ETF Competition and Market Quality

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ABSTRACT

Our paper investigates competition between ETFs that hold nearly identical baskets of securities. We provide strong evidence that incumbent-fund market quality is negatively affected when a new fund is added to an asset class. The degradation in liquidity is even more severe whenever both funds follow the same benchmark. Furthermore, increasing the number of ETFs in an asset class does not put downward pressure on expense ratios. Thus, decreasing market quality, enumerated by increasing bid-ask spreads and price impacts, is not offset by decreasing costs of fund ownership – resulting in a loss of surplus for investors and ETF providers.

JEL classification: D40, D53, G14, G23, L11, L25

Keywords: ETFs, management fees, fund flows, market quality, liquidity

Like mutual funds, exchange traded funds (ETFs) provide access to a large diversified portfolio of securities, but, unlike mutual funds, ETFs can be traded throughout the day. Utility derived from the intra-day liquidity of these portfolios is evidenced by the proliferation of new exchange traded funds over the last two decades. From 1996 to 2014, the number of exchange traded funds has risen from 18 to 1,280, and aggregate net asset value has grown from $81 million to $176 billion. Our paper analyzes whether or not this gold rush has been without consequence. Specifically, we investigate the effects of increased competition on management fees, fund flows and market quality.

Prior research has analyzed situations where multiple mutual fund providers compete in the same asset class or index (see, for example, Hortacsu and Syverson (2004)). While

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competitive forces should apply downward pressure to the management fees of both ETFs and mutual funds, the sometimes costly process of buying and redeeming ETF shares through an exchange could mitigate these benefits. When multiple ETFs or mutual funds track the same index, they derive their value from an identical pool of underlying assets. From an economic perspective, these funds should be considered perfect substitutes. Theory posits that producer market power falls as the supply side becomes more fragmented. For most goods, increasing competition leads to falling prices. Thus, investors should benefit when multiple firms provide exposure to a specific index or asset class if each fund lowers management fees to attract market share. Unlike the mutual fund case, however, the addition of new ETFs to a narrowly defined space has the potential to harm investors. As the number of substitutable funds increases, liquidity for the incumbents may become more fragmented. If this fragmentation results in a degradation of overall market quality, investors could experience higher bid/ask spreads and lower market depth.

The microstructure literature provides differing views on the effects of competition on liquidity. In the most traditional setting, studies find an improvement in liquidity in the face of increased competition and/or fragmentation (McInish and Wood (1992), Bessembinder (2003), O'Hara and Ye (2011), and Boehmer and Boehmer (2003)). While we are also concerned about execution costs, many of these previous studies look at the effects of different markets and exchanges competing for the same securities. The primary difference in our study is that competition arises from the addition of new securities that happen to be identical in every way. Corwin and Coughenour (2008) find that when NYSE specialists allocate their attention to stocks with increased trading activity, the liquidity of the other stocks in their portfolio decreases. In this setting, the effects of competition and limited attention have a significant impact on liquidity provision: ETF investor attention may be diverted due to the addition of new ETFs to a particular area.

Figure 1 illustrates three equilibrium conditions that help explain our main predictions. The picture describes the aggregate supply and demand for a specific basket of securities, like those included in the S&P 500, which can be traded any time markets are open. Investors could choose to buy all of the securities individually at great personal expense, measured by the vertical axis, or they could purchase the entire basket of securities at one time through an
exchange traded fund. Equilibrium (1) represents the stylized case without frictions associated with the buying and selling of the ETF shares.\(^1\) In this case, all of the surplus arising from the creation of the ETF is captured by either the investors, through forgone replication cost, or the fund manager, through collected management fees. Equilibrium (2) describes the more credible scenario where the exchange of a single fund does involve trading frictions. In this case, a nontrivial portion of the investors’ and managers’ potential surplus is consumed by the exchange process to support liquidity provision and price discovery. These costs are unavoidable, and the vigorous demand for exchange traded funds demonstrates the investment public’s willingness to suffer these expenses in exchange for intra-day liquidity. Trading frictions do, however, raise the combined cost of ETF ownership to a level above the reservations price of some investors. This creates the familiar deadweight loss from microeconomics, described in the figure as “Surplus lost to forgone investing with one fund”.

In the presence of fund trading frictions, Equilibrium (2) is optimal given a certain level of demand for a basket of securities that can be traded throughout the day.\(^2\) With only modest barriers to entry\(^3\) in the ETF market, however, identical, or nearly identical, funds can be created easily. Equilibrium (3) describes the case where two ETFs compete to supply the same fixed level of investor demand. For simplicity, assume that both funds are exactly the same size, and ignore, for the moment, any competitive pressures on the management fees of the funds.\(^4\) The addition of a second ETF splits the pool of investors providing liquidity and contributing to price discovery in half. A second limit order book must be maintained, and only

\(^1\) We assume that there are frictions associated with the buying and selling of the individual securities, or else there would be no demand for the ETF.

\(^2\) Hegde and McDermott (2004) actually find that the liquidity of the DJIA 30 index stocks improves after the introduction of the DJIA 30 ETF, which the authors attribute to the decline in the cost of informed trading.

\(^3\) These could include benchmark licensing fees, cultivating relationships with authorized participants, custodial fees, security acquisition, advertising, etc.

\(^4\) We have also chosen to depict the supply curves with trading frictions as parallel to supply curves without frictions. In reality, the proportional cost of trading frictions, the distance between the two curves, could decrease as the ETF market grows. If these costs fall somewhat slowly with market size, the model will overestimate the frictions from one fund, but underestimate the frictions added by the second fund.
half as many orders are now available to fill it. This implies that bid/ask spreads would likely widen and the cost of placing large orders, approximated by Amihud (2002) ratio, would likely increase. In this case, even more investor and manager surplus is consumed by trading frictions, and a much larger portion of their combined surplus is completely lost to forgone investing.

The most troubling aspect of Equilibrium (3), is that the additional relinquished surplus is a completely unforced error. In the absence of competitive price pressures, investors gain nothing by the addition of the second ETF holding exactly the same basket of securities. From the perspective of the incumbent-fund manager, more than half of their surplus is eliminated by the entrant’s arrival. Somewhat regrettably, the entrant clearly benefits in the third equilibrium as their share of the surplus increases from zero to half of the remaining manager

Figure 1. Investor costs and fund competition

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total. Thus, without significant barriers to entry, additional providers will always have some incentive to enter an asset class.

We provide strong empirical evidence that the addition of new funds to a narrowly defined asset class and benchmark dramatically increases the cost of both round-trip trades and large order executions. Thus, liquidity available to the investors of incumbent funds is reduced, and the market quality of the entire asset class is degraded. Despite the higher trading frictions, investors could still plausibly benefit from fragmentation on the supply side if a larger portion of the remaining surplus shifted towards the investors. We find no evidence that fund managers lower prices in the face of competition. In fact, expense ratios are higher within institutional categories that contain more than one fund. We also find that incumbent ETFs are able to raise their expense ratios after a new fund enters the market. Our study only analyzes competition between exchange traded funds, but most investors, especially long-term investors, could easily substitute between a mutual fund and an ETF associated with the same asset class. The absence of identifiable competitive price pressure implies that ETFs already set fees very close to marginal costs in equilibrium. Thus, we likely underestimate the level of competition in each area as it relates to management fees.

While expense ratios appear relatively “sticky” over time, we find some consolation in the fact that investors respond rationally to prices, namely that money tends to flow towards the lowest cost fund option available in each category. This result conflicts with recent research studying investors’ choice of mutual funds with disproportionately high fees and uncompetitive returns (see, for example, Boldin and Cici, (2010), and Choi, Laibson, and Madrian, (2010)). We also show that investment dollars flow towards the ETFs with higher market shares, even after controlling for management fees. This would be rational, however, if investors believe that larger exchange traded funds will offer fewer trading frictions. Overall, our results indicate that the loss in market quality resulting from the introduction of additional ETFs to a category does not appear to be offset by a decrease in the cost of fund ownership.

I. Data Description

The primary source for ETF information used in our study is the Morningstar Direct
institutional investment analysis platform. The initial universe consists of 2,018 unique funds whose primary share class\(^5\) is listed on a U.S. exchange between 1996\(^6\) and 2014. Since our study focuses on funds following the same benchmark, 129 actively managed ETFs described as “Not Benchmarked” are removed. In order to merge with the CRSP daily file and calculate market quality measures, 370 funds with missing ticker information are also eliminated. Finally, a number of the securities listed in the Morningstar Direct ETF universe are more accurately described as exchange traded notes (ETNs).\(^7\) After removing these 204 ETNs, our final sample has 1,315 ETFs.

\(^5\) When funds are listed in multiple currencies, only one is designated as the primary share class.

\(^6\) The first year with a sufficient number of funds to conduct our analysis.

\(^7\) In Morningstar Direct, the legal structure of these funds is listed as an “Uncollateralized Debt Instrument.”
Our analysis is focused on competition between ETFs, so it is important that we can accurately identify groups of competitors. Morningstar Direct provides a fund taxonomy that distinguishes funds by what they own, as well as by their prospectus objectives and styles. While the prospectus objective identifies a fund’s investment goals based on the wording in the prospectus, the Morningstar classification system also identifies funds based on their underlying portfolio holdings over the past three years. The most granular classification scheme, known as the Morningstar Institutional Categories, were intended “to help institutional investors identify true peers, build more thoroughly diversified portfolios, and gain more insight into an individual portfolio’s strategy” (Morningstar (2012)). Each

![Figure 2 Panel A](image1.png)
![Figure 2 Panel B](image2.png)

**Figure 2. Net asset values (NAV) and daily dollar volumes**

Panel A (Panel B) presents a stacked area graph describing the yearly average daily net asset value (dollar volume), in billions, of each Morningstar Global Broad Category over the sample period.

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Institutional Category is also a member of a more expansive Global Category, and each one of these classes belongs to an even more sprawling Global Broad Category.

To better understand how investors have allocated their funds across these categories, Figure 2 presents a stacked area graph describing the yearly average daily net asset value (NAV) and dollar volume of each Global Broad Category. The upper bound of the shaded region in Panel A demonstrates just how quickly the ETF industry has grown. The flow of investment dollars into this space has been so rapid that the combined NAV of all funds is visibly unaffected by the S&P 500’s -36% annual return in 2008. Despite this unabated exponential growth in net asset value, the aggregate average dollar volume, pictured in Panel B, seems to have already peaked; perhaps signaling a transformation of the ETF from trading vehicle to investment security.

Unsurprisingly, the vast majority of invested dollars and trading activity is concentrated in the “Equity” Global Broad Category. More interesting is the size of the “Alternative” group’s daily dollar volume relative to its NAV. In 2008, a dollar value of securities roughly equivalent to 66% of this Broad Category’s NAV changed hands every day. Comparable figures for “Equity” and “Fixed Income” are 17% and 2% respectively. For all broad categories, a typical dollar of ETF NAV changes hands much less frequently in 2014, with the ratio falling to 16% for “Alternative” and 4% for “Equity.” Overall, the ETF industry has experienced a dramatic increase in assets under management, and a dramatic decline in the ratio of daily dollar volume to NAV.
Figure 3. Number of fund categories and benchmarks over the sample period

This figure depicts the number of funds, fund categories, and benchmarks over the sample period. Total is the number of ETFs in our sample, by year. Cat presents the number of distinct Morningstar institutional categories over the sample period. Bench represents the number of different benchmarks over time. CatBench presents the number of distinct classifications for funds in the same Morningstar institutional category and following the same benchmark. Each institutional category is a member of a more expansive Global category, and each one of these classes belong to a more sprawling GlobalBroad category. Global and GlobalBroad describe the number of classifications in each, respectively.

Figure 3 depicts the number of categories, at all grades of classification, for each year in our sample. The total number of ETFs has increased dramatically, rising from 18 in 1996 to 1,280 in 2014. Despite this breakneck pace of fund creation, increases in the granularity of the categories have been more moderate. The number of Global Categories and Global Broad Categories has remained constant since 2013 and 2009 respectively, and just three of the most narrowly defined Institutional Categories were added in each of the last two years. While funds must compete for investment dollars within the broadly defined asset classes, the contest will be most acute between members of the same small peer group. Because the creation of new funds has far outpaced the creation of new categories, competition for investment dollars has intensified. In 1996, the market offered an average of 2.25 funds in only 8 institutional categories. By the end of 2014, an average of 9.77 ETFs traded in 131 institutional categories.

Even inside a particular Institutional Category, however, investors could have rational preferences for one fund over another unless their actual holdings were truly indistinguishable. If two members of the same Institutional Category are to be considered nearly perfect substitutes, they must also follow the same benchmark. According to Figure 3, the number of unique benchmarks in our sample has increased from 18 in 1996 to 1,097 in 2014. This amounts to an average of 8.37 different indices for each Institutional category. There are 28 different ETF benchmarks in the “Large Core” category alone, in addition to 8
unique indices in the “Large Core Growth” category and 7 in the “Large Core Value” category. These numbers are all the more surprising because “S&P 500 Tracking” is an Institutional Category all by itself. Needless to say, today’s passive investor faces a dizzying array of options when choosing a fund designed to follow the broader stock market.

For a classification scheme that would define nearly perfect substitutes, Figure 3 reports that there are 1,194 unique pairings of Institutional Categories and primary prospectus benchmarks at the end of 2014. With 1,280 firms in the sample that year, that leaves more than 86 ETFs sharing an institutional category and a benchmark with at least one other fund, up from 27 in 2008, and 4 in 2004. The steady flood of ETFs being crammed into a stable quantity of categories has increasingly resulted in entrant funds tracking exactly the same benchmarks as category incumbents.

One final empirical artifact that is noteworthy from Figure 3 is the discrepancy between the number of benchmarks and the number of Institutional Category/benchmark pairings. It is not uncommon for a particular index to appear in more than one category. The S&P 500 is listed as a primary prospectus benchmark for ETFs in four different groups: “S&P 500 Tracking,” “Large Core,” “Trading - Leveraged Equity” and “Trading - Inverse Equity.” For most major indices, investors can find a leveraged and an inverse version of the same portfolio, and these alternatives are obviously not perfectly substitutable with their insipid cousins. It is an open question, however, as to why Morningstar classifies some ETFs following the S&P 500 as “Large Core” and others as “S&P 500 Tracking.” If similar peculiarities are prevalent across the sample, our method for identifying funds that are nearly perfect substitutes could underestimate the level of competition.

The variables of interest for most of our empirical analysis are the number of competitors faced by fund \(i\) during year \(t\). The variable \(\text{Cat}#_{it}\) is an integer-valued measure describing the number of additional funds, not counting \(i\), that are also trading in the same Institutional Category during year \(t\). \(\text{Bench}#_{it}\) is similarly defined based on the number of additional funds sharing the same benchmark, and \(\text{CatBench}#_{it}\) counts the number of funds assigned to the same institutional category that also share the same index. Figure 4 describes the distribution of \(\text{CatBench}#_{it}\) for every year during the sample period. Until 2000, no ETFs faced direct competition from a nearly perfect substitute, but by the end of 2014, 82 funds competed with one other fund, 45 competed with two and 20 competed in a category crammed with three other funds following the same benchmark.
Table A-1 in the appendix provides a list of all funds with $\text{CatBench}_{i2014}$ greater than one. “Trading Tools” is the Global Category where fund competition is most severe, and the ETFs in this area are all leveraged or inverse funds. Part of the reason that these categories contain so many funds is that individual ETFs may offer different degrees of leverage. For instance, two of the funds benchmarked to the Russel 2000 found inside the “Trading – Leveraged Equity” Institutional Category are designed to have daily returns that are 200% of the benchmark, while the other two offer returns that are 300% of the index returns. While the degree of substitutability is likely to be very high inside this category, a discerning investor might rationally prefer a lot of leverage to an awful lot of leverage. Still, numerous funds listed in Table A-1 offer portfolios that are identical to their competitors in every way. For all of the “US Equity” categories in the table, investors can choose between three identical funds offered (usually) by SPDR®, Vanguard and iShares. In terms of economic impact, the competition in these categories is more consequential because of the magnitude of NAVs and dollar volumes in the “US Equity” categories.

II. Expense Ratios

For our first set of empirical tests, we analyze a traditionally favorable byproduct of industry competition: more producers lead to lower consumer prices and higher levels of consumer surplus. When the product is an exchange traded fund, the “price” is approximated
by the periodic reduction in NAVs used to pay for operating expenses, management fees, including 12b-1 fees, administrative fees, and all other asset-based costs incurred by the fund. Morningstar Direct provides each fund’s annual aggregation of these costs in the form of a net expense ratio.\(^8\) As the number of funds competing for investment dollars in a particular

![Figure 5. NAV-weighted average expense ratios by Global Broad Category](image)

This figure describes the net asset value- (NAV) weighted average annual net expense ratios of the Global Broad categories during our sample period.

category increases, the ETF expense ratios in that category should fall.

Figure 5 describes the NAV weighted average annual net expense ratios of all seven Global Broad Categories during our sample period. The main takeaway from this picture, which also foreshadows our regression results, is that average expense ratios have remained very stable over time. The groups with larger NAVs, such as “Equity” and “Fixed Income,” obviously have lower expense ratios, but there has been very little time series variation within each category. This is notable because Figure 2, Figure 3 and Figure 4 demonstrated just how much the ETF market has grown. If there are economies of scale in fund provision, market-wide NAVs have expanded exponentially; potentially dwarfing any fixed costs in fund provision. The dramatic increase in the number of funds and the growing number of categories

\(^8\) Sales charges are not included in the expense ratio. The expense ratio for fund of funds only includes the wrap or sponsor fees, and does not include the underlying fund fees.
that contain identical ETFs suggests that competition has also intensified, putting more downward pressure on prices. Anecdotally, the portion of management fees stemming from trading costs have also likely fallen over the sample period as the market infrastructure has improved. Yet, none of these forces have led to visible reductions in aggregate expense ratios.

The little time series variation that is observable in Figure 5 can be explained by a closer examination of the data. The expense ratio spike for “Equity” ETFs around the turn of century coincides with the introduction of a number of sector funds in new, at the time, Global Categories like “Consumer Goods & Services Sector Equity” or “Healthcare Sector Equity.” This marks the ETF industry’s first foray into specialized investment classes. In 1999, the number of available Institutional Categories doubles in one year from 9 to 18. The average expense ratios in these newly created categories were initially much higher than the broad market equity ETFs that had existed up until that point. Within a few years, however, they fell (sharply) to a level that persisted for the remainder of the sample period. While the number of funds participating in these sector-focused categories increases during these early years, it is not clear that competition causes the declining expense ratios. The NAVs of these funds grow so quickly that economies of scale could have easily reduced their marginal expenses. Something similar seems to be happening after the introduction of “Allocation” ETFs in 2008, but it is not clear whether this decline comes from competitive pressures or increases in scale.

Figure 5 also depicts persistent time series variation within the “Commodities” group throughout the entire sample period. The source of this variation probably has little to do with competition or scale. Relative to the other Global Categories, these funds require lots of trading because all of their holdings expire within a very short time frame. If trading costs fluctuate over time, fund expenses will be much less predictable from one period to the next. The Teucrium Sugar Fund (NYSE: CANE), whose marketing materials claim to provide “investors unleveraged direct exposure to sugar without the need for a futures account,” reported a net expense ratio of 2.93% in 2011, 9.77% in 2012 and 1.52% in 2013. These fluctuations appear common in the “Commodity” space, but are rarely observed in other categories.

In addition to asset type, there are a variety of other ETF features that should reasonably be expected to affect (usually increase) expense ratios. The first is fund leverage, where an ETF would seek to deliver multiples (such as 2x or 3x) of the performance of the index or
benchmark they track. Second, inverse funds are designed to perform as the inverse of whatever index or benchmark it is designed to track. It is very common for inverse funds to also use leverage. The third feature, known as actively managed, is a fund that has a manager or team making decisions on the underlying portfolio allocation. Finally, a fund of funds specializes in buying shares in other ETFs rather than individual securities. Figure 6 reports the growth in the number of funds possessing each of these characteristics. Since the introduction of the inverse and leveraged ETF in 2006, the pace of introduction for these specialty funds has been spectacular. Figure 6 actually understates the number of actively managed ETFs currently available because many of these funds are not benchmarked and, thus, do not appear in our sample.

Our empirical analysis in this section will determine whether the number of ETFs available in a particular category, or following a certain benchmark, has any effect on the individual fund expense ratios. Hortacsu and Syverson (2004) document the wide dispersion in fees among mutual funds in narrow asset classes. We analyze competition in three areas. First, $\text{Cat#}_{it}$ is an integer-valued variable describing the number of additional funds, not counting $i$, that are also trading in the same Institutional Category during year $t$. We assume
that all funds competing in such narrowly defined categories could reasonably be considered close substitutes from the investors perspective. However, for funds to be considered perfect substitutes, they must also follow the same benchmark. Thus, \( \text{Bench}\#_{it} \) is an integer-valued variable describing the number of additional funds sharing the same benchmark. As mentioned in Section I, many benchmarks appear in multiple Institutional Categories when leveraged or inverse offerings are available. With the goal of identifying ETFs that are the same in every way, the \( \text{CatBench}\#_{it} \) counts the number of funds assigned to the same institutional category that also share the same index.

Ignoring benchmark commonality for the moment, the analysis in this section will center on the following basic regression model:

\[ \text{NetExp}_{it} = \beta_0 + \beta_1 \text{Cat}\#_{it} + \beta_2 \text{Leverage}_i + \beta_3 \text{Inverse}_i + \beta_4 \text{FundFunds}_i \\
+ \beta_5 \text{Active}_i + \varepsilon_{it} \]  

where \( \text{NetExp}_{it} \) is the net expense ratio for ETF \( i \) in year \( t \), and \( \text{Leverage}_i, \text{Inverse}_i, \text{FundFunds}_i \) and \( \text{Active}_i \) are binary variables indicating whether the fund is leveraged, net short, a fund of funds or actively managed, respectively.

As written, the disturbances estimated from Equation (1) contain some unfavorable structure. Like most panel datasets, all of the observations occurring in year \( t \) should be related to each other because of immeasurable common forces impacting expense ratios (decimalization, market fragmentation, order book digitalization, etc.). Also, Equation (1) attempts to measure the change in expense ratios that would result from a hypothetical change in the number of competitors within an institutional category. It is possible that contemporaneous changes in expense ratios are responses to persistent changes in expense ratios occurring in previous years. To isolate the independent effect of fund competition, the specification should also account for the previous year’s expense ratio. This argument is similar to the motivation for the familiar test of Granger (1969) causality, which uses a specification containing lagged dependent variables to isolate the origins of dependence. Next, all of the fund expense ratios have a value bounded below by 0, but the error term \( \varepsilon_{it} \) is assumed to be distributed over a range of \(-\infty \) to \( \infty \). To improve the accuracy of the coefficient standard errors and avoid the possibility that predicted expense ratios are negative, the log transformation is applied to the reported net expense ratios. Finally, each of the fund characteristics included in Equation (1) are usually expected to increase the management
costs of the fund. We learned in Figure 5, however, that expense ratios also differ dramatically across Global Broad Categories. Moving up one degree of specificity, our data contains ETFs that are members of 54 unique Global Categories. Taken together, these concerns motivate the following model with Global Category and time series fixed effects and a lagged and logged dependent variable:

\[
\ln(\text{NetExp})_{it} = \phi_1 \ln(\text{NetExp})_{it-1} + \beta_0 + \beta_1 \text{Cat#}_{it} + \beta_2 \text{Leverage}_i + \beta_3 \text{Inverse}_i
\]

\[+ \beta_4 \text{FundFunds}_i + \beta_5 \text{Active}_i + \text{Glob}_i + \alpha_t + \epsilon_{it}
\]

where \(Glob_i\) and \(\alpha_t\) are the category and yearly fixed effects respectively.

The logged net expense ratio \(\ln(\text{NetExp})_{it}\) in year \(t\) for ETF \(i\) is also likely related to the expense ratio of the same ETF at all other points in time due to persistent fund-specific characteristics. The addition of fund panel effects to the specification could correct for the omitted variable bias associated with these persistent relationships:

\[
\ln(\text{NetExp})_{it} = \phi_1 \ln(\text{NetExp})_{it-1} + \beta_0 + \beta_1 \text{Cat#}_{it} + \beta_2 \text{Leverage}_i + \beta_3 \text{Inverse}_i
\]

\[+ \beta_4 \text{FundFunds}_i + \beta_5 \text{Active}_i + \text{Glob}_i + \gamma_i + \alpha_t + \epsilon_{it}
\]

where \(\gamma_i\) is a panel effect for each fund \(i\). Unfortunately, OLS estimation of Equation (3) would still be biased and inconsistent. Because the variables \(\ln(\text{NetExp})_{it}\) and \(\ln(\text{NetExp})_{it-1}\) would both be functions of the fund panel effects \(\gamma_i\), those parameters would be mechanically correlated with the disturbances. Rewriting Equation (3) in terms of first differences will remove these correlated panel effects, along with any other time-independent variables:

\[
\Delta \ln(\text{NetExp})_{it} = \phi_1 \Delta \ln(\text{NetExp})_{it-1} + \beta_0 + \beta_1 \Delta \text{Cat#}_{it} + \alpha_t + \Delta \epsilon_{it}
\]

Notice that the coefficients \(\phi_1\) and \(\beta_1\) are completely unchanged by this transformation, and that the number of estimated parameters has declined drastically with the removal of the

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9 The parameters \(\phi_1, \beta_1, .., \beta_5\) and all of the \(\text{Glob}_i\)'s will be the same across Equations (2) and (3) if the fund panel effects \(\gamma_i\) all equal to zero. If there are no unobserved persistent effects affecting net expense ratios, the inferences would be the same across both specifications.

10 In year \(t\), \(\ln(\text{NetExp})_{it-1}\) is determined by a linear function with \(\gamma_i\) on the right-hand-side. Because \(\ln(\text{NetExp})_{it-1}\) also appears in the function generating \(\ln(\text{NetExp})_{it}\), the time-independent fixed effects are correlated with the disturbances (Greene (2008)).
time-independent panel effects $\gamma_{ij}$, the fund characteristics, $Leverage_i$, $Inverse_i$, $FundFunds_i$, and $Active_i$, and the Global Category fixed effects $Glob_i$. Instrumental variables estimation is required because $\ln(NetExp)_{it-1}$ is used to calculate both $\Delta \ln(NetExp)_{it}$ and $\Delta \ln(NetExp)_{it-1}$, so OLS estimation of Equation (4) would still lead to biased estimates (Anderson and Hsiao (1981)).

Arellano and Bond (1991) argue that this procedure for dynamic panel estimation would produce consistent but not necessarily efficient results. After taking first differences, they propose using all past information about the dependent variable and all exogenous information about the independent variables as instruments, then estimating the model with the generalized method of moments.\textsuperscript{11} Building on the work of Arellano and Bond (1991) and Arellano and Bover (1995), Blundell and Bond (1998) propose a system estimator that uses moment conditions in which lagged differences are used as instruments for the level equation, similar to (3), in addition to the moment conditions of lagged levels as instruments for the differenced equation, (4). For instance, when trying to predict the period 4 change in logged net expense ratio $\Delta \ln(NetExp)_{i4}$, the lagged levels $\ln(NetExp)_{i1}$ and $\ln(NetExp)_{i2}$ and the lagged difference $\Delta \ln(NetExp)_{i2}$ are mechanically uncorrelated with $\Delta \epsilon_{i4}$ and can be included as instruments. Moving forward through time, the number of potential instruments, all historical observations of these levels and differences, continues to grow.\textsuperscript{12}

\textsuperscript{11} Blundell and Bond (1998) show that the lagged-level instruments in the Arellano–Bond estimator become weak as the autoregressive process becomes too persistent or the ratio of the variance of the panel-level effects to the variance of the idiosyncratic error becomes too large.

\textsuperscript{12} The dimensions of the instrument matrix $Z$ are much larger than typically found in other instrumental variables estimations. Individual matrices $Z_i$, with dimensions $(T - 2) \times L$, are constructed for each fund. The number of columns $L$ is a function of total years $T$ and the number of instruments chosen for estimation. The matrix $Z_i$ has the following basic structure if only lagged levels of the dependent variable are used as instruments:

\begin{equation}
Z_i = \begin{bmatrix}
\ln(NetExp)_{i1} & 0 & \cdots & 0 \\
0 & \ln(NetExp)_{i1},\ln(NetExp)_{i2} & \cdots & \vdots \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & \ln(NetExp)_{i1},\ln(NetExp)_{i2} & \cdots \ln(NetExp)_{i(T-2)}
\end{bmatrix}
\end{equation}

The addition of lagged changes in the dependent variable or exogenous independent variables to the set of instruments is straightforward. When the transpose of $Z_i$ is premultiplied by the matrix of
and future levels and differences of the independent variables, in this case $Cat_{it}$, could potentially be included as instruments if they are also believed to be uncorrelated with $\Delta \varepsilon_{it}$ (Greene (2008)). The Arellano and Bover (1995) and Blundell and Bond (1998) methodology is capable of dealing with unbalanced panels, so firm-pairs do not need a lengthy time series to be included in the estimation.

All hypotheses presented in this and subsequent sections will be tested using regression specifications similar to Equation (2), with standard errors clustered by firm-pair and time, and Equation (4), where the Arellano and Bover (1995) and Blundell and Bond (1998) results are generated by the two-step estimator with Windmeijer (2005) bias-corrected robust variance-covariance estimates of the model parameters. All specifications will include the number of additional funds, not counting $i$, that are trading in the same Institutional Category $Cat_{it}$. Some specifications will include the number of funds sharing the same benchmark, $Bench_{it}$, and others will include the number of funds assigned sharing the same benchmark and institutional category, $CatBench_{it}$.

The estimates of Equations (2) and (4) are reported in Table I. While it is not possible to calculate a reliable goodness of fit measure in the dynamic panel estimator specifications, the R-squared in the OLS results implies nearly all of the variance in logged net expense ratios can be explained with only lagged observations of the dependent variable, fund characteristics, the Global Category and year effects and the competition variables. When fund-specific panel effects are included on the right side of the table, the explanatory power is likely to be even higher. The p-values from the second order tests for serial correlation are below 2.0 in all specifications, implying that there is no evidence of persistence in the differenced residuals. Thus, the moment conditions of the dynamic panel estimator are validated.

Overall, the results in Table I provide no evidence that investors benefit when the number of competitors rises. The positive and significant coefficient on $Cat_{it}$ suggests that fund net expense ratios are actually higher within institutional categories that contain more than one fund. It should be emphasized that the economic impact of this variable is quite small, but the sign on the coefficient still conflicts with our hypothesis that investors benefit from higher explanatory variables relevant to fund $i$, the explanatory variables only interact with the appropriate set of instruments in each time period.
levels of competition. An alternative interpretation would be that the positive coefficient on \( Cat_{it} \) implies that fund providers are introducing new ETFs into categories that already have high expense ratios. However, this concern is mitigated by the inclusion of the previous year’s expense ratio as an independent variable. The positive coefficient on \( Cat_{it} \) implies that incumbent ETFs actually raise their expense ratios, if only slightly, after a new fund enters the market. Ours is not the only study to produce this seemingly anticompetitive result in the context of investment products. Hortacsu and Syverson (2004) also document an increase in fees as the number of mutual funds increases in a particular sector. Neither \( Bench_{it} \) or \( CatBench_{it} \) have any meaningful impact on net expense ratios.
Determinants of fund expense ratios

The dependent variable in all specifications is $\ln(NetExp)_{it}$, or the logged percentage of fund assets used to pay for operating expenses and management fees. Leverage$_i$, Inverse$_i$, FundFunds$_i$ and Active$_i$ are binary variables indicating whether the fund is leveraged, net short, a fund of funds, or actively managed, respectively. Based on holdings, Morningstar assigns funds into peer groups known as Global Categories, or, even more narrowly, Morningstar Institutional Categories. Cat#$_{it}$ is an integer-valued variable describing the number of additional funds, not counting $i$, that are also trading in the same Institutional Category during year $t$. Bench#$_{it}$ is an integer-valued variable describing the number of additional ETFs sharing the same benchmark. CatBench#$_{it}$ counts the number of funds assigned to the same institutional category that also share the same index. Each specification is estimated with the ordinary least squares and the dynamic panel estimation methodology. Ordinary least squares t-statistics (reported in parenthesis) are calculated from standard errors clustered by fund and year. Dynamic panel estimation results are generated using the approach described in Arellano and Bover (1995) and Blundell and Bond (1998) with bias-corrected robust variance-covariance estimates of the model parameters. All of the independent variables are included as predetermined instruments in the dynamic panel estimation.

<table>
<thead>
<tr>
<th>Ordinary Least Squares</th>
<th>Dynamic Panel Estimator</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>$\ln(NetExp)_{it-1}$</td>
<td>0.978***</td>
</tr>
<tr>
<td></td>
<td>(69.05)</td>
</tr>
<tr>
<td>Leverage$_i$</td>
<td>0.0116</td>
</tr>
<tr>
<td></td>
<td>(0.547)</td>
</tr>
<tr>
<td>Inverse$_i$</td>
<td>-0.00274</td>
</tr>
<tr>
<td></td>
<td>(-0.331)</td>
</tr>
<tr>
<td>FundFunds$_i$</td>
<td>0.0380***</td>
</tr>
<tr>
<td></td>
<td>(2.820)</td>
</tr>
<tr>
<td>Active$_i$</td>
<td>0.0260*</td>
</tr>
<tr>
<td></td>
<td>(1.714)</td>
</tr>
<tr>
<td>Cat#$_{it}$</td>
<td>0.000311***</td>
</tr>
<tr>
<td></td>
<td>(2.748)</td>
</tr>
<tr>
<td>Bench#$_{it}$</td>
<td>-0.00162</td>
</tr>
<tr>
<td></td>
<td>(-1.065)</td>
</tr>
<tr>
<td>CatBench#$_{it}$</td>
<td>-3.03e-05</td>
</tr>
<tr>
<td></td>
<td>(-0.00505)</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>Global Category Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Panel Effects</td>
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</tr>
<tr>
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<td>Observations</td>
<td>6,163</td>
</tr>
</tbody>
</table>

Figure 5 demonstrated the persistence of fund expense ratios at the level of Global Broad Category. The results in Table I confirm that this persistence can also be found at the individual fund level. No other variable appearing in Table I explains more about contemporaneous net expense ratios than the same fund’s expense ratio during the previous year. Coefficients on the lagged dependent variables near unity imply that there is very little within-fund variation left for the other included regressor to explain.
Of the fund characteristic variables included in the OLS specifications, only FundFunds has a consistently significant, positive, coefficient. All of these features are expected to increase a fund's management costs, so the lack of significance found in the coefficients of the other variables likely results from collinearity with the Global Category Fixed Effects. First, all of the leveraged and inverse funds appear in just 2 of the 54 Global Categories, “Other Alternative” and “Trading Tools,” and all of the funds in these categories are leveraged or inverse. Thus, the fixed effects representing these two categories are sufficient to span any differences in expense ratios resulting from these characteristics. Actively managed funds, however, appear in 6 of the 54 Global Categories and, perhaps more importantly, 4 of the 7 Global Broad Categories. It would be more difficult to account for this fund characteristic using only a holdings-based classification system, and therefore, we find that the coefficient on Active is positive and (weakly) significant in some of the specifications. Likewise, 12 of the Global Categories, and 5 of the Global Broad categories, offer a fund of funds option. Thus, there is a great deal of characteristic-specific variation left unexplained by the included fixed effects, and we are able to measure the portion of fund expense ratios contributed by this additional tier of management. Our paramount concern is just controlling for these characteristics, regardless of which specific regressors account for their impact.

One obvious critique of the specifications estimated in Table I is the omission of specific controls for scale. Figure 2 demonstrated that NAVs and dollar volumes can vary greatly across Global Broad Categories, and we should expect similar variation across Institutional Categories as well. Thus, assume that a large number of competitive categories also happen to be small, and nontrivial fixed costs, at the ETF level, create economies of scale in fund provision. Then, expense ratios could be higher because a fixed pool of investment dollars cannot provide enough scale to mitigate these fixed costs summed across multiple competing funds.

Scale can be controlled for in a number of ways. The most obvious metric would be the size of the fund, or in attempt to capture the scale of the entire market, the size of the category containing the fund. Unfortunately, the best measure of “size” is not immediately straightforward in all cases. When analyzing expense ratios, fund revenues are generated by confiscating a fraction of NAVs; so it is reasonable that fund providers would make growing their NAVs a primary objective. However, if investors value the exchange traded fund
primarily as a trading tool, then the most appropriate measure of scale may be the size of the secondary market for the fund’s shares.

We hypothesize that expense ratios should fall as funds and fund categories grow larger. To account for the size of the category, the variable $\ln(\text{CatVol})_{it}$ ($\ln(\text{CatNav})_{it}$) is the combined average daily dollar volume (net asset value) of all funds sharing $i$’s Institutional Category, or peer funds. Whereas, $\ln(\text{CatBenchVol})_{it}$ ($\ln(\text{CatBenchNav})_{it}$) is the combined average daily dollar volume (net asset value) of all funds sharing $i$’s Institutional Category and benchmark, or those funds that are nearly perfect substitutes. To account for the size of the fund, $\text{CatVolShr}_{it}$ ($\text{CatNavShr}_{it}$) is the percentage share of average daily dollar volume (net asset value) fund $i$ receives inside its Institutional Category. $\text{CatBenchVolShr}_{it}$ ($\text{CatBenchNavShr}_{it}$) is the percentage share of average daily dollar volume (net asset value) fund $i$ receives relative to funds in the same Institutional Category that also follow the same benchmark.

Table II

Determinants of fund expense ratios with market characteristics

The dependent variable in all specifications is $\ln(\text{NetExp})_{it}$ or the logged percentage of fund assets used to pay for operating expenses and management fees. Based on holdings, Morningstar assigns funds into peer groups known as Global Categories, or, even more narrowly, Morningstar Institutional Categories. $\text{Cat#}_{it}$ is an integer-valued variable describing the number of additional funds, not counting $i$, that are also trading in the same Institutional Category during year $t$. $\text{Bench#}_{it}$ is an integer-valued variable describing the number of additional ETFs sharing the same index. $\ln(\text{CatVol})_{it}$ ($\ln(\text{CatNav})_{it}$) is the combined average daily dollar volume (net asset value) of all funds sharing $i$’s Institutional Category. $\ln(\text{CatBenchVol})_{it}$ ($\ln(\text{CatBenchNav})_{it}$) is the combined average daily dollar volume (net asset value) of all funds sharing $i$’s Institutional Category and benchmark. $\text{CatVolShr}_{it}$ ($\text{CatNavShr}_{it}$) is the percentage share of average daily dollar volume (net asset value) fund $i$ receives inside its Institutional Category. $\text{CatBenchVolShr}_{it}$ ($\text{CatBenchNavShr}_{it}$) is the percentage share of average daily dollar volume (net asset value) fund $i$ receives relative to funds in the same Institutional Category that also follow the same benchmark. “Fund Descriptors” refers to the inclusion of variables $\text{Leverage}_i$, $\text{Inverse}_i$, $\text{FundFunds}_i$ and $\text{Active}_i$ as untabulated controls. Each specification is estimated with the ordinary least squares and the dynamic panel estimation methodology. Ordinary least squares t-statistics (reported in parenthesis) are calculated from standard errors clustered by fund and year. Dynamic panel estimation results are generated using the approach described in Arellano and Bover (1995) and Blundell and Bond (1998) with bias-corrected robust variance-covariance estimates of the model parameters. All of the independent variables are used as predetermined instruments in the dynamic panel estimation.

funds in the same Institutional Category that also follow the same benchmark.
<table>
<thead>
<tr>
<th></th>
<th>Ordinary Least Squares</th>
<th></th>
<th>Dynamic Panel Estimator</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>ln(NetExp)_{it-1}</td>
<td>0.975*** (65.16)</td>
<td>0.972*** (65.56)</td>
<td>0.971*** (65.64)</td>
</tr>
<tr>
<td>ln(CatVol)_{it}</td>
<td>-0.00302* (-1.751)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(CatBenchVol)_{it}</td>
<td>-0.00311**-0.00323***</td>
<td>(-2.424)</td>
<td>(-2.803)</td>
</tr>
<tr>
<td>ln(CatNav)_{it}</td>
<td></td>
<td>0.00384 (-1.637)</td>
<td></td>
</tr>
<tr>
<td>ln(CatBenchNav)_{it}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CatVolShr_{it}</td>
<td>-0.00457 (-0.499)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CatBenchVolShr_{it}</td>
<td>0.0323*** (13.58)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CatNavShr_{it}</td>
<td></td>
<td>-0.00814 (-0.960)</td>
<td></td>
</tr>
<tr>
<td>CatBenchNavShr_{it}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cat#_{it}</td>
<td>0.000528<em><strong>0.000317</strong>0.000248<strong>0.000512</strong></em>0.000328<strong>0.000266</strong>0.00193<em><strong>0.00173</strong></em>0.00166<em><strong>0.00306</strong></em>0.00186<em><strong>0.00177</strong></em> (3.350) (2.352) (2.008) (3.336) (2.420) (1.882) (3.878) (3.401) (3.430) (3.889) (3.279) (3.277)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bench#_{it}</td>
<td>0.00104 (0.636)</td>
<td>0.00179 (1.115)</td>
<td>0.000853 (0.244)</td>
</tr>
<tr>
<td>CatBench#_{it}</td>
<td>0.0157** (2.103)</td>
<td>0.0166** (2.071)</td>
<td>0.0166** (2.071)</td>
</tr>
<tr>
<td>Yearly Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Global Category</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fund Panel Effects</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Fund Characteristics</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.969</td>
<td>0.969</td>
<td>0.969</td>
</tr>
<tr>
<td>AR(2) Test</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>6,163</td>
<td>6,163</td>
<td>6,163</td>
</tr>
</tbody>
</table>
Table II reports the results of estimating a number specifications similar to Equations (2) and (4) that also controls for scale. Unfortunately, we are unable to add more than two of these additional controls without exhausting all available degrees of freedom.\textsuperscript{13,14} In terms of category size, fund expense ratios fall as NAVs and dollar volumes grow across the market, regardless of whether the market is defined in terms of peers or near perfect substitutes. The results with respect to firm scale, as measured by market share, are more mixed. When the market is defined in terms of near perfect substitutes in the OLS regressions, expense ratios are positively related to market share. One possible interpretation for this result is that the market leader is able to command a higher price because existing customers face some switching cost, possibly a trading commission, for changing funds. However, when fund-specific panel effects are accounted for in the dynamic panel estimations, the coefficients on these variables turn negative or become insignificant.

The inclusion of additional controls for scale do not change our findings with regards to firm competition. In fact, the coefficient on \textit{CatBench#it} becomes positive and significant in the OLS specifications implying that incumbents actually increase expense ratios after a competitor who is offering a perfectly substitutable product enters the market. This result, however, does not withstand the inclusion of unobservable fund-specific panel effects.

Overall, the results in Table I and Table II imply that individual fund expense ratios are very “sticky,” they rarely change from one period to the next, and that expense ratios fall as the market for the product increases in size. Increasing the number of players in the market, at any level, does not put downward pressure on fund prices. Any potential loss in market quality resulting from the introduction of additional ETFs to a category does not appear to be offset by a decrease in the cost of fund ownership.

\textsuperscript{13} One of the limiting factors is the persistence of the dependent variable. With very little within-fund variance on the right-hand side of the equation, the time dimension is dramatically diminished and the effective sample size shrinks. Additional controls can be included in subsequent tables because there is more variation in the right-hand side variables.

\textsuperscript{14} It was not possible to include even two additional variables in the second OLS specification without exhausting all degrees of freedom.
III. Fund Flows

The next portion of our analysis examines fund flows. In their study of the “index fund rationality paradox,” Boldin and Cici (2010) find that some investors make poor mutual fund choices and select funds with disproportionately high fees and uncompetitive returns. While some investors choose high-fee index funds due to prior returns, as in the mutual fund case (Choi, Laibson and Madrian (2010)), ETF expense ratios should be the “main differentiator” between competing funds, specifically for ETFs within the same Morningstar institutional category or those tracking the same benchmark. If ETF investors indeed make low cost, rational choices among similar funds, then fund flows should move towards those ETFs with the lowest expense ratios.

Our empirical design follows that from previous sections, however, the dependent variable in all specifications is $NetFlow_{it}$, or the calendar-year estimated fund net flow for ETF $i$ in year $t$. We pay close attention to a fund’s (logged) expense ratio, $\ln(NetExpense)_{it}$, in order to determine whether investors respond appropriately to prices. As before, we include lagged observations of the dependent variable and control for variables expected to affect fund flows. The fund’s gross return, $GrossRet_{it}$, is included to account for investor herding tendencies. Previous studies document herding behavior in mutual funds (Scharfstein and Stein (1990), and Grinblatt, Titman and Wermers (1995)). However, Gleason, Mathur, and Peterson (2004) find no evidence that traders herd using ETFs around extreme market movements. While we are intrigued by the coefficients of the competition variables, $Cat#_{it}$, $Bench#_{it}$ and $CatBench#_{it}$, we do not have strong economic inclinations on the effects of competition on fund flows.

Our controls for fund and market size for the regression reported in Table III are based on dollar volume in Panel A and NAV in Panel B. Results in both panels are similar. First and foremost, we find that ETF investors respond rationally to prices. Across almost all specifications in both panels, consumers tend to choose the low cost fund option, as seen in the negative relation between $NetFlow_{it}$ and $\ln(NetExpense)_{it}$. With the exception of the first OLS regression in Panel B, we find no significance on any of the competition variables of interest, and thus $Cat#_{it}$, $Bench#_{it}$, $CatBench#_{it}$ have no meaningful impact on fund flows. This could be somewhat surprising given the possibility of market cannibalization by
new fund entrants within the same fund classification. However, management firms interested in bringing a new ETF to market will most likely target segments where future flows are expected to be the highest. If management firms correctly forecast future demand, there will be no cannibalization evident in the data. The results in Table III paired with those in previous tables suggest that while new funds offer competitive pricing, they face difficulty gaining market share.

### Table III
#### Determinants of fund flows

The dependent variable in all specifications is $NetFlow_{it}$ or the calendar-year estimated share-class level net flow. $\ln(NetExpense)_{it}$ is the percentage of fund assets used to pay for operating expenses and management fees. $GrossRet_{it}$ is calculated by taking the fund’s total return and subtracting out the most recent net expense ratio. $Leverage_{it}$, $Inverse_{it}$, $FundFunds_{it}$, and $Active_{it}$ are binary variables indicating whether the fund is leveraged, net short, a fund of funds or actively managed, respectively. Based on holdings, Morningstar assigns funds into peer groups known as Global Categories, or, even more narrowly, Morningstar Institutional Categories. $Cat\#_{it}$ is an integer-valued variable describing the number of additional funds, not counting $i$, that are also trading in the same Institutional Category during year $t$. $Bench\#_{it}$ is an integer-valued variable describing the number of additional ETFs sharing the same benchmark. $CatVol_{it}$ ($\ln(CatNav)_{it}$) is the combined average daily dollar volume (net asset value) of all funds sharing $i$’s Institutional Category. $ln(CatBenchVol)_{it}$ ($ln(CatBenchNav)_{it}$) is the combined average daily dollar volume (net asset value) of all funds sharing $i$’s Institutional Category and benchmark. $CatVolShr_{it}$ ($CatNavShr_{it}$) is the percentage share of average daily dollar volume (net asset value) fund $i$ receives inside its Institutional Category. $CatBenchVolShr_{it}$ ($CatBenchNavShr_{it}$) is the percentage share of average daily dollar volume (net asset value) fund $i$ receives relative to funds in the same Institutional Category that also follow the same benchmark. Each specification is estimated with the ordinary least squares and the dynamic panel estimation methodology. Ordinary least squares t-statistics (reported in parenthesis) are calculated from standard errors clustered by fund and year. Dynamic panel estimation results are generated using the approach described in Arellano and Bover (1995) and Blundell and Bond (1998) with bias-corrected robust variance-covariance estimates of the model parameters. All of the independent variables are included as predetermined instruments in the dynamic panel estimation.
Table III Panel A: Market characteristics calculated from dollar volume

<table>
<thead>
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<th>Dynamic Panel Estimator</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\text{NetFlow}_{it-1}$</td>
<td>0.494***</td>
<td>0.491***</td>
</tr>
<tr>
<td></td>
<td>(3.615)</td>
<td>(3.650)</td>
</tr>
<tr>
<td>$\ln(\text{NetExpense})_{it}$</td>
<td>-399.3***</td>
<td>-386.5***</td>
</tr>
<tr>
<td></td>
<td>(-4.521)</td>
<td>(-4.023)</td>
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<tr>
<td>$\text{GrossRet}_{it}$</td>
<td>1.936</td>
<td>1.814</td>
</tr>
<tr>
<td></td>
<td>(1.607)</td>
<td>(1.588)</td>
</tr>
<tr>
<td>$\text{Leverage}_i$</td>
<td>62.23</td>
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<td></td>
<td>(1.634)</td>
<td>(-1.136)</td>
</tr>
<tr>
<td>$\text{Inverse}_i$</td>
<td>140.4</td>
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<td></td>
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<td>(0.810)</td>
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<tr>
<td>$\text{Fund Funds}_i$</td>
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<td>-348.8***</td>
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<tr>
<td></td>
<td>(-2.518)</td>
<td>(-2.755)</td>
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<td>$\text{Active}_i$</td>
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<td>472.6***</td>
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<td></td>
<td>(1.870)</td>
<td>(3.398)</td>
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<tr>
<td>$\ln(\text{CatVol})_{it}$</td>
<td>82.05*</td>
<td>206.8***</td>
</tr>
<tr>
<td></td>
<td>(1.930)</td>
<td>(3.175)</td>
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<tr>
<td>$\ln(\text{CatBenchVol})_{it}$</td>
<td>60.19***</td>
<td>69.82***</td>
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<tr>
<td></td>
<td>(3.568)</td>
<td>(3.229)</td>
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<tr>
<td>$\text{CatVolShr}_{it}$</td>
<td>480.2**</td>
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<tr>
<td></td>
<td>(2.116)</td>
<td></td>
</tr>
<tr>
<td>$\text{CatBenchVolShr}_{it}$</td>
<td>464.9**</td>
<td>309.1*</td>
</tr>
<tr>
<td></td>
<td>(2.265)</td>
<td>(1.853)</td>
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<tr>
<td>$\text{Cat#}_{it}$</td>
<td>-5.685</td>
<td>-1.692</td>
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<td></td>
<td>(-1.420)</td>
<td>(-0.750)</td>
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<td>$\text{Bench#}_{it}$</td>
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<td>$\text{CatBench#}_{it}$</td>
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<tr>
<td>Global Category Fixed Effects</td>
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<td>Yes</td>
</tr>
<tr>
<td>Fund Panel Effects</td>
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<td>No</td>
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<tr>
<td>R-squared</td>
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<td>0.283</td>
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<td>AR(2) Test</td>
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<td>Observations</td>
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Table III Panel B: Market characteristics calculated from net asset value

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<td></td>
<td>(1)</td>
<td>(2)</td>
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<tr>
<td>$NetFlow_{it-1}$</td>
<td>0.486***</td>
<td>0.491***</td>
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<tr>
<td></td>
<td>(3.508)</td>
<td>(3.664)</td>
</tr>
<tr>
<td>$\ln(NetExpense)_{it}$</td>
<td>-385.2***</td>
<td>-392.2***</td>
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<td>(-4.083)</td>
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<td>1.809</td>
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<td>(0.145)</td>
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<td>151.1</td>
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<td>(1.006)</td>
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<td>-344.3***</td>
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<td>(-2.803)</td>
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<tr>
<td>$Active_i$</td>
<td>265.3***</td>
<td>496.4***</td>
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<tr>
<td></td>
<td>(2.773)</td>
<td>(3.188)</td>
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<tr>
<td>$\ln(CatNav)_{it}$</td>
<td>125.5**</td>
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<td>(2.371)</td>
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</tr>
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<td>76.86***</td>
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<tr>
<td></td>
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<td>(3.045)</td>
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<tr>
<td>$CatNavShr_{it}$</td>
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<td></td>
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<td></td>
<td>(2.222)</td>
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<td>$CatBenchNavShr_{it}$</td>
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<td>270.6</td>
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<td>(1.541)</td>
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<td>-1.750</td>
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<tr>
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<td>(-0.750)</td>
</tr>
<tr>
<td>$Bench#_{it}$</td>
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<td></td>
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<tr>
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<td>R-squared</td>
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<td>AR(2) Test</td>
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Results from the dynamic panel estimation suggest that investors chase returns. The positive and significant coefficient on $\text{GrossRet}_{it}$ suggests that consumers invest in funds that have produced higher returns in the past. These results are in line with previous studies that document herding tendencies among mutual funds. Additionally, and as seen in both panels, consumers are attracted to larger funds ($\ln(\text{CatVol})_{it}$ and $\ln(\text{CatNAV})_{it}$) and funds that are market leaders ($\text{CatVolShr}_{it}$ and $\text{CatNAVShr}_{it}$). Either a rational choice or a consequence of behavioral inclinations, investors typically choose a larger, more established ETF. Lastly, after controlling for expenses and returns, we find that investors value active managers’ expertise in searching for mispriced assets. This outcome is interesting in light of Boldin and Cici’s (2010) results regarding investors’ poor decisions when choosing actively managed mutual funds. Regardless of the choice rationality, some ETF investors also like actively managed funds.

IV. Market Quality

Prior research has analyzed situations where multiple mutual fund providers compete in the same asset class or index. While the competitive forces should have similar effects on the expense ratios of ETFs and mutual funds, the process of buying and redeeming ETF shares through an exchange could offset these benefits.\[^{15}\] When multiple ETFs track the same index, they derive their value from an identical pool of underlying assets. From an

\[^{15}\] Agapova (2011) suggests that ETFs and conventional mutual funds are substitutes and documents a clientele effect between these investment vehicles. While ETFs are similar to index funds, many differences exist (Kostovetsky (2003)). ETFs trade on exchanges just like stocks and thus experience supply and demand price movement throughout the trading day. ETFs provide investors the ease of diversification similar to an index fund along with the ability to use limit orders, sell short, and buy on margin. ETFs are recognized for their low transaction costs especially when compared to trading the portfolio of underlying securities. While ETFs usually have lower expense ratios than mutual funds, ETF transactions incur commission charges as well as the additional cost of the bid-ask spread. ETFs typically underperform their index (Elton, et al. (2002)) and have returns similar to index mutual funds ((Gastineau (2004), and Poterba and Shoven (2002)).
economic perspective, these funds should be considered perfect substitutes, and as more ETFs are added to a particular area, liquidity for the incumbent funds will become fragmented. The addition of new competitors within a specific ETF market segment should break the investor pool into pieces. If this fragmentation results in a degradation of overall market quality, then investors might not benefit from increased competition.
The microstructure literature provides competing arguments on the effects of competition on liquidity. In numerous settings, studies find a direct relation between liquidity and increased competition and/or fragmentation (McInish and Wood (1992), Bessembinder (2003) and (O’Hara and Ye (2011)). Boehmer and Boehmer (2003) find a

Figure 7. Herfindahl concentration scores for Morningstar fund segments
These figures present the Herfindahl fund concentration scores using Morningstar classifications. Panel A (Panel B) shows the concentration of the Morningstar institutional categories using NAV (dollar volume) as the scale. Panel C (Panel D) depicts the concentration for funds that are in the same institutional category and follow the matching benchmark, using NAV (dollar volume) as the scale. Within each category, we average each funds’ share of NAV (or dollar volume) for the year, square each value, and then sum the scores. Scores closer to 1 represent very concentrated segments, whereas scores closer to 0 describe much broader sectors.

The microstructure literature provides competing arguments on the effects of competition on liquidity. In numerous settings, studies find a direct relation between liquidity and increased competition and/or fragmentation (McInish and Wood (1992), Bessembinder (2003) and (O’Hara and Ye (2011)). Boehmer and Boehmer (2003) find a
reduction in spreads and informed trading, and an increase in depth, for 30 ETFs after NYSE’s begins trading these securities. Many of these previous studies look at the liquidity effects of different markets and exchanges competing for the same securities. Our study, on the other hand, examines competition that arises from the addition of new securities. Corwin and Coughenour (2008) find that as NYSE specialists allocate their attention to stocks with increased trading activity, spreads (price improvement) of the other stocks in their portfolio increase (decreases). In this setting, the effects of competition coupled with limited attention has a significant impact on liquidity provision. Along these lines, we predict that the effects of fragmentation and ETF competition will result in a degradation of overall market quality.

We analyze two reliable liquidity metrics, %Spread$_{it}$ and Amihud$_{it}$. Chung and Zhang (2014) show %Spread$_{it}$ to be a good approximation of intraday bid-ask spreads and also to be highly correlated with the TAQ-based effective spread. We use %Spread$_{it}$ to approximate the overall costs of trade execution. %Spread$_{it}$ is calculated from CRSP daily data using the following formula:

$$\text{%Spread}_{it} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{(\text{Ask}_{itd} - \text{Bid}_{itd})}{\text{MP}_{itd}}$$  \hspace{1cm} (5)$$

where Ask$_{it}$ is the ask price of stock i on day d during year t, Bid$_{it}$ is the bid price of stock i, and MP$_{it}$ is the average of Ask$_{it}$ and Bid$_{it}$. Microstructure studies often deconstruct effective spreads into a realized spread component and a price impact/adverse selection component (Hendershott and Moulton (2011)). Realized spreads capture profits available to market makers, whereas the price impact component measures information asymmetry. In particular, we employ Amihud’s (2002) illiquidity ratio as a proxy for the price impact of trades. This measure allows us to study the “time series effects of liquidity,” and is calculated using the following formula:

$$\text{Amihud}_{it} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|\text{r}_{itd}| \cdot \$\text{Volume}_{itd}}{\text{Volume}_{itd}}$$  \hspace{1cm} (6)$$

where $r_{itd}$ is fund i’s return on day d during year t and $\$\text{Volume}_{itd}$ is fund i’s dollar volume. This measure quantifies the “daily stock price reaction to a dollar of trading
volume,” or more generally, the daily price impact of order flow. Goyenko, Holden and Trzcinka (2009) endorse the Amihud measure to capture price impact in low frequency data.

Once again, the empirical design in this section follows that in previous sections. We include additional control variables that may affect our liquidity measures, including $\text{CatVolHer}_{it}$ ($\text{CatNavHer}_{it}$) and $\text{CatBenchVolHer}_{it}$ ($\text{CatBenchNAVHer}_{it}$), which are the average daily dollar volume (net asset value) Herfindahl index calculated from the percentage shares of all funds that are members of $i$’s institutional category or institutional category and benchmark, respectively. If a fund has no competitors in their group, the Herfindahl index will take a value of 1. Coincidentally, the included control for market share will also take a value of 1 in this case. The addition of the Herfindahl index controls allows us to distinguish between situations where a particular fund has a very high market share because they are alone, or nearly alone, in their categories, or because they are vanquishing their competition. We believe that more concentrated, higher Herfindahl index, categories will have lower levels of liquidity on average because most of the member funds will have a small group of investors providing liquidity and contributing to price discovery. Figure 7 plots the category concentrations in our sample, and demonstrates that while the ETF market has become more diffuse over time, there is still great diversity in competitive balance across the different groups.

The higher variance of the dependent variables in Table IV and Table V give us more degrees of freedom and allow us to consider specifications with more controls included on the right-hand side. Ideally, these Herfindahl index variables would have also appeared in the previous tables as well, but we were unable to calculate parameter standard errors when they were included.
Table IV
Determinants of spreads

The dependent variable in all specifications is $\%\text{Spread}_it$ or the daily average of the closing bid ask spread divided by the midpoint and multiplied by 100. $\text{Amihud}_it$ is daily average Amihud (2002) ratio. $\text{Leverage}_i$, $\text{Inverse}_i$, $\text{FundFunds}_i$ and $\text{Active}_i$ are binary variables indicating whether the fund is leveraged, net short, a fund of funds or actively managed, respectively. Based on holdings, Morningstar assigns funds into peer groups known as Global Categories, or, even more narrowly, Morningstar Institutional Categories. $\text{Cat}_#it$ is an integer-valued variable describing the number of additional funds, not counting $i$, that are also trading in the same Institutional Category during year $t$. $\text{Bench}_#it$ is an integer-valued variable describing the number of additional ETFs sharing the same Institution that share the same index. $\ln(\text{CatVol})_it \ln(\text{CatNav})_it$ is the combined average daily dollar volume (net asset value) of all funds sharing $i$'s Institutional Category. $\ln(\text{CatBenchVol})_it \ln(\text{CatBenchNav})_it$ is the combined average daily dollar volume (net asset value) of all funds that follow the same benchmark and Institutional Category. $\text{CatVolShr}_it \text{CatNavShr}_it$ is the percentage share of average daily dollar volume (net asset value) fund $i$ receives relative to funds in the same Institutional Category. $\text{CatBenchVolShr}_it \text{CatBenchNavShr}_it$ is the percentage share of average daily dollar volume (net asset value) fund $i$ receives relative to funds in the same Institutional Category and benchmark. $\text{CatVolHerf}_it \text{CatNavHerf}_it$ is the average daily dollar volume (net asset value) Herfindahl index calculated from the percentage shares of all funds sharing $i$'s Institutional Category. $\text{CatBenchVolHerf}_it \text{CatBenchNavHerf}_it$ is the average daily dollar volume (net asset value) Herfindahl index calculated from the percentage shares of all funds sharing $i$'s Institutional Category and benchmark. Each specification is estimated with the ordinary least squares and the dynamic panel estimation methodology. Ordinary least squares t-statistics (reported in parenthesis) are calculated from standard errors clustered by fund and year. Dynamic panel estimation results are generated using the approach described in Arellano and Bover (1995) and Blundell and Bond (1998) with bias-corrected robust variance-covariance estimates of the model parameters. All of the independent variables are included as predetermined instruments in the dynamic panel estimation.
Table IV Panel A: Market characteristics calculated from dollar volume

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<th>Dynamic Panel Estimator</th>
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<td>(2)</td>
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<td>0.338***</td>
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<tr>
<td></td>
<td>(3.663)</td>
<td>(3.493)</td>
</tr>
<tr>
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<td>0.351***</td>
<td>0.338***</td>
</tr>
<tr>
<td></td>
<td>(8.018)</td>
<td>(8.326)</td>
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<td>Amihud&lt;sub&gt;it&lt;/sub&gt;</td>
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<td>0.150***</td>
</tr>
<tr>
<td></td>
<td>(2.892)</td>
<td>(2.712)</td>
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<tr>
<td></td>
<td>0.127**</td>
<td>0.109**</td>
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<tr>
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<td>(2.575)</td>
<td>(2.224)</td>
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<td>(0.540)</td>
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<td>(-1.073)</td>
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<td>-0.0975***</td>
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<td>-0.0492***</td>
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<td>(5.013)</td>
<td>(4.169)</td>
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<td>-0.00106*</td>
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<td>Fund Panel Effects</td>
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<td>R-squared</td>
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Table IV Panel B: Market characteristics calculated from net asset value

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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>%Spread_{it-1}</td>
<td>0.358***</td>
<td>0.339***</td>
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<tr>
<td></td>
<td>(3.642)</td>
<td>(3.474)</td>
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<tr>
<td>Amihud_{it}</td>
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<td>0.152***</td>
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<tr>
<td></td>
<td>(2.898)</td>
<td>(2.651)</td>
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<td>Leverage_{i}</td>
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<td>-0.0132</td>
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<td>-0.116***</td>
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<td>-0.0558***</td>
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<td>(1.645)</td>
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<td>R-squared</td>
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</table>

R-squared
The coefficient estimates for regressions containing \(%\text{Spread}_{it}\) (Amihud\(_{it}\)) as the dependent variable are found in Table IV (Table V). To isolate the liquidity effects specifically associated with trading costs (adverse selection), we control for Amihud\(_{it}\) (\(%\text{Spread}_{it}\)) in regressions of \(%\text{Spread}_{it}\) (Amihud\(_{it}\)). As mentioned earlier, when analyzing expense ratios, fund revenues are generated by confiscating a fraction of NAVs. Thus, it is reasonable that fund providers would make growing their NAVs a primary objective. However, if investors value the exchange traded fund primarily as a trading tool, then the most appropriate measure of scale may be the size of the secondary market for the fund’s shares. While we believe that dollar volume provides the most appropriate scale in our liquidity analysis, we also report market characteristics calculated from NAV in Panel B of Tables IV and Table V. Results in each panel across the tables are quantitatively similar. Overall, the results in both Table IV and Table V provide strong evidence that the addition of new funds to a particular area dramatically increases both the costs and information asymmetry associated with trading.

### Table V

**Determinants of Amihud ratios**

The dependent variable in all specifications is Amihud\(_{it}\) or the daily average Amihud (2002) ratio. \(%\text{Spread}_{it}\) is the daily average of the closing bid ask spread divided by the midpoint and multiplied by 100. Leverage, Inverse, Fund Funds, and Active, are binary variables indicating whether the fund is leveraged, net short, a fund of funds or actively managed, respectively. Based on holdings, Morningstar assigns funds into peer groups known as Global Categories, or, even more narrowly, Morningstar Institutional Categories. Cat\(#_t\) is an integer-valued variable describing the number of additional funds, not counting \(i\), that are also trading in the same Institutional Category during year \(t\). Bench\(#_t\) is an integer-valued variable describing the number of additional ETFs sharing the same benchmark. CatVol\(_{it}\) (CatNav\(_{it}\)) is the combined average daily dollar volume (net asset value) of all funds sharing \(i\)’s Institutional Category. CatBenchVol\(_{it}\) (CatBenchNav\(_{it}\)) is the percentage share of average daily dollar volume (net asset value) fund \(i\) receives inside its Institutional Category. CatBenchVolShr\(_{it}\) (CatBenchNavShr\(_{it}\)) is the percentage share of average daily dollar volume (net asset value) fund \(i\) receives relative to funds in the same Institutional Category that also follow the same benchmark. CatVolHerf\(_{it}\) (CatNavHerf\(_{it}\)) is the average daily dollar volume (net asset value) Herfindahl index calculated from the percentage shares of all funds sharing \(i\)’s Institutional Category. CatBenchVolHerf\(_{it}\) (CatBenchNavHerf\(_{it}\)) is the average daily dollar volume (net asset value) Herfindahl index calculated from the percentage shares of all funds sharing \(i\)’s Institutional Category and benchmark. Each specification is estimated with the ordinary least squares and the dynamic panel estimation methodology. Ordinary least squares t-statistics (reported in parenthesis) are calculated from standard errors clustered by fund and year. Dynamic panel estimation results are generated using the approach described in Arellano and Bover (1995) and Blundell and Bond (1998) with bias-corrected robust variance-covariance estimates of the model parameters. All of the independent variables are included as predetermined instruments in the dynamic panel estimation.
Table V Panel A: Market characteristics calculated from dollar volume

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<td>$Amihud_{it-1}$</td>
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<td>0.175***</td>
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<tr>
<td></td>
<td>(2.558)</td>
<td>(2.647)</td>
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<tr>
<td>%Spread$_{it}$</td>
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<td>0.166***</td>
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<tr>
<td></td>
<td>(2.892)</td>
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<td>-0.251***</td>
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<td>(-2.793)</td>
<td>(-3.212)</td>
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<tr>
<td>Active$_i$</td>
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<td>0.273**</td>
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<tr>
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<td>(2.169)</td>
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Table V Panel B: Market characteristics calculated from net asset value

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<td>Inverse$_i$</td>
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<td>(1.369)</td>
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<td>ln(CatNav)$_{it}$</td>
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<td>Bench#$_{it}$</td>
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<td>R-squared</td>
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After controlling for all persistent unobservable fund characteristics with the dynamic panel estimator, we find a positive and significant coefficient on $\text{Cat#}_{it}$ in two of the three
specifications. Thus, the liquidity of the incumbent funds is drawn away by the arrival of a competing fund. The coefficients on $Bench#_{it}$ and $CatBench#_{it}$ are large and strongly positive in all specifications, regardless of regression methodology indicating that the reduction in liquidity is much greater when competing funds hold an identical portfolio. Given that $%Spread_{it}$ proxies for trading costs, we interpret these results more precisely as not only a reduction in liquidity for the incumbent fund, but a degradation of overall market quality. While investors may have more fund options available, the increased menu of alternatives produces higher trading costs in each fund.

In the previous section, we found that that fund flows move to larger, more established funds even after controlling for fees, and we suggested that this may be a rational choice to seek out liquidity or just a consequence of behavioral failings. We note here that larger funds and funds that are market leaders within each area do, in fact, have more liquid shares. Thus, it appears that the selection of the larger market leader is a rational choice, especially if trading costs are a primary concern. As predicted, the coefficients of both $CatVolHerf_{it}$ and $CatBenchVolHerf_{it}$ are positive and significant, indicating that funds in more concentrated segments are more affected than funds in less concentrated areas. The coefficient of $FundFunds_{i}$ is negative and significant in both panels of Table IV indicating that funds specializing in buying shares of other ETFs have lower trading costs than traditional funds.

In Table IV, we find that increased ETF competition within a particular area leads to an increase in trading costs. In Table V, we examine Amihud’s illiquidity to study the effects of competition on price impact, or more specifically the cost of informed trading around the introduction of a new ETF to a particular area. Hegde and McDermott (2004) find that the liquidity of the DJIA 30 index stocks improves after the introduction of the DJIA 30 ETF, which the authors attribute to the decline in the cost of informed trading. In our situation, however, based on the direction of competition, we expect to find an increase in the cost of informed trading. While the economic inferences in Table V are almost identical to those in Table IV, the economic impacts appear stronger and more consistent across our different specifications. The coefficients on all of our competition variables are, again, positive and significant indicating an increase in the cost of informed trading. An
increase in the price impact of trades suggests that buy-and-hold investors are also adversely affected by ETF competition. Thus, not only does it cost traders more to transact, but buy-and-hold investors must also pay a premium to enter a position. In total, the results in Table IV and Table V indicate that the addition of more competitors to a particular class makes it more expensive to trade funds within that area.

V. Closing Remarks

Prior research has analyzed situations where multiple mutual fund providers compete in the same asset class or index, but we are the first to concentrate specifically on the ETF market. Utilizing a unique dataset from Morningstar Direct, we examine competition between similar ETFs. Our data allows us to identify funds that are close substitutes as well as funds that are perfect substitutes. We examine the addition of new ETFs to a particular area, paying close attention to funds in the same institutional category and/or following an identical benchmark, and question whether the market fragmentation that occurs as more ETFs are introduced follows economic theory. We expect that as more funds are added to a particular area, liquidity for the incumbent funds will become more fragmented, reducing investor surplus and creating deadweight loss in the market segment. In particular, we test whether the number of (added) funds in an asset class affects (i) the management fee paid by investors, (ii) fund flows between similar ETFs, or (iii) the market quality metrics of these securities.

Using a dynamic panel estimator that controls for persistent fund characteristics and historical measures of share liquidity, we find that the addition of new funds to a particular segment radically increases both the costs and the price impact of trading. The liquidity of an incumbent fund dries up when a competing fund enters the market. We find that expense ratios, although relatively “sticky” over time, fall as the size of the ETF market grows. However, direct competition between new entrants and incumbent funds does not lead to a reduction in fees paid to management. Not only are we unable to document price wars between competitors, we find that incumbent ETFs actually raise their expense ratios after a new fund enters the market. In contrast to studies that document investors’ irrational mutual fund choices, we find that ETF investors respond rationally to prices, that is, consumers choose funds with the lowest expense ratios. Overall, our findings indicate
that the loss in market quality resulting from the introduction of additional ETFs to a category is not offset by a decrease in the cost of fund ownership.

VI. Works Cited


### A. Supplementary descriptors

**Table A-1**  
**Regression variable definitions**

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<th>Morningstar Institutional Category</th>
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Table A-1 Panel A: $\text{CatBench}_{12014}^# = 2$
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