymptotically small. I run the following regression to reveal the average rebalance patterns for ETFs, i.e., which $HypRet_{i,t,\tau}$ is the best in predicting the true $GrossRet_{i,t}$:

$$GrossRet_{i,t} = \alpha \cdot HypRet_{i,t,OPEN} + \beta \cdot HypRet_{i,t,VWAP} + \gamma \cdot HypRet_{i,t,CLOSE} + \varepsilon.$$

I double-cluster the standard errors at the ETF and day levels. Column 1 of Table 4 shows the regression results.

[16] VWAP is the volume-weighted-average price of the continuous trading session (9:30–16:00), excluding open and close auctions. This indicates that the ETF spreads its trade over the course of the day.

[Insert Table 4 about here]

The results reported in Table 4 indicate that γ is not statistically significantly different from 1, while α and β are also not statistically significantly different from 0. Therefore, the hypothesis that Sunshine ETFs are rebalancing at the closing auction is not rejected.[17] Throughout this paper, I use the closing prices as of rebalance date T as the trading prices of the ETFs.

Is it possible that α, β, γ are heterogeneous across ETFs and dates? The following two pieces of evidence indicate that it is unlikely that heterogeneous trading schedules will be found across ETFs. First, the R-squared of the regressions is above 0.999, which indicates that the current fit is very good, suggesting that there are almost no outliers. Second, if there exists a subset of ETFs or dates that systematically include α and β greater than zero, then to obtain $\alpha, \beta = 0$ in the full sample there must be another subset of ETFs or dates that systematically include α and β *less than* zero. However, $\alpha, \beta < 0$ means that when those ETFs want to buy stocks, they must short sell those stocks at the open auction/VWAP prices and buy back more shares at the closing prices. Such actions are deemed to be economically unlikely for ETFs.[18]

C. Rebalancing Costs for Sunshine ETFs

In this subsection, I measure the execution costs that Sunshine ETFs incur. To ensure that my results are comparable to those commonly reported in the execution-cost literature, I use two measures to evaluate the execution costs for the ETFs: The execution shortfall, and the price impact.

The execution shortfall (also called "slippage") is the difference between the decision price and the final execution price for a trade. Execution shortfall measures adverse price movements after a trading intention is expressed to the market and before the

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[17] Again, this result is consistent with that reported in Bogousslavsky and Muravyev (2021), who find that higher ETF ownership can lead to higher distortion of closing auction prices.

[18] Surprisingly, some models (e.g., Back and Baruch (2004)) indeed recommend that informed traders deploy a mixed strategy and sometimes trade in the direction opposite to their information to hide their true trading intentions. ETFs are neither informed nor are they sophisticated enough to control their trades in this level.

trade executes. All major index companies announce reconstitution decisions at least 5 days before reconstitutions occur. I therefore use 5 days as a conservative estimation of the execution shortfall of ETF trades. The execution shortfall of ETF i on stock j is:

$$ES_{i,j,T} = \frac{P_{j,T} - P_{j,T-5}}{P_{j,T}} * Direction_{i,j,T},$$

where $P_{j,T}$ is the closing price of the stock on date T.[19] $P_{j,T-5}$ is the closing price of the stock on date $T-5$. $Direction_{i,j,T}$ equals 1 for addition events and -1 for deletion events. Therefore, a positive $ES_{i,j,T}$ indicates that an ETF paid a worse price than the price at the time when the trade was determined.

The price impact is the difference between the order-execution price and fair market value at a certain future time. In other words, price impact measures price movements after a trade. The price impact of ETF i on stock j at horizon H is:

$$PI_{i,j,T,H} = \frac{P_{j,T+H} - P_{j,T}}{P_{j,T}} * Direction_{i,j,T},$$

A positive price impact indicates that the price moves along the direction of a trade and the trader earns a profit. A negative price impact indicates price reversal, i.e., delaying the trade can be less costly. The absolute value of a negative price impact is the excess execution cost paid by the ETF (compared with conducting the trade H days later).

Figure 1 shows that the execution shortfall of Sunshine ETFs is 67 bps [t=14.49] and the price impact is -20 bps [t=-3.56] because the price reversal occurs after the ETF buy trade executes. Considering that the average order size for these Sunshine ETFs is 1.14% of ADV, a 67 bps execution shortfall is very large by several measures. For example, Anand et al. (2012) documents that the execution shortfall for institutional orders is 24 bps for orders sized 2.4% of ADV. The figure reported in Di Maggio et al. (2019) is 10.52 bps for trade sized 0.5% of ADV. Considering that the ETF order flows are, arguably, uninformed, a 67 bps transaction cost is remarkably high, and the potential savings are also very large. Although these results do not come with identification, the gigantic magnitudes already indicate considerable room for ETFs to improve. In the next section, I compare the execution costs for public ETFs and self-indexers.

[19] To be consistent with the definition of the price impact, I use $P_{j,T}$ instead of $P_{j,T-5}$ in the denominator. Using the $P_{j,T-5}$ does not substantially change the results.

IV. Self-Indexing ETFs

ETF benchmarks with larger index brands are able to attract more capital from investors (Kostovetsky and Warner 2021). Yet this seeming advantage suffers from a major drawback: all other investors can also subscribe to a large branded index. Public index rebalances are announced at least 5 days before rebalance dates, so there is sufficient time for other traders to buy or sell ahead of the ETFs. In this section, I explore ETFs that camouflage *what* they trade by tracking alternative indices that are less transparent to external traders. In subsection IV.A I provide more institutional details on self-indexing rules and present the rebalance paces of self-indexing ETFs. In subsection IV.B I evaluate whether Self-indexing ETFs are successful in lowering their trading costs.

A. Rebalance Timing of Self-Indexing ETFs

Although Self-indexing ETFs' reconstitutions are less transparent *ex-ante*, these ETFs disclose their portfolios on a daily basis, so their trades are known *ex-post*. Using the same methodology described in subsection III.A, in Figure 4 I plot the trading volumes around the rebalance dates of Self-indexing ETFs.

[Insert Figure 4 about here]

Figure 4 shows that self-indexing ETFs also use the 1-day rebalance schedules that Sunshine ETFs use. One possible rationale for the abrupt trading patterns favored by Self-indexers is the daily portfolio report requirement. Because the SEC requires self-indexers to publish their portfolios at daily frequency, it essentially forbids passive ETFs from camouflaging *both* what and when they trade. If a Self-indexing ETF wants to gradually rebalance its portfolio, its trade is a secret only during the first trading day. Its trade intention will then be disclosed to other market participants by the end of the first trading day. Such transparency may discourage self-indexers from using multi-day rebalance schedules.

The next question is when do self-indexing ETFs trade at intraday prices. Using the same methodology described in subsection III.B, I construct ETF-day-level hypothetical NAV returns $HypRet_{i,t,OPEN}$, $HypRet_{i,t,VWAP}$, and $HypRet_{i,t,CLOSE}$ on Self-indexing ETFs had they rebalanced at the open, VWAP, or closing prices. I then run a similar regression to see which hypothetical return can best explain the realized gross-fee NAV changes:

$$GrossRet_{i,t} = \alpha \cdot HypRet_{i,t,OPEN} + \beta \cdot HypRet_{i,t,VWAP} + \gamma \cdot HypRet_{i,t,CLOSE} + \varepsilon.$$

Similarly, I double-cluster the standard errors at the ETF and day levels. I report the regression results in column 2 of Table 4.

The results reported in column 2 of Table 4 indicate that γ is not statistically significantly different from 1 while α and β are also not statistically significantly different from 0.[20] Therefore, the hypothesis that self-indexing ETFs are rebalancing at the closing auction is also not rejected. Therefore, I can use the closing price on rebalance date T as the trading price of a Self-indexing ETF.

B. Costs of Rebalancing: Self-Indexing ETFs vs. Sunshine ETFs

In this subsection, I compare the rebalancing cost differences between Self-indexing ETFs and ETFs that use non-affiliated indices. As described in Subsection II.C, I identify 122,492 rebalance events, 90,475 of which are conducted by Sunshine ETFs and 32,017 of which are conducted by Self-indexing ETFs. The universes of stocks being rebalanced generally overlap, and I run the following regression to evaluate the effectiveness of self-indexing on execution cost savings:

$$Rebalance\ Cost_{i,j,t} = \theta \cdot Public_{i,j} + Controls_{i,j,t} + \eta_i + \xi_t + \varepsilon_{i,j,t},$$

where i is the index of the stock being rebalanced, j is the index of the ETF, and t is the index of the rebalancing date. Considering that the Self-indexing ETFs' rebalances might be smaller, the control variables include the log(rebalancing size) of a trade. I also control for log(market cap) and log(price) of the underlying stocks as well as η_i as the stock fixed effect and ξ_t as the year fixed effect. I use execution shortfalls and negative price impacts to measure execution costs, as in Section III, to compare the execution costs.[21] Standard errors are clustered at the stock and year levels. The coefficient of interest is θ, which is the additional execution cost paid by ETFs that use public indices. Table 5 presents the regression results.

[20] The results reported in column 3 of Table 4 also indicate that, when tested jointly, daily-reporting ETFs do not significantly deviate from the strategy of trading solely at the close.

[21] Again, both Sunshine and Self-indexing ETFs choose to rebalance at the closing price, so I use the closing price as trade prices to infer the ETFs' execution costs.

[Insert Table 5 about here]

The results reported in Table 5 indicate that, when trading the same stock, the execution cost is higher for public indexed ETFs than for self-indexers, and the results are robust to adding various controls and fixed effects. The execution shortfall results reported in column (2) indicate that the average adverse price movements before Self-indexing ETFs' trades are executed is 14 bps lower than the movements for Sunshine ETFs when they are trading the same stock. The price reversals following rebalance trades are even higher than the execution shortfall: 19 bps at the 20-day horizon (column 4) and 30 bps at the 60-day horizon (column 6). Therefore, self-indexers incur lower execution costs than public-indexed ETFs. A larger rebalance is typically associated with higher transaction costs for an ETF.

C. Magnitudes

Savings of 30 bps per trade translates to savings of 9.6 bps per year for the median fund that exhibits a 16% (one-way) turnover rate. These numbers represent a substantial cost of passive investments. By way of comparison, the AUM-weighted ETFs' management fee is only 15.1 bps. Therefore, the execution costs (not including brokerage fees and exchange fees) represent as much as 60% of the fee charged by the ETF manager. Employing a slightly more sophisticated order-execution strategy would almost certainly not require a 60% greater effort on the part of the index ETF manager. As indicative evidence, note that the 16 Opaque ETFs charge management fees that are comparable to those charged by their Sunshine ETF counterparts.

Management fees include all operational costs of an ETF, so a better benchmark for self-indexing would be the costs that are directly associated with developing indices. The most often-cited reason for self-indexing identifies the hefty licensing fees that branded public indices charge (Kostovetsky and Warner 2021). For example, the index licensing revenue of S&P Dow Jones Indices LLC is $647 million, or 3.2 bps per year, for the $2 trillion passive funds that track S&P indices. The cost the S&P Dow Jones Indices LLC charges to develop these indices is only 1.0 bps per year. Using "in-house" indices, ETF managers can pocket the difference of 2.2 bps. In other words, the savings in execution costs (which goes to investors) are 4.4 times larger than the savings in licensing fees.

V. Opaque ETFs

There are two distinct views regarding the impact of ETF portfolios and trade transparency on execution costs. On the one hand, most ETF advisors believe that the transparency associated with daily ETF holdings reports does not necessarily harm investment outcomes. For example, Paul Lohrey, the head of U.S. iShares product design and quality, has mentioned to the Wall Street Journal that "*We're not afraid of the transparency. Our daily holdings disclosure does not necessarily provide actionable information.*"[22] Therefore, the majority of ETFs use publicly available indices and publish their ETFs' daily portfolio holdings on their websites, essentially deploying a sunshine trading strategy. On the other hand, Vanguard believes that the daily reporting of ETF holdings can encourage front-running and free-riding by opportunistic traders. Therefore, Vanguard ETFs publish only month-end portfolio data with 15-day lags, so I classify them as Opaque ETFs. Monthly portfolio announcements made it impossible to reverse-engineer the exact timing of or prices associated with rebalance trades at the stock-day level. In this section, I directly compare the trading outcomes generated by these two approaches by comparing twin ETFs' NAVs at the fund level.

A. Matched ETF Pairs

For each benchmark index of an opaque ETF, I search exhaustively for Sunshine ETFs that track exactly the same indices. Therefore, the NAVs and daily holdings of the matched Sunshine ETFs can serve as the benchmark for Opaque ETFs. The search identifies 16 pairs of ETFs. Table 6 presents the results for the matched ETF pairs.

[Insert Table 6 about here]

In Table 6 I list the ETF pairs that track the same indices. To conduct a sanity check of the matching, I calculate the NAV return correlation between the fund pairs. Outside the

[22] https://www.wsj.com/articles/why-vanguard-is-secretive-about-its-stock-etfs-1425870188

quarterly rebalancing windows of the underlying indices, I obtain a correlation coefficient of at least 0.9999 for all pairs of ETFs. The holdings of the ETFs pairs at month ends are also largely identical. Table 7 presents the summary statistics of matched Opaque and Sunshine ETFs.

[Insert Table 7 about here]

B. Excess Returns on Opaque ETFs

Opaque ETFs camouflage their rebalance trades and use alternative rebalance schedules, so a natural question is whether Opaque ETFs save on execution costs. In this section I evaluate the trading results for Opaque funds by calculating the NAV differences between the funds. Although I do not observe daily holdings of Opaque ETFs, I have sufficient data to partially reverse-engineer the strategies that Opaque ETFs deploy at the fund level. Specifically, I pull NAV returns from the CRSP mutual fund database for each ETF-day, and I calculate the pairwise NAV return-difference-adjusted management fee:

$$ReturnDiff_{i,t} = GrossRetOpaque_{i,t} - GrossRetSunshine_{i,t},$$

where i is the index for ETF pairs and t is the index for the date. $GrossRetOpaque$ ($GrossRetSunshine$) is the net NAV return for Opaque (Sunshine) funds added back with the management fee charged on that day. Because the management fees are charged every day, the numbers added back are the annual management fees (in bps) divided by the number of trading days in the year.

During non-rebalancing periods, Opaque and Sunshine funds hold the same portfolio and the $ReturnDiff$ should be near zero.[23] In rebalancing periods, the $ReturnDiff$ should be different from zero. I accumulate and aggregate the $ReturnDiff$ as:

$$CumulativeReturnDiff_t = \sum_{i=1}^{16} \sum_{\tau=T-20}^{t} ReturnDiff_{i,\tau} / 16,$$

where T is either the rebalance date of the Sunshine ETFs or the placebo date, each of which is set as one calendar month following the rebalance dates. The cumulation begins

[23] The NAVs are reported in two significant digits. For an ETF with a nominal price of \$100, the rounding error can be as large as \$0.005/\$100 = 0.5 bps. The error does not accumulate over time because the true underlying NAVs are not "rounded."

20 days before date T. I take the average of the $ReturnDiff$ across all 16 ETFs. Figure 2 (in the introduction) plots the time series of $CumulativeReturnDiff_t$.

Figure 2 shows that Vanguard funds outperform BlackRock funds by 1.8 bps around the rebalance dates. As the rebalance is scheduled quarterly, this outperformance translates to 7.3 bps in annual returns. I find that Opaque ETFs' portfolio returns diverge from those of Sunshine ETFs only during the quarterly index reconstitution periods, and the cumulative return difference remains at zero around non-rebalance dates. This further indicates that opaque ETFs used alternative rebalance schedules relative to the schedules of the underlying indices and peer ETFs.[24] Around Sunshine ETFs' rebalance dates, the return divergence does not occur until $T-5$, which coincides with the index reconstitution announcement date. The divergence ends around $T+5$, indicating that Opaque ETFs rebalance their portfolios in the $[T-5, T+5]$ interval.

C. Risk–Return Tradeoff of Opaque ETFs' Rebalance Strategy

How great is the risk of camouflaging a portfolio and using alternative rebalance strategies? I measure the risk–return tradeoff by the information ratio, which is defined as:

$$IR = \frac{Portfolio\ Return - Benchmark\ Return}{\sigma_{Tracking\ Error}}.$$

By my calculations, the portfolio return equals the NAV returns on Opaque funds, $GrossRetOpaque_{i,t}$, and I use Sunshine ETFs' returns, $GrossRetSunshine_{i,t}$, as the proxy of the return on the benchmark index. The denominator is the standard deviation of the tracking error, $ReturnDiff_{i,t}$. I find that the annualized standard deviation of $ReturnDiff_{i,t}$ is 10.6 bps. Combined with the 7.3 bps of annual returns, Opaque ETFs exhibit an information ratio of 7.3/10.6 = 0.69 during index reconstitutions.

The information ratio of 0.69 should be considered very appealing to regular ETF investors. By comparison, Warren Buffett's information ratio is 0.64 (Frazzini, Kabiller, and Pedersen 2018). To be fair, the information ratio is sustained for only 10 days per quarter and consists of only 13% of a portfolio (the annual turnover rate of Opaque ETFs)

[24] Anecdotally, Doug Yones, Vanguard's head of domestic equity indexing and ETF product management, says that Vanguard is "gradually building positions over time in stocks that are scheduled to be added." The report is available at https://www.bloomberg.com/news/articles/2015-07-07/the-hugely-profitable-wholly-legal-way-to-game-the-stock-market.

and cannot easily be arbitraged directly because the cost of buying Opaque ETFs while short-selling Sunshine ETFs can easily overwhelm the return difference of 7.3 bps per year. Still, the relative risk–return tradeoff indicates that an alternative rebalance schedule is desirable to most ETF investors. On the other hand, the high information ratio also indicates the high profits that other market participants who trade against the index rebalances earn.[25]

D. Why do most ETFs trade abruptly and not camouflage their trades?

So why do sunshine ETFs insist on tracking public indices and deploying such an abrupt rebalance strategy? Kostovetsky and Warner (2021) answer the first half of the question: they find that an ETF that benchmarks with larger index brands can attract more capital from investors. The second half of the question is more interesting: what discourages most ETFs from adopting opaque rebalance strategies?

The first answer could be that these ETFs aim to minimize their tracking errors. ETF managers might be concerned that a high rate of tracking errors could falsely signal poor management skills, therefore negatively affecting fund flows.[26] ETF managers might therefore be inclined to follow index changes mechanically at any cost. This argument is also related to the agency issue because mechanically following an index is arguably not in the best interest of ETF shareholders. As I show in section V.C., the alternative rebalancing strategy exhibits an information ratio as high as 0.69 during (and *only* during) index reconstitution periods. A regular ETF holder should not be so risk-averse that she rejects such a good, relatively low-risk deal.[27] If tracking error minimization is a reason for the managers to rebalance trades mechanically, it is likely a good idea to design an index

[25] As far as I am concerned, although index reconstitutions can be modified or cancelled, this has never happened in the [T-5, T] interval, so there's no survivorship bias in my calculations.

[26] Empirically, I do not find any statistically significant order-flow difference between Opaque ETFs and Sunshine ETFs. Two factors might drive this result. First, the return difference might be too small to be distinguishable. In Berk and Green (2004), 1 bps of outperformance can induce about 2.5 bps of extra fund flows in the next year. The average 7.3 bps outperformance is too small to be noticeable by external investors. Second, the higher tracking errors of opaque ETFs might induce lower fund flows, cancelling out the positive fund flows induced by higher returns.

[27] Given that the investor has put her money into an equity ETF, she should not have such an extreme risk-aversion profile.

with a multi-day rebalance schedule.[28]

The second factor that might be involved with this trading pattern is the agency issue that arises between ETF managers and their clients. Unlike hedge fund managers, who usually share a fund's profits, ETF managers are not compensated for beating their benchmarks. Therefore, large buy-side institutional traders, proprietary trade shops, and hedge funds usually develop sophisticated order-execution systems or rely on brokers to help them execute orders (Bacidore 2020). Yet ETF managers charge fixed management fees, so they are not incentivized to deploy those strategies to minimize execution costs. Rather, they are quite sophisticated at minimizing their ETFs' operational costs. In my sample, passive ETF managers manage, on average, 6.98 ETFs. This makes it difficult for managers to customize trading strategies for every ETF they manage. Active ETF managers manage, on average, only 1.38 ETFs.[29] If the agency issue is the reason, ETF sponsors and investors should consider more favorable structured incentive plans for ETF managers.[30]

VI. Conclusion

In this paper I analyze the trading behaviors of passive-investing ETFs and calculate their transaction costs. I find that 56% of ETFs follow mechanical trading strategies that abruptly rebalance *at* the closing price of an index reconstitution date, although their trading dates and tickers are both publicly known 5 days before a reconstitution. These ETFs experience a hefty 67 bps execution shortfall for their trades. This high cost is especially surprising because ETF rebalance trades are generally rule-based and not information-driven. Given these poor execution strategies, these uninformed mechanical traders are paying higher execution costs than informed traders.

[28] Such initiatives require collaboration between ETF managers and indexing companies. As David Blitzer, chairman of the index committee at S&P Dow Jones Indices, puts it: *"We don't require [ETFs] to trade in a certain way, that's their business not ours."* The current 1-day abrupt rebalance schedule of the S&P 500 index was designed in 1957, long before the inception of the passive funds that track it. Brogaard, Heath, and Huang (2021) show that ETFs customize their creation/redemption baskets to overweight liquid stocks, and I show that the liquidity issue should also be considered when ETFs themselves are trading.

[29] In the most extreme case one manager oversees a family of 38 ETFs. See https://www.vaneck.com/wsj-exchange-traded-funds-what-etf-managers-do-pdf.

[30] On the other hand, private communication with practitioners in the ETF industry suggests that the reverse is true today: ETF managers are compensated directly for reducing tracking errors, so in certain cases the managers could be disincentivized to outperform the benchmark.

Camouflaging either *what* or *when* to trade reduces transaction costs for ETFs. Self-indexing ETFs choose to track private indices to hide their trading interests. Opaque ETFs camouflage their rebalancing schedules and use alternative rebalance paces. The savings per trade involved with these two approaches are about 30–34 bps, which translates to about 9.6 bps per year of AUM. If 56% of U.S. ETFs operating in the $3 trillion passive ETF industry are not rebalancing optimally, $1.7 billion in rebalancing costs can be saved with smarter rebalancing strategies.[31]

The optimal order-execution problem is complex for all market participants, so large buy-side institutional traders typically develop complex algorithms to execute their trades. For example, these investors deploy various order-splitting algorithms (Almgren and Chriss 2000, Obizhaeva and Wang 2013, Li and Ye 2021), use sophisticated order types (Li, Ye, and Zheng 2021), or even use atomic clocks (Baldauf and Mollner 2020) to minimize transaction costs and avoid being exploited by front-runners. I provide evidence that even not-so-complex execution strategies, e.g., simply camouflaging either the timing or the underlying stock of a trade, can lead to considerable execution-cost savings for passive investors.

[31] The 56% figure represents the percentage of ETFs that track public indices and use mechanical rebalance strategies. It is a conservative estimate because branded public index trackers are usually larger than self-indexers. Also, the number does not count passive mutual funds or other products that implicitly track public indices.

References

Admanti, A. R., & Pfleiderer, P. (1991). Sunshine trading and financial market equilibrium. *The Review of Financial Studies*, *4*(3), 443-481.

Almgren, R., & Chriss, N. (2001). Optimal execution of portfolio transactions. *Journal of Risk*, *3*, 5-40.

Anand, A., Irvine, P., Puckett, A., & Venkataraman, K. (2012). Performance of institutional trading desks: An analysis of persistence in trading costs. *The Review of Financial Studies*, *25*(2), 557-598.

Baldauf, M., & Mollner, J. (2020). High-frequency trading and market performance. *The Journal of Finance*, *75*(3), 1495-1526.

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

Beneish, M. D., & Whaley, R. E. (1996). An anatomy of the "S&P Game": The effects of changing the rules. *The Journal of Finance*, *51*(5), 1909-1930.

Bessembinder, H., Carrion, A., Tuttle, L., & Venkataraman, K. (2016). Liquidity, resiliency and market quality around predictable trades: Theory and evidence. *Journal of Financial economics*, *121*(1), 142-166.

Brogaard, J., Heath, D., & Huang, D. (2021). The Heterogeneous Effects of Passive Investing on Asset Markets. Available at https://ssrn.com/abstract=3510359.

Brunnermeier, M. K., & Pedersen, L. H. (2005). Predatory trading. *The Journal of Finance*, *60*(4), 1825-1863.

Chinco, A., & Vyacheslav F. (2021). "The sound of many funds rebalancing," *Review of Asset Pricing Studies*, forthcoming.

Di Maggio, M., Franzoni, F., Kermani, A., & Sommavilla, C. (2019). The relevance of broker networks for information diffusion in the stock market. *Journal of Financial Economics*, *134*(2), 419-446.

Duffie, D. (2010). Presidential address: Asset price dynamics with slow-moving capital. *The Journal of finance*, *65*(4), 1237-1267.

Frazzini, A., & Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of financial economics*, *88*(2), 299-322.

Grossman, S. J., & Miller, M. H. (1988). Liquidity and market structure. *the Journal of Finance*, *43*(3), 617-633.

Harris, L., & Gurel, E. (1986). Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures. *the Journal of Finance*, *41*(4), 815-829.

Gabaix, X., & Koijen, R. S. (2021). *In search of the origins of financial fluctuations: The inelastic markets hypothesis* (No. w28967). National Bureau of Economic Research.

Hendershott, T., & Menkveld, A. J. (2014). Price pressures. *Journal of Financial Economics*, *114*(3), 405-423.

Kostovetsky, L., & Warner, J. B. (2021). The Market for Fund Benchmarks: Evidence from ETFs. *Available at SSRN 3804002*.

Li, S., & Ye, M. (2020). The Tradeoff between Discrete Pricing and Discrete Quantities: Evidence from US-listed Firms. *Available at SSRN*.

Li, S., Ye, M., & Zheng, M. (2021). *Financial Regulation, Clientele Segmentation, and Stock Exchange Order Types* (No. w28515). National Bureau of Economic Research.

Lou, D., "A Flow-Based Explanation for Return Predictability," *The Review of Financial Studies*, 12 2012, 25 (12), 3457–3489.

Lynch, A. W., & Mendenhall, R. R. (1997). New evidence on stock price effects associated with changes in the S&P 500 index. *The Journal of Business*, *70*(3), 351-383.

Obizhaeva, A. A., & Wang, J. (2013). Optimal trading strategy and supply/demand dynamics. *Journal of Financial Markets*, *16*(1), 1-32.

Petajisto, A. (2011). The index premium and its hidden cost for index funds. *Journal of Empirical Finance*, *18*(2), 271-288.

Sharpe, W. F. (1991). The arithmetic of active management. *Financial Analysts Journal*, *47*(1), 7-9.

Shleifer, A. (1986). Do demand curves for stocks slope down?. *The Journal of Finance*, *41*(3), 579-590.

Wurgler, J., & Zhuravskaya, E. (2002). Does arbitrage flatten demand curves for stocks?. *The Journal of Business*, *75*(4), 583-608.

Appendix. Long-Short Portfolio that Bets Against ETF Rebalances

In this appendix, I construct a long–short portfolio that bets against rebalance trades of Sunshine ETFs. I show that the portfolio yields an annual alpha of 3.45% while controlling for Fama-French 3 factors and Carhart 4 factors.

Specifically, I construct a long–short portfolio that rides stock returns in the $(T-5, T]$ window. The portfolio enters at the $T-4$ market open price and exits at the date T market close price. Therefore, it trades against the ETF rebalance orders on the rebalance date, i.e., "provides liquidity" to the ETFs. Before each day's market opening, I check the list of stocks that are being rebalanced by Sunshine ETFs over the next 4 days in the future. For each stock j, I construct the signed turnover rate of the underlying stock from ETF trades:

$$SignedTurnover_{j,T-4} = \frac{\sum_{t=T-4}^{t=T} Signed\ Rebalance\ Trades_{j,t}}{Market\ Cap_{T-4}}$$

Note that the signed turnover rate allows ETF flows to cancel out some stocks. I then require at least 100 stocks in the cross-section with a non-zero $SignedTurnover$ to avoid small-sample bias. The portfolio then longs the top 20% of stocks with large anticipated ETF flows to buy (large positive $SignedTurnover$) and shorts the bottom 20% of stocks with the most negative $SignedTurnover$. The portfolio returns are aggregated at end-of-day using the close prices.

[Insert Table A1 about here]

Table A1 shows the daily return regression results for the portfolio that bets against ETFs. The daily alpha of betting against ETFs is significantly positive at 1.37 bps [t=3.35], or 3.45% per year. The alpha is robust to Fama-French 3 factors and Carhart 4 factors. As a daily-rebalanced portfolio, the alpha remains robust to transaction costs because the portfolio turnover is only 9.55 times per year. Notably, although it might be a concern that ETF rebalances or index inclusions favor buying larger stocks with positive momentum, the return series of the portfolio that best against ETFs does not exhibit statistically significant loading on SMB or MOM.

Table 1
Summary statistics for U.S. unlevered equity ETFs

	Mean	Min	Q1	Median	Q3	Max	Std.Dev	N
AUM ($bn)	4.6408	0.0003	0.0246	0.2344	1.3246	327.7875	21.5146	732
Daily Trading Volume (Million)	0.8894	0.0000	0.0084	0.0372	0.2138	76.6160	5.1118	732
Inception Date		19930100	20060900	20131000	20170600	20201100		732
Net Expenses (bps)	38.2575	3.0000	20.0000	35.0000	57.5000	106.1000	21.9935	732

This table presents the summary statistics for U.S. unlevered equity ETFs. AUM is total assets under management. The net expense ratio is the sum of management fees and other expenses minus fee waivers. Refer to subsection II.A for the procedure used to identify U.S. unlevered equity ETFs. Numbers are calculated as of the end of 2020 or the last day of the ETF in my sample, whichever is earlier.

Table 2
Summary statistics for three types of ETFs

Panel A: Sunshine ETFs

	Mean	Min	Q1	Median	Q3	Max	Std.Dev	N
AUM ($bn)	5.4474	0.0008	0.0380	0.3582	2.0623	327.7875	23.9735	416
Daily Trading Volume (Million)	1.3292	0.0000	0.0090	0.0499	0.3223	76.6160	6.5208	416
Inception Date		19930122	20060301	20110419	20160920	20201116		416
Net Expenses (bps)	33.6771	3.0000	20.0000	35.0000	44.0000	95.0000	19.1721	416

Panel B: Self-Indexing ETFs

	Mean	Min	Q1	Median	Q3	Max	Std.Dev	N
AUM ($bn)	0.3811	0.0003	0.0123	0.0581	0.2707	11.9669	1.2542	265
Daily Trading Volume (Million)	0.1370	0.0000	0.0058	0.0159	0.0475	4.0094	0.4908	265
Inception Date		20000925	20130211	20160912	20180607	20201104		265
Net Expenses (bps)	50.1884	6.2800	35.0000	50.0000	63.0000	128.3600	21.5313	265

Panel C: Opaque ETFs

	Mean	Min	Q1	Median	Q3	Max	Std.Dev	N
AUM ($bn)	20.1529	0.3609	2.0137	4.3829	14.9567	190.8309	40.4993	51
Daily Trading Volume (Million)	0.5560	0.0131	0.0824	0.2041	0.6375	4.0047	0.8827	51
Inception Date		20010524	20040126	20060817	20100907	20180918		51
Net Expenses (bps)	10.5814	3.0000	7.0000	10.0000	15.0000	20.0000	5.1419	51

This table presents the summary statistics for the three types of ETFs. AUM is total assets under management. The net expense ratio is the sum of management fees and other expenses minus fee waivers. Refer to Section II for the procedure used to identify Self-indexing ETFs and Opaque ETFs. Numbers are calculated as of the end of 2020 or the last day of the ETF in my sample, whichever is earlier.

Table 3
Summary statistics for the rebalancing trades of U.S. unlevered equity ETFs

	Mean	Min	Q1	Median	Q3	Max	Std.Dev	N
Rebalance Date		20120430	20160628	20180319	20190624	20200630		122,492
Stock Closing Price ($)	61.3088	0.0266	17.4400	36.1500	69.9650	4394.9702	135.9766	122,492
Daily Trading Volume (Million Shares)	3.4571	0.0001	0.3505	0.9998	2.7814	348.6395	10.2756	122,492
Best Bid & Offer Depth (100 shares)	22.8173	1.0000	1.5000	2.5000	6.5000	7551.5000	166.9738	122,492
Intraday Price Range (%)	3.7951	0.0000	1.7212	2.6566	4.3378	174.6193	4.6247	122,492
log10(Rebalance Size/$)	5.3782	1.5557	4.6021	5.4409	6.1555	8.3662	1.1003	122,492
Rebalance Size / Market Cap (%)	0.0857	0.0000	0.0014	0.0115	0.0491	4.7509	0.3015	122,492
Rebalance Size / Trading Volume (%)	4.5803	0.0001	0.1514	1.1547	5.2771	39.4344	7.5487	122,492

This table presents the summary statistics for the rebalance trades conducted by U.S. unlevered equity ETFs. Refer to subsection II.B for the procedure used to identify rebalance trades. All numbers are calculated on the rebalance day. The Best Bid & Offer Depth is one-half of the total number of shares at the national best bid and offer prices at 1 p.m., aggregated across all markets. The Intraday Price Range is the difference between the daily high and low prices divided by the average of the daily high and low prices.

Table 4
Reverse-engineering the intraday timing of trades conducted by Sunshine and Self-indexing ETFs

$$GrossRet_{i,t} = \alpha \cdot HypRet_{i,t,OPEN} + \beta \cdot HypRet_{i,t,VWAP} + \gamma \cdot HypRet_{i,t,CLOSE} + \varepsilon.$$

	(1)	(2)	(3)
Sample	Sunshine ETFs	Self-Indexers	Combined
$HypRet_{i,t,OPEN}$	0.110*	0.004	0.016
	(0.061)	(0.004)	(0.013)
$HypRet_{i,t,VWAP}$	-0.271*	0.003	-0.039
	(0.150)	(0.009)	(0.033)
$HypRet_{i,t,CLOSE}$	1.167***	0.996***	1.028***
	(0.089)	(0.009)	(0.020)
Obs.	555,197	192,842	748,039
Adj. R^2	0.9993	0.9992	0.9992

For this table I infer the intraday timing of ETF trades by assessing the predictive power of hypothetical NAV returns regarding the true NAV return, $GrossRet_{i,t}$. Three hypothetical NAV returns have been constructed for each ETF (index i) date (index t). $HypRet_{i,t,\tau}$ is the hypothetical NAV return of ETF i on date t if the ETF has rebalanced at the intraday timing τ. τ can be the open auction price, volume-weighted-average-price, or closing auction price. Standard errors are reported in parentheses. Standard errors are clustered at the ETF and day levels. The coefficients of interest are α, β, and γ, which represent the estimated percentage of shares being traded at open, VWAP, and close, respectively. The null hypothesis is that all non-Vanguard ETFs rebalance at the closing auction prices, i.e., $\alpha = \beta = 0$, and $\gamma = 1$. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *Reads: The null hypothesis that all non-Vanguard ETFs rebalance at the closing price is not rejected at the 5% level.*

Table 5
Rebalance costs for Sunshine vs. Self-indexing ETFs

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Execution Shortfall (T-5 to T)		Negative Price Impact (T to T+20)		Negative Price Impact (T to T+60)	
Public	**25.72*** **	**14.69*** **	**30.59*** **	**19.03** **	**37.58*** **	**29.82** **
	(5.30)	(5.17)	(7.95)	(8.40)	(12.16)	(14.97)
Log(Trade Size)		**1.75** **		**7.54*** **		**8.43*** **
		(0.75)		(1.28)		(2.42)
Log(MKTCAP)		**-91.8*** **		17.07		56.85
		(34.45)		(37.96)		(70.05)
Log(Price)		-43.84		10.78		143.66*
		(33.79)		(41.69)		(79.38)
Stock FE	N	Y	N	Y	N	Y
Year FE	N	Y	N	Y	N	Y
Obs.	122,492	122,492	115,659	115,441	111,815	111,603
Adj. R^2	0.0004	0.1355	0.0002	0.0890	0.0001	0.1072

This table presents the rebalance costs for public indexing and Self-indexing ETFs. The left-hand side variables are Execution Shortfall $ES_{i,j,T}$ and the Negative Price Impact at both 20-day and 60-day horizons, $-PI_{i,j,T,20}$ and $-PI_{i,j,T,60}$. The regression formula is $Rebalance\ Cost_{i,j,t} = \theta \cdot Public_{i,j} + Controls_{i,j,t} + \eta_i + \xi_t + \varepsilon_{i,j,t}$, where i is the index of the stock being rebalanced, j is the index of the ETF, and t is the index of the rebalancing date. *Log(Trade Size)* is the log of the ETF's rebalance trade size, *Log(MKTCAP)* is the log of the market cap of the underlying stock, and *Log(Price)* is the log of the nominal price of the underlying stock. η_i represents stock fixed effects. ξ_t represents year fixed effects. Standard errors are clustered at the stock and year levels. The coefficient of interest is θ, which is the additional execution cost paid by ETFs who use public indices. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6
16 Pairs of twin ETFs that track the same indices

#	Ticker	Name	Benchmark Index
1	IJS	iShares S&P Small-Cap 600 Value ETF	S&P Smallcap 600 Value Index
	VIOV	Vanguard S&P Small-Cap 600 Value ETF	S&P Smallcap 600 Value Index
2	IJR	iShares S&P SmallCap 600 ETF	S&P SmallCap 600 Index
	VIOO	Vanguard S&P Small-Cap 600 ETF	S&P SmallCap 600 Index
3	IJT	iShares S&P Small-Cap 600 Growth ETF	S&P Smallcap 600 Growth Index
	VIOG	Vanguard S&P Small-Cap 600 Growth ETF	S&P Smallcap 600 Growth Index
4	IJJ	iShares S&P Mid-Cap 400 Value ETF	S&P Midcap 400 Pure Value Index
	IVOV	Vanguard S&P Mid-Cap 400 Value ETF	S&P Midcap 400 Pure Value Index
5	IJK	iShares S&P Mid-Cap 400 Growth ETF	S&P Midcap 400 Pure Growth Index
	IVOG	Vanguard S&P Mid-Cap 400 Growth ETF	S&P Midcap 400 Pure Growth Index
6	IJH	iShares S&P 400 MidCap ETF	S&P Midcap 400 Index
	IVOO	Vanguard S&P Mid-Cap 400 ETF	S&P Midcap 400 Index
7	IVE	iShares S&P 500 Value ETF	S&P 500 Value Index
	VOOV	Vanguard S&P 500 Value ETF	S&P 500 Value Index
8	IVV	iShares S&P 500 ETF	S&P 500 Index
	VOO	Vanguard S&P 500 ETF	S&P 500 Index
9	IVW	iShares S&P 500 Growth ETF	S&P 500 Growth Index
	VOOG	Vanguard S&P 500 Growth ETF	S&P 500 Growth Index
10	IWV	iShares Russell 3000 ETF	Russell 3000 Index
	VTHR	Vanguard Russell 3000 ETF	Russell 3000 Index
11	IWN	iShares Russell 2000 Value ETF	Russell 2000 Pure Value Index
	VTWV	Vanguard Russell 2000 Value ETF	Russell 2000 Pure Value Index
12	IWM	iShares Russell 2000 ETF	Russell 2000 Index
	VTWO	Vanguard Russell 2000 ETF	Russell 2000 Index
13	IWO	iShares Russell 2000 Growth ETF	Russell 2000 Growth Index
	VTWG	Vanguard Russell 2000 Growth ETF	Russell 2000 Growth Index
14	IWD	iShares Russell 1000 Value ETF	Russell 1000 Value Index
	VONV	Vanguard Russell 1000 Value	Russell 1000 Value Index
15	IWB	iShares Russell 1000 ETF	Russell 1000 Index
	VONE	Vanguard Russell 1000	Russell 1000 Index
16	IWF	iShares Russell 1000 Growth ETF	Russell 1000 Growth Index
	VONG	Vanguard Russell 1000 Growth ETF	Russell 1000 Growth Index

This table lists the ETF pairs that track the same underlying indices, thus facing the same rebalancing problems. To create these pairs, I start with the benchmark indices of all Vanguard ETFs and search for ETFs with different advisors that track the same indices.

Table 7
Summary statistics for 16 pairs of ETFs

Panel A: Opaque ETFs

	Mean	Min	Q1	Median	Q3	Max	Std.Dev	N
AUM ($bn)	12.7985	0.3609	0.6099	1.0842	2.6593	179.6151	44.5103	16
Daily Trading Volume (Million)	0.2806	0.0131	0.0239	0.0476	0.1308	3.3826	0.8298	16
Inception Date		20100907	20100907	20100907	20100920	20100920		16
Net Expenses (bps)	15.5625	3.0000	14.2500	15.0000	20.0000	20.0000	4.5894	16

Panel B: Sunshine ETFs

	Mean	Min	Q1	Median	Q3	Max	Std.Dev	N
AUM ($bn)	39.3414	4.8794	9.7904	21.7094	51.3641	238.3741	56.7152	16
Daily Trading Volume (Million)	3.2547	0.1892	0.4384	1.0808	2.4966	28.8124	6.9738	16
Inception Date		20000522	20000522	20000522	20000724	20000724		16
Net Expenses (bps)	16.5000	3.0000	16.5000	18.0000	20.0000	24.0000	6.3246	16

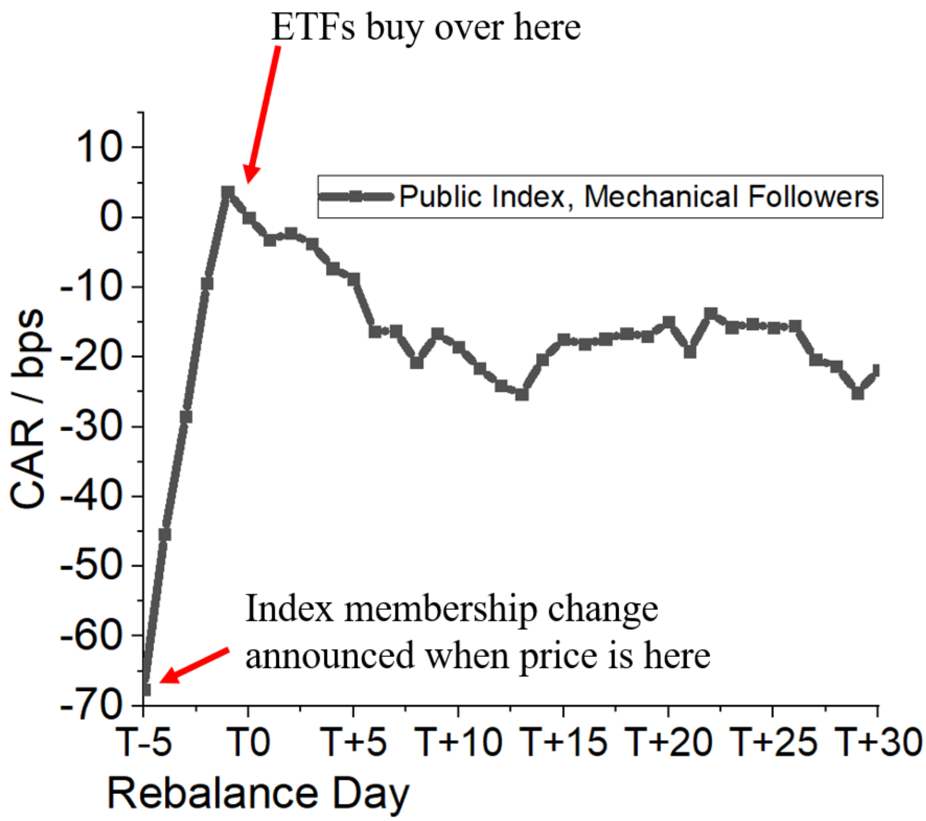
This table presents summary statistics for the 16 pairs of ETFs. They track the same index but follow varying rebalance schedules. AUM is total assets under management. The net expense ratio is the sum of management fees and other expenses minus fee waivers. Refer to subsection V.A for the procedure used to match ETFs that track the same indices. To make numbers comparable, all are calculated as of the end of 2020.

Table A.1
Daily Portfolio Returns on Betting Against ETF Rebalances

	(1)	(2)	(3)
Dependent Variable	Betting Against ETF Rebalance Daily Returns (bps)		
Alpha	**1.37*** **	**1.38*** **	**1.38*** **
	[3.35]	[3.36]	[3.36]
MKT		-0.01	-0.01
		[-1.37]	[-1.41]
SMB		0.02	0.02
		[1.07]	[1.26]
HML		-0.02	-0.01
		[-1.70]	[-0.87]
MOM			0.01
			[0.98]
Obs.	1886	1886	1886
Adj. R^2	-	0.13%	0.13%

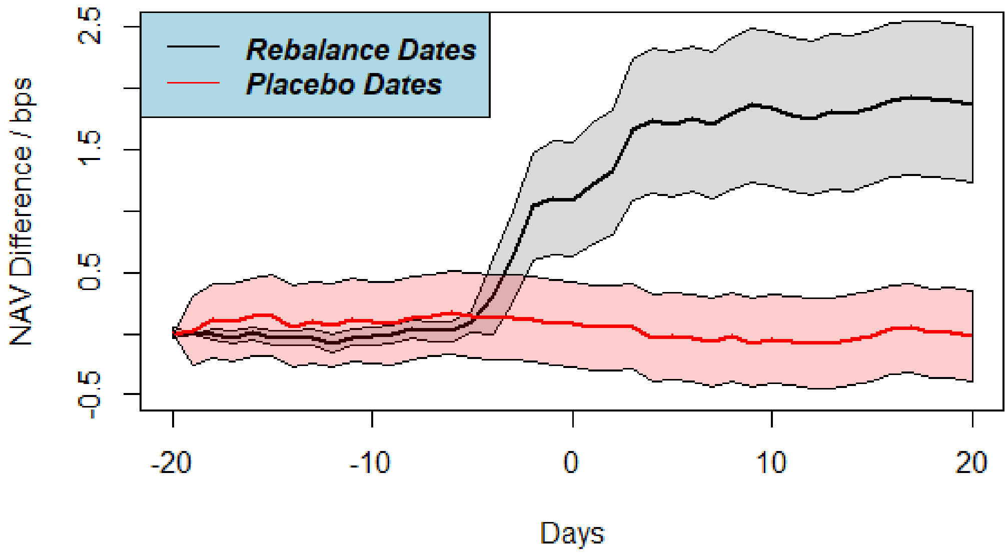
This table presents daily portfolio returns on betting against ETF rebalances. The portfolio longs the top 20% of stocks that will be purchased by ETFs over 4 days into the future and shorts the bottom 20% of stocks that will be sold by ETFs over 4 days into the future. For column (1) I regress the portfolio returns on constants, and for columns (2) and (3) I regress the portfolio returns on the returns of Fama-French 3 factors and Carhart 4 factors, respectively. Robust t-statistics are reported in square brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Figure 1
Stock returns around Sunshine ETF rebalance trades



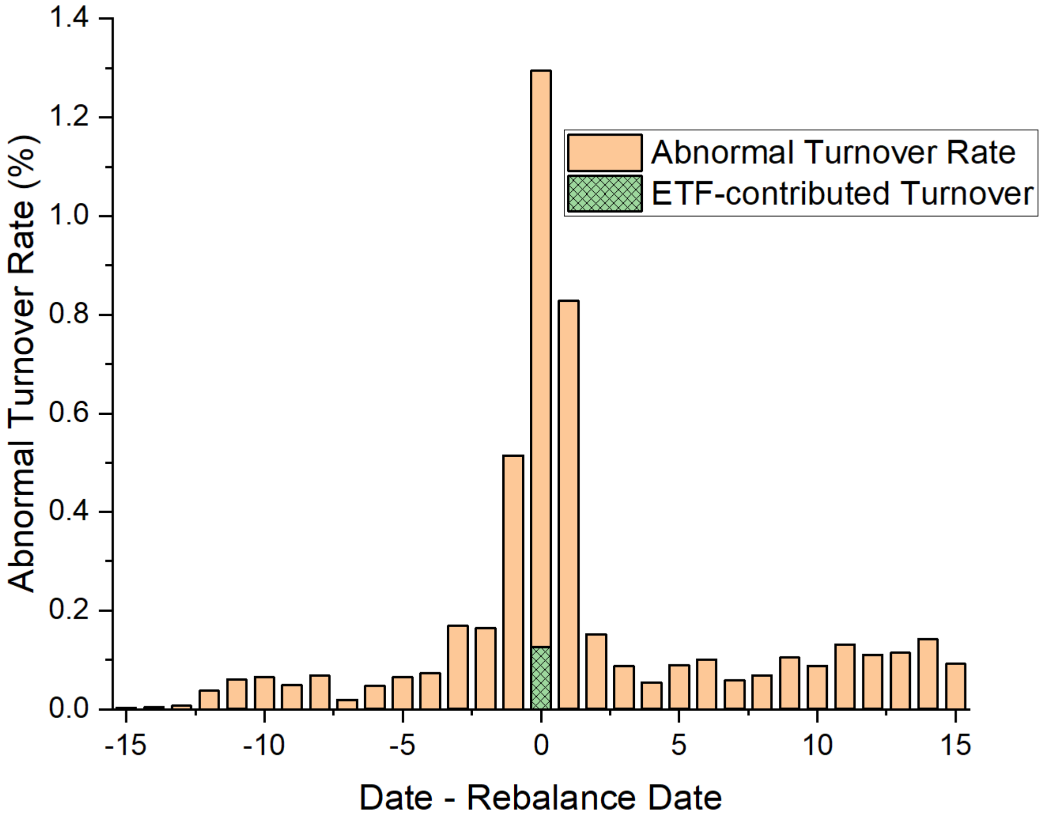
Large public indices announce a reconstitution at least 5 days prior to the ex-date. Sunshine ETFs mechanically follow the rebalance schedule set by large public indices, buying and selling the underlying stocks entirely on the rebalance ex-dates. This figure displays the trade-size weighted average cumulative adjusted return (CAR) on stocks being traded by those ETFs. The CAR is adjusted for Fama-French 5 factors as well as trading directions, i.e., multiplied by -1 for deletion events. The reference date T0 is set as the rebalance ex-date, and the CAR is normalized to 0 for that date. *Reads: Stock prices went up 67 bps before public indexed ETF buys and a reversal of 20 bps happens afterwards.*

Figure 2
NAV divergence of Sunshine and Opaque ETFs



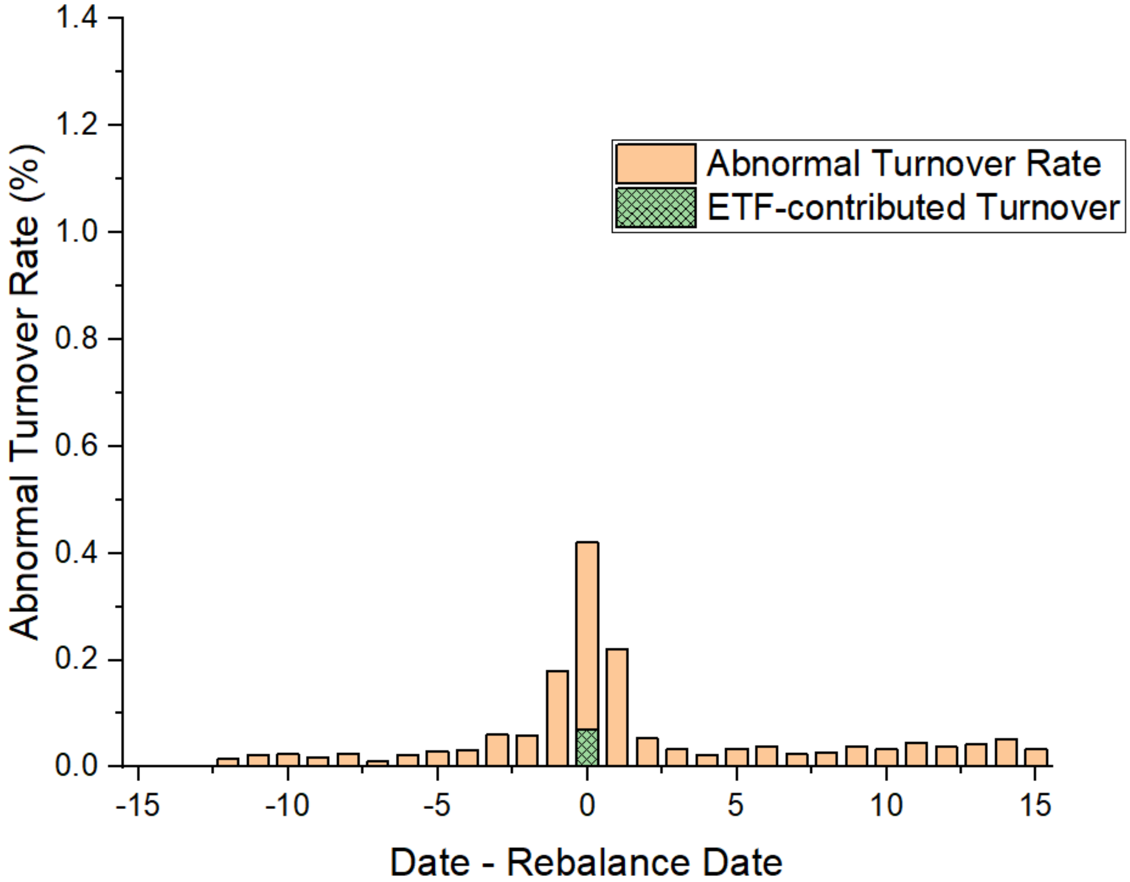
In this figure I plot the NAV divergence between Sunshine and Opaque ETFs around index rebalance ex-dates and placebo dates. The placebo dates are selected as 1 calendar month after the rebalance dates. I identify 16 pairs of Opaque and Sunshine ETFs that track the same publicly available index. I then calculate the daily pairwise NAV return differences between the ETFs and take the average across the 16 pairs. I then plot the cumulative NAV return differences adjusted for management-fee differences. The NAV differences around rebalance dates are shown in black (robust 95% confidence intervals are shown in grey), and the NAV differences around placebo dates are shown in red (robust 95% confidence intervals are shown in pink). The NAV differences are normalized to zero on date $T - 20$. *Reads: Opaque ETFs do not dump all their trading at the close of the rebalance date, so their NAVs outperform NAVs of Sunshine ETFs within* ± 5 *days around the index rebalance ex-date.*

Figure 3
Stock abnormal turnover rate and rebalance paces for Sunshine ETFs



In this figure I plot the abnormal turnover rates around rebalance dates and the contributions from rebalancing ETFs. The unshaded yellow bars represent abnormal turnover rates, which represent differences between turnover rates on a given day and the average turnover rates in $[T-60, T-30]$. The shaded green bars represent the turnover rate that is directly attributable to rebalancing ETFs' trades. The green bars are too small to be visible except on date T. The differences between the yellow and green bars reflect abnormal turnover from trades involving other market participants. *Reads: Sunshine ETFs trade only on rebalancing days, but rebalancing events attract more abnormal trading volume around rebalancing days. Even on rebalancing days, an ETF's rebalancing trade represents only 10% of abnormal trading activity, and most abnormal trading activities do not involve ETFs.*

Figure 4
Stock abnormal turnover rate and rebalance paces for Self-indexing ETFs



In this figure I plot abnormal turnover rates around rebalance dates and contributions from rebalancing Self-indexing ETFs. The unshaded yellow bars represent abnormal turnover rates, which represent the difference between turnover rates of a given day and the average turnover rates in $[T-60, T-30]$. The shaded green bars represent turnover rates that directly reflect the rebalancing ETFs' trades. The green bars are too small to be visible except on date T. The difference between the yellow and green bars reflect abnormal turnover from trades involving other market participants. *Reads: Self-indexing ETFs also trade only on rebalancing days, and rebalancing event attract less abnormal trading volume than rebalancing events for Sunshine ETFs.*