The Rise of ETF Trading and the Bifurcation of Liquidity*

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Abstract

In the last two decades the assets under management of passively managed exchange traded funds (ETFs) has risen dramatically. At the same time liquid stocks have become more liquid while illiquid stocks have not experienced a similar improvement. We model investors shifting from trading individual stocks to trading ETFs and generate predictions consistent with the documented bifurcation in liquidity. Using daily ETF creation and redemption activity, we provide empirical evidence that closely matches the model's predictions. The results show that the effects of ETFs on underlying asset markets are driven by their index replication strategy.

JEL: G11, G12, G20

In recent years the structure of U.S. equities has changed dramatically. In 1998 there was \$2 billion of assets under management (AUM) in exchange traded funds (ETFs); in 2018 the total AUM of U.S. equity ETFs was over \$3.5 trillion. In terms of trading volume ETFs went from near zero to accounting for 32% in two decades. During this same period of time the U.S. stock market has become more liquid (Angel, Harris, & Spatt, 2015). However, the improvement in liquidity has not been uniform: liquid stocks have become more liquid while illiquid stocks have not experienced such gains.[1] Figure 1 shows how the liquidity of U.S. equities has evolved since 2000. In this paper we examine whether the rise of ETF trading can help explain the recent bifurcation of liquidity in U.S. equity markets.

Insert Figure 1 About Here

We develop a theoretical model that suggests that ETF trading may have a differential effect on asset liquidity. Two key features of ETFs produce this differential effect. First, ETFs are a substitute for trading individual stocks. Investors will transfer their trading activity from individual stocks to a single ETF that represents those holdings. The second feature is that ETFs that passively track an index can, and frequently do, deviate from the precise weights of the index. The trading activity of the investors is not simply substituted one for one by the ETF but is tilted towards the stocks the ETF chooses to sample. Based on these two features we generate a number of predictions that follow from investors migrating from investing in individual stocks to ETFs. The model predicts that ETFs will systematically underweight or omit index assets that are less liquid *ex ante*. Consequently there will be a bifurcation in stock liquidity as noise trading flows preferentially into more liquid index members.

[1] Hendershott, Jones, and Menkveld (2011); Jones (2013); Haslag and Ringgenberg (2016).

Empirically we find that both predictions are borne out in the data. ETFs are more likely to omit less liquid index stocks from their holdings, and ETF primary flows have a differential effect on stock liquidity. As the magnitude of ETF primary flow increases – in either direction – liquid stocks become more liquid, while illiquid stocks become less liquid. This effect is separate from the documented effects of market fragmentation and algorithmic trading.

Although straightforward in principle, replicating a target index entails nontrivial problems of implementation. Models of index investing often assume that index funds simply mirror the weights of their target index. In practice ETFs have considerable discretion in defining their creation / redemption basket (Lettau & Madhavan, 2018) and many ETF redemption baskets diverge from the weights of their target index. Six of the ten largest ETFs as of 2018 state in their prospectus that they statistically replicate their target index by investing in a basket of representative securities.[2]

We model the fundamental tradeoff faced by index funds: To simultaneously minimize expected tracking error and expected transactions costs. The model applies to both ETFs (that set the creation and redemption basket for authorized participants) and traditional open-ended index funds (that rebalance their portfolio after inflows and outflows). For fund holdings the model predicts that index assets' optimal weighting is driven by their transaction costs, volatility, and correlation with other index assets. The more expensive to trade and the less correlated with the index the more likely the asset will be underweighted or omitted.

[2]One example is the Vanguard Total Stock Market ETF (VTI), the third largest ETF by assets as of 2018. 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 not only popular with funds that track relatively illiquid indexes, but is also used by ETFs that track highly liquid indexes. For example, the second largest ETF as of 2018, the iShares Core S&P 500 ETF (IVV), states in its prospectus that BlackRock "uses a representative index sampling strategy to manage the Fund."

We examine these predictions and find support for them in the fund holdings data.

We next turn to the effects of ETF trading on underlying asset markets. The most important prediction of the model is that ETF trading activity due to primary flows (i.e. the creation and redemption of ETF shares in exchange for the posted basket of index assets) amplifies preexisting differences in liquidity as less liquid index assets are systematically underweighted or omitted in the ETF's basket. The fund's replication strategy moves noise trading out of illiquid index assets and into liquid index assets. We test these predictions and find support for them in the stock-level daily data. On days when ETF primary flow is higher, both positively and negatively, we find that liquidity is higher for index stocks that are more liquid *ex ante* and lower for index stocks that are illiquid *ex ante*.

A unique prediction of the model is that the effects on index asset liquidity should be different for ETFs that follow a sampling strategy compared to ETFs that follow a full replication strategy. We test this prediction by exploiting the fact that investors and traders are indifferent whether a given ETF is a sampler or a full replicator. We find that the bifurcation in stock liquidity is driven entirely by primary flows in sampling ETFs.

Unobserved variables such as the arrival of market-moving news could also drive ETF primary flows and asset liquidity at the same time. We address this concern in two ways. First, we explicitly add daily market movements as a competing factor; second, we restrict the sample to only include days when market-moving news does not arrive. The differential effects of ETF activity on asset liquidity are larger, inconsistent with market-wide news driving our results.

Finally, the rise of ETFs is not the only possible explanation for the differential liquidity effects across the U.S. stock market in recent years. Two alternative explanations are often mentioned: 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 for a segment of the stock market (Weller, 2017). We find that measures of market fragmentation and algorithmic trading activity do not explain the differential effects of ETF activity on asset liquidity.

The findings are consistent with the hypothesis that the effects of ETFs on underlying asset markets depend on their index replication strategy. This paper makes contributions to both theoretical and empirical research on passive investing. Theoretical studies of passive investing assume that passive funds replicate the weights of their benchmark index *pro rata*. But this is not the case. Our results demonstrate that models of the impact of passive investing on asset prices can be made richer and more realistic by taking into account the replication strategy of passive funds. Moreover, empirical studies of passive investing often implicitly take full replication as given by using index assignment to study the treatment effects of index investing. Our results show that as a result the effects of index investing on the underlying assets may be mismeasured.

This paper focuses on two strands of the literature. First, a large literature has investigated the growth of passive and ETF investing and its effects on individual stocks and firms. 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. The finding is supported by Da and Shive (2018), who attribute the 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 increases the intraday bid-ask spreads of the underlying stocks. Sağlam, Tuzun, and Wermers (2019) find that increased ETF ownership makes the underlying stock in the indexes more liquid. Agarwal, Hanouna, Moussawi, and Stahel (2018) find that increased ETF ownership increases the commonality in liquidity of the underlying stocks.

We add to the literature by focusing on the implications of the infrastructure used in ETF trading. ETFs often sample a subset of liquid index assets, and underweight or omit less liquid index assets. We show that this replication strategy amplifies preexisting differences in asset liquidity: Liquid assets become more liquid, while illiquid assets become less liquid. We explicitly examine the create/redeem mechanism as the primary channel through which ETFs affect the underlying index assets, and the implications for the liquidity of underlying index assets.

Second, this paper relates to theoretical work on ETFs. We construct a model of optimal index replication and show how index replication strategy determines the effects of ETF trading on underlying asset markets.Carpenter (2000) and Basak, Pavlova, and Shapiro (2007) show that fund flows tilt the portfolio toward stock that belong to the benchmark because of fund managers' risk aversion. 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 assume the ETF basket replicates the underlying index. By contrast we show that create/redeem activity tilt the ETF portfolio toward more liquid stocks within its benchmark as ETF providers jointly minimize the trading cost and tracking error.We characterize the optimal strategic differences between the basket and the index and the resulting differential effects on asset markets.

I. Model

We construct a simple one-period model that captures the fundamental tradeoff faced by all passively managed index funds: To simultaneously minimize expected tracking error and expected transaction costs. The model is written from the point of view of an ETF provider; we show in Appendix B that the same decision problem and solution applies to traditional open-ended index funds as well.

A. Setup

There are N assets in the market with a vector of prices $\boldsymbol{p}$, and one-period excess returns $\tilde{\boldsymbol{r}}$ which are normally distributed with expectation 0 and covariance matrix Σ.

There are three types of agent: ETF providers, authorized participants, and investors. We consider the market for ETFs that track a specified index such as the S&P 500 or the Russell 2000 or the CRSP value-weighted equity index. The index is a vector of weights $\boldsymbol{v}$ that add to 1 and are exogenous and fixed.[3]

An ETF provider enters the market by publishing a basket, which is a vector of weights $\boldsymbol{w}$ that add to 1. She agrees to create or redeem shares of the ETF in exchange for that basket of individual assets.[4] The net asset value (NAV) of ETF shares is $NAV = \boldsymbol{w}'\boldsymbol{p}$.

[3] We do not consider the complexities introduced when a fund specifies its own index, as is apparently common among smaller niche funds (Robertson, 2019). While numerous, such funds represent a tiny fraction of ETF trading volume.

[4] Some ETF providers also allow the authorized participants to create or redeem ETF shares in exchange for cash. After netting the daily primary flow from its authorized participants, the provider may transact in derivatives or the underlying asset markets to zero out its residual position. As long as the ETF provider

The provider incurs administrative costs and collects a management fee, both of which are proportional to its assets under management. There is free entry, so in equilibrium ETF providers' fees equal their costs.

The ETF provider also nominates one or more authorized participants (APs) who have access to the creation and redemption mechanism. The AP continuously posts bid and offer prices for one ETF share. When he gets lifted (hit), he immediately buys (sells) the basket of underlying assets $\boldsymbol{w}$. In so doing, he incurs a transaction cost $C(\boldsymbol{w})$. He then immediately exchanges the basket for one ETF share.

The AP never bears any risk, and simply makes the market for ETF shares by carrying out the arbitrage with the basket of individual assets. Thus, the bid and offer prices that the AP posts are pinned down by the transaction costs. Specifically, the AP's profit from posting the offer $NAV + b$ and being lifted is:

$$
\begin{aligned}
&= (NAV + b) - (\boldsymbol{w'p} + C(\boldsymbol{w})) \\
&= b - C(\boldsymbol{w})
\end{aligned}
$$

As long as the provider nominates at least two APs, if one posts an offer that is above the zero-profit bound, the other will undercut them. That is, competition between APs is Bertrand. Thus, the bid and offer prices that investors face to trade the ETF shares are $NAV \pm C(\boldsymbol{w})$.

There is a unit mass of atomistic investors. In the competition between ETFs, all investors prefer an ETF that has a lower bid/ask spread and a lower tracking error. The expected

faces nonzero transaction costs of doing so, the model is the same.

squared tracking error of the ETF is

$$E[(\boldsymbol{w}\tilde{\boldsymbol{r}} - \boldsymbol{v}\tilde{\boldsymbol{r}})^2] = (\boldsymbol{w} - \boldsymbol{v})'\Sigma(\boldsymbol{w} - \boldsymbol{v})$$

Thus, in equilibrium the ETF that captures the market is the one that minimizes

$$U = C(\boldsymbol{w}) + \lambda(\boldsymbol{w} - \boldsymbol{v})'\Sigma(\boldsymbol{w} - \boldsymbol{v})$$

where λ is the shadow price that investors attach to a higher tracking error (term 2) relative to a higher bid/ask spread (term 1).[5]

B. Fund Weights

The first order condition for the optimal weight of the fund in asset i is:

$$0 = \frac{\partial C}{\partial w_i} + 2\lambda \sum_j (w_j - v_j)\sigma_i \sigma_j \rho_{ij}$$

$$\frac{Cov(\tilde{r}_i, \tilde{r}_{ETF} - \tilde{r}_{Index})}{\partial C / \partial w_i} = -1/2\lambda$$

That is, the optimality condition for each asset is that the marginal increase in trading

[5]We assume that all investors have the same preference λ. Relaxing this assumption would result in a "frontier" of ETFs that express different tradeoffs between tracking error and transaction costs and cater to investors with different preferences. In practice, the multiplicity of funds tracking the same index seems to be driven by investor search costs and not by different investor preferences (Hortaçsu & Syverson, 2004). Appendix B shows that the same decision problem and solution applies to traditional open-ended index funds as well.

costs equals the marginal decrease in the expected tracking error, which is a product of the covariance of $\tilde{r}_i$ with the fund's total tracking error.

To solve for w explicitly, we specify the trading cost as quadratic and additively separable:[6]

$$C(\boldsymbol{w}) = \sum_i c_i w_i^2$$

where c_i measures the the trading cost of stock i.

It follows that:

$$0 = 2c_i w_i + 2\lambda w_i \sigma_i^2 - 2\lambda v_i \sigma_i^2 + 2\lambda \sum_{j \neq i} (w_j - v_j)\sigma_i \sigma_j \rho_{ij}$$

$$w_i^* = \left(\frac{1}{1 + c_i/\lambda\sigma_i^2}\right) v_i + \left(\frac{1}{1 + c_i/\lambda\sigma_i^2}\right) \sum_{j \neq i} (v_j - w_j)\beta_{j,i} \tag{1}$$

Intuitively, the first term says that in general, index holdings are underweighted relative to their index weight v_i. The optimal weight balances transaction costs against the direct contribution to tracking error (hence, c_i over $\lambda\sigma_i^2$). The second term captures the indirect second-order effects on tracking error: An asset that covaries positively with other index constituents that are underweighted has a higher optimal weight, and vice versa.

In general we expect the first term, which captures the direct effects on trading costs and tracking error, to dominate. However, there are exceptions, such as index futures and

[6] Almgren, Thum, Hauptmann, and Li (2005) propose that trading cost is exponential in order size for each asset, and using a large set of execution data they estimate the exponent to be 1.375. Our quadratic cost function yields the same predictions in simple closed form.

redundant (highly correlated) assets. Appendix B analyzes these cases in detail.

The model predicts that the optimal weight w_i^* is

- Decreasing in c_i, as

$$\frac{\partial w_i^*}{\partial c_i} = -\frac{1}{(1 + c_i/\lambda\sigma_i^2)^2}\left(v_i + \sum_{j \neq i}(v_j - w_j)\beta_{j,i}\right) < 0$$

  because in general $v_i > w_i$. This means a more illiquid stock has a lower optimal weight in the basket.

- Increasing in ρ_{ij}, as

$$\frac{\partial w_i^*}{\partial \rho_{ij}} = \frac{1}{1 + c_i/\lambda\sigma_i^2}(v_j - w_j)\sigma_i\sigma_j > 0$$

  because again, in general $v_i > w_i$. This means when the stock has higher correlation with other index assets, its optimal weight is higher.

- Ambiguous in σ_i, as

$$\frac{\partial w_i^*}{\partial \sigma_i} = \frac{2\lambda c_i \sigma_i}{(\lambda\sigma_i^2 + c_i)^2}v_i + \frac{\lambda(c_i - \lambda\sigma_i^2)}{(\lambda\sigma_i^2 + c_i)^2}\sum_{j \neq i}(v_j - w_j)\sigma_j\rho_{ij}$$

  can be either positive or negative. The first term is always positive: the second term may be positive or negative.

C. Asset Liquidity

Our model predicts that ETFs, and passive index funds in general, are more likely to omit index assets with relatively 1) high trading costs, 2) low correlation with the index, and 3) high volatility. Next we explore the effects of ETF trading on underlying asset markets.

Consider two index assets that are identical except for their liquidity: The market for A is relatively liquid while the market for B is relatively illiquid, i.e. the price impact of trading $c_A < c_B$. In the Kyle (1985) equilibrium, this means

$$\beta_A = \frac{1}{2}\frac{\sigma_f^A}{\sigma_z^A} < \beta_B = \frac{1}{2}\frac{\sigma_f^B}{\sigma_z^B}$$

We model the difference in liquidity as more noise traders participating in the market for asset A, i.e. $\sigma_z^A > \sigma_z^B$. When an index ETF is introduced to the market, the noise traders who previously traded in both assets ("homemade indexing") migrate out of the individual asset markets into the ETF market because the ETF is cheaper to trade.

Because assets A and B have the same index weight, the same portion $\delta \in (0, 1)$ of noisy traders move out of both individual asset markets. This causes both assets' liquidity to fall:

$$\beta_A' = \frac{1}{2}\frac{\sigma_f}{\sigma_z^A(1-\delta)} > \beta_A$$
$$\beta_B' = \frac{1}{2}\frac{\sigma_f}{\sigma_z^B(1-\delta)} > \beta_B$$

At the same time, as they move to trading the ETF instead, whose creation/redemption basket includes A but omits B,[7] authorized participants will trade asset A on behalf of the noise traders. The trading volume generated by APs is still noise trading, as the APs simply serve as a conduit for execution. Let $\kappa > 0$ be the additional noisy volume generated by APs.

[7] We focus on the case in which asset B is omitted, but the predictions are qualitatively the same if asset B is included but underweighted.

Then the overall effect of the introduction of the ETF on the individual assets' liquidity is

$$\beta_A'' = \frac{1}{2}\frac{\sigma_f}{\sigma_z^A(1-\delta)(1+\kappa)}$$
$$\beta_B'' = \frac{1}{2}\frac{\sigma_f}{\sigma_z^B(1-\delta)}$$

Thus, the liquidity of asset B becomes worse (price impact of trading is larger). For asset A, if the ETF's low trading cost attracts additional volume into the ETF market so that $(1+\kappa)(1-\delta) > 1$, asset A becomes more liquid. Otherwise, the liquidity of asset A can stay the same or become worse.

Regardless, our model predicts an unambiguous decline of the liquidity of asset B *relative* to asset A:

$$\begin{aligned}(\beta_B'' - \beta_A'') - (\beta_B - \beta_A) &= \frac{\sigma_f}{2}\left((\frac{1}{\sigma_z^B(1-\delta)} - \frac{1}{\sigma_z^A(1-\delta)(1+\kappa)}) - (\frac{1}{\sigma_z^B} - \frac{1}{\sigma_z^A}) \right) \\ &> 0\end{aligned}$$

Thus, because of the ETF provider's optimal underweighting or omission of illiquid assets when they form the creation/redemption basket, the introduction of the ETF creates a "Matthew Effect" – an effect that amplifies pre-existing inequality – in the liquidity of index assets. Liquid assets become relatively more liquid, while illiquid assets become relatively less liquid.

II. Data

Our holdings data covers all stocks in the Russell 3000 index from 2009 to 2018. Thus, we exclude (as the Russell 3000 does) micro-cap and foreign stocks. We obtain quarterly fund holdings from the union of the CRSP mutual fund holdings database and the Thompson-Reuters S12 database, as both databases have gaps in their coverage. Returns, trading volume and other market data for both stocks and ETFs are from the CRSP monthly file. We use index membership and weights by month, directly from Russell Investments, for the Russell 1000 (large-cap) and Russell 2000 (small-cap) indexes.

Table 1 Panel A shows that our sample stocks, the monthly Russell 3000 list from 2006 to 2018, are a representative majority of large, mid and small-cap U.S. listed stocks. Note that the Russell 3000 index (and thus our sample) excludes very small micro-cap stocks.

Insert Table 1 About Here

Table 1 Panel B shows summary statistics for the ETFs in our sample, which is all U.S. equity ETFs from 2006 to 2018 in the CRSP mutual funds database with at least $10 million in assets under management. Figure 2 shows how the total assets under management of U.S. equity ETFs has evolved over time.

Insert Figure 2 About Here

We split the sample ETFs on the basis of their index replication strategy, which we obtain from Bloomberg and verify via manual checks. 71% of fund-years are fully replicating, meaning they (in principle) replicate the weights of their target index. 22% of fund-years are listed as "optimized", meaning they statistically replicate their target index with a basket of representative securities. The remaining 7% of fund-years either do not have a replication strategy flag, or say that they replicate their target index using derivatives.

We see that sampler ETFs have slightly larger assets under management (AUM) than replicator ETFs on average, although there is almost perfect overlap (common support) across the distributions of the AUMs of the two types. The expense ratios are also strikingly similar between the two types of ETF. The main difference appears in their yearly turnover: Replicator ETFs trade roughly 50% more actively than sampler ETFs do, despite their close similarity in both size and management fees. ETFs whose replication strategy is in the "Other" category are on average much smaller, higher-fee, and higher-turnover, suggesting that they are a separate category to themselves. We drop ETFs in the "Other" category in all subsequent tests.

III. ETF Trading and Stock Liquidity

This section tests the model's predictions. We first test whether ETFs overweight stocks that are *ex ante* liquid and underweight stocks that are *ex ante* illiquid. Next we test how this"tilting effect" changes the *ex post* liquidity of the underlying index assets. Finally we test whether ETFs that follow a sampling strategy have a larger effect than those that follow a full replicating strategy. The empirical results in all tests are consistent with the model predictions.

A. Omitted Holdings

Because ETFs jointly minimize the tracking error and trading cost at the same time, they prefer to hold stocks that are ex ante more liquid. To test our predictions on fund holdings, we use the quarterly holdings of ETFs that track the Russell 1000 (large-cap) and the Russell 2000 (small-cap) index. Table 2 shows regressions of how funds' holdings deviated from the target index, for each index asset on a quarterly basis. The dependent variable "Omitted" is a dummy variable that equals 1 when the stock is in the index but is not in the fund's holdings – that is, the fund did not hold that stock, although the stock was a member of its target index.

Insert Table 2 About Here

In Table 2 presents the results. Columns 1 uses fund fixed effects to compare within each fund's portfolio and quarter fixed effects to sweep out aggregate trends over time. Column 2 uses fund-by-quarter fixed effects, and thus compares within each fund's quarterly holdings snapshot. Finally, because Russell index weights are float-adjusted, the index weight for each stock covaries strongly with its liquidity. In Column 3 we assign each index stock in each quarter to one of 300 index "buckets", sorted by their index weight. Each bucket contains 10 stocks per quarter of similar size and liquidity. Adding bucket fixed effects thus compares each stock with a small set of peer stocks, in the same index, that were equally important and equally liquid *ex ante*.

In all cases a stock's liquidity, measured by its effective spread, positively predicts omission by ETFs. Less liquid index stocks are more likely to be omitted from funds' holdings. This finding agrees with our model's main prediction. Further, a stock's correlation with the index negatively predicts omission, that is, a stock that is more correlated with the index is less likely to be omitted. This finding also agrees with our predictions because stocks that are highly correlated with the target index help reduce the fund's overall expected tracking error. More volatile stocks are consistently more likely to be omitted. This finding suggests that the second-term indirect effects of stock volatility may dominate the first-term direct effects from Equation (1).

In sum, the holdings data show that ETF holdings systematically deviate from their target index, in ways that are consistent with our model.

B. Create/Redeem Activity and Liquidity

As liquid (illiquid) stocks are overweighted/underweighted in ETFs' portfolio compared to index, ETFs generate more (less) trading activity on the markets of the underlying index assets that are more liquid (illiquid). We test this hypotheses in this section. To emphasize, our objective is not to isolate the direct effects of variation in ETF trading as in e.g., Ben-David et al. (2018). Rather, our hypothesis is that *in equilibrium* as investors move from trading single stocks to trading ETFs, trading volume and liquidity will decline in *relative* terms for index assets that are more illiquid *ex ante*. Specifically, our model predicts that the differential effects on index asset markets are mediated by the arbitrage activity between ETF shares and the underlying assets.

ETF trading volume is a poor proxy for this activity for two reasons. First, much of the trading activity in ETF shares is bilateral between secondary market investors, and does not involve an AP on either side. For such trades there is no accompanying trading in the underlying assets. Second, large block trades may be executed directly through an AP, but do not appear in the exchange volume. To directly measure ETF creation and redemption ("Primary flow"), we collect daily data from Bloomberg on the shares outstanding of each ETF in our sample. The daily change in shares outstanding is the net creation/redemption activity in that ETF. Multiplied by the ETF's share price, this is the dollar create/redeem activity, or in other words, the net inflow or outflow of funds to the ETF.

Our ETF primary flow measure has two main differences with the “mutual fund flows” literature (i.e. Coval-Stafford, Goldstein, Li, and Yang (2013). First, in that setting the funds are open-ended mutual funds, and dollars flow directly between investors and the fund. Second, in that setting the mutual funds are actively managed, and thus they naturally have discretion in adjusting their holdings. By contrast, in our setting, ETF fund flows occur *only* through the authorized participants, and the link with the underlying assets is determined by the ETF provider.

Figure 3 plots the overall relation between ETF primary flows and asset liquidity.

Insert Figure 3 About Here

Each month, we sort our sample stocks into quintiles based on their average effective spread in month $t-1$. Thus, the first quintile contains the most liquid stocks and the fifth quintile contains the least liquid stocks as of the previous month. Figure 3 panel A shows that there is *no* significant relation between the daily total ETF primary flow and daily changes in the effective spreads of the most liquid stocks. That is, ETF primary flows in either direction have no effect on the liquidity of highly liquid stocks.

By contrast, Figure 3 panel B plots the relation between ETF primary flows and changes in stock liquidity for stocks that were relatively illiquid *ex ante*. There is a strongly upward-sloping relation in both directions: On days with more negative or more positive ETF primary flows, the effective spreads of illiquid stocks widened significantly. That is, ETF primary flows – in both directions – are strongly associated with negative changes in the liquidity of illiquid stocks.

To formally examine the relation between ETF primary flows and asset liquidity we regress each stock i's daily percentage change in effective spread on the magnitude of the total ETF primary flow that day, interacted with a dummy variable for the stock's lagged liquidity quintile, *Liquid j* (so that the relation is estimated separately for the stocks in each quintile), plus stock-level control variables $X_{i,t}$ and fixed effects by stock and date:

$$\%\Delta\ ESpread_{it} = \sum_{j=1}^{5} \beta^{Liquid\ j} \times |PrimaryFlow_{it}| \times Liquid_{it-1}\ j + \chi X_{it} + \gamma_i + \kappa_t + \epsilon_{it} \quad (2)$$

The fixed effects by date sweep out all observed or unobserved factors, for each day, that changed stock liquidity in the same direction across all stocks. In other words, our specification isolates daily changes in stock liquidity in *relative* terms across the quintiles. Thus, one dummy variable *Liquid j* must be omitted as including all five is collinear with the daily fixed effects. In our estimates the omitted dummy variable is always for quintile 3. This convention lets us estimate the relative effects of daily ETF primary flows, and other variables, on the most-liquid and least-liquid stocks. The results are reported in Table 3.

Insert Table 3 About Here

Table 3 Column 1 shows that there is a differential association of individual stocks' trading activity with daily ETF primary flows in dollar terms. On days with larger ETF primary flows, in either direction (i.e. positive or negative), *ex ante* liquid stocks' liquidity improved while *ex ante* illiquid stocks' liquidity worsened. However, as Figure 2 panel B showed, ETF primary flows have increased steadily throughout our sample period; hence, we scale the daily dollar amounts so that that our main independent variable has a stationary distribution. Table 3 Column 2 repeats the estimates, scaling the daily ETF primary flows by the total AUM in the sample ETFs as of the previous business day. The results are the same.

Table 3 Columns 3 and 4 break the sample into days when the total ETF primary flow was positive (column 3) versus days when it was negative (column 4). In these disjoint subsamples, we see consistent and symmetric results: the larger the magnitude of ETF primary flow, in either direction, the larger the bifurcation of individual stocks' liquidity.

For trading activity (share turnover) in individual stocks, the pattern is in the opposite direction. Table 3 Columns 5 through 8 show that regardless of the unit of measurement, and symmetrically, a larger magnitude of ETF primary flows in either direction is associated with a relative decrease in trading activity in illiquid stocks. These results are consistent with the main predictions of our model.

C. Replicator versus Sampler ETFs and Stock Liquidity

A key prediction that is unique to our model is that ETFs that follow a sampling strategy should cause a bigger differential effect in asset markets than ETFs that follow a full-replication strategy. From an investor's point of view there is no difference between an ETF that samples and an ETF that fully replicates. Because an ETF's replication strategy is set at inception, and because investors are indifferent − indeed ignorant − if they are trading a replicator or sampler, confounding factors such as news arrival, algorithmic trading, or investor behavior predict no difference in the relation for replicator versus sampler funds. Thus, comparing the effects of primary flows through the two types of ETF is a clean test of our model.

One concern with such a comparison is that replicator and sampler funds differ on other dimensions. For example, funds that track an index of large liquid assets such as the S&P500 are more likely to be fully replicating, while funds that track an index containing small and illiquid assets such as the Russell 2000 are more likely to be samplers. This fact is consistent with the main hypothesis of our paper, but it potentially distorts the comparison between replicator and sampler ETFs' effects.

To address this concern, we construct a matched set of replicator and sampler ETFs. For each fund-year in our data that is a sampler (i.e. replicates their target index statistically and is not fully replicating), we attempt to match it to a replicator fund in the same year. Matched fund-year pairs must have the same detailed four-character CRSP objective code and assets under management (AUM) at the beginning of the year that is within 25% of each other. When there are multiple matches we pick the closest match in terms of AUM. For example, the ALPS Dividend Dogs ETF (ticker SDOG, AUM $1.86B, replicator), which tracks a subset of the SP500 index consisting of the five firms in each sector with the highest dividend yield, is matched with the WisdomTree U.S. Large-Cap Dividend Fund (ticker DLN, AUM $1.88B, sampler) which tracks the 300 largest companies ranked by market capitalization from the WisdomTree U.S. Dividend Index. Thus, these are two large-cap dividend funds, which began the year with almost identical assets under management.

In all we construct 599 matched fund-year pairs, for an average of 60 matched pairs per year. The average total AUM per year in 2018 dollars is $114B for the sampler funds and $118B for the replicator funds, so the average sampler (replicator) fund has $1.90B ($1.97B) in assets under management. Figure 4 compares the distributions of fund AUM, expense ratio and turnover between the matched samples. By construction, the distributions of fund AUM are nearly identical. The replicator funds have slightly higher expense ratios and slightly lower turnover on average, but overall the distributions of those fund characteristics are also very similar.

Insert Figure 4 About Here

Table 4 compares the effects of daily ETF primary flows, between the matched ETFs that are replicators versus samplers.

Insert Table 4 About Here

We see that primary flows for both types of ETF affect trading activity (share turnover) in a consistent direction (Columns 2 and 4). However, the effects of ETF primary flow on liquidity are of opposite sign between the two types of ETF. Primary flows for replicator ETFs (column 1) are associated with a relative *improvement* to liquidity for illiquid stocks, which is also much smaller than the effects we document. By contrast, and consistent with our main results, primary flows for sampler ETFs (column 3) are associated with a relative *fall* in liquidity for illiquid stocks and vice versa. The different signs between different types of ETF are consistent with our model's specific predictions, and are difficult to explain via other confounding factors because (i) the matched fund pairs follow similar indexes and have similar assets under management, and (ii) traders and investors are indifferent whether a given fund is a replicator or a sampler.

In summary, ETFs overweight (underweight) the index underlying assets that are *ex ante* liquid (illiquid). This creates a "Matthew effect" that makes the liquid (illiquid) assets even more liquid (illiquid). In the next section, we test some alternative explanations.

IV. Alternative explanations

One concern with our results is that market dynamics change over time, and could covary with both ETF turnover and stock turnover and liquidity. For example, the arrival of index-relevant information could drive increased ETF trading activity, and also cause market makers to reduce their trading activity and widen their bid/ask spreads, particularly in less liquid stocks. We examine these potential confounds in two ways.

First, it could be that when there is market-moving news (or the risk of market-moving news arriving), market makers reduce liquidity more in stocks that were less liquid *ex ante*. To examine this possibility, we first 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 quintile. Table 5 columns 1 and 2 show that the relationship between ETF primary flows and asset liquidity is effectively unchanged when we add the daily market return as an additional explanatory factor (compare with Table 3 column 3).

Insert Table 5 About Here

Second, we drop from the sample any days in which the U.S. stock market had a return outside the range [-0.5%, +0.5%]. This filter leaves us with a subsample of 1,291 trading days on which the stock market hardly moved. Table 5 columns 3 and 4 show the results. The differential relationship between ETF primary flows and stock liquidity is even stronger than in the full sample, particularly for the least liquid set of underlying stocks, and the relationship with stock-level trading activity is again apparent. Thus, in the absence of market-moving news, on quiet market days, the relationship between ETF primary flows and stock liquidity is actually stronger than on days when the market moved a lot.

The third way that we examine the influence of other market factors is to control for time-varying factors such as high frequency trading activity and market fragmentation. We use the SEC MIDAS data to construct measures of both high frequency trading activity (Trade to order ratio) (Weller, 2017) and market fragmentation (HHI of trading volume across market venues), for each stock by month individually from 2012 to 2018. The results when we add those stock-level measures as controls are shown in Table 6.

Insert Table 6 About Here

We see that the differential relations of daily total ETF primary flow with stock liquidity and turnover are still present, both across all days in the more recent sample (columns 1 and 2) and when we condition down to days on which the market did not move (columns 3 and 4). We conclude that daily stock-level changes in high frequency trading activity and market fragmentation do not subsume our results.

V. Conclusion

An index fund or ETF's objective is to deliver a low expected tracking error at a low expected cost. In this paper we document the direct consequences of ETF replication strategy, most prominently a bifurcation effect on the liquidity of the underlying index assets. Liquid stocks become more liquid, and illiquid stocks become more illiquid, due to ETF trading activity.

We construct a stylized model to characterize the trade-off between tracking error and trading cost. The model predicts that for stocks that are illiquid and expensive to trade, index funds and ETF providers are better off underweighting or omitting these stocks. This is an important point for the academic literature on the effects of the rise of index investing.

Our contribution is two-fold. First, although comovement in stock liquidity is well studied over the past two decades, the widening liquidity gap in the U.S. stock market since 2006 has received little attention. Our theory not only helps explain this fact, but also predicts that as long as ETF trading activity continues to increase the liquidity gap is expected to widen even further. Second, we point out a treatment effect that has been ignored by empirical studies in this field – index constituents being systematically underweighted or omitted from the ETF basket. Mistakenly classifying omitted stocks as treated stocks (as will happen using either index weights or index assignment to proxy for fund ownership) can result in biased estimates of the effects of index investing. Thus, our results should inform future empirical research as well.

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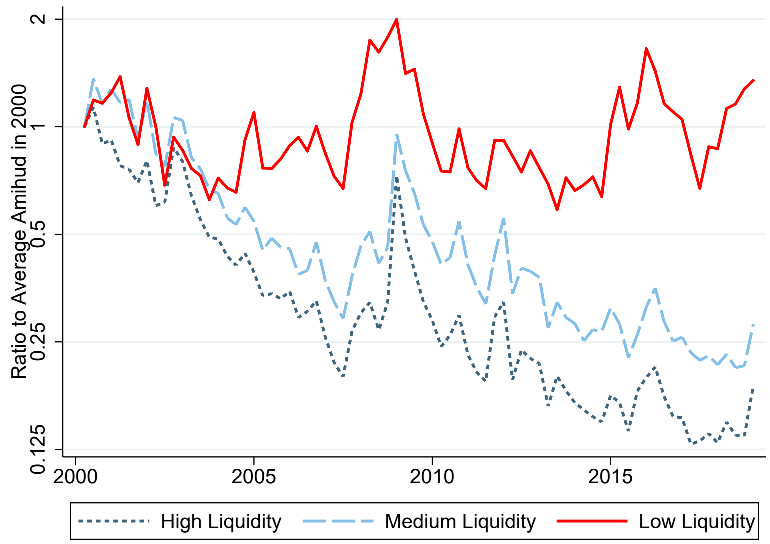
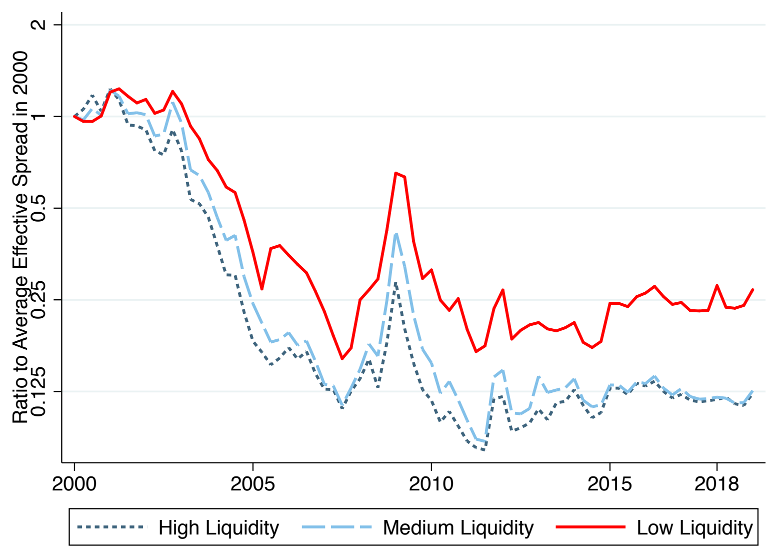


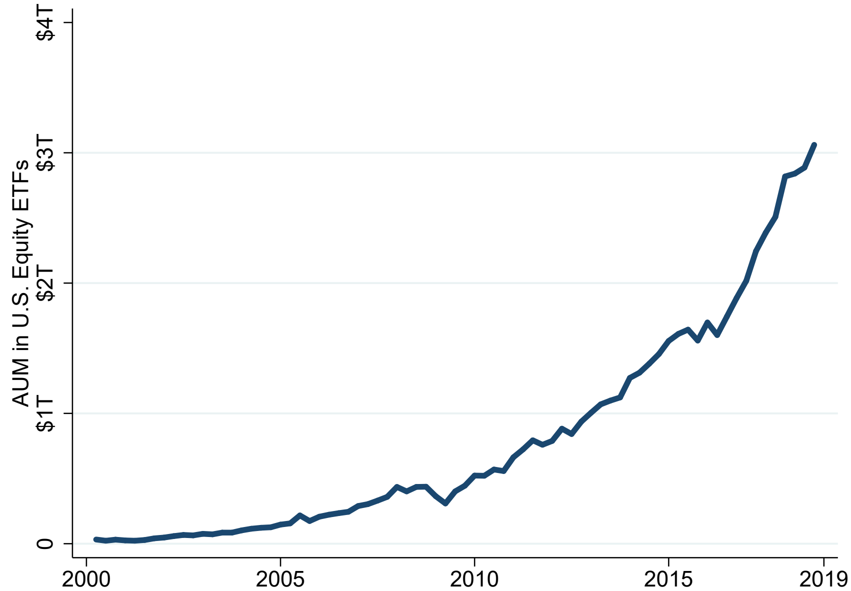
(a) Amihud price impact



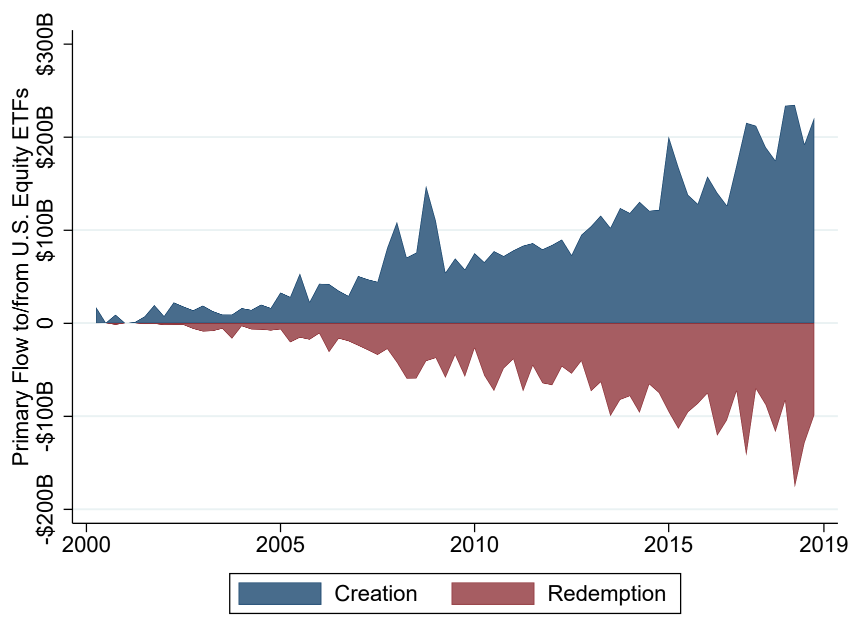
(b) Effective Spread

Figure 1. The evolution of U.S. stock liquidity

The figure plots the distribution of liquidity across U.S. common stocks over time. Stocks are sorted into terciles on the basis of their liquidity each quarter. Panel A plots quarterly Amihuds from 1990 to 2018, while panel B plots quarterly effective spreads from 2000 to 2018. The plots show the average in each tercile, by quarter, scaled by the average measure for that tercile as of the start of the sample period. The sample includes all U.S. common stocks with market capitalization greater than \$300M in 2018 dollars.



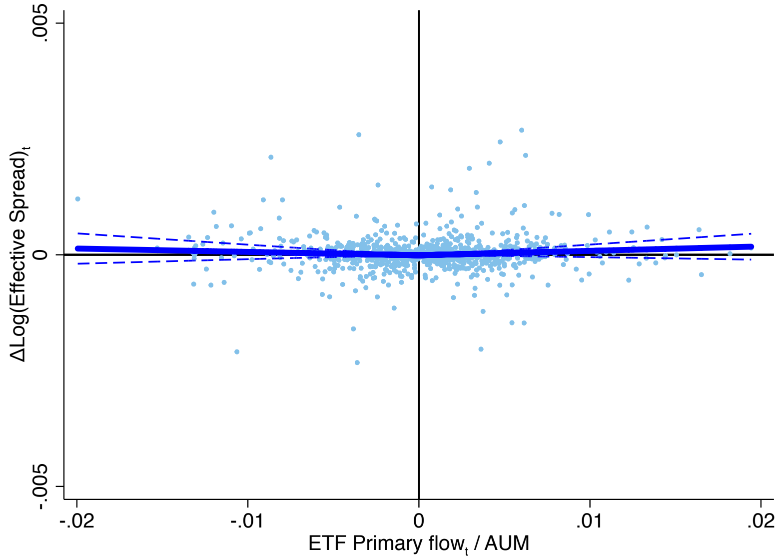
(a) ETF assets under management



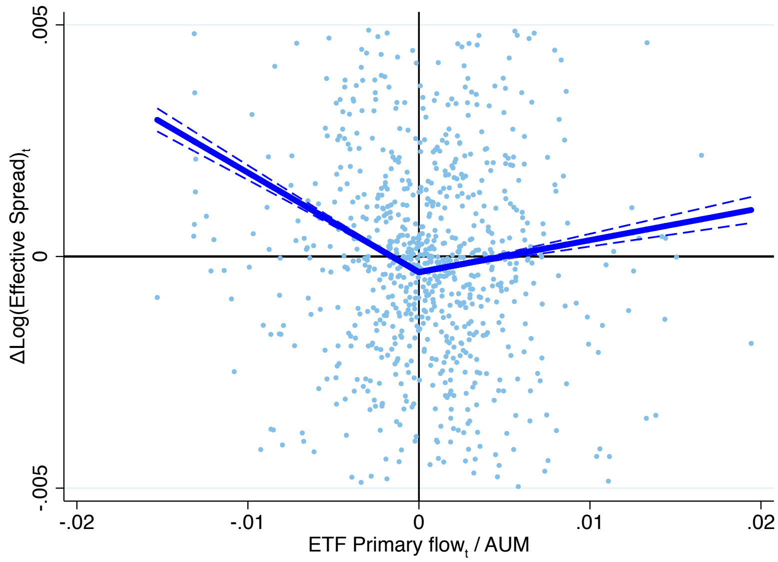
(b) ETF primary flows

Figure 2. ETF assets under management and primary flows

Panel A plots total assets under management 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 1993 to 2018.



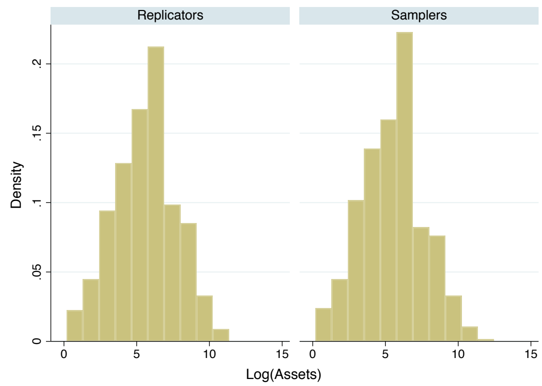
(a) Quintile 1 (Most liquid *ex ante*)



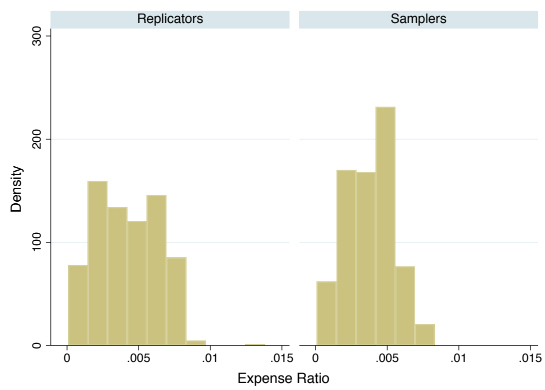
(b) Quintile 5 (Least liquid *ex ante*)

Figure 3. ETF primary flow and changes in asset liquidity

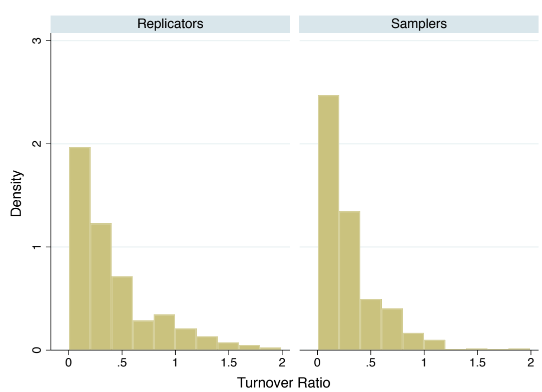
The figure plots daily changes in effective spreads for individual stocks, against daily total primary flows (total dollar creations minus redemptions scaled by AUM) for U.S. equity ETFs. Panels A and B plot the relation for stocks that were in the first and fifth quintile respectively sorted by effective spread as of the previous month (the most liquid and least liquid stocks *ex ante*). The blue lines show the linear best-fit line, separately estimated for positive and negative ETF primary flows. The dashed lines show 95% confidence intervals.



(a) Fund AUM



(b) Fund expense ratio



(c) Fund turnover ratio

Figure 4. The figure plots histograms of log assets under management (a), expense ratios (b), and yearly turnover ratios (c), comparing the matched samples of replicator ETFs (left) and sampler ETFs (right).

Table 1
Summary Statistics

Panel A presents summary statistics of our sample stocks, which consist of all Russell 3000 members (including both the Russell 1000 large-cap index and the Russell 2000 small-cap index) monthly from 2009-2018. The sample contains 5,743 unique stocks. Panel B displays summary statistics of ETFs in our sample, which consists of all U.S. equity ETFs in the CRSP mutual fund database from 2009-2018. The table is split on the basis of each fund's replication strategy.

Panel A: Index Stocks

	Mean	StDev	P10	Median	P90
Market Cap ($ Millions)	6,700	25,267	198	1,198	12,672
Amihud (%/$100 Million)	0.0137	0.0347	0.000095	0.00175	0.0356
Volatility	0.025	0.014	0.011	0.021	0.042

Panel B: Exchange Traded Funds

	Observations	Mean	StDev	P10	Median	P90
	Full Replication					
AUM ($ Millions)	4,233	1,921	9,239	23	203	3,902
Expense Ratio (%)	4,059	0.45	0.22	0.14	0.48	0.70
Turnover	4,043	0.41	0.55	0.06	0.25	0.94
	Sampling / Optimized					
AUM ($ Millions)	1,279	2,802	9,894	22	282	4,725
Expense Ratio (%)	1,226	0.44	0.17	0.20	0.48	0.63
Turnover	1,220	0.28	0.28	0.05	0.20	0.61
	Other					
AUM ($ Millions)	425	268	538	15	60	816
Expense Ratio (%)	397	0.81	0.27	0.45	0.95	0.99
Turnover	386	1.00	2.03	0.07	0.45	2.66

Table 2
Stock characteristics and ETF holdings

The table presents regressions of quarterly fund holdings by ETFs on the characteristics of index stocks. The dependent variable $\mathbb{1}_{Omitted_{ijt}}$ is a dummy variable that equals 1 if fund j omitted stock i in its holdings in quarter t, and 0 if fund j held any number of shares of stock i in quarter t. The sample unit is stock-fund-quarter and includes all stocks that were in the Russell 1000 or 2000 index and all Russell 1000 and 2000 ETFs that reported their holdings in quarter t, from 2009 to 2018. Standard errors are clustered by stock. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
$Spread_{it}$	0.0142***	0.0141***	0.0148**
	(0.00501)	(0.00503)	(0.00556)
$Volatility_{it}$	0.0163***	0.0166***	0.0158***
	(0.00395)	(0.00397)	(0.00378)
$Correlation\_w\_Index_{it}$	-0.00724	-0.00525	-0.00639
	(0.0127)	(0.0130)	(0.0130)
$IndexWeight_{it}$	1.683	1.663	-0.683
	(2.131)	(2.130)	(2.531)
Fund FE	Yes	No	No
Year-Quarter FE	Yes	No	No
Fund x Year-Quarter FE	No	Yes	Yes
Index Bucket FE	No	No	Yes
Observations	1,005,002	1,005,002	1,005,002
R-squared	0.22	0.23	0.24

Table 3
ETF primary flows and asset liquidity

The table presents regressions of the daily percent changes in effective spreads $\%\Delta\ ESpread_{it}$ and turnover $\%\Delta\ Turnover_{it}$ of individual stocks on the magnitude of daily ETF primary flow i.e. creation and redemption activity, $|PrimaryFlow_t|$. The sample consists of all Russell 3000 member stocks daily from 2009 to 2018. We divide sample stocks each month into quintiles on the basis of their liquidity in the previous month: *Liquid* 1 contains the most liquid stocks, while *Liquid* 5 contains the least liquid stocks. Standard errors are clustered by stock. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) $\%\Delta\ ESpread_{it}$	(2) $\%\Delta\ ESpread_{it}$	(3) $\%\Delta\ ESpread_{it}$	(4) $\%\Delta\ ESpread_{it}$	(5) $\%\Delta\ Turnover_{it}$	(6) $\%\Delta\ Turnover_{it}$	(7) $\%\Delta\ Turnover_{it}$	(8) $\%\Delta\ Turnover_{it}$
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 1 (*Most*)	-0.0246***	-2.1142***	-3.7304***	0.0696	-0.0069	-0.3426	-1.4326**	0.7451
	(0.0029)	(0.2422)	(0.3680)	(0.3924)	(0.0046)	(0.4162)	(0.6622)	(0.7509)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 2	-0.0141***	-1.4726***	-1.9275***	-0.8181*	0.0022	0.8811*	0.6219	1.0401
	(0.0032)	(0.2689)	(0.4393)	(0.4500)	(0.0051)	(0.4720)	(0.7322)	(0.8418)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 3	-	-	-	-	-	-	-	-
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 4	0.0065*	1.4916***	2.4867***	0.1206	-0.0123**	-1.0232**	-1.3472*	-0.6536
	(0.0040)	(0.3524)	(0.5496)	(0.5847)	(0.0054)	(0.4767)	(0.7591)	(0.8909)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 5 (*Least*)	0.0845***	9.9056***	8.6286***	11.1198***	-0.0421***	-3.1018***	-2.8624***	-3.6285***
	(0.0117)	(1.4671)	(1.5107)	(3.2305)	(0.0069)	(0.5148)	(0.7853)	(0.8717)
Quintile Main Effects	Yes	Yes	Yes	Yes				
Stock-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,219,418	7,219,418	4,207,821	3,011,594	7,219,418	7,219,418	4,207,821	3,011,594
R-squared	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02
PrimaryFlow Units	$Trillion	($/AUM)/100	($/AUM)/100	($/AUM)/100	$Trillion	($/AUM)/100	($/AUM)/100	($/AUM)/100
Sample Dates	All	All	CR>0	CR<0	All	All	CR>0	CR<0
$\beta^{Liquid\ 5} - \beta^{Liquid\ 1}$	0.109***	12.001***	12.35***	11.01***	-0.0352***	-2.759***	-1.432**	-4.369***
F-stat	90.1	68.6	69.8	11.8	32.8	42.8	5.1	39.8

Table 4
ETF primary flows and asset liquidity: Replicator vs sampler ETFs

The table presents regressions of the daily percent changes in effective spreads $\%\Delta\ ESpread_{it}$ and turnover $\%\Delta\ Turnover_{it}$ of individual stocks on the magnitude of daily ETF primary flow i.e. creation and redemption activity, $|PrimaryFlow_t|$. The daily ETF primary flows are calculated using a matched sample of pairs of replicator and sampler fund-years that have the same Lipper objective code and similar assets under management (AUM). We divide sample stocks each month into quintiles on the basis of their liquidity in the previous month: *Liquid* 1 contains the most liquid stocks, while *Liquid* 5 contains the least liquid stocks. Standard errors are clustered by stock. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) $\%\Delta\ ESpread_{it}$	(2) $\%\Delta\ Turnover_{it}$	(3) $\%\Delta\ ESpread_{it}$	(4) $\%\Delta\ Turnover_{it}$
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}\ 1\ (Most)$	0.21***	0.40***	-1.47***	-0.15
	(0.08)	(0.13)	(0.33)	(0.30)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}\ 2$	0.34***	0.33**	-0.24	0.36
	(0.09)	(0.16)	(0.38)	(0.35)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}\ 3$	-	-	-	-
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}\ 4$	-0.41***	-0.39**	0.31	-1.53***
	(0.13)	(0.19)	(0.44)	(0.56)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}\ 5\ (Least)$	-0.63**	-0.55***	3.15***	-2.96***
	(0.32)	(0.17)	(0.90)	(0.42)
ETF Type	Replicators	Replicators	Samplers	Samplers
Quintile Main Effects	Yes	Yes	Yes	Yes
Stock-level Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	7,219,418	7,219,418	7,219,418	7,219,418
R-squared	0.01	0.02	0.01	0.02
PrimaryFlow Units	($/AUM)/100	($/AUM)/100	($/AUM)/100	($/AUM)/100
$\beta^{Liquid\ 5} - \beta^{Liquid\ 1}$	-0.85**	-0.95***	4.63***	-2.81***
F-stat	7.2	43.9	28.4	57.7

Table 5
ETF primary flows and asset liquidity: Controlling for market-wide news

The table presents regressions of the daily percent changes in effective spreads $\%\Delta\ ESpread_{it}$ and turnover $\%\Delta\ Turnover_{it}$ of individual stocks on the magnitude of daily ETF primary flow i.e. creation and redemption activity, $|PrimaryFlow_t|$. The "No News" sample in columns 3 and 4 consists only of days on which the market return was smaller than +/- 50 basis points. We divide sample stocks each month into quintiles on the basis of their liquidity in the previous month: *Liquid* 1 contains the most liquid stocks, while *Liquid* 5 contains the least liquid stocks. Standard errors are clustered by stock. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) $\%\Delta\ ESpread_{it}$	(2) $\%\Delta\ Turnover_{it}$	(3) $\%\Delta\ ESpread_{it}$	(4) $\%\Delta\ Turnover_{it}$
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 1 $(Most)$	0.2148***	0.3993***	-1.4735***	-0.1530
	(0.0808)	(0.1340)	(0.3341)	(0.3016)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 2	-1.52***	-0.65	-3.61***	0.38
	(0.31)	(0.54)	(0.70)	(1.10)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 3	-	-	-	-
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 4	0.42	-0.82	1.98**	-0.97
	(0.41)	(0.54)	(0.90)	(1.12)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 5 $(Least)$	9.06***	-1.51***	17.03***	-3.11***
	(2.15)	(0.57)	(4.07)	(1.14)
$\lvert Benchmark\ Ret_{it}\rvert \times Liquid_{t-1}$ 1	-0.00*	0.01***	-0.01*	0.02**
	(0.00)	(0.00)	(0.01)	(0.01)
$\lvert Benchmark\ Ret_{it}\rvert \times Liquid_{t-1}$ 2	0.00	0.01***	-0.00	0.03***
	(0.00)	(0.00)	(0.00)	(0.01)
$\lvert Benchmark\ Ret_{it}\rvert \times Liquid_{t-1}$ 3	-	-	-	-
$\lvert Benchmark\ Ret_{it}\rvert \times Liquid_{t-1}$ 4	0.01***	-0.00	0.02***	0.02***
	(0.00)	(0.00)	(0.01)	(0.01)
$\lvert Benchmark\ Ret_{it}\rvert \times Liquid_{t-1}$ 5	0.01	-0.01***	0.02	0.02***
	(0.01)	(0.00)	(0.01)	(0.01)
Sample Dates	All	All	No News	No News
Quintile Main Effects	Yes	Yes	Yes	Yes
Stock-level Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	7,219,418	7,219,418	3,834,554	3,834,554
R-squared	0.01	0.02	0.01	0.02
PrimaryFlow Units	($/AUM)/100	($/AUM)/100	($/AUM)/100	($/AUM)/100
$\beta^{Liquid\ 5} - \beta^{Liquid\ 1}$	10.95***	-0.196	22.02***	-2.033**
F-stat	26.2	0.2	29.6	5.3

Table 6
ETF primary flows and asset liquidity: Controlling for market fragmentation and HFT activity

The table presents regressions of the daily percent changes in effective spreads $\%\Delta\ ESpread_{it}$ and turnover $\%\Delta\ Turnover_{it}$ of individual stocks on the magnitude of daily ETF primary flow i.e. creation and redemption activity, $|PrimaryFlow_t|$. The Herfindahl of trading volume across venues HHI_{it} measures market fragmentation. The trade-to-order ratio TOR_{it} measures high frequency trading activity. The results are similar using other measures such as Odd-lot ratio, average trade size, and cancel-to-trade ratio. We divide sample stocks each month into quintiles on the basis of their liquidity in the previous month: *Liquid* 1 contains the most liquid stocks, while *Liquid* 5 contains the least liquid stocks. Standard errors are clustered by stock. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) $\%\Delta\ ESpread_{it}$	(2) $\%\Delta\ Turnover_{it}$	(3) $\%\Delta\ ESpread_{it}$	(4) $\%\Delta\ Turnover_{it}$
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 1 (*Most*)	-3.90***	1.68*	-7.97***	2.03
	(0.68)	(0.93)	(1.04)	(1.53)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 2	-1.58**	2.17**	-4.42***	3.20**
	(0.77)	(0.97)	(1.35)	(1.57)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 3	-	-	-	-
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 4	-1.86**	-3.50***	0.17	-2.71*
	(0.92)	(1.01)	(1.67)	(1.53)
$\lvert PrimaryFlow_t\rvert \times Liquid_{t-1}$ 5 (*Least*)	6.57***	-10.43***	11.71***	-11.20***
	(2.17)	(1.14)	(3.87)	(1.68)
HHI_{it}	0.11***	0.08***	0.13***	0.09***
	(0.03)	(0.01)	(0.04)	(0.01)
TOR_{it}	-1.29***	11.56***	-1.20***	11.83***
	(0.05)	(0.20)	(0.06)	(0.27)
Sample Dates	All	All	No News	No News
Control for Market Returns	Yes	Yes	Yes	Yes
Quintile Main Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	4,527,432	4,527,432	2,646,165	2,646,165
R-squared	0.02	0.04	0.02	0.04
PrimaryFlow Units	($/AUM)/100	($/AUM)/100	($/AUM)/100	($/AUM)/100
$\beta^{Liquid\ 5} - \beta^{Liquid\ 1}$	10.47***	-12.11***	19.68***	-13.24***
F-stat	24.9	127.5	27.4	70.1

Appendix

A. Variable Definitions

Table A1: Variable Definitions

Variable Names	Description
$\%\Delta$ESpread	The percentage change in effective spread of stock i on day t is calculated as following: $$\%\Delta\text{ESpread}_{i,t} = \log(\text{ESpread}_{i,t}) - \log(\text{ESpread}_{i,t-1})$$
$\%\Delta$Turnover	The percentage change in turnover of stock i on day t is calculated as following: $$\%\Delta\text{Turnover}_{i,t} = \log(\text{Turnover}_{i,t}) - \log(\text{Turnover}_{i,t-1})$$
$\mathbb{1}_{\text{Omitted}}$	Dummy variable that equals 1 if ETF j omitted stock i in quarter t.
Amihud	Absolute value of monthly return of stock i divided by monthly dollar trading volume in month t. Monthly dollar trading volume is calculated as monthly share trading volume times end of month closing price.
AUM (ETF)	Price of ETF i times shares outstanding of ETF i on day t.
Benchmark Ret_{it}	Russell 1000 or Russell 2000 Index return, depending on which one stock i belongs to, on day t.
Correlation with Index	The correlation between daily returns of stock i and the daily returns of the index that includes stock i in quarter t .

Continued on next page

Table A1 – continued from previous page

Variable Definitions	Description
Effective Spread	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: $$\sum_s \frac{\lvert \log(\text{price}_{its}) - \log(\text{midpoint}_{its}) \rvert \cdot \text{price}_{its} \cdot \text{size}_{its}}{\sum_s \text{price}_{its} \cdot \text{size}_{its}}$$ Buy-sell indicator are created using method in Lee and Ready (1991) and quotes prior to 2015 are interpolated using method in Holden and Jacobsen (2014).
Expense Ratio	Expense ratio of ETF i in year t from CRSP Mutual Fund Database.
HHI	Let i denote stock, j denote exchange, and t denote month. Herfindahl-Hirschman Index is calculated monthly as following: $$\text{HHI}_{it} = \sum_j \left(\frac{\text{Trading Volume}_{ijt}}{\sum_j \text{Trading Volume}_{ijt}} \right)^2$$
Index Weight	Stock i's weight in index j at month t, from Russell proprietary data.
Market Cap	Closing price of stock i times shares outstanding of stock i on day t.
Primary Flow, dollar unit	The change of the shares outstanding of ETF i from day *t-1* to day t times closing price of ETF i on day t.
Primary Flow, percent unit	The dollar unit primary flow of ETF i on day t divided by the AUM of ETF i on day t, calculated daily.

Continued on next page

Table A1 – continued from previous page

Variable Definitions	**Description**
TOR	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	Trading volume of ETF i divided by shares outstanding of ETF i on day t.
Volatility	Standard deviation of daily return of stock i in month t.

B. Further discussion of the model

B.1. Open-ended index funds

As noted before, our model also applies to traditional open-ended index funds that rebalance their portfolios after inflows and outflows. The index fund manager chooses their replication strategy to attract investors, who again have the same utility function over expected tracking error and expected trading costs (which investors now bear directly via the management fee, instead of indirectly via the bid/ask spread):

$$U = \boldsymbol{C}(\boldsymbol{w}) + \lambda(\boldsymbol{w} - \boldsymbol{v})'\Sigma(\boldsymbol{w} - \boldsymbol{v})$$

The rest of the solution and all comparative statics are the same.

B.2. Trading in index futures

Recall that

$$w_i^* = \frac{1}{1 + c_i/\lambda\sigma_i^2} v_i + \frac{1}{1 + c_i/\lambda\sigma_i^2} \sum_{j \neq i} (v_j - w_j)\beta_{j,i}$$

Consider an index for which there is a liquid futures contract. The futures contract has $v_i = 0$, so the first term is zero. That is, the futures contract is not an index constituent, and for such assets we would think w_i^* should also be zero. But the futures contract is perfectly correlated with the weighted return of the index constituents, and has very low trading costs c_i. In this case, the optimal weights w_j on all the index constituents themselves are close to zero and the optimal weight on the futures contract is close to one.

B.3. Redundant assets

Recall that

$$w_i^* = \frac{1}{1 + c_i/\lambda\sigma_i^2} v_i + \frac{1}{1 + c_i/\lambda\sigma_i^2} \sum_{j \neq i} (v_j - w_j)\beta_{j,i}$$

Consider two perfectly substitutable assets ($\rho_{1,2} = 1$) with different relative trading costs ($c_1/\sigma_1^2 \neq c_2/\sigma_2^2$). Assume for simplicity that $\rho_{1,j}, \rho_{2,j} = 0, \forall j \neq 1, 2$.[8] We have a system of equations with two equations and two unknowns:

[8] More general case with arbitrary ρ gives the same qualitative result.

$$w_1^* = \kappa_1 v_1 + \kappa_1 v_2 \frac{\sigma_2}{\sigma_1} - \kappa_1 w_2 \frac{\sigma_2}{\sigma_1}$$
$$w_2^* = \kappa_2 v_2 + \kappa_2 v_1 \frac{\sigma_1}{\sigma_2} - \kappa_2 w_1 \frac{\sigma_1}{\sigma_2}$$

where

$$\kappa_i = \frac{1}{1 + c_i/\lambda\sigma_i^2}$$

Solve for:

$$w_1^* = \frac{\kappa_1(1-\kappa_2)}{1-\kappa_1\kappa_2}\left(v_1 + \frac{\sigma_2}{\sigma_1} v_2\right)$$

Note that, if security one is almost costless to trade, then $\kappa_1 \to 1$, and $w_1^* = v_1 + v_2(\sigma_2/\sigma_1)$. In other words, security one completely takes security two's place in the basket. Alternatively, if security one is infinitely expensive to trade, then $\kappa_1 \to 0$ and its optimal weight is zero. Between the two corner solutions, the optimal weights tilt in favor of holding the asset that is relatively cheaper to trade. The cheaper asset does not completely take over because of the quadratic trading cost.

B.4. Short selling revenues

On top of the utility function used in our paper and discussed above in appendix, fund managers may have additional incentives to hold certain assets if they collect the lending fees from offering their shares to short sellers (Blocher & Whaley, 2016). Short borrow fees will shift the optimal holdings, but has no impact on our other directional predictions. To see this, consider the modified utility function:

$$U = \boldsymbol{C(w)} - \boldsymbol{S'w} + \lambda(\boldsymbol{w} - \boldsymbol{v})'\Sigma(\boldsymbol{w} - \boldsymbol{v})$$

where $\boldsymbol{S}$ is the expected short borrow fee per asset, which offsets the expected trading costs. Solving for asset i, we have:

$$w_i^* = \frac{1}{1 + c_i/\lambda\sigma_i^2}v_i + \frac{1}{1 + c_i/\lambda\sigma_i^2}\sum_{j\neq i}(v_j - w_j)\beta_{j,i} + \frac{1}{c_i + \lambda\sigma_i^2}s_i$$

Notice that the optimal weights are higher than before, but the comparative statics with respect to $c_i, \rho_{i,j}$ and σ_i^2 are unchanged.