Should Passive Investors Actively Manage Their Trades?

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Abstract

Using a novel daily holding data of ETFs, I find most ETF's reconstitution trades are mechanical: the entire position is traded on the reconstitution day *at* the closing price. Since most ETFs track public indices that pre-announce their rebalances, the predictable large trade suffers from 67 bps of execution costs, three times higher than similar-sized institutional trades. Camouflaging on either *what* or *when* to trade can help save execution costs. 37% of ETFs use self-designed indices to avoid the pre-announcement of rebalancing stocks and save 30 bps. Another 7% of ETFs track public indices, but they camouflage on their rebalance schedules and save 34 bps. Deploying less predictable rebalance strategies can help passive investors to save 9.6 bps per year, which is about two-thirds of the management fees.

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

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I. Introduction

Passive investing has gained a great expansion in the past two decades, including the use of index mutual funds and exchange-traded funds (ETFs). The total asset under management (AUM) of index-tracking funds has come to 7 trillion dollars, or 33% of the U.S. stock market cap as of 2020. One of the most powerful insights that support passive investment is Sharpe (1991), which states that one active investor's gain is another active investor's loss, which aggregates to zero for all active investors. Therefore, after accounting for the hefty costs of active investing, passive funds will outperform active funds.

Yet the passive investment strategy implicitly assumed a static portfolio to hold, and the constituents in the portfolio never change. In reality, passive funds also need to trade due to index constituent changes in response to IPOs, M&A, and delists. The median portfolio turnover rate of U.S. indexed equity ETFs is 16% in the year 2020. For added/deleted stocks, the number of shares traded by the ETFs represents, on average, 1.14% of the daily trading volume of the stock. This paper evaluates the passive funds' efforts in minimizing trading costs. How *do* passive funds trade? How *should* they trade? These questions are largely unanswered because the mutual funds disclose their holdings in quarterly frequency. The ETFs, on the other hand, usually disclose their portfolio by the end of the trading day, which creates an ideal opportunity to evaluate the trading sophistication of index funds.

Using a novel daily holding data of ETFs, I identify 3 types of ETF trading strategies. The vast majority of ETFs use the "sunshine trading" strategy as Admati and Pfleiderer (1988) suggested. First, they track publicly available indices which announce the stock list to be added or deleted at least 5 days prior to the rebalance date. Second, they add and dump the stocks within only one day: the index rebalance day (but not the announcement day). Furthermore, I use the NAVs and daily portfolio compositions to reverse-engineer the *intraday* trading patterns of the ETFs, and I find almost all ETFs trade *at* the closing auction prices at 4 PM. Therefore, those ETFs' trades are abrupt in pace but fully predictable to other market participants. I find that these ETFs pay gigantic execution costs, as the stock prices rise before they buy and fall before they sell, and the price reversal happens after they trade. Figure 1 plots the stock returns around the ETFs' rebalance trades.

[Insert Figure 1 about here]

Two types of ETFs deviate from the public-indexing ETFs that use sunshine trading strategies. One way is to camouflage *when* will an ETF trades. Unlike other major ETF providers, Vanguard doesn't divulge the daily holdings of its stock ETFs. Instead, Vanguard's ETFs report only their month-end portfolios. Therefore, the trading pace of Vanguard ETFs is neither known to potential front-runners nor do they appear in my dataset. Fortunately, I am able to partially reverse engineer the Vanguard funds' rebalance schedules using its NAVs, and I find it uses alternative rebalance schedules. Specifically, I exploit the fact that some Vanguard ETFs track the identical index with some public-indexing ETFs sponsored by Blackrock. The pairwise NAVs correlation between Vanguard and Blackrock ETFs outside index rebalances windows are 0.999 because they track the same index and their portfolios are almost identical. However, during quarterly index reconstitution periods, their NAV correlation decreases to 0.97. Thus, the portfolio for the ETF pairs is largely identical outside the index rebalance windows, but Vanguard ETFs diverge from the index during the rebalance periods. [1]

[Insert Figure 2 about here]

To further identify Vanguard ETFs' trading schedule, I plot the pairwise NAV difference between Vanguard and Blackrock funds during the rebalance periods and placebo periods in Figure 2. Figure 2 shows that the Vanguard ETFs outperform Blackrock ETFs during the [T-5, T+5] period of index quarterly rebalancing dates, while the NAV difference is largely unchanged during other periods. Therefore, since the returns are different in the [T-5, T] period, it is evident that the Vanguard ETFs performed some rebalances before the index rebalancing date. Since the returns continue to diverge in the [T, T+5] period, it is evident that the Vanguard ETFs have also delayed some rebalance trades, too. On average, the

[1] Blackrock ETFs' portfolios are daily disclosed, and I find the portfolio fully replicates the index and strictly follows the index rebalance schedule.

camouflaged rebalancing schedule for Vanguard ETFs saved 1.8 basis points (bps) per quarter or 7.3 bps per year.

The second set of ETFs (that deviate from sunshine trading) camouflage *what* do they trade. Instead of using index companies, they invent their own indices to track. For example, the Schwab 1000 ETF tracks the Schwab 1000 Index, which is 99% correlated to 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 subscription to external investors, nor does it announce the stocks to be rebalanced before the rebalance happens. Therefore, the ETF's rebalancing trades are less vulnerable to front-runners. Indeed, I find the self-indexing ETFs' rebalance cost is 30 bps-per-trade lower than ETFs that track publicly available indices. Considering the 16% turnover rate of ETFs, the annual rebalance cost saving for these ETFs is $16\% \times 2 \times 30 = 9.6$ bps. The results are robust after controlling for rebalancing sizes and various fixed effects. Therefore, camouflage on *what* to trade also helps reducing execution costs for ETFs. For the $7 Trillion passive investment business in the U.S., if 56% of them are public-indexers, $3.9 billion of rebalancing cost can be saved with smarter rebalancing strategies.

My paper contributes to the literature on trade transparency. On one hand, Admati and Pfleiderer (1991) suggest that uninformed traders can pre-announce their trades to lower price impact. In their one-period model, the pre-announcement helped market participants to better estimate the size of informed order flow, so the market becomes more liquid. On the other hand, the Brunnermeier and Pedersen (2005) continuous-time model suggests that strategic traders ("predators") can front-run liquidity traders, i.e. sell before the liquidity trader and buy back later at a lower price. Thus, it becomes an empirical question on which effect is stronger. For example, Bessembinder et al. (2016) find that Crude Oil futures traders supply liquidity to U.S. Oil Fund's predictable trades.

However, establishing identification strategies to test the models is empirically challenging: given a transparent trade, it is hard to answer "what if" the trader had conducted the trade in a camouflaged way. I contribute to the literature by examining the ETF pairs that track the same index, therefore face the same trading problem. Moreover, the trading problem is separated from the underlying investment decisions, because the ETF managers do not make investment decisions. Therefore, the different trading approach of Vanguard and Blackrock provides a clean head-to-head comparison and shed light on the "what if" question. Since the NAVs of Vanguard and Blackrock ETFs diverge *only* around the index rebalancing periods, Vanguard's approach of camouflaging the trading schedule appears to have a lower trading cost than the sunshine trader (Blackrock).

In the view of textbook theories, the price of a stock is an unbiased estimator of the stock's fundamental value. With an investment universe consists of tens of thousands of stocks, the idiosyncratic risk of a single security is negligible, and the investors are able to arbitrage away any mispricing of a stock. In this view, the stock prices are perfectly elastic to uninformed supply and demand shocks. Yet there is a long literature on the inelastic demand curve of stocks. [2] For example, Shleifer (1986) finds that stock additions into the S&P 500 Index have a significant positive abnormal return at the *announcement* of the inclusion. Koijen and Gabaix (2021) find that investing $1 in the stock market increases the market's aggregate value by as high as $5. My paper provides the first exhaustive study across hundreds of benchmark indices. Since I can see the actual trading activity of index funds, I find that the abnormal return peaked around the trade execution dates. Also, my results indicate that shock in the asset prices due to large demands is partially permanent and partially transitory: As Figure 1 shows, the prices moved 67 bps before the execution date and a reversal of 20 bps happened afterward (trading volume weighted). The volume-weighted ETF trade size in my sample is 0.39% of the market cap, so for each $1 traded by the ETF, it created $\frac{0.67\%}{0.39\%} = 1.72$ dollars change in the underlying stock's market cap.

My paper also contributes to the literature measuring institutional traders' execution costs. Anand et al. (2012) use the Ancerno data estimates the execution shortfall of 24 bps for institutional orders sized 2.4% ADV. In Di Maggio et al. (2019), the price impact is 10.52 bps for 0.5% ADV. I document 67 bps of

[2] 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.

execution shortfall for those mechanical ETF rebalance trades. Considering the average ETF rebalances size is 1.14% ADV, 67 bps should be considered very large, indicating poor execution strategies. More interestingly, index reconstitutions are generally not driven by private information possessed by the index compilers, so it is striking that these ETFs pay higher execution costs than potentially informed traders. This surprising finding, however, echoes Collin-Dufresne and Fos (2015), who find that informed traders pay lower execution costs because they select times of higher liquidity to trade. In this paper, the uninformed traders pay higher execution costs because they do *not* time the liquidity. If optimized properly, uninformed ETF flows should have been able to get lower execution costs than potentially informed traders.

This paper also adds to the literature of the impact of passive investment flows on the cross-section of equity prices including Frazzini and Lamont (2008), Lou (2012), Ben-David et al. (2018), and Chinco and Fos (2021). The most related paper is Ben-David et al. (2018), who find that higher ETF holdings for a stock will lead to higher return volatilities. The authors conjecture that the liquidity shocks from short-horizon liquidity traders on ETFs can propagate to the underlying stocks, so ETFs may increase the nonfundamental volatility of the securities in their baskets. My paper provides a micro foundation to their findings, as I find the trading behaviors of most ETF managers are mechanical and abrupt. Either intentional or not, 93% of ETFs fully add/dump a stock within 1 day *at* the closing auction price. The rebalance events incite abnormal trading volumes that are tens of times larger than the size of rebalancing trades themselves. Therefore, the sub-optimal execution of the passive funds not only costs their own investors but also significantly affects the underlying stocks.

The trading cost of mechanical rebalance is large in many senses. First, it is comparable to the total management fee charged by ETF managers. Deploying the mechanical, predictable rebalance strategies costs ETFs about 30 bps per trade more than those ETFs who camouflage their trades. The 30 bps of one-way saving combined with 16% average turnover rate of passive funds translate to 9.6 bps of round-trip savings per year. For the $7 Trillion passive investment business, assuming 56% of them are not rebalancing optimally, $3.9 billion of rebalancing cost can 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% of the management fees. Another comparable number is that the cost for the indexing companies in developing the indices is only ~1 bps per year. [3] The index licensing fee is about 3 bps, while the hidden cost in using publicly available indices is three times larger. Finally, for a $2 million retirement account accrued over 30 years, fail to save 9.6 bps per year translates to $29 thousand of losses at retirement.

The paper proceeds as follows. Section II describes the data and provides summary statistics on the ETFs and rebalancing trades. Section III calculates and reverse engineers the trading pace of ETFs. Section IV evaluates the public-indexing ETFs' execution costs. Section V comparisons between self-indexing ETFs and public-indexing ETFs. Section VI conducts pairwise comparisons between Vanguard and Blackrock funds. Section VII discusses possible interpretations that drive the heterogenous trading behaviors among ETFs. Section VIII concludes.

II. Data and Summary Statistics for ETF Rebalance Trades

I use the ETF Global data for daily holdings of ETFs. The data covers all U.S. and Canada listed ETFs in 2012 – 2020 and records the daily holdings for all non-Vanguard ETFs. [4] Therefore, the data provides a unique opportunity to assess the trading behavior of institutional traders because the traditional 13-F holding data is quarterly. The data also provides 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. I compliment the data with the CRSP and the millisecond Trade and Quote (TAQ) data.

[3] Source: S&P Dow Jones Indices LLC annual report 2020.
[4] Again, Vanguard ETFs only report the holdings on month-end days, with a 15-day lag.

A. Summary Statistics of ETFs

I focus on the unlevered passive ETFs that list and invest in the U.S. equity market. Specifically, I require an ETF to have a leverage ratio equals to 1 to exclude leveraged ETFs. [5] I require an ETF's asset class to be "Equity" to exclude fixed income and commodity funds. I require an ETF's investment region equals to "North America" and its currency exposure for USD to be larger than 0.8 to pick funds that mainly invest in U.S. equity markets. [6] When the currency exposure is missing, I hand-pick the ETFs based on the fund name to exclude funds that focus on Canada and Mexico. To exclude active funds, I require an ETF's active management dummy equals to zero and the fund focus is not "alpha-seeking". I end up with 732 ETFs, and Table 1 presents their summary statistics.

[Insert Table 1 about here]

B. Summary Statistics of Rebalance Trades of Non-Vanguard ETFs

This subsection constructs the sample of ETF trades from the daily holding data. For each trading day in my sample, I compare each ETF's stock holdings with the day before. Specifically, I record the first appearance date of a stock as the addition day of a stock 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. [7] I require the stock being added or deleted has a continuous appearance in the dataset for at least 60 days to avoid data irregularities. [8] I merge the addition/deletion events with the CRSP for stock prices

[5] Leveraged ETFs often choose not to hold or trade the underlying stocks. Instead, they use swaps and other derivatives to achieve intended market exposure. The derivatives usually directly track the underlying index. Similar to the public-indexed ETFs, the indices *per se* also use a mechanical 1-day rebalance schedule. Thus, public-indexed leverage ETFs also suffer from the costly rebalances. Nevertheless, leveraged ETFs have much lower AUMs than unlevered ones, and I exclude them from my sample.

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

[7] Here I focus on the cleanest addition/deletion events for my studies and exclude constituent weight changes. This is very likely an underestimation of ETF turnovers (and their annual trading costs in dollar terms), as the index weight of a stock can changes due to share buy backs, SEOs, and *other* stocks' addition and deletion from/to the index.

[8] The number of 60 is selected because index rebalances could be as frequent as quarterly.

and stock characteristics. In addition, I merge the data with the millisecond TAQ data for stock intraday prices and liquidity measures. I exclude observations that can't find a match based on the ticker and CUSIP, then winsorize the data at the 0.01 level on both sides. I end up with 122,492 addition and deletion events in 9 years. Table 2 presents the summary statistics of the addition/deletion events. The median rebalance represents 0.01% of the stock's market cap or 1.14% of the stock's trading volume on the rebalance day.

[Insert Table 2 about here]

III. Rebalance Paces of non-Vanguard ETFs

This section documents the rebalance patterns for public-indexed ETFs and self-indexers. For these ETFs, my data provides daily portfolio holdings, and I compare the holdings of two consecutive days to calculate the daily trades for each ticker. Subsection III.A summarizes the rebalancing pace of ETFs and compares it with the abnormal trading volumes around the rebalancing date.

Detailed daily holding data provides a unique opportunity to detect the *intraday* trading pattern of ETFs. Although the ETFs do not disclose when do they trade within the rebalance day, different trade timing would lead to different end-of-day NAVs. Thus, subsection III.B reverse engineer the intraday trading patterns of public ETFs and self-indexers and find they systematically trade at close prices.

Vanguard ETFs only report their holdings on month-end days, making it harder to infer their rebalance paces. Fortunately, Vanguard ETFs follow public indices, and there exist ETFs advised by Blackrock that track the same indices. In Section VI, I use a different methodology to reverse engineer the rebalance strategy of Vanguard ETFs.

A. Rebalance Trade Paces for non-Vanguard funds

In this subsection, I evaluate the rebalance paces of non-Vanguard ETFs' trades. For addition events, the first day for a stock to appear in the portfolio of ETF is called date T. For deletion events, the day following the last day for a stock to appear in the portfolio of ETF is called 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 of ETF i on stock j in 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 CRSP.
2. Denote the stock's total trading volume recorded on CRSP is $VOL_{j,T+k}$. The regular trading volume on date $[T - 60, T - 30]$ 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 directly traded by the ETF.

[Insert Figure 3 about here]

Figure 3 leads to several interesting empirical findings. First, the shaded green bar(s) plot the turnover rates directly due to the ETFs' trades, yet the only visible green bar is on the date T. In other words, the ETFs almost always use a 1-day trade schedule, and they do not spread their trades to multiple trading days. Second, the unshaded yellow bars plot the general abnormal turnover rates around date T. In contrast to the ETFs' abrupt 1-day trading schedule, there is a remarkable amount of abnormal trading volume around date T. In other words, the ETFs' rebalance trades stimulated other market participants to trade more. [9] Third, the ETFs' trade size accounts for only about one-tenth of the abnormal trading volume on date T, indicating the strong market impact of ETF reconstitution trades.

[9] Those market participants might be index reconstitution arbitragers, front-runners, or investors that are encouraged by the index reconstitution news.

B. Intraday Trade Timing for non-Vanguard funds

Daily portfolio holdings reports allow me to reverse engineer the intraday trading pattern of ETFs. This task is econometrically challenging because the action space of ETFs is gigantic: they could have traded any stock at any moment within a day. On the other hand, I can only observe the day-end portfolios and NAVs with $0.01 accuracy. In other words, the ETFs' action space has a higher dimension than the number of known variables.

Although the exact trading time and price of a specific ETF-stock-day is undeterminable, I have ample rebalance events to infer the average timing of the ETF trades. Specifically, I make hypotheses on the trading time of the ETF (e.g. open, intraday time-weighted average price, 1 PM, and close) and calculate the hypothetical day-end NAVs. The best hypothesis should lead to the best guess of true NAVs. Therefore, I measure the prediction accuracy of these hypothetical NAVs and make statistical inferences on the intraday trading pattern of ETFs.

The first step is to build true NAV returns before 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:

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

Then, I build the hypothetical returns based on different trade timing hypotheses. The correct hypothesis on the trading time should lead to a precise estimation of the gross-fee return. Denote the day-end holding for ETF i on stock j in day t is $H_{i,j,t}$ shares. I denote the price of stock j in day t at time τ as $P_{j,t,\tau}$, where τ can be OPEN, VWAP, and CLOSE. [10] Therefore, for the stock j in day t being traded at time τ, it contributed a dollar Profit and Loss of:

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

[10] VWAP is the volume-weighted-average-price of the continuous trading session (9:30 – 16:00), excluding open and close auctions. It indicates that the ETF spread out the trade throughout the day.

For stock j that has not been traded in 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 of 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 at date $t-1$. Thus, $HypRet_{i,t,\tau}$ is the reverse-engineered gross-fee return of the ETF.

Suppose the ETF i on date t chooses to trade α portion of their rebalance trade 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, the prediction can be very noisy due to rounding errors in NAVs, fund-flows, and data errors. [11] Taken all observations together, though, the prediction errors should be asymptotically small. I run the following regression to see the average rebalance pattern of 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 ETF and day level. Table 3 shows the regression result.

[Insert Table 3 about here]

Table 3 shows that γ is not statistically significantly different to 1, and α and β are not statistically significantly different to 0. The results are not different between public-indexers and self-indexers. Therefore, the hypothesis that all non-

[11] There are 1.2% of observations where all three hypothetical portfolios' predictions are off by more than 10 bps. To minimize the impact of data errors, I exclude observations where: (1) all three hypothetical portfolios' predictions are off by more than 10 bps, and (2) $GrossRet_{i,t}$ is not explainable by any combination of $\alpha, \beta, \gamma > 0$. In other words, $GrossRet_{i,t}$ is either greater than $\max\left(HypRet_{i,t,\tau}\right)$ or smaller than $\min\left(HypRet_{i,t,\tau}\right)$ for any hypothetical τ, which is clearly erroneous.

Vanguard ETFs are rebalancing at the closing auction is not rejected. [12] Throughout this paper, I use the closing price of the 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 reasons indicate that it is unlikely to have heterogeneous trading schedules across ETFs. First, the R-squared of the regressions is more than 0.999, which indicates that the current fit is very good, allowing almost no outliers. Second, if there exists a subset of ETFs or dates that systematically have 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 have α and β *smaller* than zero. However, $\alpha, \beta < 0$ means that when those ETFs want to buy a stock, they must short sell the stock in the open auction/VWAP prices and buy back more shares at the closing prices. Such actions are deemed to be economically unlikely for ETFs. [13]

IV. Rebalancing Cost of Public-Indexed ETFs

In this section, I measure the execution costs of public-indexed ETFs. To be comparable to the execution cost literature, I use two measures to evaluate the execution costs of the ETFs. The first is the execution shortfall (also called "slippage"), which is the difference between the decision price and the final execution price for a trade. Execution shortfall measures the adverse price movements after the trading intent is expressed to the market and before the trade happens. The second is the price impact, which is the difference between the execution price and the price at a certain future time. Price impact measures the price movements after the trade.

A. Definition of the Execution Shortfall

All major index companies announce the reconstitution decisions at least 5 days

[12] This result is consistent with Bogousslavsky and Muravyev (2021) who find that a higher ETF ownership can lead to higher distortion in the closing auction prices.
[13] Such "sell to buy" behavior is surprisingly possible under certain circumstances for sophisticated traders who optimize their order executions (Back and Baruch 2004). ETFs arguably do not have such sophistication.

before the reconstitution happens. Therefore, I 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.[14] $P_{j,T-5}$ is the closing price of the stock on date $T-5$. $Direction_{i,j,T}$ is 1 for addition events and -1 for deletion events. Therefore, a positive $ES_{i,j,T}$ indicates that the ETF paid a worse price than the price when the trade is determined.

B. Definition of the Price Impact

The price impact is traditionally being used to measure the informativeness of a trader. 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 (compare to conducting the trade H days later).

C. The Rebalancing Cost of ETFs

Figure 1 shows that the execution shortfall of public ETFs is 67 bps [t=14.49], and their price impact is -20 bps [t=-3.56] because the price reversal happens after the ETF buy trade happens. Although these results do not come with identification, the gigantic magnitudes already indicate a large room for ETFs to improve. In the next section, I compare the execution costs for public ETFs and self-indexers.

VI. Rebalancing Cost of ETFs that Track Alternative Indices

[14] 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.

ETF benchmarks with larger index brands are able to attract more capital from investors (Kostovetsky and Warner 2021). Yet there's a major drawback: everyone else can subscribe to a large branded index, too. Since the public index rebalances are announced at least 5 days before the rebalance date, there is sufficient time for the other traders to buy or sell ahead of the ETFs. In this section, I explore ETFs that camouflage *what* do they trade by tracking alternative indices that are less transparent to external traders.

I find 37% of ETFs in my sample choose not to track indices from large index companies. Instead, these ETFs track private indices, usually 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 roughly the largest 1000 stocks listed on the U.S. market. Its return series is 99%+ correlated to both the S&P 500 ETF (SPY) and the Russell 1000 ETF (IWB). One of the most important distinctions is that the Schwab 1000 Index is not open for subscription, so the external traders can only guess on what stock will be added and deleted in an index reconstitution. [15] Therefore, the self-indexing ETFs disguised their trading intents from front-runners. In subsection VI.A, I will provide more institutional details on self-indexing rules and present summary statistics. In subsection VI.B, I evaluate whether the self-indexing ETFs are successful in lowering their trading costs.

A. Self-Indexing ETFs

In a series of exemptive orders, [16] the SEC allowed self-indexing ETFs to use affiliated index providers to compile their benchmark indices. Furthermore, the underlying index methodology and index components are not required to be

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[15] Certainly, other traders certainly *can* guess on what stocks will be added and deleted, either based on the ETF's (potentially out-dated) self-indexing methodology or the ETF's historical rebalance patterns. Such guesses are arguably less accurate, which add substantial risks to front-runners and discourages front-running activities.

[16] 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).

publicly disclosed. Therefore, self-indexers are more advantageous in camouflaging *what* they will trade. Meanwhile, the SEC requires all self-indexing ETFs to disclose their daily portfolios for additional transparency. Thus, it is impossible for the self-indexers to simultaneously camouflaging on *what* and *when* they trade. [17]

To identify self-indexing ETFs, I parse the "benchmark index" column 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 index includes its own investment adviser's name, 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 the benchmark index compiler. I end up with 265 self-indexing ETFs.

B. Costs for Rebalancing: Self-indexing ETFs vs. Non-affiliated Index ETFs

In this subsection, I compare the cost of rebalancing the difference between self-indexing ETFs and ETFs that use non-affiliated indices. First, I present the summary statistics of the two types of ETFs in Table 4.

[Insert Table 4 about here]

Table 4 shows that the self-indexing ETFs are generally smaller, less liquid, incepted later, and charge higher expense ratios. Then, I run the following regressions to evaluate the effectiveness of self-indexing on saving the execution costs:

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

where i is the index of the stock being rebalanced, j is the index of the ETF, and t is the index of rebalancing date. Considering that the self-indexing ETFs' rebalances might be smaller, the control variables include the log(rebalancing size)

[17] ETFs that use unaffiliated public index compilers are not required to disclose their daily holdings. Although most ETFs (sunshine traders) disclose the daily holdings anyway, Vanguard ETFs choose be secretive on their daily holdings, and I'll analysis Vanguard's strategy in Section VI.

of the trade. I also control for log(market cap), log(price), and the rebalancing direction, as well as η_i as the stock fixed effect and ξ_t as the year fixed effect. Recall that section III.C shows that there's almost no daily-disclosing ETFs systematically choose a rebalance schedule that deviates from 1-day rebalancing. This is true both for the public-indexers and self-indexers. [18] Therefore, the stock returns around date T are also roughly the same as the actual execution costs of self-indexing ETFs. I use execution shortfalls and the negative price impacts as the measure of execution costs. Standard errors are clustered at the stock level and year level. The coefficient of interest is θ, which is the extra execution cost paid by ETFs who use public indices. Table 5 presents the regression results.

[Insert Table 5 about here]

Table 5 shows that the execution cost for public indexed ETFs is higher than self-indexers, and the results are robust under various controls and fixed effects. The execution shortfall result in column (2) indicates that the average adverse price movements before self-indexing ETFs' trades is 14 bps lower than public indexed ETFs. The price reversals after the rebalance trades are even higher than the execution shortfall: 19 bps at the 20 days horizon (Column 4) and 30 bps at the 60 days horizon (Column 6). Therefore, self-indexers have lower execution costs than public indexed ETFs.

IV. Rebalancing Patterns and Costs of Vanguard ETFs

There are two distinct views regarding the impact of ETF portfolio and trade transparency on execution costs. On one hand, most ETF advisors believed that the transparency associated with the daily ETF holding reports does not necessarily lead to worse investment outcomes. Therefore, they 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 publishes only month-end portfolio data

[18] Section VII will discuss on the possible reasons of why the self-indexers do not use alternative (multi-day) rebalance schedules.

with a 15-day lag. In this section, I directly compare the trading outcomes of these two approaches.

A. Matched ETF Pairs

For each benchmark index of a Vanguard ETF, I exhaustively search for non-Vanguard ETFs that are exactly tracking the *same* index. Therefore, the NAV and daily holdings of the matched ETF can be the benchmark for the Vanguard ETF. The search ends up with 16 pairs of ETFs between Vanguard and Blackrock.[19] Table 6 presents the matched ETF pairs.

[Insert Table 6 about here]

Table 6 lists the ETF pairs that track the same indices. As a sanity check of the matching, I calculate the NAV return correlation between Vanguard and Blackrock funds. I obtain a correlation coefficient of at least 0.999 for all pairs of ETFs. Table 7 presents the summary statistics of Vanguard and Blackrock funds.

[Insert Table 7 about here]

B. Excess Return of Using the Vanguard Rebalance Strategy

Since Vanguard camouflaged on its rebalance trades and uses alternative rebalance schedules, a natural question is whether Vanguard succeeded in saving execution costs. This section evaluates the trading results of Vanguard funds by calculating the NAV differences between the funds. Although I do not have daily holdings of Vanguard ETFs, it is enough to partially reverse engineer the strategies that Vanguard uses. Specifically, I pull the NAV returns from the CRSP mutual fund database for each ETF-day, then I calculate the pairwise NAV return difference adjusted the management fee:

$$ReturnDiff_{i,t} = GrossRetVanguard_{i,t} - GrossRetBlackrock_{i,t},$$

where i is the index for ETF pairs and t is the index for the date. $GrossRetVanguard$ ($GrossRetBlackrock$) is the NAV return for the Vanguard (Blackrock) fund added back with the management fee charged on that day. Since

[19] State Street also has 6 ETFs that track the same index with one of those 16 ETF pairs. Replacing Blackrock with State Street for those 6 ETFs lead to almost identical results.

the management fee are charged daily, the number added back is the annual management fee divided by the number of trading days in the year. In non-rebalancing times, the Vanguard and Blackrock funds hold the same portfolio, and the $ReturnDiff$ should be around zero. [20] In rebalancing episodes, 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 Blackrock fund or the placebo date, which are set as 1 calendar month after the rebalance dates. The cumulation starts 20 days before the 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 the Vanguard funds outperform BlackRock funds by 1.8 bps around the rebalance dates. Since the rebalance is scheduled quarterly, this outperformance translates to 7.3 bps of annual returns. I find that Vanguard's portfolio returns diverge with Blackrocks' *only* during the quarterly index reconstitution periods, and the cumulative return difference remained at zero around placebo dates. This further proves that Vanguard used alternative rebalance schedules relative to the underlying index and peer ETFs. [21] Around Blackrock rebalance dates, the return divergence does not happen until $T-5$, which coincides with the index reconstitution announcement date. The divergence ends around $T+5$, indicating that the Vanguard rebalances its ETFs' portfolio in the $[T-5, T+5]$ interval.

C. Risk-Return Tradeoff of Using the Vanguard Rebalance Strategy

[20] 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 underlying true NAVs are not "rounded".

[21] As an anecdotal evidence, Doug Yones, Vanguard's head of domestic equity indexing and ETF product management, says that Vanguard "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.

How large is the risk in camouflaging the portfolio and using alternative rebalance strategies? I measure the risk-return tradeoff with the information ratio, which is defined as:

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

In my calculation, the portfolio return is the Vanguard funds' NAV returns $GrossRetVanguard_{i,t}$, and I use Blackrock ETFs' returns $GrossRetBlackrock_{i,t}$ as the proxy of the return of the benchmark index. The denominator is the standard deviation of $ReturnDiff_{i,t}$. I find the annualized standard deviation of $ReturnDiff_{i,t}$ is 10.6 bps. Combine with the 7.3 bps of annual return, the Vanguard has an information ratio of 7.3/10.6 = 0.69 during index reconstitutions. The information ratio should be considered very appealing to regular ETF investors. As a comparison, Warren Buffett's information ratio is 0.64 (Frazzini, Kabiller, and Pedersen 2018). To be fair, the information ratio sustains only 10 days per quarter, consists of only 13% of the portfolio (the annual turnover rate of the Vanguard ETFs), and can hardly be arbitraged directly. [22] 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 profit of other market participants who trade against the index rebalances. [23]

VII. Interpretations of Results

The last three sections evaluated the order execution costs of three types: mechanical public-index followers, public-indexed ETFs who hide their rebalance schedules, and self-indexers who hide their underlying rebalance stocks. The last two categories have lower execution costs than the first category. Why the ETFs in the first category does not camouflage their trades? Why there's no ETF camouflage on *both* what and when they trade (which is a common practice for most traders)? In this section, I discuss several possible answers to these questions.

[22] The cost of buying Vanguard ETFs while short selling Blackrock ETFs can easily overwhelm the difference of 7.3 bps per year.

[23] As far as I am concerned, although index reconstitutions can be modified or cancelled, it has never happened in the [T-5, T] interval, so there's no survivorship bias in my calculation, and the front-runners are subject to almost no reconstitution cancellation risks.

Then, I perform back-of-envelop calculations on the magnitudes of optimal trading for passive funds.

A. Why most ETFs does not camouflage their trades?

So, why do 57% of ETFs insist to track the public indices and use the abrupt rebalance strategy? Kostovetsky and Warner (2021) answer the first half of the question: ETF that benchmarks with larger index brands can attract more capital from investors. Here I discuss the possible answers of on second half of the question: what discouraged most ETFs from adopting Vanguard-like rebalance strategies?

The first possible answer is the agency issue between ETF managers and their clients. Unlike hedge funds managers who usually share the profit of the fund, ETF managers are not compensated by 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). [24] Yet ETF managers charge a fixed amount of management fee, so they have less incentive in deploying those strategies to minimize execution costs. [25] It is worth point out that the marginal cost of routing a rebalance order to a broker's execution algorithm is at least an order of magnitude less than 67 bps. If cost-saving is the only reason, the agency issue is in its extreme form.

The second possible answer is that the ETFs aim to minimize their tracking errors. ETF managers might be concerned that a high tracking error could falsely signal a low management ability, therefore negatively affecting its fund flows. [26] Therefore, ETF managers are inclined to mechanically follow the index change at

[24] Minimizing transaction cost is a huge topic for practitioners. 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), and use atomic clocks (Baldauf and Mollner 2020) to minimize transaction costs and avoid being exploited by front-runners.

[25] Rather, they are quite sophisticated in minimizing their ETFs' operation costs. In my sample, passive ETF managers, on average, manage 6.98 ETFs. Therefore, it's hard for managers to customize trading strategies for each ETFs they manage. The most extreme case is that one manager being allocated to oversee 38 ETFs. (See https://www.vaneck.com/wsj-exchange-traded-funds-what-etf-managers-do-pdf.) Active ETF managers, on average, manage only 1.38 ETFs.

[26] Communication with practitioners indicates that some ETF managers are even explicitly compensated based on how close they get to their benchmark indices.

any cost. This argument is also a type of agency issue because mechanically following the index is arguably not in the best interest of the ETF holders. As section VI.B shows, the alternative rebalance schedule has an information ratio of as high as 0.69 during index reconstitution periods. A regular ETF holder should not have an extreme risk aversion that rejects such a good deal with a relatively small risk. [27] If tracking error minimization is the reason for mechanical rebalance trades, it is probably a good idea to design an index with a multi-day rebalance schedule. [28]

B. Why do self-indexers also choose to abruptly trade?

One rationale for the abruptly trading pattern of self-indexers is the daily portfolio report requirement of self-indexers. Since the SEC requires self-indexers to publish their portfolios at daily frequency, it essentially forbids passive ETFs in camouflage on *both* what and when they trade. If a self-indexing ETF wants to gradually rebalance its portfolio, its trade is a secret only for the first trading day. Then, its trade intention will 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.

Nevertheless, the daily portfolio reporting requirement does not forbid self-indexers in optimizing their trades *within* the rebalance date. Yet Section III.C finds that self-indexers do not spread out their trades in intraday trading. This result suggests that the self-indexers also paid limited attention to optimizing their trades. Therefore, the self-indexers may also suffer from the agency issue to some degree, i.e. their managers are not compensated by beating the benchmark indices. There exist other incentives for ETF managers to avoid using public indices. The most cited reason is the hefty licensing fee of branded public indices (Kostovetsky and

[27] Given the fact that the investor has put her money into a volatile equity ETF, she should not have such an extreme risk aversion profile in the first place.

[28] Such initiatives require collaboration among 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, decades before the inception of the passive funds that tracks it.

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 tracking the S&P indices. The cost of developing these indices is only 1.0 bps per year. By using "in-house" indices, the ETF managers can pocket the difference of 2.2 bps. More likely than not, the execution-cost saving is a byproduct of self-indexing, although the saving in execution costs (which goes to investors) is three times larger than saving in licensing fees.

C. Economic Magnitudes

In section VI, I show that the Vanguard ETFs are able to save 7.3 bps per year compare to their counterparties who track the same indices. In this section, the saving is 30 bps per trade or 9.6 bps per year for the median fund with a 16% turnover rate. These numbers represent a substantial cost of passive investments. As a comparison, the AUM-weighted ETFs' management fee is only 15.1 bps. Therefore, the execution costs (not including brokerage fees, exchange fees) represent as much as 60% of the fee charged by the ETF manager. [29] For the $7 Trillion passive investment business, assuming 56% of them are not rebalancing optimally, the potential annual saving of deploying smarter rebalancing strategies comes to $3.9 billion. [30]

VIII. Conclusion

This paper evaluates the trading behaviors of passive-investing ETFs and their transaction costs. I find 57% of ETFs follow mechanical trading strategies that abruptly rebalance *at* the closing price of the index reconstitution date, although their trading dates and tickers are both publicly known 5 days before the reconstitution. These ETFs experience a hefty 67 bps of execution shortfall for their trades. The high cost is especially surprising because ETF rebalances trades are

[29] Employing a slightly more sophisticated order execution strategies almost certainly would not take 60% more efforts from the index ETF manager. As an indicative evidence, the 16 Vanguard funds in section VI charge similar management fees with their counterparties.

[30] 56% is the percent of ETFs that track public indices and use mechanical rebalance strategies. It is a conservative estimation because the branded public index trackers are usually larger than self-indexers.

generally rule-based and not information-driven. Due to the poor execution strategies, these uninformed mechanical traders are paying higher execution costs than informed traders.

Either camouflaging *what* or *when* to trade leads to lower transaction costs of ETFs. 37% of ETFs choose to track private indices to hide their trading interests. 7% ETFs are managed by Vanguard, who camouflage on the schedule of rebalancing and use alternative rebalance paces. The savings per trade of these two approaches are about 30 bps, which translates to about 9.6 bps per year of the AUM. For the $7 Trillion passive investment business in the U.S., assuming 56% of them are not rebalancing optimally, $3.9 billion of rebalancing costs can be saved with smarter rebalancing strategies.

For every complex problem, there is an answer that is clear, simple, and wrong. The optimal order execution problem is complex for all market participants, so large buy-side institutional traders usually develop complex algorithms to execute their trades (Li, Wang, and Ye, 2021). This paper is not intended to persuade low-cost ETF managers to adopt state-of-art technologies in executing their orders. Rather, I show evidence that simply camouflages either on the timing or the underlying stock of the trade can lead to great savings. Mechanically following the index reconstitution is not the right answer to the optimal order execution problem.

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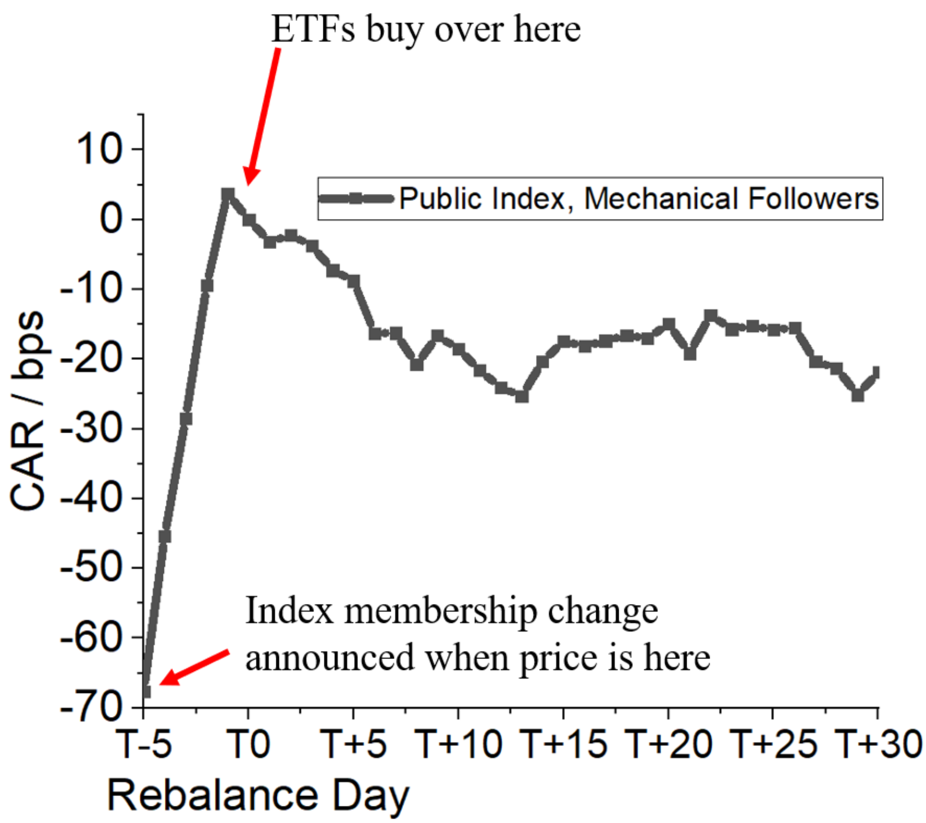
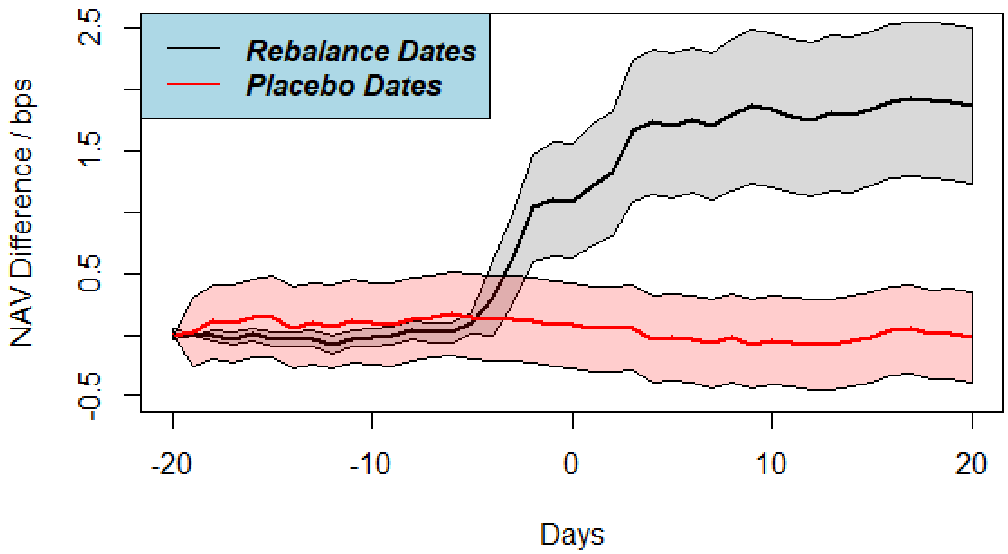
Figure 1
Stock returns around ETF rebalance trades



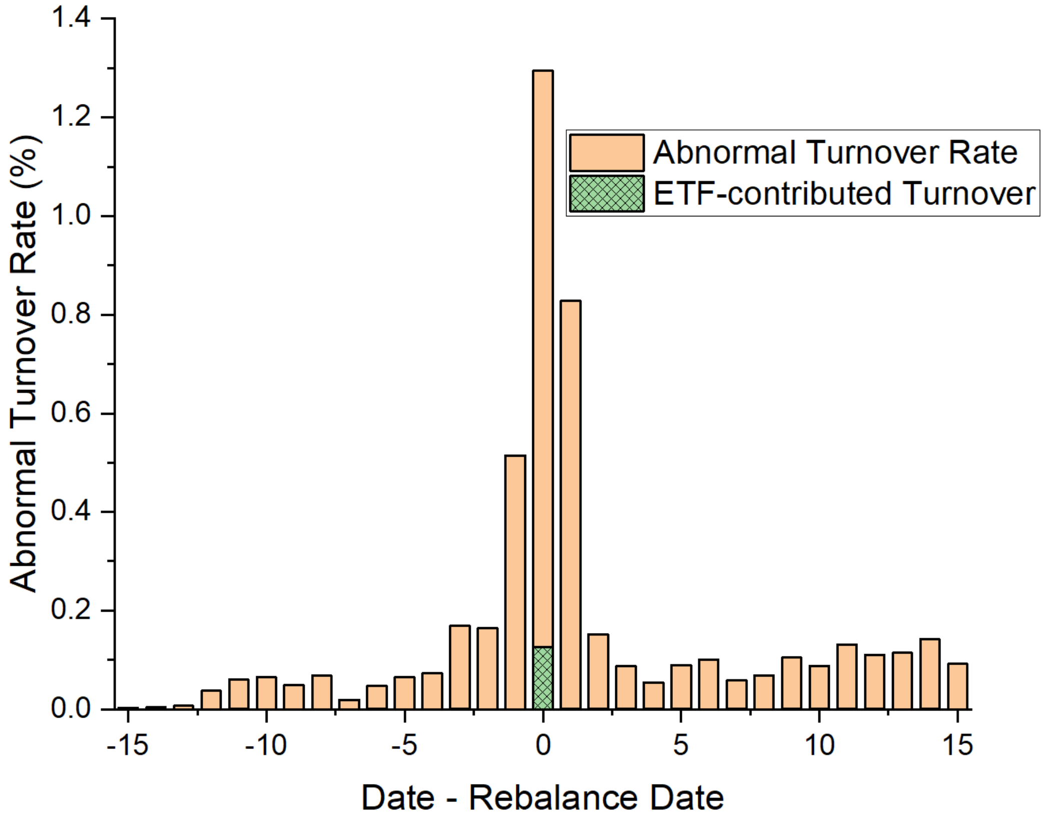
Large public indices usually announce a reconstitution at least 5 days prior to the ex-date. 57% ETFs mechanically follow the rebalance schedule set by large public indices, buy and sell the underlying stocks entirely on the rebalance ex-dates. This figure displays the trade-size weighted average cumulative adjusted return (CAR) for 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 Vanguard and Blackrock ETFs



In this figure I plot the NAV divergence between Vanguard and Blackrock ETFs around index rebalance ex-dates and placebo dates. I identify 16 pairs of Vanguard and Blackrock ETFs that track the same publicly available index. Then, I calculate the daily pairwise NAV return difference between the ETFs and take average across the 16 pairs. I then plot the cumulative NAV return difference adjusted for management fee differences. The placebo dates are selected as 1 calendar month after the rebalance dates. The NAV differences around rebalance dates are in black (robust standard errors in grey), and the NAV differences around placebo dates are in red (robust standard errors in pink). The NAV differences are normalized to zero on date $T - 20$. *Reads: Since Vanguard ETFs use alternative rebalance schedules, their NAVs outperform Blackrock ETFs in* ± 5 *days around the index rebalance ex-date.*

Figure 3
Stock Abnormal Turnover Rate and Rebalance paces for non-Vanguard ETFs



In this figure I plot the abnormal turnover rate around the rebalance date and the contribution from the rebalancing ETF. The unshaded yellow bars represent the abnormal turnover rate, which is the difference between the turnover rate of the day and the average turnover rate in $[T-60, T-30]$. The shaded green bars represent the turnover rate directly due to the rebalancing ETF's trade. The green bars are too small to be visible except on date T. The difference between the yellow and green bars are the abnormal turnover due to trades of other market participants. *Reads: Non-Vanguard ETFs trade only on the rebalancing day, but the rebalancing event attracts more abnormal trading volume around the rebalancing day. Even on the rebalancing day, the ETF's rebalancing trade consists of only 10% of the abnormal trading activity.*

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

Panel A of this table presents the summary statistics for the U.S. unlevered equity ETFs. The AUM is the total asset 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 of identifying 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 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 of identifying 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 PM, 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 3
Reverse engineering the intraday timing of non-Vanguard ETF trades

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

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

This table infers the intraday timing of ETF trades by assessing the prediction power of hypothetical NAV returns in predicting 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 the 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, and closing auction price. Standard errors are reported in parentheses. Standard errors are clustered at the ETF level and day level. 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% level, respectively. *Reads: The null hypothesis that all non-Vanguard ETFs rebalance at the closing price is not rejected at the 5% level.*

Table 4
Summary statistics for public-indexing vs. self-indexing ETFs

Public Index Trackers	Mean	Min	Q1	Median	Q3	Max	Std.Dev	N
AUM ($bn)	6.7913	0.0008	0.0463	0.4503	3.1136	327.7875	26.5814	451
Daily Trading Volume (Million)	1.2855	0.0000	0.0108	0.0648	0.3944	76.6160	6.1633	451
Inception Date		19930122	20051108	20100405	20160803	20201116		451
Net Expenses (bps)	31.5459	3.0000	15.0000	30.0000	44.0000	95.0000	19.5126	451

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

This table presents the summary statistics for the public-indexing ETFs and the self-indexing ETFs. The AUM is the total asset 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 of identifying self-indexing ETFs. Numbers are calculated as of the end of 2020 or the last day of the ETF in my sample, whichever is earlier.

Table 5
Rebalance costs for public indexing 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*****	**14.39*****	**30.59*****	**18.99****	**37.58*****	**29.80****
	[4.85]	[2.78]	[3.85]	[2.26]	[3.09]	[1.99]
Controls	N	Y	N	Y	N	Y
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 vs. self-indexing ETFs. The left-hand side variables are Execution Shortfall $ES_{i,j,T}$ and the Negative Price Impact at both 20 days and 60 days horizons, $-PI_{i,j,T,20}$ and $-PI_{i,j,T,60}$. The regression formula is $Rebalance\ Cost_{i,j,t} = \beta Public_{i,j} + Controls_{i,j,t} + \eta_i + \xi_t + \varepsilon_{i,j,t}$, where i is the index of the stock being rebalanced, j is the index of the ETF, and t is the index of rebalancing date. The Control variables include log(rebalancing size), log(market cap), log(price), and the rebalancing direction. η_i is the stock fixed effect. ξ_t is the year fixed effect. Standard errors are clustered at the stock level and year level. The coefficient of interest is β, which is the extra execution cost paid by ETFs who use public indices. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 6
16 Pairs of 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

Vanguard	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

Blackrock (iShares)	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 the summary statistics for the 16 pairs of Vanguard and Blackrock ETFs. The AUM is the total asset under management. The net expense ratio is the sum of management fees and other expenses minus fee waivers. Refer to subsection IV.A for the procedure of matching ETFs that track the same indices. To make numbers comparable, all of them are calculated as of the end of 2020.