The Heterogeneous Effects of Passive Investing on Asset Markets*

Jonathan Brogaard
David Eccles School of Business
University of Utah

Davidson Heath
David Eccles School of Business
University of Utah

Da Huang
David Eccles School of Business
University of Utah

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Abstract

This paper shows that passive funds systematically underweight or omit illiquid index assets. As a result, their trading activity consumes liquidity and reduces market quality for liquid assets, but has no effect on illiquid assets. Focusing on the unconditional average effects and ignoring funds' index deviations underestimates the local treatment effect by up to 58%. Overall, the effects of passive investing on underlying asset markets depend on how intermediaries replicate their target index.

JEL: G11, G12, G20

Keywords: Passive investing, exchange traded funds, market quality

I. Introduction

Over the last two decades the structure of U.S. equity trading has changed dramatically. There has been a vast rise in the popularity of passive investing, in particular the use of exchange traded funds (ETFs). In 2002 there was $102 billion of assets under management (AUM) in U.S. ETFs; by 2020 there was $5.4 trillion.[1] At the same time, ETFs went from less than 3% to over 30% of daily equity trading volume (see Figure 1). There is an extant literature that studies the effects of passive investing on the activity and quality of the underlying asset markets that they track. Studies of the effects of passive investing – both theoretical and empirical – assume that passive funds simply replicate their target index. This paper shows that passive funds systematically deviate from their target index; specifically, they underweight or omit illiquid index assets. As a result, passive investing has heterogeneous effects on underlying asset markets.

In empirical studies of the effects of passive investing, it is important to take into account that these intermediaries do not simply replicate their benchmark one-for-one. Estimates that average across all underlying assets will understate the impact on liquid stocks and overstate the impact on illiquid stocks. We show that based on the unconditional average effects, the effect of passive investing is misstated by up to 58%. These facts also matter for theoretical models of passive investing, because it means one of the common assumptions in that literature is false. Models in which funds tilt their portfolios away from illiquid assets produce different predictions from those in which funds simply replicate their target index.

Although straightforward in principle, replicating a target index involves tradeoffs in its implementation. The most basic tradeoff faced by a passive fund is to simultaneously minimize tracking error and transaction costs. This tradeoff is faced by both traditional

[1] https://www.statista.com/statistics/295632/etf-us-net-assets/

open-ended index funds, who rebalance their portfolio after inflows and outflows, and by ETF providers, who set the creation and redemption basket for authorized participants.[2] If the fund simply replicates the target index, this minimizes tracking error, but leads to high transaction costs. On the other hand, underweighting illiquid assets lowers transaction costs and (at least initially) leads to only a small increase in tracking error. As a result, the optimal fund weights are a function of the assets' liquidity: Assets that are more expensive to trade should be underweighted or omitted.

We find clear empirical support for this prediction. In practice, ETFs have considerable discretion in defining their creation/redemption baskets (Lettau & Madhavan, 2018) and many ETFs' holdings diverge from the weights of their target index.[3] Six of the ten largest ETFs as of 2019 state in their prospectus that they only statistically replicate their target index by investing in a basket of representative securities.[4] We find that funds' index replication strategy is predictable based on asset liquidity. For example, a one standard deviation wider effective spread for a stock is associated with an 8 percentage point higher probability that the stock is omitted by the Vanguard Total Market Index ETF (VTI), the most popular total market ETF in the U.S. market.[5]

[2]We study the effect of ETFs in the paper due to higher granularity of publicly available data, but this prediction applies to all passive intermediaries that face such a tradeoff.

[3]This aspect of index replication is distinct from the observation of Easley, Michayluk, O'Hara, and Putnins (2019) that many ETFs diverge from the value-weighted market portfolio, and the observation that funds strategically tilt their holdings toward their benchmark index (Van Binsbergen, Brandt, & Koijen, 2008; Basak & Pavlova, 2013). Funds also strategically tilt their holdings within their benchmark index.

[4]One example is the Vanguard Total Stock Market ETF (VTI). The fund's prospectus states, "The Fund invests by sampling the Index, meaning that it holds a broadly diversified collection of securities that, in the aggregate, approximates the full Index in terms of key characteristics." Sampling, or "optimized," index replication is most popular with funds that track relatively illiquid indexes, but is also used by ETFs that track more liquid indexes. For example, the iShares Core S&P 500 ETF (IVV), states in its prospectus that BlackRock "uses a representative index sampling strategy to manage the Fund." Full replication might be optimal for funds that track their index closely intraday.

[5]This finding holds when we include controls for other characteristics including the stock's index weight, volatility, and correlation with the index.

Next, we examine the effects of ETF trading activity on underlying asset markets. Our central prediction is that trading activity due to index arbitrage activity (the creation and redemption of ETF shares in exchange for the posted basket of index assets) is channeled into liquid index assets and not in to illiquid index assets. As a result, the effects of ETF trading on underlying asset markets differ according to those assets' ex ante liquidity. We test these predictions and find clear support for them in the stock-level daily data.

Because index arbitrage activity varies with other market conditions, there is the potential for endogeneity with other market forces. To isolate the causal effects, we instrument the daily primary flows in each individual ETF with the ETF's lagged monthly return. Dannhauser and Pontiff (2019) and Broman (2020) document that retail investors "return chase" based on stale lagged returns. We lag each ETF's prior-month return by five trading days in order to rule out reverse causality from flows to returns. We show that stale lagged ETF returns strongly predict net fund flows in and out of each ETF. Instrumented ETF flows are correlated with lagged stock returns, but not with contemporaneous or subsequent returns, suggesting there is no asset-relevant information that drives them. Consistent with naive investors' return-chasing, lagged prior-month returns predict each ETF's retail order flow identified using the method of Boehmer, Jones, Zhang, and Zhang (2020) and its popularity on Robinhood, a retail trading app.

As the magnitude of (instrumented) ETF primary flows increases, liquid stocks show altered patterns of activity during the trading day, as well as lower liquidity, lower price efficiency, higher volatility, and higher correlation with the market, consistent with prior studies. For illiquid stocks, we find that all these effects are absent.

Thus, our results provide an important distinction as to how passive investing impacts asset markets. Ignoring this distinction means that the unconditional estimates, which average across all sample stocks, understate the true treatment effects. For example, our IV estimates show that one standard deviation increase in ETF primary flow causes volatility of stocks in most liquid tercile to increase by 2.23% while have no effect on the other two terciles of stocks. Using the same instrumental variable but estimating the treatment effect unconditionally will yield a treatment effect of 1.37%. Averaging across all stocks results in estimates that are up to 58% smaller in magnitude than the local treatment effects, which are confined to the most liquid stocks.

These results are robust to various high-dimensional fixed effects structures. We also examine specific alternative explanations. We first examine market fragmentation and algorithmic trading. Regulation National Market System (Reg NMS) was established in 2005 and had significant effects on quoted spreads, market fragmentation, and market quality that differ by stock market capitalization (Haslag & Ringgenberg, 2016). Algorithmic and high frequency trading have risen significantly in some segments of the stock market (Weller, 2017). We control for these effects directly, and find that stock-by-day measures of market fragmentation and algorithmic trading activity do not explain the differential effects of ETF activity on asset markets. Second, we control for the arrival of market-moving news in two ways by directly controlling for daily market returns and by restricting the sample to "no-news" days on which the market return is less than ±1%. The results are unchanged, inconsistent with the arrival of market-wide news explaining our results.

This paper relates to two main strands of the literature. First, a growing empirical literature investigates the growth of passive investing and its average effects on individual stocks. Greenwood (2007) finds that a higher index weight leads a stock to co-move more with the index and less with stocks that are not in the index. Glosten, Nallareddy, and Zou (2021) find a positive relation between ETF ownership and stock information efficiency. Da and Shive (2018) attribute increased co-movement to ETF arbitrage activity. Ben-David, Franzoni, and Moussawi (2018) find that increased ETF ownership leads to higher stock volatility, due to arbitrage trading between ETFs' market price and net asset value (NAV). Israeli, Lee, and Sridharan (2017) find that increased ETF ownership leads to lower price efficiency, higher return synchronicity, and lower analyst coverage of the securities in the underlying basket. Evans, Moussawi, Pagano, and Sedunov (2019) find that increased ETF ownership widens the intraday bid-ask spreads of the underlying stocks. Sağlam, Tuzun, and Wermers (2019) find that increased ETF ownership makes underlying index stocks more liquid. Agarwal, Hanouna, Moussawi, and Stahel (2018) find that increased ETF ownership increases the commonality in liquidity of the underlying stocks.

We make three contributions to this literature. First, we add to this literature by focusing on the implications of passive funds' index tracking strategy. We show that ETFs sample a subset of liquid index assets, and underweight or omit less liquid index assets, and that this strategy causes them to have heterogeneous treatment effects on index assets. We examine the creation/redemption mechanism as a channel through which ETFs affect the liquidity of the underlying assets in the index. Our results demonstrate that the institutional details of how these funds replicate their target index has first-order implications for their effects on underlying asset markets.

Second, we draw a clear distinction between the effects of passive fund *ownership* and the effects of passive fund-driven *trading activity*. Higher levels of passive-fund ownership that are observed and known to market participants ex ante plausibly lead to better information efficiency and liquidity, as the prior literature has shown (Glosten et al., 2021; Sağlam et al., 2019). At the same time, we show that a higher level of ETF trading activity on a given day consumes liquidity and worsens information efficiency. Third, we develop an instrumental variable, the prior-month fund return, that predicts plausibly exogenous variation in trading activity in ETFs. ETF primary flow is highly correlated with market-wide information arrival and trading activity, and therefore is endogenous with overall market quality. Indeed, we find that the analogous OLS estimates detect large spurious effects, suggesting it is necessary to isolate exogenous variation in ETF primary flow.

This paper also relates to theoretical work on the impact of ETFs on underlying asset markets. Theoretical studies of passive investing have commonly assumed that passive intermediaries simply replicate the weights of their benchmark index. Carpenter (2000), Basak, Pavlova, and Shapiro (2007), and Basak and Pavlova (2013) show that funds tilt their portfolio toward stocks that belong to their benchmark. Malamud (2016) constructs a general equilibrium model in which ETF creation/redemption serves as a shock propagation mechanism; Pan and Zeng (2019) construct a model in which a liquid ETF tracks a single illiquid asset, and they analyze the effects of authorized participants' market making activity on the asset's liquidity. These models all implicitly assume that the fund replicates its benchmark pro rata. By contrast, we show that passive funds replicate their index strategically. Models of passive investing can be made richer and more realistic by taking into account their index replication strategy.

II. Data

Data for both stocks and ETFs are from the CRSP daily file. The stock-level data covers all U.S. listed common stocks in CRSP, daily from January 2015 through December 2019. Our sample begins in January 2015 because we use the millisecond TAQ data to compute high-frequency measures of market quality. We exclude any stocks with a prior-month closing market capitalization of less than $300 million ("micro-caps") and exclude any stocks with a prior-month closing price per share less than $5, following Asparouhova, Bessembinder, and Kalcheva (2013). We end up with 3309 stocks in the sample.

Table 1 Panel A reports the summary statistics from the sample. The sample stocks' market capitalization has a mean of $10.9 billion and a median of $2.0 billion. The definition of all variables can be found in Appendix A.

Insert Table 1 About Here

The ETF data covers all U.S. equity ETFs from January 2015 to December 2019 in the CRSP mutual funds database with a prior-month closing assets under management (AUM) of at least $100 million. Table 1 Panel B shows summary statistics for the ETFs in the sample, which covers 102 unique ETFs and covers over 90% of AUM and primary flow for U.S. equity ETFs over this time period. Figure 1 Panel A shows how the aggregate trading volume of U.S. ETFs has evolved over time.

Insert Figure 1 About Here

We obtain each ETF's daily shares outstanding from Bloomberg.[6] Each ETF j's primary flow on day t is calculated as the change in shares outstanding on day t compared to day $t-1$ times the closing price on day $t-1$:

$$\text{Primary Flow}_{j,t} = (\text{Shares Outstanding}_{j,t} - \text{Shares Outstanding}_{j,t-1}) \times \text{Price}_{j,t} \ .$$

We compute the daily fund-level primary flow as defined above for all ETFs in the sample.

[6]Ben-David et al. (2018) point out that compared to CRSP, Bloomberg's data on daily ETF shares outstanding is more accurate.

Figure 1 Panel B shows how the aggregate primary flow (creation and redemption) activity of U.S. ETFs has evolved over time.

We focus on ETF primary flow rather than ETF holdings or total trading activity, because only ETF primary flow is associated with trading activity in the underlying index assets (See Section III.B).

We exclude ETF-days when the ETF provider performed a "heartbeat trade," a swap of ETF shares and a bespoke set of one or more securities, intended to defer capital gains tax (Moussawi, Shen, & Velthuis, 2020). We filter out heartbeat trades because they do not originate from authorized participants' market making activities in the ETF, and they introduce considerable noise in the ETF flow data. We define a heartbeat trade as a paired inflow and outflow that satisfy: (i) both are greater than 1% of the fund's assets under management, (ii) the inflow is the largest primary flow during the surrounding two months, and (iii) the outflow occurs less than five trading days following the inflow. Our results are qualitatively similar but noisier if we do not filter out heartbeat trades.

III. ETF mechanics and trading activity

A. Basket Choice

An exchange-traded fund (ETF) is an investment intermediary that tracks a basket of underlying securities. ETF shares are listed on an exchange and traded throughout the day. ETF shares track the underlying basket because of the arbitrage activity of authorized participants (APs), which are large market making firms. APs have access to the creation and redemption mechanism which allows them to exchange ETF shares for the basket of underlying securities with the ETF provider at the end of each trading day. If the ETF's shares trade sufficiently above the basket's net asset value, which the ETF provider publishes in real time,[7] an AP sells ETF shares and buys the underlying basket of securities, and vice versa. Authorized participants thus provide a liquid two-sided market for the ETF's shares, which facilitates secondary trading activity (Lettau & Madhavan, 2018; Evans et al., 2019).

The creation and redemption baskets are set daily by the ETF provider. The ETF provider has carte blanche to define the baskets, and even "heartbeat" transactions for a single index asset are common (Moussawi et al., 2020). In setting the baskets, the basic tradeoff that the ETF provider faces is to minimize expected transaction costs, which reduces the bid/ask spread that APs are willing to offer and promotes trading, and to simultaneously minimize expected tracking error against the ETF's target index.

In the Internet Appendix we present a formal model of the ETF provider's problem. The main prediction is that index assets that are relatively illiquid are strategically underweighted in the basket. Interestingly, the model predicts that on average all index assets will be strategically underweighted. In general, underweighting an asset adds tracking error but reduces transaction costs; overweighting an asset adds to tracking error and transaction costs.

Figure 2 displays the weights of stocks in the basket for VTI, the Vanguard Total U.S. Stock Market ETF, relative to their weight in the fund's target index, the CRSP value-weighted U.S. stock market index. Both sets of weights are as of January 3, 2015, the first date in our sample. Stocks are sorted into terciles based on their liquidity measured by their prior-month effective spread. An asset's basket weight is set to zero if it is omitted from the ETF basket. In all three terciles, on average, assets are underweighted relative to the target index. Among the most liquid stocks, their index weight and basket weight are closest – the

[7]For more details see https://www.sec.gov/investor/alerts/etfs.pdf

average ratio of basket weight to index weight is 83%. In the middle and least liquid terciles of stocks, the average ratio of basket weight to index weight is 24% and 3% respectively. Over 98% of stocks in the least liquid tercile were omitted from the ETF basket.

These observations are consistent with our model, but they only capture a single snapshot in time and other stock characteristics – in particular the index weight – covary with liquidity. Table 2 shows regression estimates, quarterly from 2015-2019. These estimates include year-quarter fixed effects and other stock characteristics including the stock's index correlation, volatility, and linear, quadratic or cubic controls for the stock's index weight. For ease of interpretation, the dependent variable is an indicator that equals 1 if a stock in the index was included in the fund's basket and 0 otherwise. Again, more illiquid stocks as measured by either the prior month effective spread (Columns 1-3) or the prior month CRSP bid-ask spread (Columns 4-6) are more likely to be omitted from the fund's basket. Overall, the data are consistent with our prediction: ETF providers strategically underweight or omit illiquid index assets.

B. Primary flow and trading activity

The creation and redemption of ETF shares at the end of the day, through which assets move in and out of the fund, is referred to as ETF primary flow. Authorized participants internalize their own intraday order flow and then trade to close out their residual position, generating ETF primary flow when ETF shares are created and redeemed with the ETF provider. Thus, primary flow is the channel through which index arbitrage occurs, affecting the markets for the underlying assets. By contrast, internalized trading, when an AP nets its own buying and selling activity, and secondary trading activity, in which a buyer and a seller trade ETF shares between themselves, need not have any effect on the underlying asset markets (Lettau & Madhavan, 2018).

As a measure of fund flows, ETF primary flow has two main differences with the literature on mutual fund flows (i.e. Coval and Stafford (2007); Goldstein, Li, and Yang (2014); Wardlaw (2020)). First, in that literature, the funds are open-ended mutual funds and money flows directly between investors and the fund. By contrast, ETF primary flows are resolved by authorized participants via the creation/redemption mechanism. Second, in the fund-flows literature, the funds are actively managed funds, and thus they have near-total discretion in adjusting their holdings in response to flows. By contrast, all the ETFs in our sample are passive funds that track an index, and the basket of underlying assets that are exchanged for ETF shares are posted prior to each trading day by the ETF provider.

Insert Figure 3 About Here

To examine the effects of ETF primary flow on underlying markets, we first graphically compare trading days with low ETF primary flow to days with high ETF primary flow. The prediction is that days with high ETF primary flow should see an increase in trading activity in underlying assets, but (i) only in the most liquid assets and (ii) toward the end of the trading day, when authorized participants close out their residual positions.

Figure 3 plots the difference in average stock turnover between high-primary-flow days versus low-primary-flow days, during the trading day divided into 10-minute increments. Panel A shows the most liquid tercile of sample stocks. We see that during high-primary-flow days, the most liquid stocks experience a large relative increase in trading activity, but only during the last 30 minutes of the trading day. Panel B shows the most illiquid tercile of sample stocks. We see that, by contrast, on high-primary-flow days illiquid stocks do not experience a significant increase in trading activity at the end of the day. In fact, on high-primary-flow days, trading activity among illiquid stocks is lower overall.

This observation suggests the market making of authorized participants both internalizes primary trading in ETF shares, and delays secondary trading in the underlying assets. Without ETFs present in the market, the secondary trading in the underlying assets would be more continuous throughout the day. With ETFs in the market, authorized participants internalize the trading activity in ETF shares and pool their trading in underlying assets at the end of the trading day.

This delay and pooling of trading activity in the underlying assets has interesting implications. As trading activity is siphoned out of the underlying asset market earlier in the day, a Glosten and Milgrom (1985) effect is predicted – if noise trading volume is reduced, market makers widen the bid-ask spread. In other words, during days when *ex post* realized ETF trading activity is high, the *delay* of trading activity in the underlying market will itself consume liquidity and worsen information efficiency for the underlying assets. Consistent with our model, these effects are concentrated in liquid assets due to funds' strategic basket weighting.

In conclusion, the broad day-by-day patterns in the turnover of underlying stocks are consistent with our prediction that daily ETF-driven trading activity (primary flow) has specific effects on asset markets that are conditional on the assets' liquidity. Next, we test these predictions by identifying exogenous variation in ETF primary flow with our "return-chasing" instrumental variable.

IV. The effects of ETF activity on asset markets

The main research question in this paper is to examine the effects of ETF trading on underlying asset markets. The hypothesis is that because illiquid assets are underweighted or omitted relative to the index, ETF-driven trading activity is channeled into assets that are more liquid ex ante and not into assets that are less liquid ex ante.

We measure ETF trading activity as the magnitude of daily total ETF primary flow, that is, the daily net creation or redemption of ETF shares. This measure is defined as:

$$|\text{Primary Flow}_t| = \sum_j |\text{Primary Flow}_{j,t}| \ .$$

This measure captures the magnitude of authorized participants' trading activity as a result of net ETF creation and redemption on day t. We focus on $|\text{Primary Flow}_t|$ as the main independent variable in all subsequent tests.

Each month from January 2015 through December 2019, we sort stocks into terciles based on their average effective spread over the previous month. The first tercile contains the most liquid stocks and the third tercile contains the most illiquid stocks ex ante. To examine the relation between ETF primary flows and underlying asset markets, we examine how daily measures of market quality for each stock i varies with the magnitude of ETF primary flow that day, separately for the stocks in each liquidity tercile.

A. Instrumenting for ETF primary flow

The challenge for identification is that there are many market forces that affect both asset market activity and ETF primary flows. To address this concern, we introduce a novel instrument for ETF primary flow – namely, the lagged monthly return on that ETF. Research on fund flows has found that uninformed investors return-chase. As a result, investor dollars flow into funds that recently had high returns and out of funds that recently had low returns, even though lagged fund returns do not predict future returns (Dannhauser & Pontiff, 2019;

Broman, 2020).

Table 3 presents the results of the regression:

$$\text{Primary Flow}_{j,t} = \sum_{k=1}^{4} \beta_k \text{Return}_{j,t-k} + \beta \text{Return}_{j,t-26\to t-5} + \gamma_j + \kappa_t + \epsilon_{j,t} \tag{1}$$

where j denotes ETF and t denotes trading day. $\text{Return}_{j,t-k}$ is the lagged individual daily return of ETF i for the last four trading days and $\text{Return}_{j,t-26\to t-5}$ is the cumulative return of ETF j over the last month from $t-5$ to $t-26$ (22 trading days).[8] γ_j is ETF fixed effects and κ_t is day fixed effects.

Insert Table 3 About Here

The key independent variable is the fund's lagged prior-month return from trading day $t-26$ to trading day $t-5$. We lag the prior return by five business days to avoid the possibility of reverse causation from flows to returns. Evans et al. (2019) document that authorized participants sometimes take several trading days to balance their accounts – in particular, APs create "operational shorts" by creating new shares of the ETF, which they sell, then waiting one or more business days to deliver the basket of underlying assets. Because the lagged prior-month fund return is determined five trading days prior to the instrumented ETF primary flow, any relationship we find is unlikely to be driven by omitted variables or reverse causation.[9]

[8] The results are robust to the choice of lag from t-1 to t-10.

[9] Some ETFs use T+1 accounting while others use T+0 accounting to report their shares outstanding (Staer, 2017). The lagged IV also helps solve this issue, because the instrument strongly predicts the primary flows on subsequent days regardless of whether they are four or five trading days later. We thank Markus Broman for this point.

Table 3 Column 1 shows that a higher lagged prior-month return predicts a higher ETF primary flow five trading days (approximately one calendar week) later. This is consistent with investor return-chasing. To verify that the predictability in ETF primary flows is driven by uninformed retail trading, first, we identify the daily net flow of retail trades for each ETF using the methodology in Boehmer et al. (2020).[10] Column 2 shows the results: We see that indeed, the net flow of identified retail trades is strongly positively predicted by the lagged prior-month return. Second, we identify the daily ETF holdings of a subset of retail investors using Robintrack, a website that tracks the daily holdings of users of Robinhood, a smartphone trading app popular among young retail investors. Table 3 Column 3 shows that an ETF's lagged prior-month return even more strongly predicts its popularity with Robinhood investors. In sum, the results are consistent with our proposed mechanism of return-chasing by uninformed retail investors.[11]

We use the predicted values of ETF primary flows, based on our first-stage estimates above, to examine the causal effects of ETF primary flows on underlying asset markets. Specifically, we multiply the coefficient on $\text{Return}_{j,t-26\to t-5}$ from Table 3 Column 1 by each ETF's lagged prior-month return on each day, to produce daily predicted primary flows for each ETF.[12] By construction, these predicted primary flows only reflect fund-by-day variation in lagged prior-month returns, and no other information from the subsequent five business days:

[10] In the TAQ trade file, transactions reported to a FINRA TRF (exchange code "D" in TAQ) with fractional sub-penny improvement are identified as signed retail flows.

[11] The relationship between lagged prior-month returns and fund flows is also pervasive across individual ETFs. When we regress daily ETF primary flows on lagged returns as in Table 3 Column 1 separately for each ETF in the sample, the coefficient on the lagged prior-month return is positive for 74 out of 102 funds and positive and significant with $p < 0.05$ for 45 out of 102 funds.

[12] The first-stage F-statistic is 13.6 ($p < 0.01$).

$$\widehat{\text{Primary Flow}}_{j,t} = \beta_{FirstStage} \times \text{Return}_{j,t-26\to t-5}$$

We then sum the predicted ETF flow magnitudes by day to obtain the total daily instrumented ETF primary flow [13]:

$$|\widehat{\text{Primary Flow}}_t| = \sum_i |\widehat{\text{Primary Flow}}_{j,t}|$$

Figure 4 plots the daily value of $\widehat{\text{Primary Flow}}$ over the sample. The important feature of $\widehat{\text{Primary Flow}}$ is that it *only* reflects fund flows stemming from each ETF's lagged prior-month return. Such flows are plausibly due to return-chasing by uninformed retail investors, and are unlikely to be correlated with any information or predictive power about the ETF itself. Moreover, because it was realized five trading days prior, the instrument cannot be influenced by the dependent variable. Thus, $\widehat{\text{Primary Flow}}$ plausibly satisfies the exclusion restriction of being directly related to ETF primary flows but not otherwise related to trading activity or market quality in individual stocks.

Insert Figure 4 About Here

B. Effects on Trading Activity

We first examine the relationship between ETF primary flows and trading activity in individual stocks. Recall that the aggregate data suggest that authorized participants absorb intraday flows and trade in the underlying asset markets near the end of the trading day.

[13] One may be concerned by fact that the instrumental variable in the second stage is a generated variable, of which the first stage only estimates individual components. To address this concern, we calculate and report the block-bootstrapped standard errors by ETF, stock, and day, for all the results using instrumental variable.

As a result, when ETF trading activity is high, end-of-day trading activity in liquid stocks increases differentially compared to their mid-day trading activity. We calculate the share turnover for each individual stock within each day divided into 10 minute time-of-day blocks. We define the end-of-day turnover, $TurnoverClose$, as share turnover in the last ten minutes (15:50 to 16:00). The mid-day turnover, $TurnoverMid$, is defined as the average ten-minute turnover from 9:40 to 15:50. We define $Close - Mid$ as the difference between the two.

To formally test whether ETF primary flows drive a differential change in trading activity during the trading day, we examine the effects on $Close - Mid$. We interact the primary flow magnitude with a stock's preexisting liquidity. $Liquid^q_{i,t}$ are a set of three dummy variables that equal 1 if stock i is in liquidity tercile q for the last month as of day t. We add stock-level lagged controls, and fixed effects by stock and date:

$$Y_{i,t} = \sum_{q=1}^{5} \beta^q \times |\widehat{\text{Primary Flow}}_t| \times \text{Liquid}^q_{i,t} + \text{Liquid}^q_{i,t} + \chi \boldsymbol{X}_{i,m-1} + \boldsymbol{Y}_{i,t-1} + \gamma_i + \kappa_t + \epsilon_{i,t} \ , \quad (2)$$

$\boldsymbol{X}_{i,m-1}$ includes lagged stock-level controls – turnover, market capitalization, price per share, and effective spread measured as of the end of last month. Stock fixed effects, γ_i, sweep out any non time varying stock-specific factors that affect liquidity, observed or unobserved. The monthly fixed effects κ_m sweep out all observed or unobserved factors in each month, that affect trading activity across all stocks. Note that while we present coefficients on lagged ETF returns in Table 1, we do not use those variables in predicting $\widehat{\text{Primary Flow}}_t$, so they are not included in the second stage (2) either.

Insert Table 4 About Here

Table 4 displays estimates of the causal effects of daily ETF primary flow from equation

(1) on trading activity. The results show clear differential effects of ETF primary flow on stock-level share turnover. Table 4 Column 1 shows that a one standard deviation larger ETF primary flow is associated with a 3.8% higher turnover for stocks in the most liquid tercile and a 2.4% higher turnover for stocks in the least liquid tercile. The difference in coefficients between the most and the least liquid stocks is significant (F-stat = 8.4; p-value < 0.01).[14]

The picture is similar after we add stock-level controls for lagged market activity and quality (Column 2). When we add monthly fixed effects (Column 3), which sweep out overall fluctuations in trading activity, the level effects disappear in each tercile. However, the differential effect between terciles: Larger instrumented ETF primary flows are accompanied by higher trading activity in liquid stocks relative to illiquid stocks (F-stat = 4.0; p¡0.05).

The picture is clearer when we examine changes in the pattern of intraday trading activity. In Table 4 columns 4-6 the dependent variable is trading activity in each stock at the close (in the last 10 minutes of trading) relative to the average trading activity per 10 minutes over the rest of the day. We see that the overall pattern in levels is similar across all terciles and specifications. However, the differential effect between the most liquid and least liquid stocks is more than twice as large as in columns 1-3. Even in our most exhaustive specification (Column 6) we see a significant effect in levels for the most liquid stocks – there is a 1.54% shift of trading activity out of the midday trading and into the close – and the differential effect between liquid and illiquid stocks is highly significant (2.22% ; F-stat = 19.0 ; p¡0.01).

[14] To adjust for the fact that the predicted ETF primary flow is a generated regressor, we bootstrap the estimates in Table 4 Columns 3-4 as follows. We repeatedly resample both the ETF-level and stock-level datasets, with replacement, blocked (i.e. clustered) by ETF and stock respectively and also by trading day, and rerun the first and second stage estimates on the resampled data. These results account both for the variance in the first stage estimate and for arbitrary serial correlation within each ETF, stock, and trading day. The mean and median bootstrap coefficients are effectively identical to the unadjusted coefficients. The bootstrap standard errors, displayed in brackets, are similar to the analytical standard errors in all cases.

These results are consistent with the broad patterns in share turnover documented in Figure 3. In effect, ETF primary flow channels trading activity out of the underlying asset markets during the day, and then back into those markets near the close – but only in liquid stocks. By contrast, there are no such effects in illiquid stocks.

In sum, we find that ETF primary flows have differential effects on share turnover in individual stocks. In particular, the differential effects are seen only in liquid stocks, toward the end of the trading day.

C. Effects on asset market quality

Next, we investigate the effects of ETF activity on the functioning of underlying asset markets. To our knowledge, it is an open question whether ETF index arbitrage is liquidity-improving or liquidity-consuming. On one hand, trading by authorized participants is uncorrelated with information about any particular index asset, and noise trading volume is liquidity-improving (Kyle, 1985). On the other hand, the data show that ETF-driven trades appear mostly at the end of the trading day, pooling with other rebalancing activity. Thus, orders driven by ETF index arbitrage might be liquidity-consuming on average (consistent with Dannhauser (2017) and Eaton, Green, Roseman, and Wu (2021)).

Table 5 shows estimates of the effects of ETF primary flows on measures of asset market quality. In each case the independent variable is the instrumented magnitude of ETF primary flows.[15] In Column 1 the outcome variable is each stock's liquidity as measured by its intraday effective spread. We see that larger instrumented ETF primary flows lead to wider effective spreads – lower liquidity – in the most liquid tercile of stocks. Yet, there is no significant change in liquidity in the two less liquid terciles. These results suggest that the trading

[15]The corresponding OLS results using realized daily ETF primary flow are presented in the Internet Appendix.

activity of authorized participants consumes liquidity in the underlying assets, consistent with Dannhauser (2017), but only in the liquid assets that the ETFs' baskets are tilted toward.

Insert Table 5 About Here

Table 5 Columns 2-4 examine other aspects of market quality that have been shown in the prior literature to be affected by ETF activity. In Column 2 the outcome variable is the short-run price inefficiency (volatility of pricing error, Pricing $\text{Error}_{i,t}$) as in Hasbrouck (1993). We find that larger ETF primary flows lead to worse price efficiency – but only for stocks in the most liquid tercile. A one standard deviation increase in the magnitude of ETF primary flows leads to a 1.5% increase in the short-run pricing error, comparable to the estimates in (Israeli et al., 2017). Yet in the two least liquid terciles, the effect is statistically and economically insignificant (in the least liquid tercile the effect is actually slightly negative).

In Table 5 Column 3 the outcome variable is the intraday return volatility of the stock. Consistent with Ben-David et al. (2018), who find a positive effect of ETF ownership on stock volatility on average, we find that larger instrumented ETF primary flows are accompanied by higher return volatility in the two most liquid terciles. A one standard deviation increase in the magnitude of ETF primary flows leads to a 2.2% increase in liquid stocks' volatility. Yet in the least liquid tercile of stocks, the effect is statistically and economically insignificant.

In Table 5 Column 4 the outcome variable is the intraday correlation between the returns of the individual stock and the SPDR S&P 500 ETF (SPY). Consistent with Greenwood (2007) and Da and Shive (2018), who find a positive effect of ETF ownership on index correlation, we find that larger instrumented ETF primary flows are accompanied by a higher correlation with the market – but only in the most liquid tercile of stocks. In the least liquid tercile of stocks, the effect is slightly negative and statistically insignificant.

Our estimates of the effects of ETF activity on underlying assets' liquidity, pricing error, volatility and return correlation are all of the same signs and similar magnitudes as those reported in prior studies (Dannhauser, 2017; Israeli et al., 2017; Ben-David et al., 2018; Da & Shive, 2018) – for the subset of liquid stocks. Our research design and sample are entirely different from those papers, so these results represent out-of-sample confirmation of their findings. However, we find that all these effects are absent in the subset of illiquid stocks. These results support our model's predictions, and suggest that the treatment effects of ETFs on asset markets that prior research has documented are confined to a subset of liquid underlying assets.

Crucially, this means that unconditional estimates of the average treatment effect, which are equally-weighted across all sample stocks, will tend to understate the true effects. The bottom row of Table 5 reports the unconditional treatment effects (that is, without conditioning on asset liquidity). We see that all of them are significantly smaller in magnitude than the treatment effect on the most liquid tercile; the understatement varies from -39% for volatility to -58% for effective spread.

D. Effects on stock returns

Since ETF primary flows have significant impacts on trading activity and market quality, a natural question is whether they have significant effects on index assets' returns. To examine this, we repeat our research design as above with daily stock returns as the dependent variable. Recall our results for asset turnover. If ETF primary flows have significant price impact, we would expect to see a differential treatment effect, confined to the most liquid tercile of stocks, on stock returns on the same (contemporaneous) day. If our instrumented ETF primary flows contain information about future fund flows or about asset value, we would expect to see a differential treatment effect on stock returns on future days.

Table 6 presents the results. Predicted ETF flows, based on the lagged ETF returns, are positively associated with lagged stock returns over the two previous trading days. This is to be expected as the ETF flow predicted by past returns mechanically contains information of past returns of index assets. However, there is no significant relation with contemporaneous returns (price impact) or with returns on future trading days (information content). The magnitudes in each case are small, 5 to 6 basis points per one standard deviation change in ETF primary flow, and the estimates are well powered to detect similarly-sized treatment effects if they were present. That is, there is no evidence of significant price impact or information content – in any of the three liquidity terciles.

More importantly, given the differential effects of instrumented ETF primary flows on trading activity and market quality, we find there is no significant differential effects for returns across the liquidity terciles. Thus, we conclude that our results are consistent with zero, or very little, price impact or information content of trading activity due to ETF primary flows. The finding of little or no price impact is consistent with our motivating assumption that ETF providers and authorized participants take care to minimize their trading costs and tracking error. The finding of little or no information content is consistent with the finding that trading in individual stocks due to passive intermediaries is uninformative (Dannhauser & Pontiff, 2019).

V. Alternative explanations

One concern with our estimates is that market dynamics change over time, and could covary with both ETF primary flow and stock turnover and liquidity. For example, the arrival of market-relevant information could drive increased ETF trading activity, and also cause market makers and participants to alter their trading activity in individual stocks. In addition, market structure evolves through time and time-varying factors such as high frequency trading activity and market fragmentation are well known to impact market quality. We examine these potential confounds in the following ways.

First, it could be that the increase in high frequency trading activity and the increasing fragmentation of equity markets differentially affects stocks based on their liquidity. To examine this possibility, we include two control variables that measure high frequency trading activity and market fragmentation for each stock by month, using SEC MIDAS data. For high frequency trading activity, we construct the trade-to-order ratio following the same procedure in Weller (2017). For market fragmentation, we construct an Herfindahl-Hirschman Index (HHI) of trading volumes across market venues:

$$HHI_{i,t} = \sum_{j} \left(\frac{\text{Trading volume}_{i,j,t}}{\sum_j \text{Trading volume}_{i,j,t}} \right)^2$$

where i denotes stock, j denotes market venue, and t denotes month.

Insert Table 7 About Here

Table 7 shows the results. The differential relationships driven by ETF primary flows between the most and least liquid stock have qualitatively the same pattern compared to Table 5. Notably, the economic magnitude of the point estimates for the most liquid stocks remains essentially the same, suggesting that the instrumented primary flow captures the variation that is orthogonal to the market regime shift such as the rise of high-frequency trading and the market fragmentation. Thus, changes in high frequency trading activity or market fragmentation do not drive the differential effects of ETF primary flow on market quality.

Second, it could be that when there is market-moving news (or the risk of market-moving news arriving), market makers and participants change their trading behavior differentially in liquid versus illiquid assets. To examine this possibility, we add the magnitude (absolute value) of the CRSP value-weighted U.S. market index as an additional explanatory variable, interacted with each stock's lagged liquidity tercile. Furthermore, we restrict the sample to days in which the CRSP value-weighted U.S. market index return is within [-1%,1%]. With this specification, we examine the influence (if any) of market-moving news.

Insert Table 7 About Here

Table 8 shows the results. The differential relationships driven by ETF primary flows between the most and least liquid stock have qualitatively the same pattern compared to Table 5. The magnitude of the market return does have some differential effects on the trading pattern, the price efficiency, and the volatility of stocks. However, the differential effects driven by ETF primary flow remain statistically significant and economically meaningful. We therefore conclude that market-moving news does not explain the differential effects of ETF primary flow on market quality.

VI. Conclusion

An exchange traded fund (ETF)'s objective is to closely track a target index at low cost. In this paper we examine the direct consequences of ETFs' index replication strategy on the markets for the underlying index assets.

We characterize the fundamental trade-off for passive funds between tracking error and transaction costs. A simple model predicts that for assets that are illiquid and expensive to trade, ETF providers are better off underweighting or omitting these stocks. As a result, the effects of ETF trading activity on underlying asset markets is heterogeneous and determined by the asset's liquidity and the fund's index replication strategy. This is an important point for the theoretical literature on the effects of the rise of passive investing.

We introduce a novel instrument for ETF primary flow – the lagged prior-month return of the ETF. Using instrumental variables estimates, we find empirical evidence consistent with the model's predictions as well as with the existing literature. Specifically, on days with greater (instrumented) ETF activity, in the tercile of index assets that has the highest liquidity ex ante, end-of-day trading activity rises, liquidity and price efficiency fall, and volatility and correlation with the market rise. Conversely, in the tercile of index assets that has the lowest liquidity ex ante, these effects are absent. These results are robust to controlling for other market factors and to dropping days with major market movements.

Our results do not only add additional nuance to prior results in the literature. They also show that unconditional estimates of the treatment effect, which average across all assets, misstate the true effects of ETF trading, and passive investing more generally. The unconditional estimates understate the true treatment effects on liquid assets, by up to 58% in our sample, and overstate the true treatment effects on illiquid assets, which our findings suggest are essentially unaffected.

The contribution of this paper is two-fold. First, we point out an aspect of ETFs' industrial organization that has been largely ignored to date – index assets being systematically underweighted or omitted from the ETF basket. Second, we show that ignoring this aspect of ETF trading activity mistakenly classifies omitted assets as "treated" (as will happen using either index weights or index assignments to proxy for ETF ownership), and results in biased estimates of the effects of passive investing on asset markets. Thus, our results should inform future empirical research on passive investing as well.

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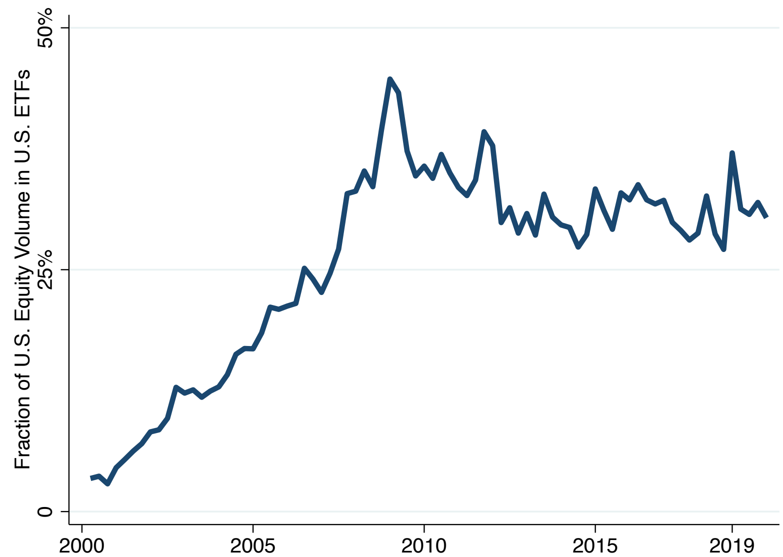
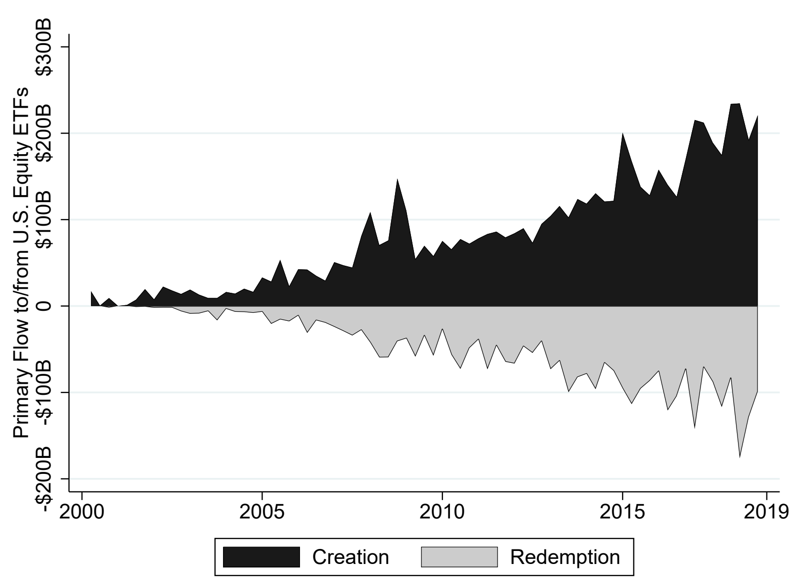
Figure 1. ETF trading volume and primary flows

(a) ETF trading volume

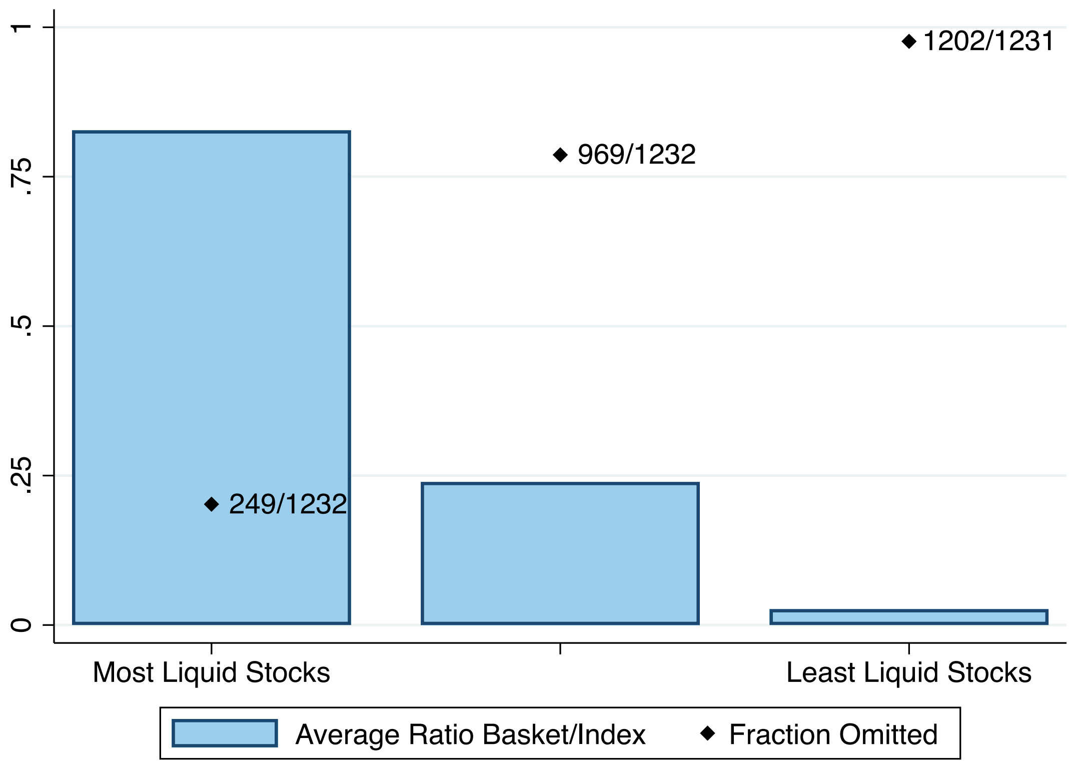


(b) ETF primary flows



Panel A plots ETF trading volume as a fraction of all U.S. equity trading volume and panel B plots total positive and negative primary flows (total dollar create and redeem activity, respectively) in U.S. equity exchange traded funds (ETFs), quarterly from 2000 to 2019.

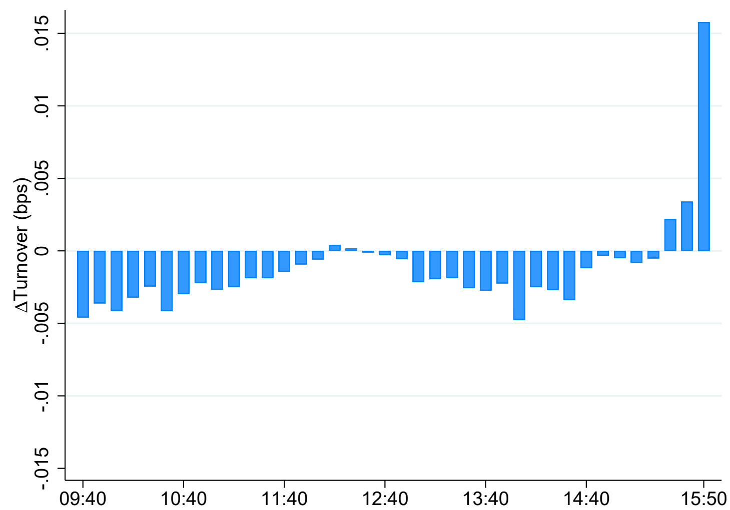
Figure 2. ETF basket weights vs index weights



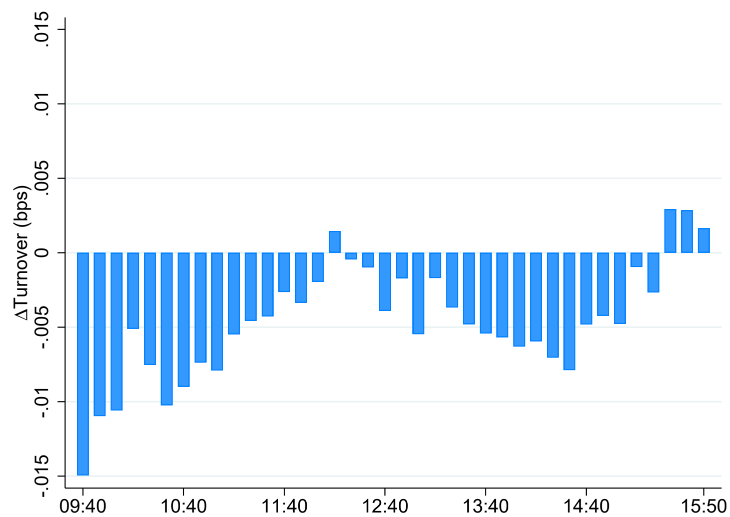
The figure bars display the average ratio of the weight of each stock in the creation/redemption basket of the Vanguard Total U.S. Stock Market ETF (VTI) to their weight in the fund's target index (the CRSP value-weighted U.S. stock market index) as of January 3 2015. The stocks are divided into terciles by their liquidity, measured as the prior month's mean effective spread. The figure markers plot the fraction of index stocks in each tercile that were omitted entirely from the ETF's basket.

Figure 3. ETF primary flow and asset turnover during the trading day

(a) Most liquid stocks

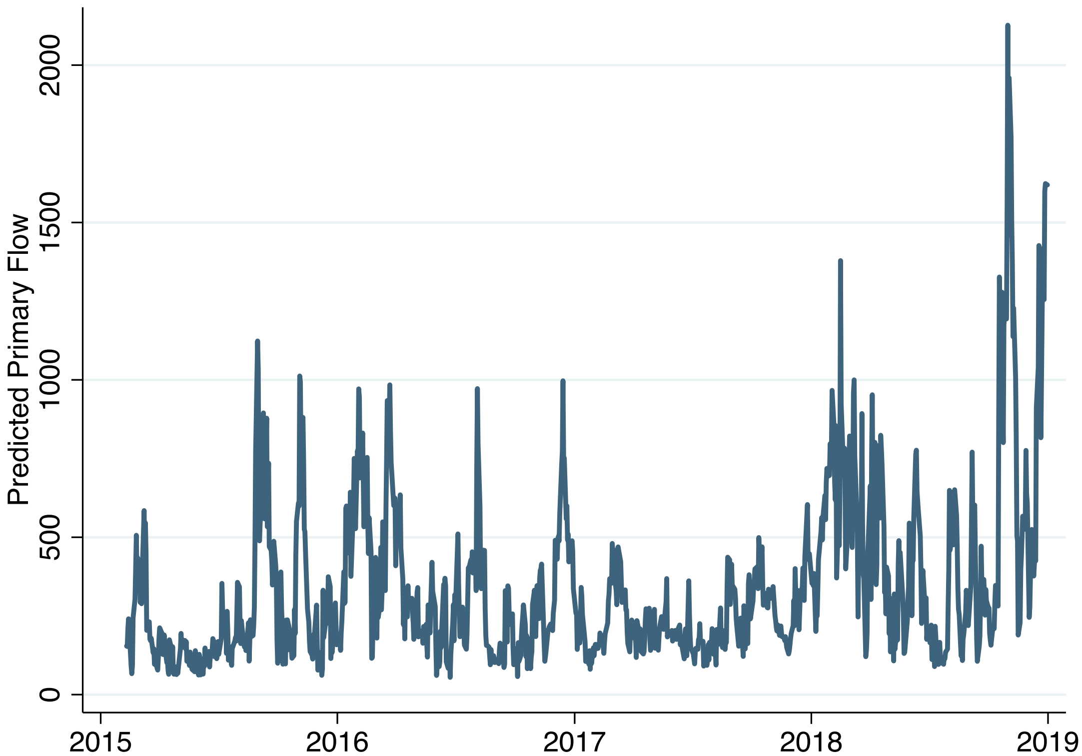


(b) Least liquid stocks



The figure plots the difference in share turnover for U.S. equities between days with large ETF primary flow and days with small ETF primary flow. Large (small) primary flow days are defined as days with the magnitude of primary flow in the top (bottom) decile. Each bar corresponds to a 10-minute interval during daily trading hours. Panel A shows the difference in turnover (large flow days - small flow days) for ex ante liquid stocks in the tercile with lowest effective spread as of last month; Panel B shows the difference for ex ante illiquid stocks in the tercile with highest effective spread tercile as of last month. The sample consists of U.S. common stocks measured daily from 2015-2019.

Figure 4. Instrumented ETF primary flows



The figure plots aggregate ETF primary flows predicted using each individual ETF's lagged return from t-26 to t-5. The sample consists of U.S. equity ETFs from 2015-2019.

Table 1
Summary statistics

Panel A presents summary statistics of the sample stocks, which consists of all U.S. common stocks with a lagged market capitalization of at least $300 million from January 2015 through December 2019. The sample contains 3,404 unique stocks. Panel B displays summary statistics of ETFs in the sample, which consists of U.S. equity ETFs in the CRSP mutual fund database with at least $100 million of assets under management from January 2015 through December 2019. The sample contains 102 unique ETFs. Variable definitions can be found in Appendix A.

Panel A: U.S. Common Stocks

	Mean	StDev	P10	Median	P90	N
Market Capitalization ($ Millions)	10,866	38,741	462	2,046	21,009	2,686,887
Trade Turnover (bps)	0.10	0.16	0.02	0.07	0.19	2,686,887
Effective spread (bps)	17	116	3	10	34	2,686,887
log(Pricing Error)	-7.26	1.63	-8.80	-7.54	-5.81	2,686,887
Intraday Volatility (bps)	13.90	9.42	5.67	11.59	24.41	2,686,887
Intraday Correlation with SPY	0.19	0.17	0.00	0.16	0.42	2,686,887

Panel B: Exchange Traded Funds

	Mean	StDev	P10	Median	P90	N
Assets under Management ($ Millions)	14,533	27,544	2,080	6,587	30,322	123,252
Expense Ratio (bps)	19	14	5	15	39	123,252
Turnover Ratio	0.19	0.18	0.04	0.14	0.43	123,252

Table 2
Stock characteristics and inclusion of ETF basket

The table presents regressions of the creation/redemption basket weights for the Vanguard Total Market Index ETF (VTI) on characteristics of index stocks. The sample consists of all stocks included in the CRSP value-weighted equity index, quarterly from 2015 to 2019. $\mathbb{1}_{included,it}$ is an indicator variable that equals 1 if stock i was in VTI's creation/redemption basket at the end of quarter t and 0 if not. Correlation$_{i,t}$ is the correlation of the stock's daily returns with the index, $Volatility_{i,t}$ is the stock's average daily return volatility, log(Effective Spread$_{i,t}$) is the log average effective spread of the stock, and log(Bid-Ask Spread$_{i,t}$) is the log average percent bid-ask spread of the stock, all over the quarter t. Index Weight Ctrl refers to the degree of the polynomial control for each stock's index weight. Variable definitions can be found in Appendix A. All independent variables have been transformed to have mean = 0 and standard deviation = 1. Standard errors are clustered by stock. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}_{included,it}$	$\mathbb{1}_{included,it}$	$\mathbb{1}_{included,it}$	$\mathbb{1}_{included,it}$	$\mathbb{1}_{included,it}$	$\mathbb{1}_{included,it}$
Correlation$_{i,t}$ (monthly)	0.16***	0.15***	0.13***	0.17***	0.16***	0.14***
	(24.3)	(23.3)	(22.1)	(29.4)	(27.9)	(26.2)
Volatility$_{i,t}$ (monthly)	-0.05***	-0.04***	-0.04***	-0.06***	-0.05***	-0.04***
	(-12.7)	(-11.8)	(-10.8)	(-15.0)	(-14.0)	(-13.0)
log(Effective Spread$_{i,t}$)	-0.08***	-0.07***	-0.07***			
	(-7.0)	(-7.0)	(-7.0)			
log(Bid-Ask Spread$_{i,t}$)				-0.05***	-0.05***	-0.04***
				(-5.5)	(-5.5)	(-5.5)
Index Weight Ctrl	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69,627	69,627	69,627	69,627	69,627	69,627
Adj. R-squared	0.299	0.335	0.381	0.288	0.325	0.373

Table 3
ETF primary flows and lagged ETF returns

The table presents regressions of daily ETF flows on the funds' lagged returns:

$$y_{j,t} = \boldsymbol{\beta} \sum_{k=0}^{4} \text{Return}_{j,t-k} + \beta_{lm}\text{Return}_{j,t-26\rightarrow t-5} + \gamma_j + \kappa_m + \epsilon_{j,t}$$

where j denotes ETF and t denotes day. Primary $\text{Flow}_{j,t}$ is the daily creation/redemption of ETF j on day t. Retail $\text{Flow}_{j,t}$ is daily retail order flow following Boehmer, Jones, Zhang, and Zhang (2021). Flows are scaled by the ETF's lagged assets under management. $\text{Robinhood}_{j,t}$ is the daily number of Robinhood users who held stock j. The independent variables are the daily returns for days t to $t-4$ and the prior month's lagged return from $t-5$ to $t-26$ (22 trading days). All variables are standardized to a mean of zero and standard deviation of one. Definitions can be found in Appendix A. γ_j is a ETF fixed effect and κ_m is a month fixed effect. The sample consists of U.S. equity ETFs in the CRSP Mutual Fund database with at least $100 million AUM, daily from 2015 to 2019. Standard errors in parentheses are robust and clustered by fund and day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Primary $\text{Flow}_{j,t}$	(2) Retail $\text{Flow}_{j,t}$	(3) $\text{Robinhood}_{j,t}$
$\text{Return}_{j,t}$	0.076***	0.051***	0.009
	(0.017)	(0.010)	(0.014)
$\text{Return}_{j,t-1}$	0.059***	0.032***	0.006
	(0.008)	(0.007)	(0.028)
$\text{Return}_{j,t-2}$	0.046***	0.026***	0.060***
	(0.007)	(0.006)	(0.018)
$\text{Return}_{j,t-3}$	0.029***	0.020***	0.023
	(0.007)	(0.006)	(0.016)
$\text{Return}_{j,t-4}$	0.023***	0.011**	0.023*
	(0.008)	(0.005)	(0.013)
$\text{Return}_{j,t-26\rightarrow t-5}$	0.059***	0.050***	0.092***
	(0.016)	(0.011)	(0.027)
F-stat ($\text{Return}_{j,t-26\rightarrow t-5}$)	13.48***		
Weak IV p-value	0.0004		
Fund FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Observations	97,354	77,739	25,652
Adj. R-squared	0.035	0.034	0.248

Table 4
ETF primary flows and asset trading activity: Overall level and intraday pattern

The table presents regressions of daily trading activity in individual stocks on the magnitude of aggregate daily ETF primary flow. $\text{Liquid}^q_{i,t}$ equals one if stock i is in liquidity tercile q the prior month and zero otherwise. Tercile 1 contains the most liquid stocks and tercile 3 contains the least liquid stocks. $\text{Turnover}_{i,t}$ is the trade volume of stock i on day t divided by its shares outstanding. $\text{Turnover(Close-Mid)}_{i,t}$ is the difference between the trade volume in the last 10 minutes of the day and the average 10-minute trade volume from 9:40 to 15:50, divided by shares outstanding. $|\widehat{\text{Primary Flow}_t}|$ is the instrumented magnitude of aggregate ETF primary flow using the regression reported in Table 3 Column (1), standardized to a standard deviation of 1. Variable definitions can be found in Appendix A. The sample is stock-by-day from January 2015 to December 2019. Standard errors in parentheses are robust and clustered by stock and day. Standard errors in brackets are block-bootstrapped by ETF, stock, and day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\text{Turnover}_{i,t}$			$\text{Turnover(Close-Mid)}_{i,t}$		
$\lvert\widehat{\text{Primary Flow}_t}\rvert \times \text{Liquid}^1_{i,t}$ (Most Liquid)	3.788***	3.104***	0.370	4.745***	4.267***	1.537**
	(0.507)	(0.538)	(0.661)	(0.526)	(0.566)	(0.728)
	[0.521]	[0.565]	[0.699]	[0.540]	[0.594]	[0.763]
$\lvert\widehat{\text{Primary Flow}_t}\rvert \times \text{Liquid}^2_{i,t}$	3.181***	2.582***	-0.131	2.832***	2.338***	-0.275
	(0.496)	(0.487)	(0.626)	(0.503)	(0.504)	(0.679)
	[0.502]	[0.486]	[0.657]	[0.503]	[0.509]	[0.724]
$\lvert\widehat{\text{Primary Flow}_t}\rvert \times \text{Liquid}^3_{i,t}$ (Least Liquid)	2.385***	2.053***	-0.569	1.959***	1.709***	-0.685
	(0.534)	(0.512)	(0.606)	(0.602)	(0.589)	(0.707)
	[0.449]	[0.430]	[0.547]	[0.506]	[0.506]	[0.635]
Stock-level Controls	No	Yes	Yes	No	Yes	Yes
Tercile Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	No	No	Yes
Observations	2,686,929	2,676,914	2,676,914	2,675,838	2,666,516	2,666,516
Adj. R-squared	0.605	0.630	0.639	0.481	0.497	0.508
$\beta^1 - \beta^3$	1.403	1.052	0.939	2.786	2.558	2.222
F-stat	8.424***	5.054**	4.032**	31.03***	26.45***	19.02***
Unconditional Treatment Effect	3.256***	2.671***	-0.108	3.307***	2.827***	0.198
	(0.456)	(0.464)	(0.592)	(0.491)	(0.504)	(0.664)

Table 5
ETF primary flows and asset market quality

The table shows instrumental variables estimates of the effects of ETF primary flow on individual stocks' market quality. Effective Spread$_{i,t}$ is the share-weighted and measured as percentage of the price, Pricing Error$_{i,t}$ is based on Hasbrouck (1993), Volatility$_{i,t}$ is the intraday volatility based on 1-minute returns of stock i, and Correlation$_{i,t}$ is the intraday correlation between the 1-minute returns of stock i and the SPDR S&P 500 ETF. The main independent variable is the instrumented magnitude of aggregate ETF primary flow, standardized to a standard deviation of 1. Variable definitions can be found in Appendix A. The sample is daily from 2015 to 2019. Standard errors in parentheses are robust and clustered by stock and day. Standard errors in brackets are block-bootstrapped by ETF, stock, and day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Effective Spread$_{i,t}$	(2) Pricing Error$_{i,t}$	(3) Volatility$_{i,t}$	(4) Correlation$_{i,t}$
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^1_{i,t}$ (Most Liquid)	1.806***	1.496***	2.225***	0.864***
	(0.448)	(0.536)	(0.484)	(0.316)
	[0.525]	[0.556]	[0.567]	[0.344]
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^2_{i,t}$	0.639	0.524	1.308***	0.324
	(0.415)	(0.422)	(0.412)	(0.231)
	[0.470]	[0.435]	[0.496]	[0.270]
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^3_{i,t}$ (Least Liquid)	-0.171	-0.109	0.554	-0.083
	(0.438)	(0.436)	(0.397)	(0.198)
	[0.479]	[0.450]	[0.492]	[0.247]
Stock-level Controls	Yes	Yes	Yes	Yes
Tercile Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,676,869	2,676,914	2,676,893	2,676,893
Adj. R-squared	0.794	0.836	0.747	0.627
$\beta^1 - \beta^3$	1.977***	1.605***	1.671***	0.947***
F-stat	29.14	7.840	35.12	15.69
Unconditional Treatment Effect	0.762*	0.640	1.366***	0.370
	(0.399)	(0.392)	(0.415)	(0.233)

Table 6
ETF primary flows and stock returns

The table shows instrumental variables estimates of the effects of ETF primary flow on individual stocks' daily returns. $\text{Return}_{i,t}$ is the log return to stock i on day t, in percentage terms (i.e. 1.0 = 1%). The main independent variable is the instrumented magnitude of aggregate ETF primary flow, standardized to a standard deviation of 1. Variable definitions can be found in Appendix A. The sample is daily from 2015 to 2019. Standard errors in parentheses are robust and clustered by stock and day. Standard errors in brackets are block-bootstrapped by ETF, stock, and day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) $\text{Return}_{i,t-2}$	(2) $\text{Return}_{i,t-1}$	(3) $\text{Return}_{i,t}$	(4) $\text{Return}_{i,t+1}$	(5) $\text{Return}_{i,t+2}$
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^1_{i,t}$ (Most Liquid)	0.110**	0.103**	0.055	0.051	0.046
	(0.047)	(0.047)	(0.042)	(0.047)	(0.047)
	[0.053]	[0.057]	[0.045]	[0.049]	[0.052]
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^2_{i,t}$	0.114**	0.112**	0.059	0.049	0.046
	(0.052)	(0.052)	(0.046)	(0.052)	(0.052)
	[0.058]	[0.059]	[0.049]	[0.052]	[0.056]
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^3_{i,t}$ (Least Liquid)	0.116**	0.111**	0.058	0.050	0.047
	(0.050)	(0.050)	(0.045)	(0.052)	(0.051)
	[0.054]	[0.057]	[0.047]	[0.053]	[0.055]
Stock-level Controls	Yes	Yes	Yes	Yes	Yes
Tercile Controls	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	2,676,883	2,676,886	2,676,914	2,676,316	2,675,721
Adj. R-squared	0.017	0.015	0.013	0.014	0.013
$\beta^1 - \beta^3$	-0.00545	-0.00795	-0.00318	0.00134	-0.00072
F-stat	0.146	0.318	0.050	0.008	0.002
Unconditional Treatment Effect	0.113**	0.109**	0.057	0.050	0.046
	(0.049)	(0.050)	(0.044)	(0.050)	(0.050)

Table 7
ETF primary flows and asset market quality: Controlling for market returns and market structure

The table repeats the analyses in Table 4 columns (6) and Table 5 with additional variables that control for market returns and stock-by-day market structure. $\text{Return}_{mkt,t}$ is the market return measured as with-distribution return of CRSP Value-Weighted Index, $\text{Trade-to-Order}_{i,t}$ is the trade-to-order ratio of stock i measured as of last month, and $\text{HHI}_{i,t}$ is the Herfindahl–Hirschman Index on trading volume across venues for stock i measured as of last month. The main independent variable is the instrumented magnitude of aggregate primary flow of U.S. equity ETFs, standardized to a standard deviation of 1. Standard errors in parentheses are robust and clustered by stock and day. Standard errors in brackets are block-bootstrapped by ETF, stock, and day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) $\text{Turnover(Close-Mid)}_{i,t}$	(2) $\text{Effective Spread}_{i,t}$	(3) $\text{Pricing Error}_{i,t}$	(4) $\text{Volatility}_{i,t}$	(5) $\text{Correlation}_{i,t}$
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^1_{i,t}$ (Most Liquid)	1.550**	1.863***	1.523***	2.235***	0.858***
	(0.735)	(0.447)	(0.537)	(0.482)	(0.315)
	[0.717]	[0.477]	[0.478]	[0.557]	[0.342]
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^2_{i,t}$	-0.226	0.665	0.522	1.303***	0.323
	(0.680)	(0.416)	(0.424)	(0.412)	(0.231)
	[0.709]	[0.452]	[0.413]	[0.501]	[0.293]
$\lvert\widehat{\text{Primary Flow}}_t\rvert \times \text{Liquid}^3_{i,t}$ (Least Liquid)	-0.757	-0.268	-0.137	0.545	-0.076
	(0.707)	(0.438)	(0.435)	(0.397)	(0.197)
	[0.702]	[0.445]	[0.439]	[0.503]	[0.257]
$\text{Trade-to-Order}_{i,t}$	2.803***	-0.681***	-0.673***	-1.286***	-0.005
	(0.347)	(0.198)	(0.169)	(0.142)	(0.021)
$\text{HHI}_{i,t}$	-0.677***	-0.391***	-0.012	0.101***	0.038***
	(0.073)	(0.055)	(0.049)	(0.029)	(0.008)
Market Return Controls	Yes	Yes	Yes	Yes	Yes
Stock-level Controls	Yes	Yes	Yes	Yes	Yes
Tercile Controls	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	2,656,401	2,666,734	2,666,779	2,666,758	2,666,758
Adj. R-squared	0.511	0.795	0.835	0.751	0.631
$\beta^1 - \beta^3$	2.307***	2.131***	1.660***	1.690***	0.934***
F-stat	19.17	34.54	8.497	37.80	15.28
Unconditional Treatment Effect	0.195	0.757*	0.638	1.363***	0.370
	(0.664)	(0.400)	(0.392)	(0.415)	(0.233)

Table 8
ETF primary flows and asset market quality: No news

The table repeats the analyses in Table 4 columns (6) and Table 5, with the additional stock-by-day controls as in Table 7, plus controlling for market-wide returns. $\text{Return}_{mkt,t}$ is the market return measured as with-distribution return of CRSP Value-Weighted Index, and the estimates in this table drop all days on which the aggregate market return was larger in magnitude than 1%. Standard errors in parentheses are robust and clustered by stock and day. Standard errors in brackets are block-bootstrapped by ETF, stock, and day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) $\text{Turnover(Close-Mid)}_{i,t}$	(2) $\text{Effective Spread}_{i,t}$	(3) $\text{Pricing Error}_{i,t}$	(4) $\text{Volatility}_{i,t}$	(5) $\text{Correlation}_{i,t}$
$\lvert\widehat{\text{Primary Flow}_t}\rvert \times \text{Liquid}^1_{i,t}$ (Most Liquid)	1.162*	1.613***	1.447**	1.663***	0.744**
	(0.705)	(0.544)	(0.566)	(0.507)	(0.337)
	[0.743]	[0.603]	[0.608]	[0.556]	[0.344]
$\lvert\widehat{\text{Primary Flow}_t}\rvert \times \text{Liquid}^2_{i,t}$	-0.270	0.449	1.008**	1.166***	0.455*
	(0.685)	(0.514)	(0.458)	(0.446)	(0.254)
	[0.702]	[0.558]	[0.497]	[0.508]	[0.267]
$\lvert\widehat{\text{Primary Flow}_t}\rvert \times \text{Liquid}^3_{i,t}$ (Least Liquid)	-0.548	-0.262	0.574	0.615	0.263
	(0.759)	(0.538)	(0.425)	(0.432)	(0.219)
	[0.661]	[0.540]	[0.480]	[0.486]	[0.249]
$\lvert\text{Return}_{mkt,t}\rvert \times \text{Liquid}^1_{i,t}$ (Most Liquid)	9.900***	0.562	6.752***	3.275***	0.736
	(1.789)	(1.172)	(1.578)	(1.245)	(0.903)
$\lvert\text{Return}_{mkt,t}\rvert \times \text{Liquid}^2_{i,t}$	7.571***	-0.569	1.285	2.045**	-0.270
	(1.744)	(1.184)	(1.166)	(1.039)	(0.599)
$\lvert\text{Return}_{mkt,t}\rvert \times \text{Liquid}^3_{i,t}$ (Least Liquid)	6.948***	-1.594	-0.599	1.621	-0.577
	(2.044)	(1.410)	(1.126)	(0.996)	(0.428)
$\text{Trade-to-Order}_{i,t}$	2.880***	-0.667***	-0.614***	-1.228***	0.010
	(0.350)	(0.208)	(0.172)	(0.150)	(0.021)
$\text{HHI}_{i,t}$	-0.720***	-0.417***	-0.048	0.081***	0.034***
	(0.075)	(0.058)	(0.051)	(0.030)	(0.008)
Market Return Controls	Yes	Yes	Yes	Yes	Yes
Stock-level Controls	Yes	Yes	Yes	Yes	Yes
Tercile Controls	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	2,192,530	2,201,349	2,201,388	2,201,368	2,201,368
Adj. R-squared	0.508	0.796	0.837	0.751	0.621
$\beta^1 - \beta^3$	1.710***	1.875***	0.873**	1.048***	0.481***
F-stat	8.926	22.79	2.598	16.49	3.744
Unconditional Treatment Effect	0.119	0.603	1.011**	1.150**	0.488*
	(0.666)	(0.499)	(0.419)	(0.448)	(0.254)

Appendix

A. Variable Definitions

Variable Names	Description
$\mathbb{1}_{included,it}$	A dummy variable that equals 1 if stock i is included in the creation/redemption basket of Vanguard Total Market Index ETF (VTI) on day t and 0 otherwise.
Asset under Management$_{i,t}$ (ETF)	Price of ETF i times shares outstanding of ETF i on day t.
Bid-Ask Spread$_{i,t}$	Let i denote stock, t denote day, and s denote intraday time. The dollar-weighted percentage bid-ask spread of stock i on day t is calculated as following: $$\sum_s \frac{(\text{ask}_{its} - \text{bid}_{its})}{\text{price}_{its}} \cdot \frac{\text{price}_{its} \cdot \text{size}_{its}}{\sum_s \text{price}_{its} \cdot \text{size}_{its}}$$
Correlation$_{i,t}$	The correlation between the minute-to-minute returns of stock i and the minute-to-minute returns of S&P 500 Index on day t.
Correlation$_{i,t}$ (monthly)	The correlation between daily returns of stock i and the daily returns of the index that includes stock i in month t.
Effective Spread$_{i,t}$	Let i denote stock, t denote day, and s denote intraday time. The dollar-weighted percentage effective spread of stock i on day t is calculated as following: $$\sum_s \frac{2D_{its} \cdot (\text{price}_{its} - \text{midpoint}_{its})}{\text{midpoint}_{its}} \cdot \frac{\text{price}_{its} \cdot \text{size}_{its}}{\sum_s \text{price}_{its} \cdot \text{size}_{its}}$$ where D_{its} is a buy-sell indicator that equals 1 if the transaction is a buy and -1 if the transaction is a sell. Transactions are signed using method in Lee and Ready (1991).

Continued on next page

Table A1 – continued from previous page

Variable Definitions	**Description**
Expense Ratio$_{i,t}$	The amount that shareholders pay for the ETF i's operating expense divided by total investment for year t. CRSP Mutual Fund Database item *exp_ratio*.
HHI$_{i,t}$	Let i denote stock, j denote exchange, and t denote month. Herfindahl-Hirschman Index is calculated monthly as following: $$\text{HHI}_{i,t} = \sum_j \left(\frac{\text{Trading Volume}_{ijt}}{\sum_j \text{Trading Volume}_{ijt}} \right)^2$$
Liquid$^k_{i,t}$	A dummy variable that equals 1 if stock i is included in the kth tercile as of previous month on day t and 0 otherwise.
Market Capitalization$_{i,t}$	Closing price of stock i times shares outstanding of stock i on day t.
Pricing Error$_{i,t}$	The volatility of pricing error estimated using method in Hasbrouck (1993).
|Primary Flow$_{j,t}$|	The absolute value of the change in the shares outstanding of ETF j from day *t-1* to day t times closing price of ETF j on day t.
|Primary Flow$_t$|	The sum of the magnitude of all individual ETFs' primary flow, Primary\$Flow$_{j,t}$, on day t, then scaled by the total market value of the ETFs in the sample.
Return$_{j,t-k}$	The return of ETF j on day t-k.
Return$_{j,t-26\rightarrow t-5}$	The cumulative return of ETF j from day $t-26$ to $t-5$.

Continued on next page

Table A1 – continued from previous page

Variable Definitions	**Description**
Retail Flow$_{j,t}$	Let i denote stock, t denote day, and s denote intraday time. The retail flow of ETF j on day t is calculated as following: $$\text{Retail Flow}_{j,t} = \frac{D_{jts} \cdot \text{size}_{jts}}{\text{Shares Outstanding}_{j,t}}$$ where D_{its} is a retail buy-sell indicator that equals 1 if the transaction is a buy and -1 if the transaction is a sell. Retail transactions are identified and signed using method in Boehmer et al. (2020).
Robinhood Number$_{j,t}$	The number of Robinhood users that held ETF j on day t, scaled by Shares Outstanding$_{j,t}$.
Trade-to-Order$_{i,t}$	Trade to order ratio, calculated as the trading volume of stock i on day t divided by the order volume of stock i on day t.
Turnover$_{i,t}$	Trading volume of stock i divided by shares outstanding of stock i on day t.
Turnover(Close-Mid)$_{i,t}$	The difference of the turnover of the last 10 minutes of trading session (15:50 to 16:00 EST) and the average 10-minute turnover of of trading session mid-day (9:40 to 15:50 EST). Turnover is calculated as trading volume divided by shares outstanding.
Turnover Ratio$_{i,t}$	The minimum of aggregated sales or aggregated purchases divided by the average 12-month total net asset for ETF i in year t. CRSP Mutual Fund Database item *turn_ratio*).
Volatility$_{i,t}$	The standard deviation of the minute-to-minute returns of stock i on day t.
Volatility$_{i,t}$ (monthly)	Standard deviation of daily return of stock i in month t.
Volume$_{i,t}$	Trading volume of stock i on day t.