Research Statement

Cindy Zheng, 11 August 2020

My PhD research focuses on the field of asset management and I am specifically interested in studying the decision-making processes of various fund families. In the two papers that I have been working on, I examined the launching decisions of exchange-traded fund (ETF) families and the turnover decisions on subadvisors by mutual fund (MF) families, respectively.

In my first year of PhD, I was trained by taking several course modules on the topics of continuous-time finance, behavioural economics and microeconomics. Passing the comprehensive exam helped ensure a well-rounded understanding of the academic literature on both corporate finance and asset pricing. Moreover, I conducted an individual research project looking at the impact of incentive fee structure on MFs versus the separate accounts. I found that funds/products adopting the incentive-fee structure typically generate higher excess returns and risk-adjusted returns, which is especially evident in the separate account sample. I also showed that the incentive-fee funds/products tend to have higher risk-taking by not following the benchmark closely or gaining exposure to other factors. The rigorous research trainings I received in my first year has equipped me with the necessary knowledge and skills to conduct future research.

During my second year of PhD, which is essentially my first year of research, I jointly worked with David Chambers and Pedro Saffi on a paper which studies the effect of competition in the sub-advised mutual fund industry. In this paper, we look at a novel dataset on the performance of subadvisors around turnover decisions from January 1995 to December 2016, which is hand collected by Julia Arnold. The research is still on-going due to an unexpected issue on the validity of sub-advisory fee data collected. Nevertheless, we have got several interesting results up to now. Panel probit regressions show that underperforming funds are more likely to make turnover decisions on subadvisors. However, the fund advisors do not seem to possess skills in picking subadvisors. As they tend to chase past performance, though the subadvisor performance post hiring/firing reverts back to the mean. In the full sample, hiring/firing activities do not appear to improve fund performance. The only exception is in the pure hiring sample, where fund performance is shown to improve marginally using an event study framework. The improvement in overall fund performance may partly due to the disciplinary effect of hiring a new subadvisor on the existing subadvisors. We also conduct a survival analysis on the tenure of subadvisors. Empirical results confirm that smaller and better performing subadvisors hired by younger fund advisors are more likely to be kept for longer. We are now hand collecting data on the location of the advisors versus subadvisors, through which we want to investigate the impact of geographic distance on the cross section of fund turnover decisions.

During my third year of PhD, I drafted my solo job market paper titled “Determinants on ETF Launching Decisions”. This paper studies the decision by an asset manager to launch an exchange-traded fund (ETF). Using U.S. data, I find that fund families are concerned with profit maximization when making launching decisions through both revenue generation and cost reduction. ETF launches are more likely to be driven by investor demand, rather than based on past performance. Further, there are significant economies of scale and scope in the ETF industry, allowing larger families to benefit from specialization. Families tend to follow the behaviour of the three largest ETF providers, though they are less likely to launch in less liquid or highly concentrated objective markets. Finally, a time-to-event analysis shows that ETFs launched by larger and higher-fee families and whose initiation is not driven by excessive flows into the family are more likely to survive for longer. This paper contributes to the industrial organization literature of ETFs and show how the decision to launch an ETF is affected by fund characteristics in distinct ways relative to the open-ended MFs. I also provide evidence on how market conditions, including liquidity and market concentration, affect the competition and growth of the ETF industry.

I have presented my solo paper in seminars and Cavalcade of Cambridge Endowment for Research in Finance (CERF) and received valuable advice for shaping my paper. Further presentation plan has been interrupted by the outbreak of COVID-19 and the subsequent lockdown. Throughout the two years of research, I have also benefited from the guest lectures by Prof. Richard Evans, Prof. Adam Reed, Prof. Ronald Masulis and Prof. Jon Lukomnik.

For the remainder of my PhD, I aim to complete these aforementioned dissertation papers and develop a third section of my thesis by further exploring the behaviour of ETF families. I also aim to take more opportunities to present my work at various conferences and target for submission to a US tenure journal. Upon completing the PhD, I intend to carry on my research in the field of asset management by pursing an academic career.

Determinants on ETF Launching Decisions

Abstract: This paper studies the decision by an asset manager to launch an exchange-traded fund (ETF). Using U.S. data, I find that fund families are concerned with profit maximization when making launching decisions through both revenue generation and cost reduction. ETF launches are more likely to be driven by investor demand, rather than based on past performance. Further, there are significant economies of scale and scope in the ETF industry, allowing larger families to benefit from specialization. Families tend to follow the behaviour of the three largest ETF providers, though they are less likely to launch in less liquid or highly concentrated objective markets. Finally, a time-to-event analysis shows that ETFs

launched by larger and higher-fee families and whose initiation is not driven by excessive flows into the family are more likely to survive for longer.

Introduction

The exchange-traded fund (ETF) industry has grown rapidly ever since the launch of SPDR by State Street in 1993. As of August 2019, US-based ETFs alone control over 4 trillion USD in asset under management (AUM), and ETFs now regularly contribute to nearly a third of the trading activities on the US stock market.[1] In each year of the past decade, we witnessed over a hundred new launches of ETFs, and there is an increasing trend in the number of new ETF inceptions through years (Figure 1). Competition and innovation in the ETF marketplace are encouraged by the regulators. For instance, in September 2019 the SEC adopted a new rule to facilitate new entrants by effectively watering down the 'exemptive relief' of ETFs.[2]

One distinguishing feature of the ETF market relative to open-ended mutual funds (MFs) is the extreme market concentration, over 80% of the total net asset (TNA) in ETFs is under the control of the three industry giants, namely BlackRock, Vanguard, and State Street, hence force I call them the "Big Three" (Figure 2). Regulators including the SEC are concerned about whether the triopoly structure in the ETF market would stifle competition.[3] With the exponential growth, the popularity among financial advisors as well as the special attention from the regulators, the ETF industry has undoubtedly been placed under the spotlight of the investment world. However, academic research on the industrial organization of the ETFs is limited, and more specifically, the decision of fund families to launch new ETFs has not been academically studied before.[4]

This paper therefore fills in this gap by addressing the following three questions. First, what are the rationales behind ETF launching decisions? In other words, which characteristics of the fund family and the investment objective are associated with higher likelihood of new ETF launches? Second, how does the presence of the Big Three shape the ETF industry? Third, could we predict the lifespan of an ETF upon its inception based on characteristics of the family and the investment objective?

With respect to the first question, research has been conducted on the determinants of opening and terminating decisions of open-ended MFs. The study by Khorana and Servaes (1999) is the closest to my paper. They find that the opening decisions of open-ended MFs are related to three broad sets of factors: the ability to generate additional fee income, economics of scale, and follow-the-leader strategy. In this paper, I examine the intuitive question of whether common characteristics shared between ETFs and open-ended MFs affect their initiations in the same way. In addition, the structural difference between ETFs and open-ended MFs indicates the potential existence of additional factors in determining ETF inceptions that are not present in the MF literature. Unlike the open-ended funds, ETFs are traded on stock exchanges and enjoy intra-day liquidity. I therefore take a further look at exchange variables that are unique to ETFs to study the effect of market liquidity on ETF launching decisions. Moreover, given the extensive debate on active versus passive management (Levy & Lieberman, 2016; Garleanu & Pedersen, 2019), this paper explores whether family decision to launch new ETFs in a particular investment objective is correlated with characteristics of the MF counterparty.

First, I show that ETF launching decisions are also affected by families' desire to generate incremental profits, but through different channels relative to open-ended MFs. Prior literature documented the predominant role played by past performance on both the family level and the investment objective level in determining the initiation and termination of open-ended MFs (Khorana & Servaes, 1999; Brown & Goetzmann, 1995; Lunde et al., 1999). Superior abnormal returns have been shown to attract investor flows (Ippolito, 1992; Sirri & Tufano, 1998) and hence facilitate growth of the family, the emphasize on past performance by MF families can therefore be justified.[5] However, the majority of ETFs are still passive index trackers with no deliberate intent to search for alpha.[6] Without the need to generate abnormal returns, it is rational for ETF families to focus on flows, AUM and fees to gain a competitive edge. Our results suggest that ETF launching decisions are more likely to be driven by investor demand. To be more specific, ETF families are more inclined to profit from flow and volume. Consistently, I find no significant correlation between ETF initiations and past performance, either at the family level or the investment objective level. Instead, there exists a positive and significant relationship between the likelihood of ETF inceptions and the prior-12-month dollar volume of the fund family as well as the corresponding investment objective.[7] Similar pattern has been found on the prior-12-month net flow into the investment objective.

On the supply side, I find that families are more likely to launch in objectives with more arbitrage opportunities, measured by those with larger tracking errors. As market makers of the ETF products, the authorized participants (APs) can make arbitrage profits through in-kind creation and redemption of ETF shares whenever its value deviates from the value of the underlying basket (Ben-David et al., 2018). Investigating the ETF launching decisions is somewhat analogous to studying the IPOs. Loughran and Ritter show that the issuers do not get upset about leaving significant amount of money on the table during IPOs and argue that it may serve as indirect compensation to the underwriters (Loughran & Ritter, 2002). Inspired by the IPO literature, I argue that families are willing to leave arbitrage opportunities on the table when making new ETF launches, through which they may be able to attract more participation from the market makers, i.e. the APs.

Similar to the open-ended MFs, fees charged by ETFs consist of a percentage of its TNA. Hence to maximize the fee income, families benefit from both a larger asset base and a higher percentage fee. To ensure a substantial asset base for the ETF offering, the potential size of the market is an important consideration of family launching decisions. Consistently, I find that new ETFs are more likely to be launched in objectives with larger AUM. Also, families are more likely to launch in objectives experiencing larger inflows, supporting the argument that families care about the growth potential of the objective market. Moreover, since investors may switch between the active and passive alternatives with the same investment objective (Garleanu & Pedersen, 2019), the aggregate TNA of all open-ended MFs in the given objective may serve as a proxy for the customer base and hence the growth potential of the objective market. Consistently, I find that ETFs are more likely to be launched in objectives where the aggregate TNA of MFs is larger. However, the impact of the percentage fee on family launching decisions is less clear. On the one hand, charging a higher percentage fee would bring additional fee income to the launching family. On the other hand, the fee competition among ETFs is widely reported.[8] Empirical findings in this paper suggest that ETFs are more likely to be launched by families charging higher expense ratios, although are less likely to be launched in objectives with higher average expense ratios. The mixed results on expense ratios lend support to the literature showing that the widely publicized ETF fee reduction is not representative of the entire industry (Box et al., 2020).

In addition to revenue generation, profit maximization can also be achieved via cost reduction. On top of the common costs on research & development, marketing and maintenance, trading costs can be a significant concern for ETFs. Portfolio turnover measures the degree of activeness in portfolio management, a lower portfolio turnover generally implies less trading activities and hence lower trading costs. Consistent with the cost reduction argument, I find that new ETFs are more likely to be launched in objectives with lower average portfolio turnover.

Another way to effectively reduce the overall per unit cost is through cost sharing in the presence of economies of scale and scope, which is related to the second set of factors affecting MF initiations. ETFs are more likely to be launched by larger families and families who have launched in the prior year. Notably, I find supporting evidence to the argument that equity ETFs benefit from specialization that outweighs the potential cost of cannibalization. Specifically speaking, under a panel logistic regression framework, I find that families are more likely to launch in objectives representing a greater proportion of the family TNA. This contradicts the finding on equity MFs by Khorana and Servaes (Khorana & Servaes, 1999) but is consistent with Evans (2010).[9] To further understand the choice by families to launch in a new objective versus an objective in which the family has previous investment, I perform a multinomial logit regression to examine both decisions relative to no launching. I find that smaller families dominate the decision to launch in objectives where the family has no prior investment. These families face more pressure to grow and expand in order to achieve the economies of scope needed to compete in the ETF industry.

With respect to the second question, I investigate how the presence of the Big Three affect competition among new market entrants. Figure 2 shows the time series of aggregate ETF market share controlled by the Big Three during the sample period from 1996 to 2018, along with the number of new ETF launches by families within and outside the Big Three. Though the graph indicates that the number of new entrants from non-Big Three families has increased dramatically through years, regulators including the SEC are still concerned about whether the triopoly structure in the ETF market would stifle competition.[10] The Big Three enjoying better brand recognition and wider customer base, are able to attract more flows and provide better liquidity. The competitive advantages allow them to develop more effectively and become the first movers. By following asset allocation decisions of the Big Three, other families can save substantially on research costs and customer development. On the other hand, with the scale and scope economies favouring the Big Three and switching cost being substantial within less liquid investment objectives, the first mover advantage is more likely to sustain. Therefore, additional barriers are posed on the new market entrants into such objectives. From a panel logistic regression on the subsample of non-Big Three families, I find that they tend to make new ETF launches in objectives where the Big Three has launched in the prior year, which is consistent with the findings on open-ended MFs (Khorana & Servaes, 1999). However, to the extent that the market for an investment objective is less liquid or dominated by the Big Three, the follow-the-leader behaviour among non-Big Three families are diminished. As a robustness check in the analysis, I tested if the family and objective level characteristics would affect launching decisions of the Big Three differently, compared to the non-Big Three. Empirical pattern suggests that the impact of most characteristics is in the same direction for both the Big Three and non-Big Three, though the economic significance may vary.

Finally, with respect to the third question, I conduct a time-to-event analysis to study the survival time of ETF offerings. There are significant costs in launching an ETF. It typically takes between $750,000 and $1.25 million to get through the exemptive relief, the prospectus and all the contracts, besides costs associated with research, marketing and maintenance.[11] Therefore, a fund needs to grow rapidly and attract sufficient inflows to remain profitable in the long run. I find that the lifespan of an ETF offering can be predicted from family and objective level characteristics upon its inception. ETFs launched by larger families and families charging higher expense ratios are more likely to survive for longer. In the presence of substantial scale economies, it is easier for larger families to attract flows and save on the per unit cost. Besides, families charging higher fees are able to maintain a higher profit margin. However, I find that ETFs launched following large inflows into the fund family are more likely to fail at an earlier age. One possible explanation is that excessive inflows into the fund family may evoke managerial hubris as proposed in the corporate takeover literature (Roll, 1986). On the objective level, ETFs launched in objectives with lower expense ratios are more likely to survive for longer. This is consistent with the notion that the ETF industry is extremely competitive on expense ratios due to the fact that most ETFs are passive. Moreover, previous literature on MFs documented that launching a new fund into hot or trendy objectives may lead to future underperformance (Greene & Stark, 2016). In a similar vein, I find that ETFs who are launched due to large trading activities in the objective market are more likely to fail at a younger age.

This is the first paper studying the determinants on ETF initiations and it contributes to the literature from several perspectives. First, I build upon the literature concerning the industrial organization of the open-ended funds to show how the decision to launch an ETF is affected by fund characteristics in distinct ways relative to the open-ended MFs. Second, I provide evidence on how market conditions, including liquidity and market concentration, affect the competition and growth of the ETF industry. Prior literature has documented the effect of market quality on ETF flows (Clifford et al., 2014). In this paper, I discuss a more direct channel of the industry expansion, namely the emergence of new market entrants.

The rest of this paper is organized as follows. Section I lists the major hypotheses. Section II describes the data and shows some summary statistics. Section III explains the research design and elaborates the empirical results from the analysis. Section IV contains the robustness check. And Section V concludes.

1. Hypotheses

Our purpose is to examine the determinants of ETF launches by fund families and how they compare to open-ended MFs. Rationally, the expected benefits of the launching activity must outweigh the associated costs. This necessary condition holds for both the ETFs and the open-ended MFs. Families benefit from additional fee income, which consists of a percentage of the total AUM. Therefore, expanding the asset base and charging a higher percentage fee are of the best interest to both types of funds. However, the channels through which families generate profits can be different. While active funds rely on superior past performance to advertise managerial skills and attract investments, most ETFs are passively managed tracking their benchmark index. I hence expect no significant correlation between ETF launching decisions and the abnormal returns on either the family level or the investment objective level. Instead, I posit that family decisions to launch new ETFs are more likely to be driven by investor demand. The growth potential of an objective market may be signalled by prior flows and trading volume. Moreover, families who have attracted large inflows may enjoy the “halo effect” and flows are more likely to spill over to the newly launched product. This leads to the first major hypothesis:

Hypothesis 1.a (demand side): The likelihood of new ETFs being launched is positively related to prior net flows and trading volume in the family and the investment objective.

While the argument above is related to the demand side, the launch of a fund also depends on supply-side characteristics. ETF shares are created and redeemed through in-kind transactions between the providers and the authorized participants (APs) on the primary market. As market makers, the APs are essential for the distribution and marketing of the ETF products. They make profits through the bid-ask spread, smart management of their securities inventory, and through arbitrage activities. In an efficient market, when price discrepancies between the ETF shares and the underlying basket emerge, the APs may buy whichever is cheaper on the secondary market in exchange for the other with the ETF provider on the primary market. In this way, the APs are able to earn arbitrage profits and effectively drive prices to convergence. Higher tracking error in a given objective market can be viewed as an indicator of more arbitrage opportunities for the APs. Therefore, in the same spirit as the IPO firms leave money on the table as indirect compensation to the underwriters (Loughran & Ritter, 2002), I posit that fund families deliberately leave arbitrage opportunities to attract participation of the APs. This leads to the following hypothesis:

Hypothesis 1.b (supply side): The likelihood of new ETF launches in a given investment objective is positively related to the average tracking error of all funds in the objective.

Similar to the market for open-ended MFs, there exist substantial scale and scope economies in the ETF market. I hence posit that larger families, families offering a wider range of products, and families who have launched in the prior year are more likely to launch a new ETF. Smaller families facing the curse to "grow-or-die" are more likely to expand their product line to withstand competitions in the earlier stage of their lives, while more established families may benefit from specialization and the associated economies of scale. This leads to the second major hypothesis:

Hypothesis 2: The decision to launch a new ETF in an objective with no prior investment within the family is dominated by smaller-sized families or families with smaller scope. The likelihood of launching a new ETF in an existing objective is positively related to the percentage of family asset invested in the corresponding investment objective.

The ETF industry is highly concentrated, with over 80% of the aggregate AUM controlled by the Big Three. The presence of significant scale and scope economies favours the Big Three and allow them to become the first innovators. However, to the extent that non-Big Three families could replicate the innovation without incurring significant costs and benefit from the overall growth of the market, it is rational for them to follow the leader and take the second mover advantage (Reinganum, 1985). Hence, similar to the behaviour of MF families, I posit that an ETF launched in a given objective by the Big Three during the previous year would increase the likelihood of non-Big Three families to launch in the same objective. However, the profitability of the second mover is related to factors such as brand loyalty and switching cost in the market. Therefore, I take a closer look at the impact of the Big Three on the competition of other families. Though the follow-the-leader strategy found in the MF literature still exists in the ETF sample, I posit that other families would hesitate in entering investment objectives dominated by the Big Three. Also, in objectives with less liquidity and thus higher switching cost, the first-mover advantage of the Big Three are more likely to sustain, which poses additional barrier on new market entrants. Here follows the third major hypothesis:

Hypothesis 3: The likelihood of non-Big Three families to launch new ETFs in an objective where the Big Three has launched in the previous year is negatively related to the market share of the objective controlled by the Big Three and the average spread of the objective.

Given the inevitable costs to launch an ETF, the fund needs to attract sufficient inflows and grow rapidly to remain profitable. I argue that family and objective characteristics upon inception have significant predicting power on the lifespan of ETF offerings. At the family level, size can be an important determinant. It is generally harder for smaller families to attract flows due to the disadvantage on brand recognition and customer base, etc. Also, families charging higher fees are able to maintain a higher profit margin. However, families that experienced excessive inflows in the prior year may be affected by hubris beliefs as proposed in the corporate takeover literature (Roll, 1986). At the objective level, the ETF industry is extremely competitive on expense ratios due to the passive nature. Hence, ETF products launched in lower-fee objectives possess a competitive advantage on this end. Moreover, previous literature on MFs documented that launching a new fund into hot or trendy objectives may lead to future underperformance (Greene & Stark, 2016). In a similar vein, I argue that ETFs who are launched due to large trading activities in the objective market are more likely to fail in a younger age. Overall, the above arguments are summarized into the following hypothesis:

Hypothesis 4: ETFs launched by larger and higher-fee families, and whose initiations are not driven by capital flows into the families are more likely to survive for longer. ETFs launched in lower-fee objectives and whose launching decision is not affected by large trading activities in the objective market are more likely to live a longer life.

In Table 1, I summarize all the ex-ante predictions on how various family and objective level characteristics may affect the likelihood of new ETF launches. The hypotheses are divided into three broad categories, namely profit maximization, scale and scope economies and the impact of the Big Three. Predictions are posed in either the whole sample or two different subsamples of the existing families and the non-Big Three families where appropriate.

2. Data and Sample Descriptions

The sample contains 1,859 US equity ETFs over a 23-year period from January 1996 to December 2018, taken from Morningstar Direct Institutional Investment Analysis Platform. I begin with 3,305 ETFs whose primary share class is listed in U.S. exchanges between 1996 and 2018. Morningstar uses ETF as an umbrella term to refer to a range of different Exchange-Traded Products (ETPs), including ETFs, ETNs and ETCs. Unlike ETFs, ETNs and ETCs are more accurately described as debt securities that are less relevant to our study, hence I exclude the 359 ETNs/ETCs from the original sample. This study is confined to equity ETFs only, leaving the non-equity ETFs for future research. Both surviving and delisted funds are included in the sample to avoid survivorship bias.

During the sample period, I observe 1,756 cases of ETF launches across 155 fund families and 74 investment objectives, identified as the Morningstar Institutional Category. From Morningstar Direct Database, I obtained fund-month observations on gross and net returns, as well as the total net assets (TNAs). Fund flows are then calculated as the change in assets net of any return effect, i.e.

[Equation]

where [Equation] denotes the total net assets in fund [Equation] at the end of month [Equation], and [Equation] is the gross return of fund [Equation] during month [Equation]. I also obtained daily observations on the prices, trading volumes and bid-ask spreads. The daily dollar volumes are then calculated as

[Equation]

Monthly averages are computed on the daily observations to fit in the fund-month panel. Finally, expense ratios and portfolio turnovers are reported annually on Morningstar. The annual report net expense ratio represents the percentage of fund TNA used to pay for operating expenses, management fees, administrative fees, and all other asset-based costs incurred. The portfolio turnover is defined as

[Equation]

where the numerator denotes either the total amount of purchase or the total amount of sale by fund [Equation] during year [Equation] whichever is less. Family and objective level measures are obtained by aggregating all ETFs within the family or objective into one portfolio and taking the equally weighted average. The TNA weighted averages are also computed and included as robustness checks.

Fund-month observations for the open-ended MFs are also obtained on the returns, TNAs and expense ratios. Further, monthly returns on the benchmark indices are collected from the Morningstar Direct Database. Benchmark-adjusted returns of the funds are then calculated as the difference between the realized returns and the predicted returns with beta estimates from the following regression using a prior 36-month rolling window:

[Equation]

where [Equation] denotes the excess return of the primary benchmark over the risk-free rate for fund [Equation] in month [Equation]. For fund observations whose primary benchmark is missing, the default benchmark (Appendix 1) of the corresponding investment objective is assigned. The default benchmark of each investment objective is obtained by taking the most commonly used (sorted by the aggregate TNA of funds following the index) primary benchmark of ETFs in each Morningstar Institutional Category.

Table 2 contains the descriptive statistics of the fund-month observations on major fund characteristics. In panel A, summary statistics are reported for all funds in the sample on net flow, dollar volume, tracking error, expense ratio, portfolio turnover, TNA, family TNA, bid-ask spread and benchmark-adjusted return. Panel B compares the above characteristics between subsamples of the Big Three versus non-Big Three families. The “MeanDiff” column in Panel B reports the difference in the sample means, together with the statistical significance from a two-sided t-test.

3. Results

3.1 General Factors Affecting ETF launching decisions

In this section, I investigate the overall determinants of the ETF launching decisions using the following panel logistic framework.

[Equation]

[Equation]

The dependent variable is an indicator variable taking a value of one if family [Equation] launches in objective [Equation] during month [Equation], and zero otherwise. In the matrix [Equation] of explanatory variables, I include various characteristics on both the family level and the investment objective level. In Table 3, I present the coefficient estimates together with the marginal effect of the panel logistic regression using all family observations of the sample. In Model (1), I include only the explanatory variables of our main interest as discussed in Hypothesis 1 and 2. As a flow measure, I include the prior-12-month average flow rank as in (Evans, 2010). A fractional rank between zero and one is assigned to each family or investment objective in each month according to the net flow computed in the above data description. By using the flow rank instead of the percentage flow, the regression is immune from the distortion by the outliers and the undesired market turbulence through time. As a measure of liquidity, I include the prior-12-month average rank of the dollar trading volumes, which is constructed in the same manner as the flow ranks. To measure the arbitrage potential in an objective market, I include the mean tracking error of all ETFs within the same investment objective, calculated as the standard deviation of the prior-12-month excess returns over their primary benchmarks. The default objective benchmark (as listed in Appendix 1) is assigned when the primary benchmark is missing. As for the performance measure, I use the prior-12-month average benchmark-adjusted alphas of the family and investment objective. Unlike the actively managed funds, for whom the Carhart four-factor alpha (Carhart, 1997) may be a better indicator of the absolute performance. In the realm of the ETFs, it makes more sense to compare the performance of a fund with the stated benchmark index. Benchmark-adjusted alphas are computed using a 36-month rolling window as explained in the data description.

Apart from the variables discussed above, in Model (2) I also include the mean expense ratio of the family and the objective in the prior year as a measure of the percentage fee charged. To account for cost reduction considerations of the families, the mean portfolio turnover of the family and investment objective in the prior year are included. Finally, to explore the scale economies as well as to control for the well-documented relationship between flow and fund size, I include the logarithm of lagged family and objective size. In Model (3), I explore the effect of economies of scope on the decision to launch new ETFs. The family size variable is replaced by the number of objectives covered in the family. The two measures of size and scope could not be included together in the same model due to collinearity concerns, as the pairwise correlation of the two variables is [Equation]. In Model

(4), I consider several objective characteristics of the open-ended MFs, given the documented competition on investor flows between active and passive funds (Levy & Lieberman, 2016; Garleanu & Pedersen, 2019). I substitute the objective flow, size, expense ratio and performance with the respective measures for the open-ended MF sample.

I make the assumption that the ETF launching decisions are independent across different families, though decisions made by the same family are more likely to be correlated. Therefore, I apply the heteroscedasticity robust standard errors clustered on the fund families. I also include the year dummies in the regression to take out the time trend. All the explanatory variables are standardized to have a mean of zero and a standard deviation of one to allow for easier interpretation of the estimates and direct comparisons of the economic magnitudes. In the columns 'Marginal Effect', I report the annualized percentage change in the probability of a new ETF being launched when each explanatory variable is increased by one standard deviation and all other variables are set equal to the mean of zero. For indicator variables, this represents the percentage change in probability when the indicator variable increases from zero to one.

The regression results from Model (1) – (3) confirm the hypothesis on both the demand side and the supply side. On the demand side, I first notice that the coefficients on the objective flow are positive and significant in all models, even after controlling for performance and objective size, etc. A one standard deviation increase in the rank of the objective flow increases the likelihood of a new ETF being launched by 3.02%–5.07% across the three model specifications. Coefficients on the family flow rank are always positive though not significant. In the meantime, coefficients on the performance measures, i.e. the benchmark-adjusted returns of the family and the investment objective, rarely show any significance in affecting the launching decisions of ETFs. This suggests that families pay relatively little attention to prior performance when deciding to launch a new ETF, but instead rely more on the prior flows to gauge the growth potential of an objective market. This finding is in direct contrast to that of the open-ended MFs (Khorana & Servaes, 1999).

Next, I explore some liquidity features that are unique to the ETFs as they are traded on the stock exchanges. In all four models, the objective dollar volume appears to be a significant determinant on the ETF launching decisions both statistically and economically. A one standard deviation increase in the objective dollar volume leads to a 1.16%-9.89% increase in the annualized probability of new ETF launches across the four model specifications. Dollar volume on the family level also appears to be positively correlated with the family decision to launch a new ETF. The economic significance is particularly evident in

Model (2), where a one standard deviation increase in the family dollar volume leads to a 11.99% increase in the annualized probability of new ETF launches. These results suggest that families and objectives who are able to attract more investor attention and hence enjoy higher liquidity are more likely to witness new entrants of ETFs.

On the supply side, the positive and significant correlation between the objective tracking error and the likelihood of launching a new ETF is persistent across all four model specifications. The probability of a family deciding to launch a new ETF in a certain objective increases by 2.05%-4.85% annually with a one standard deviation increase in the average tracking error of the investment objective. This empirical result confirms our conjecture that fund families may make indirect compensation to the APs to attract market makers by launching new ETFs in objectives with more arbitrage opportunities.

Model (2) and (3) show that the average expense ratio of the investment objective has a positive and significant impact on the ETF launching decision of fund families. A one standard deviation increase in the objective expense ratio increases the annualized probability of a new ETF being launched in the objective by 5.73%-6.66%. The average expense ratio of the family also affects the likelihood of ETF launching decisions positively though not significantly. The above shows that families are indeed concerned with the capability to generate additional fee income when making ETF launching decisions, which is consistent with the open-ended MF literature (Khorana & Servaes, 1999). Next, I go one step further to investigate whether families care about cost reductions on top of revenue generation. Cost reduction can be achieved by a fund family through at least two ways, namely cost sharing on research, marketing and operations, etc. and reduced trading activities. Cost sharing can be realized through exploring the economics of scale and scope, which I will discuss in more details in the next section. Meanwhile, the activeness of a fund can be measure by the portfolio turnover, a lower portfolio turnover indicates lower trading activities and hence less transaction cost is incurred. Coefficients from Model (2)-(4) confirm a negative and significant relationship between the likelihood of new ETF launches and the average portfolio turnover on both the family level and the investment objective level. The annualized probability of new ETF launches decreases by 2.03%-3.70% with a one standard deviation increase in objective portfolio turnover, and 2.09%-7.38% with a one standard deviation increase in family portfolio turnover across the three model specifications.

In addition to the factors of the ETF market itself, I also investigate whether family decisions to launch new ETFs are affected by characteristics of the corresponding objective in the open-ended MF market. Coefficient estimates in Model (4) show that objective level flow, expense ratio and size measures of the open-ended MFs all appear to have positive and significant impact on the likelihood of new ETF launches. It can be seen by comparing with the results in Model (2) that these objective level measures of the open-ended MFs affect ETF launching decisions in the same direction as measures of the ETF objectives, though with smaller economic magnitude. Families may pay attention to prior flow into the MF objective as it signals the investor sentiments towards the asset class. Though ETFs generally charge much lower fees than the corresponding open-ended MFs, the average expense ratios of funds within the same investment objectives are positively correlated (with a pairwise correlation of [Equation]). Given the competition on investor flows between the active and passive world, the size of the MF objective measures the potential size of the capital pool. Poor risk-adjusted performance of the active funds may make the investors doubt if the active management add value and hence drive investors to the passive alternatives. As a measure of the objective level performance, I compute the Carhart four-factor alpha using a prior 36-month rolling window and take the prior 12-month average of all funds within the same investment objective. However, the empirical evidence does not support this intuition, no statistical significance is shown from the regression coefficient.

3.2 Economics of Scale and Scope

I find strong support to the economics of scale and scope argument which is persistent across all model specifications in both the full sample and the subsample of existing families. Families are able to effectively reduce the per unit cost through cost sharing on research, operation, marketing and distribution, etc. There exist significant cost complementarities across ETF products in different objectives within a family. Also, families who have gone through the launching process in the previous period could save on the fixed costs associated with product development. Table 3 applies to all families in the sample, in Model (2) and (3), it is shown that family decisions to make new ETF launches are positively affected by both the size of the family and the width of their offerings. A one standard deviation increase in the family size and the number of objectives covered in the family increases the annualized probability of new ETF launches by 13.49% and 5.57% respectively. Recognizing that the launching decisions by new families might differ from that of the existing ones, in Table 4 I look at the subsample of the existing families. The positive and significant impact of family size on the ETF launching decisions persists. In addition, the positive and significant coefficient on the dummy variable indicating the family launched in the prior year shows that families benefit from prior launching experience. An ETF launched in the prior year increases the probability of a new ETF launch by 9.65%-16.35% across the two model specifications.

In Model (1) of Table 4, the dummy indicating a new objective without prior family investment demonstrates the strongest impact on the ETF launching decision, which is consistent with the idea of expanding the breadth of fund offerings to explore the economics of scope. The probability of family making new launches in an objective increases by 25.60% annually if the new fund offering broadens the product line of the family. Next, I consider whether there exists a desire to specialize when families make decisions to launch in existing objectives. To approach this problem, I fist have a look at the objective distribution within existing families. Figure 3 presents the number of ETF offerings in each objective against the percentage family asset invested in that objective for the Big Three[12]. A clear positive relationship emerges, indicating the desire by families to specialize in objectives of their expertise and capitalize on the economics of scale. Result in Model (2) of Table 4 confirms that families with a large percentage of their assets in a given investment objective are more likely to open an additional fund in that investment objective. This pattern is consistent with the findings by Evans (Evans, 2010) but inconsistent with the findings by Khorana and Servaes (Khorana & Servaes, 1999).

The presence of significant scale and scope economies may on the one hand benefit the larger families, and on the other hand bring additional pressure on the new market entrants to expand quickly to gain a competitive edge. I therefore study how families balance between the need to expand the breadth of their offerings and the desire to benefit from specialization and the associated economics of scale. Under a multinomial logistic regression framework, I separately examine the determinants of family decisions to launch an ETF in a new and existing objective in the family, both relative to the decision of no launching. The dependent variable takes a value of one if, in a given month, the family launches a new ETF in a new objective with no prior investment within the family. It takes a value of two if the family launches a new ETF in an existing objective of the family in that given month and takes a value of zero otherwise. As in the panel logistic regressions, all explanatory variables are standardized to have a mean of zero and standard deviation of one. Year dummies are included, and standard errors are clustered on the family level. Table 5 contains the results from this multinomial logit analysis. Family size and the number of objectives in the family are included separately in two different model specifications due to the collinearity concern mentioned above (pairwise correlation of the two variables is [Equation]). Under each model specification, the first column presents the coefficient estimates corresponding to the determinants of launching in a new objective, with standard errors in the brackets and statistical significance shown by the asterisks. The second column presents the above results corresponding to the determinants of launching in an existing objective within the family. The third column presents the p-value of a difference test between the coefficients in the first two columns.

Column (1) and (3) in Table 5 suggest that the decision by existing families to launch in a new objective without previous investment is predominately made by smaller-sized families and families with smaller scope, while the statistical significance on all other explanatory variables largely disappeared. Patterns emerged from column (2) and (4) in Table 5 suggest that factors affecting the decision of existing families to launch in existing objectives within the family conform with those of the full sample. The two columns showing the p-value of the difference test shed light on how the family level and objective level characteristics affect the decisions to launch in new and existing objectives differently. Families who possess larger scale and scope, who enjoy higher average dollar volume and who are able to charge higher expense ratios are more likely to launch in existing objectives. The family decision to launch within an objective is more sensitive to the size of the objective, flows into existing fund offerings in the same objective and average dollar volume of ETFs within the same objective if the family already have ETF offerings in that objective than if it represents a new objective without previous family investment. Overall, the results from Table 4 and 5 are consistent with the notion in Hypothesis 2 that families with smaller scope face the pressure to expand the breadth of offerings to withstand market competition which favours the larger families, while more established families benefit from specialization and the associated economics of scale.

3.3 Role of the Big Three in the ETF Market

In this section, I examine the impact of the Big Three behaviour on the launching decision of other non-Big Three families. In Table 6, I repeat the panel logistic regression of Table 3 in the subsample of non-Big Three families. All the family and objective level characteristics specified in Table 3 are included as control variables, while the main variable of interest is the dummy indicating the Big Three launched in a certain objective in the prior year. The positive and significant coefficients on this dummy variable in both model specifications in Table 6 indicate that families indeed tend to follow the leader in deciding the investment objective of new launches. An ETF launched by the Big Three in the prior year increases the probability that non-Big Three families launch a new ETF in the same objective by 4.83% and 3.96% according to the two model specifications. The statistical pattern on most control variables persists though the economic significance is somewhat attenuated.

To the extent that product innovation in the ETF industry could be imitated without incurring significant costs and the follower could benefit from the overall growth of the market, it is rational for the non-Big Three families to follow the leader and take the second mover advantage (Reinganum, 1985). However, the profitability of the second mover is related to factors such as brand loyalty and switching cost in the market. To examine whether families are concern with such frictions when pursuing follow-the-leader strategy, I include interaction terms with the Big Three objective market share and the average objective bid-ask spread in Model (1) and (2) respectively. Result in Model (1) shows that non-Big Three families are less likely to make new ETF launches in an objective where the market is dominated by the Big Three, even if the Big Three launched in the prior year. This is consistent with the notion that the presence of significant scale economies favours the Big Three. It is easier for the Big Three to develop brand recognition and customer loyalty especially in markets where they possess the monopoly power. Hence the first mover advantage of the Big Three is more likely to sustain in such objectives. Result in Model (2) shows that non-Big Three families are less likely to enter an objective market where the bid-ask spread is high, even if the Big Three launched in the prior year. Higher bid-ask spread signals less liquidity in the objective market and hence higher switching cost for the existing customers, which makes the second mover harder to compete. Overall, empirical evidence from Table 6 supports the conjecture in Hypothesis 3.

3.4 Lifespan of the ETF Offerings

In this last section of analysis, I use a time-to-event survival analysis to examine the research question of which ETF launches would survive for longer. More specifically, I am interested in whether family and objective level characteristics upon inception could signal the lifetime of the new ETF offering. The lifetime of ETFs is measured in months and right-censored. In our full sample, the lifetime of ETFs has a distribution of mean 43 and median 30, which is equivalent to an average life of 3.6 years and median life of 2.5 years. In Table

7, I apply a fully parametric Accelerated Failure Time model with Weibull distribution to allow for a nonlinear hazard function, noticing that the hazard rate of ETF offerings may be higher in the earlier stage and decreases at later times. As before, all explanatory variables are standardized to have a mean of zero and standard deviation of one to allow for consistent interpretation of regression results.

In Model (1) and (2) of Table 7, I look at characteristics related to the family and the investment objective separately. Both are included in Model (3) to test for the robustness of results. The empirical pattern on several explanatory variables persists. For instance, a one unit (one standard deviation) increase in the logarithm of the family size and family expense ratio extends the lifespan of an ETF offering by 35.53%[13] and 709.30% respectively according to Model (1). Both the statistical and economic significance of the above family characteristics persist in Model (3). In the meantime, a one unit (one standard deviation) increase in the flow rank of the family shortens the survival time of the ETF offering by 95.16% and 92.65% across the two model specifications. Similarly, on the objective level, a one unit (one standard deviation) increase in the dollar volume and expense ratio shortens the survival time of the ETF offering by 65.87% and 68.21% respectively in Model (2). The statistical pattern persists in Model (3).

Overall, the results in Table 7 confirms the notion in Hypothesis 4. ETFs launched by larger and higher-fee families, and whose initiations are not driven by capital flows into the families are more likely to survive for longer. ETFs launched in lower-fee objectives and whose asset allocation decision is not affected by large trading activities on the market are more likely to live a longer life.

4. Robustness Check

In unreported results, I checked different measures of performance. The benchmark-adjusted alphas are substituted by the excess returns and the value added measure[14] proposed by Berk and Green (Berk & Green, 2004). None of the performance measure shows any persistent statistical significance towards the ETF launching decision. Also, I examine both the equally weighted average and the asset weighted average on returns, expense ratios and portfolio turnovers, etc. The statistical patterns are largely unaffected by the weighting method. For the sake of brevity, only the equally weighted measure is reported in the tables.

Recognizing the triopoly structure of the ETF market, I examine whether the Big Three may have different considerations when it comes to ETF launching decisions. In Table 8, I interact the Big Three dummy with all major characteristics on the family and objective level. All explanatory variables in Table 3 are included as control variables. Coefficients on the interaction terms are in general positive and insignificant, suggesting that the determinants on the Big Three are consistent with those of the whole sample.

Evans (Evans, 2010) showed that MF families apply the incubation strategy to increase performance and attract flows. In a similar spirit, I consider whether certain factors make families decide to incubate when launching new ETF products. Funds whose listing date is at least 12 months after the inception date are classified as incubated. In the full sample, there exist 124 such cases with complete data, which represents less than 10% of the total number of funds. Under a multinomial logistic regression framework, I separately examine the determinants of family decisions to launch an incubated ETF and a non-incubated ETF, both relative to the decision of no launching. The dependent variable takes a value of one if a family launches an incubated fund in the given objective during a given month. It takes a value of two if the family launches a non-incubated fund and zero otherwise. As before, year dummies are included, standard errors are clustered on the family level. Results from this multinomial logistic regression are shown in Table 9, with the first column showing determinants of an incubated fund, second column showing determinants of a non-incubated fund, and the last column showing the p-value of the difference test on the coefficients in the first two columns. The p-value in Table 9 suggests hardly any significant difference across the incubated and non-incubated specifications. Hence, our main findings are robust to family decisions on incubation.

5. Conclusion

In this paper, I investigate the factors that determine family decisions to launch new ETFs and compare with the determinants on the launching decisions of open-ended MFs. ETF launching decisions by 155 families across 74 investment objectives over a 23-year period from January 1996 to December 2018 are examined. The empirical patterns are persistent and robust to different model specifications and subsample tests, which lend strong support to the following conclusions.

Families are concerned with profit maximization in their launching decisions. They care about both revenue generation and cost reduction. Additional revenue generation is achieved through several channels. First, families could attract flows and expand their asset base by matching investor demands, that is to launch in objectives enjoying higher flows and trading volumes. Second, families may attract market makers (APs) by launching in objectives with more arbitrage opportunities. Third, families charging higher percentage fees are able to extract more value from the fee income. In stark contrast to the findings on open-ended MFs, I find no significant impact of past performance on family launching decisions of ETFs. Cost reduction is achieved through two major channels. First, families applying passive strategies with lower portfolio turnover could save on trading costs. Second, families could effectively reduce the per unit cost by exploring the economics of scale and scope, which are both significant in the ETF industry.

This leads to the second consideration of fund families in making ETF launching decisions. On the one hand, the presence of significant scale economies makes the specialization strategy attractive. On the other hand, the presence of significant scope economies pushes the new market entrants to expand quickly in order to gain a competitive edge. As a trade-off, smaller families facing the pressure to expand the breadths of their offerings are more likely to launching in a new objective without previous family investment. In the meantime, larger families are more likely to specialize in objectives of their expertise and benefit from the associated economics of scale.

Similar to the behaviour of open-ended MFs, ETF families also tend to follow the leader, that is they are more likely to make new ETF launches in objectives where the Big Three has launched in the prior year. However, after a closer look at the market condition of the given objectives, I find that the willingness of non-Big Three families to follow the leader is reduced significantly when the objective market is less liquid with higher switching cost or when the objective market is dominated by the Big Three.

Finally, family and objective characteristics upon inception have significant predicting power on the lifespan of ETF offerings. ETFs launched by larger and higher-fee families; whose inception is not driven by excessive flows into the family are more likely to survive for longer. Also, ETFs launched in lower-fee objectives and whose launching decision is not affected by large trading activities in the objective market are more likely to live a longer life.

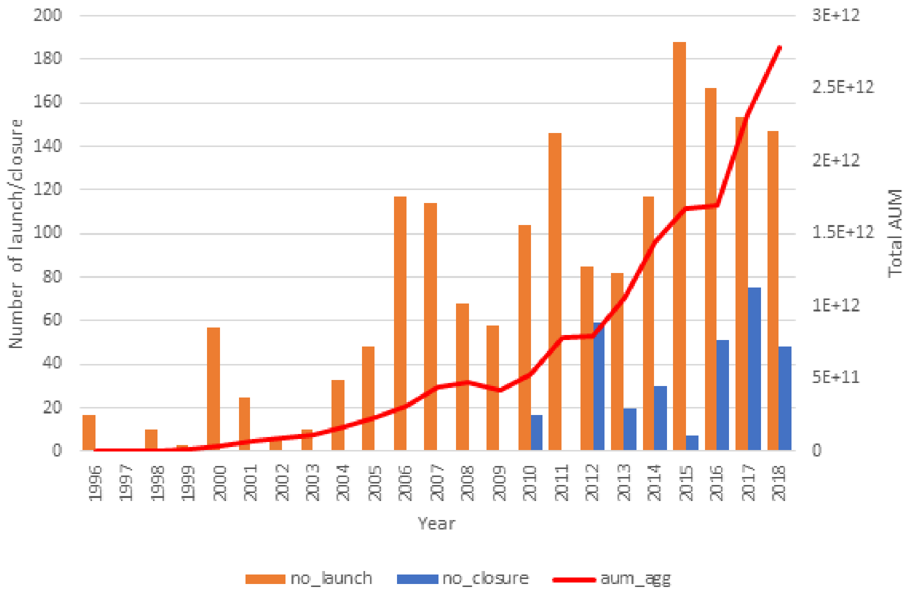


Figure 1: Aggregate AUM growth of US equity ETFs and the number of launches versus closures from 1996 to 2018

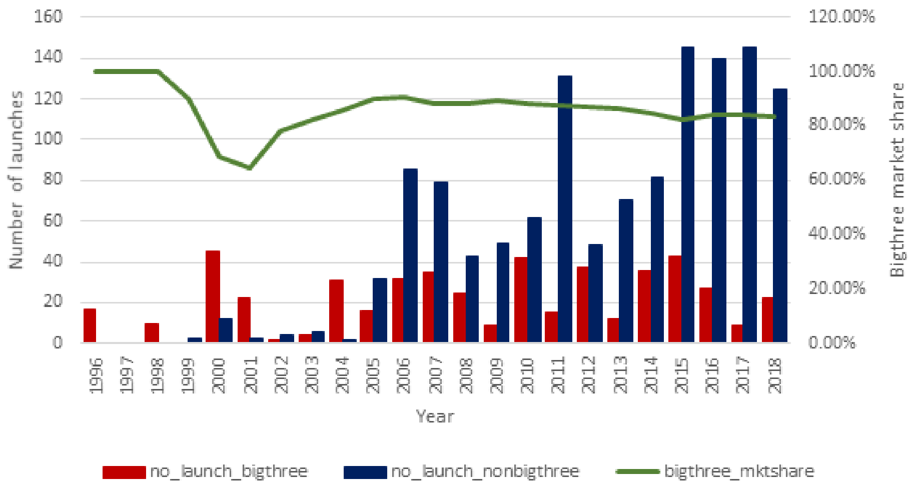
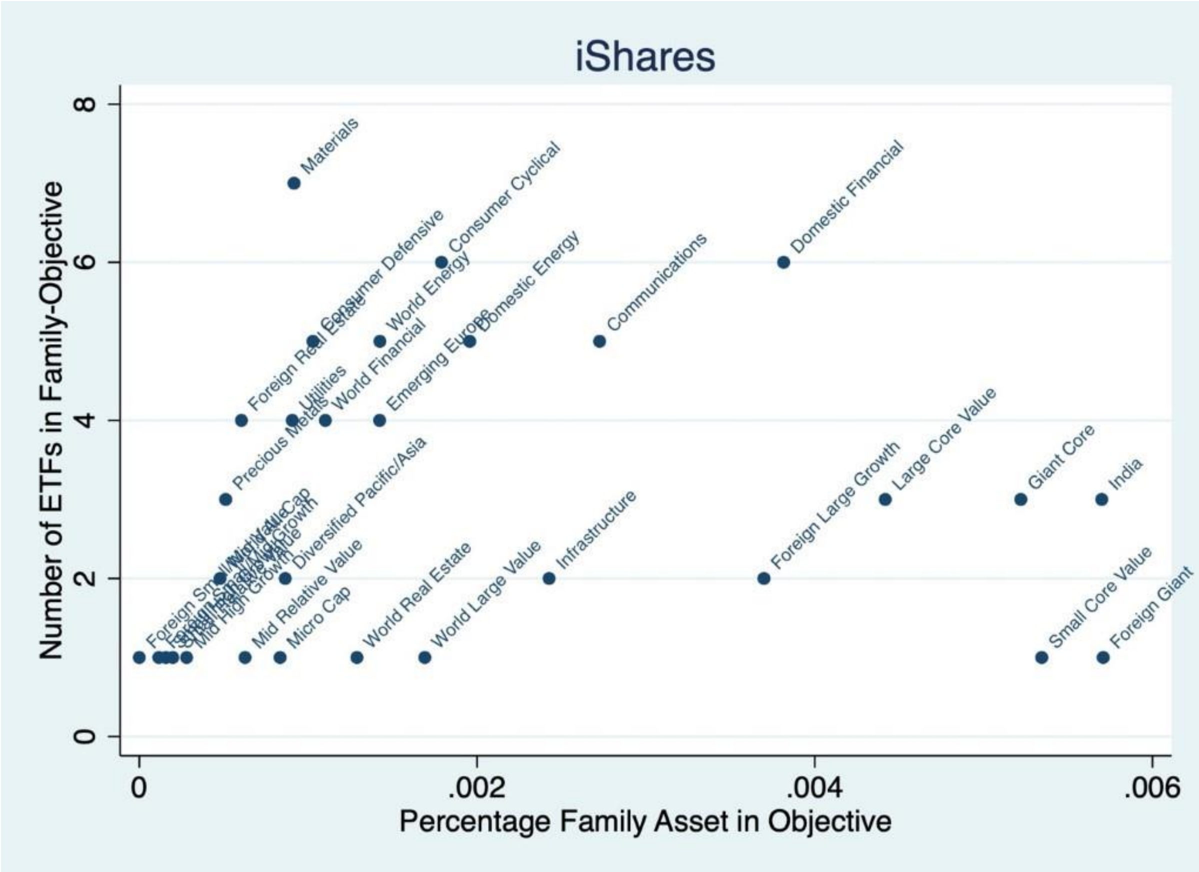
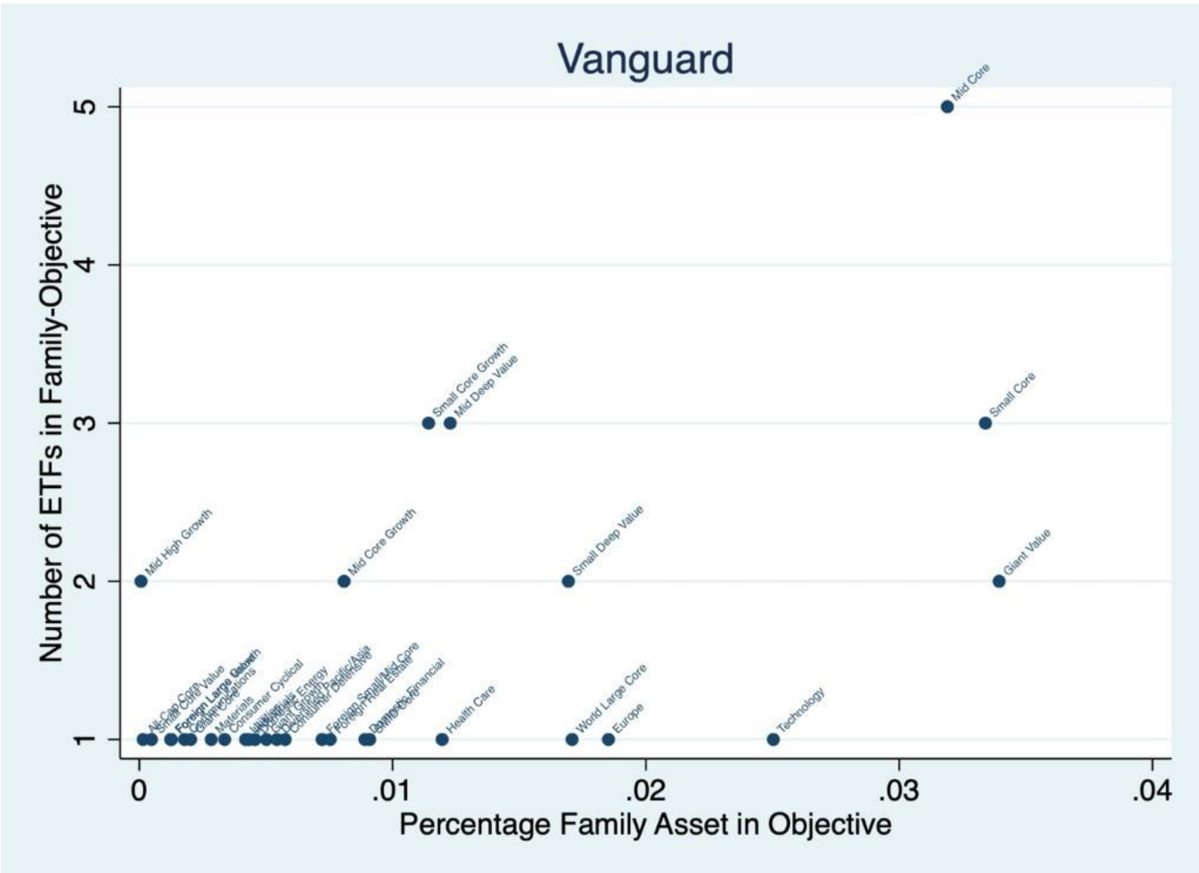


Figure 2: Time series of the Big Three market share and the number of launches within and outside the Big Three from 1996 to 2018


iShares
Number of ETFs in Family-Objective
Percentage Family Asset in Objective
0
2
4
6
8
0
.002
.004
.006
Materials
Consumer Cyclical
Consumer Defensive
Domestic Financial
World Energy
Domestic Energy
Communications
Foreign Real Estate
World Financial
Emerging Europe
Utilities
Precious Metals
Large Core Value
Foreign Large Growth
Giant Core
India
Diversified Pacific/Asia
Mid Relative Value
Micro Cap
World Real Estate
World Large Value
Infrastructure
Small Core Value
Foreign Giant
Mid High Growth


Vanguard
Number of ETFs in Family-Objective
Percentage Family Asset in Objective
1
2
3
4
5
0
.01
.02
.03
.04
Mid Core
Small Core Growth
Mid Deep Value
Small Core
Mid High Growth
Mid Core Growth
Small Deep Value
Giant Value
Health Care
World Large Core
Europe
Technology

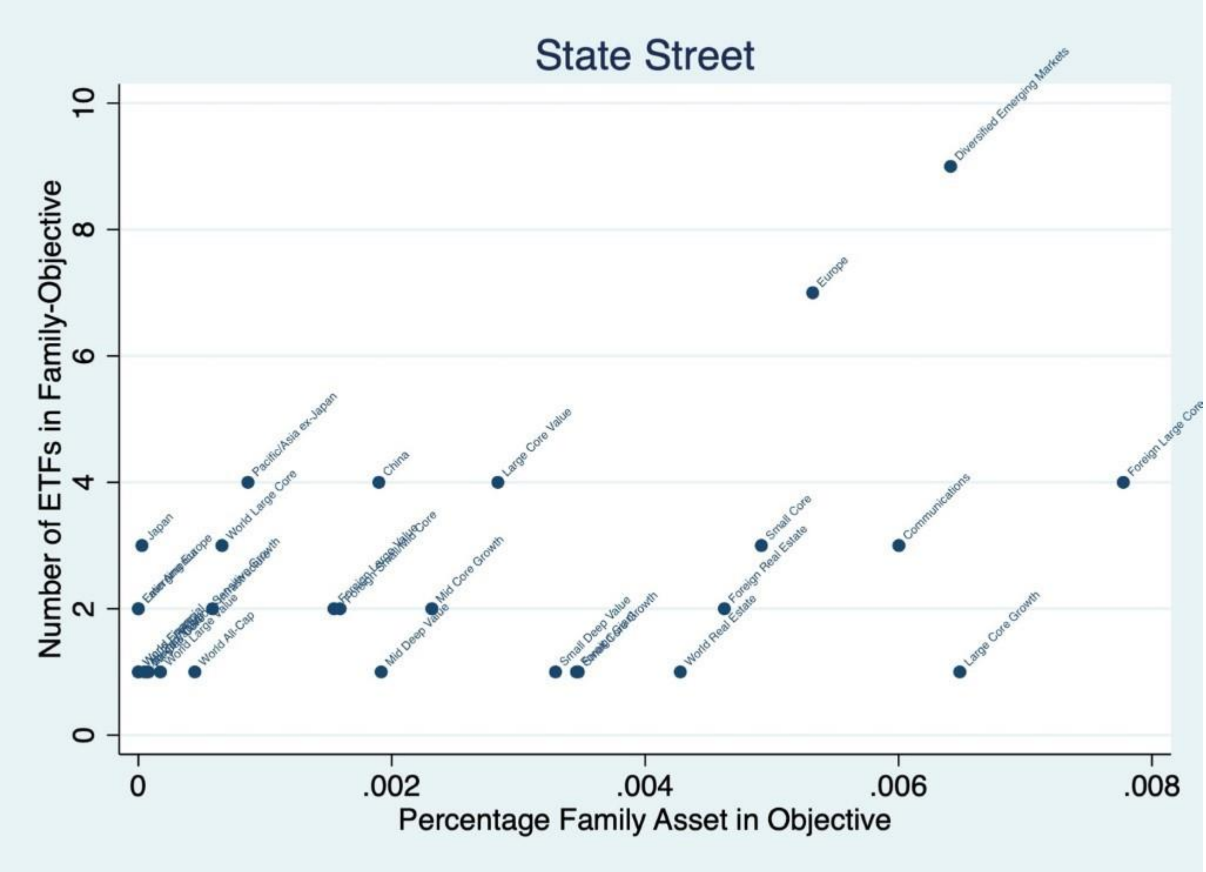


Figure 3: Distribution of the number of ETF offerings against the percentage family TNA invested in the top twenty investment objectives of the Big Three, as of December 2018

Table 1: Hypotheses

This table outlines the ex-ante expectations regarding the effect of each explanatory variable on the likelihood of new ETF launches. The hypotheses are divided into three broad categories, namely profit maximization, scale and scope economies and the impact of the Big Three. Predictions are posed in either the whole sample or two different subsamples of the existing families and the non-Big Three families where appropriate. Interaction terms are expressed with a “#” between the two different explanatory variables.

Variables	Likelihood of new ETF Launches All Families	 Existing Families	 Non-big-three Families
Panel A: Profit Maximization			
Revenue Generation			
Demand Side			
Flow_objective (ETF/MF)	Positive		
Flow_family		Positive	
Dollar Volume_objective	Positive		
Dollar Volume_family		Positive	
Supply Side			
Tracking Error_objective	Positive		
Expense Ratio_objective (ETF/MF)	Positive		
Expense Ratio_family		Positive	
Performance_objective	Insignificant		
Performance_family		Insignificant	
Cost Reduction			
Portfolio Turnover_objective	Negative		
Portfolio Turnover_family		Negative	
Panel B: Scale and Scope Economies			
Size_objective (ETF/MF)	Positive		
Size_family		Positive	
Number of Objectives_family		Positive	
Prior Launch_family		Positive	
Benefit of Specialization			
Percentage family asset in objective		Positive	
Panel C: Impact of the Big-three			
Prior Launch_bigthree			Positive
Market Share # Prior Launch_bigthree			Negative
Bid/Ask Spread # Prior Launch_bigthree			Negative

Table 2: Descriptive Statistics

This table contains descriptive statistics of the fund-month observations on major fund characteristics. Expense Ratio and Portfolio Turnover are annualized. Dollar Volume and Bid-ask Spread are computed as the monthly average of daily measures and winsorized at 1% and 99% level. Net Flow is calculated from monthly TNAs and monthly gross returns. Benchmark-Adjusted Return is calculated by regressing the monthly net returns on the primary benchmark returns through a prior-36-month rolling window. Default benchmark of the investment objective (Appendix 1) is used when the primary benchmark is missing. In panel A, summary statistics are reported for all ETFs in the sample. Panel B compares the above characteristics between subsamples of the Big Three versus non-Big Three families. The “MeanDiff” column reports the difference in the sample means, together with the statistical significance from a two-sided t-test. The asterisks denote statistical significance as follows: *** significant at 0.1%, ** significant at 1%, and * significant at 5%.

Panel A: Funds in All Families						
Variables	Obs.	Median	Mean	Std. Dev.	Min	Max
Net Flow ($ millions)	122,559	0.00	13.67	329.47	-27,705.38	22,707.20
Dollar Volume ($ thousands)	41,822	12.61	15.78	11.97	0.68	66.23
Tracking Error (%)	123,972	1.56	2.14	2.09	0.00	25.62
Expense Ratio (%)	122,856	0.48	0.48	0.25	-0.14	5.07
Portfolio Turnover (%)	124,308	22.00	64.64	2,669.59	0.00	271,677.00
TNA ($ millions)	126,829	107	1,493	7,468	0.48	306,671
Family TNA ($ millions)	284,760	23,997	122,960	213,294	0.56	1,117,689
Bid-Ask Spread	61,280	0.08	0.13	0.18	0.01	1.26
Benchmark-Adjusted Return (%)	114,272	0.04	0.00	2.94	-168.00	35.93

Panel B: Comparision Between Big-three and Non-big-three					
	Non-Big-three		Big-three		
Variables	Obs.	Mean1	Obs.	Mean2	Mean Diff
Net Flow ($ millions)	66,985	4.88	55,574	24.27	-19.388***
Dollar Volume ($ thousands)	29,315	13.86	12,507	20.29	-6.427***
Tracking Error (%)	67,762	2.41	56,210	1.83	0.581***
Expense Ratio (%)	67,272	0.57	55,584	0.37	0.203***
Portfolio Turnover (%)	67,452	102.60	56,856	19.59	83.018***
TNA ($ millions)	70,071	406	56,758	2,835	-2.4e+03***
Family TNA ($ millions)	150,921	21,000	133,839	240,000	-2.2e+05***
Bid-Ask Spread	38,980	0.14	22,300	0.12	0.014***
Benchmark-Adjusted Return (%)	61,984	-0.04	52,288	0.05	-0.096***

Table 3: Panel Logistic Regressions on the likelihood of new ETF Launches

This table presents the results from panel logistic regression models on the likelihood of new ETF launches. The dependent variable is an indicator variable taking a value of one if a family launches in a given investment objective during a given month, and zero otherwise. Various family and objective characteristics of ETFs are included as explanatory variables across Model (1) to (3). In Model (4), objective characteristics are substituted by the MF counterparty. The models assume independence of ETF launching decisions across families, but not within families. Heteroscedasticity robust standard errors are clustered on the fund families. Year dummies are included. All the explanatory variables are standardized to have a mean of zero and a standard deviation of one. In the columns 'Marginal Effect', I report the annualized percentage change in the probability of a new ETF being launched when each explanatory variable is increased by one standard deviation and all other variables are set equal to the mean of zero. For indicator variables, this represents the percentage change in probability when the indicator variable increases from zero to one.

	All Families							
	Model (1)		Model (2)		Model (3)		Model (4)	
VARIABLES	Coefficients	Marginal Effect	Coefficients	Marginal Effect	Coefficients	Marginal Effect	Coefficients	Marginal Effect
Objective Flow	0.287***	3.022	0.120***	5.068	0.120***	4.427		
	(0.050)		(0.031)		(0.031)			
MF Objective Flow							0.186***	2.288
							(0.035)	
Family Flow	0.096	0.918	0.016	0.644	0.042	1.493	0.005	0.056
	(0.078)		(0.080)		(0.081)		(0.075)	
Objective Dollar Volume	0.120***	1.161	0.223***	9.888	0.224***	8.686	0.137***	1.644
	(0.037)		(0.042)		(0.040)		(0.035)	
Family Dollar Volume	0.110	1.059	0.265***	11.988	0.141*	5.254	0.242***	3.062
	(0.098)		(0.081)		(0.078)		(0.084)	
Objective Tracking Error	0.203***	2.048	0.115**	4.845	0.117**	4.310	0.247***	3.134
	(0.050)		(0.056)		(0.056)		(0.055)	
Objective Expense Ratio			0.155**	6.655	0.153**	5.734		
			(0.063)		(0.064)			
MF Objective Expense Ratio							0.151**	1.825
							(0.067)	
Family Expense Ratio			0.146	6.242	0.137	5.096	0.157	1.903
			(0.100)		(0.087)		(0.100)	
Objective Portfolio Turnover			-0.097*	-3.702	-0.097*	-3.231	-0.199***	-2.027
			(0.058)		(0.057)		(0.057)	
Family Portfolio Turnover			-0.203**	-7.381	-0.226**	-7.094	-0.206**	-2.091
			(0.088)		(0.090)		(0.087)	
Objective Size			0.592***	31.369	0.581***	26.829		
			(0.126)		(0.126)			
MF Objective Size							0.379***	5.145
							(0.041)	
Family Size			0.294***	13.486			0.243***	3.077
			(0.106)				(0.094)	
Number of Objectives in Family					0.149**	5.574		
					(0.069)			
Objective Benchmark-Adjusted Return	0.047*	0.438	0.037	1.503	0.039	1.385		
	(0.028)		(0.027)		(0.027)			
MF Objective Alpha_FF4F							0.008	0.090
							(0.063)	
Family Benchmark-Adjusted Return	-0.031	-0.278	-0.039	-1.529	-0.040	-1.368		
	(0.056)		(0.053)		(0.054)			
Constant	-4.865***		-3.333***		-3.478***		-4.654***	
	(0.138)		(0.348)		(0.425)		(0.142)	
Observations	72,973		71,423		72,658		71,518	
Number of Family-Objectives	852		843		852		841	
Clustered on families	YES		YES		YES		YES	
Time Dummy	YES		YES		YES		YES	
Wald chi-square	4.689e+06		1.124e+06		2.474e+06		1.227e+06	
Regression p-value	0.000		0.000		0.000		0.000	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Economies of Scale and Scope, Benefit of Specialization

This table presents the results from panel logistic regression models on the likelihood of new ETF launches in the subsample of existing families. The dependent variable is an indicator variable taking a value of one if an existing family launches in a given investment objective during a given month, and zero otherwise. In Model (1), *No Prior Family Investment in Objectiv*e is a dummy variable indicating a new objective within the family. In Model (2), only observations within existing families and existing objectives are considered. The models assume independence of ETF launching decisions across families, but not within families. Heteroscedasticity robust standard errors are clustered on the fund families. Year dummies are included. All the explanatory variables are standardized to have a mean of zero and a standard deviation of one. In the columns ‘Marginal Effect’, I report the annualized percentage change in the probability of a new ETF being launched when each explanatory variable is increased by one standard deviation and all other variables are set equal to the mean of zero. For indicator variables, this represents the percentage change in probability when the indicator variable increases from zero to one.

	Model (1)		Model (2)	
	Existing Families		Existing Family-Objectives	
VARIABLES	Coefficients	Marginal Effect	Coefficients	Marginal Effect
No Prior Family Investment in Objective	1.108***	25.601		
	(0.192)			
Percentage Family Asset in Objective			0.189***	2.358
			(0.048)	
Family Launched in Prior Year	0.562***	9.650	0.900***	16.349
	(0.184)		(0.339)	
Objective Size	0.702***	12.986	1.112***	22.731
	(0.126)		(0.091)	
Family Size	0.367***	5.692	0.863***	15.362
	(0.130)		(0.115)	
Objective Flow	0.091**	1.228	0.143***	1.743
	(0.036)		(0.038)	
Objective Dollar Volume	0.217***	3.118	0.349***	4.725
	(0.047)		(0.042)	
Family Dollar Volume	0.200***	2.849	0.323***	4.314
	(0.077)		(0.097)	
Objective Tracking Error	0.145***	2.009	0.144***	1.756
	(0.055)		(0.056)	
Objective Expense Ratio	0.183**	2.585	0.201**	2.523
	(0.072)		(0.082)	
Family Expense Ratio	0.115	1.570	0.429**	6.053
	(0.113)		(0.190)	
Objective Portfolio Turnover	-0.058	-0.727	-0.218**	-2.229
	(0.062)		(0.107)	
Family Portfolio Turnover	-0.120	-1.461	-0.231***	-2.347
	(0.087)		(0.076)	
Constant	-4.511***		-4.641***	
	(0.349)		(0.559)	
Observations	67,540		48,061	
Number of famcatid	704		669	
Clustered on families	YES		YES	
Time Dummy	YES		YES	
Wald chi-square	2.540e+07		2.090e+07	
Regression p-value	0.000		0.000	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Multinomial Logit Regression on the Choice of Objectives

This table presents the results from multinomial logistic regression models on the decision to launch in a new objective versus an existing objective within the family, both relative to no launching. The dependent variable takes a value of one if, in a given month, the family launches a new ETF in a new objective with no prior investment within the family. It takes a value of two if the family launches a new ETF in an existing objective of the family in that given month and takes a value of zero otherwise. The column “Difference p-value” presents the p-value of a difference test between the coefficients across two model specifications. The models assume independence of ETF launching decisions across families, but not within families. Heteroscedasticity robust standard errors are clustered on the fund families. Year dummies are included. All the explanatory variables are standardized to have a mean of zero and a standard deviation of one. Pseudo R^2 is computed as one minus the log-likelihood ratio at convergence over the log-likelihood ratio at zero.

	Existing Families Launch in					
	New Objective	Existing Objective	Difference p-value	New Objective	Existing Objective	Difference p-value
VARIABLES	(1)	(2)	(1) - (2)	(3)	(4)	(3) - (4)
Family Size	-0.827***	1.112***	0.000			
	(0.158)	(0.110)				
Number of Objectives in Family				-1.040***	0.599***	0.000
				(0.115)	(0.078)	
Objective Size	-0.094	1.318***	0.000	-0.162*	1.320***	0.000
	(0.091)	(0.093)		(0.092)	(0.093)	
Objective Dollar Volume	-0.040	0.385***	0.000	-0.064	0.387***	0.000
	(0.054)	(0.048)		(0.050)	(0.047)	
Family Dollar Volume	-0.118	0.359***	0.001	0.109	0.014	0.411
	(0.124)	(0.092)		(0.089)	(0.079)	
Objective Tracking Error	-0.101	0.158***	0.014	-0.085	0.162***	0.034
	(0.087)	(0.047)		(0.088)	(0.052)	
Objective Flow	0.104*	0.121***	0.801	0.083	0.120***	0.576
	(0.061)	(0.037)		(0.061)	(0.035)	
Objective Expense Ratio	0.120	0.263***	0.226	0.098	0.267***	0.173
	(0.095)	(0.082)		(0.097)	(0.083)	
Family Expense Ratio	0.040	0.420**	0.026	-0.025	0.299**	0.026
	(0.074)	(0.172)		(0.075)	(0.146)	
Objective Portfolio Turnover	-0.052	-0.172	0.403	-0.044	-0.181	0.328
	(0.054)	(0.126)		(0.052)	(0.125)	
Family Portfolio Turnover	-0.223*	-0.142**	0.512	-0.149	-0.174**	0.803
	(0.114)	(0.065)		(0.098)	(0.069)	
Family Launched in Prior Year	0.388*	0.967***	0.067	0.521***	1.157***	0.085
	(0.204)	(0.333)		(0.175)	(0.373)	
Constant	-4.331***	-4.997***		-4.135***	-5.770***	
	(1.029)	(0.397)		(0.508)	(0.458)	
Observations		67,540			68,427	
Clustered on families		YES			YES	
Time Dummy		YES			YES	
Pseudo R^2		0.094			0.099	

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Impact of the Big Three on Competition

This table presents the results from panel logistic regression models on the likelihood of new ETF launches in the subsample of non-Big Three families. The dependent variable is an indicator variable taking a value of one if a family launches in a given investment objective during a given month, and zero otherwise. *Bigthree Launched in Prior Year* is a dummy variable taking a value of one if an ETF was launched by the Big Three in a given objective in the prior year, and zero otherwise. Interaction terms are expressed with "##" between the two explanatory variables. The models assume independence of ETF launching decisions across families, but not within families. Heteroscedasticity robust standard errors are clustered on the fund families. Year dummies are included. All the explanatory variables are standardized to have a mean of zero and a standard deviation of one.

	Non-Bigthree Families	
VARIABLES	(1)	(2)
Bigthree Launched in Prior Year	0.802***	0.861***
	(0.204)	(0.227)
Bigthree Launched in Prior Year	-0.566***	
## Bigthree Objective Market Share	(0.137)	
Bigthree Launched in Prior Year		-1.084***
## Objective Bid-Ask Spread		(0.253)
Objective Flow	0.116***	0.133*
	(0.044)	(0.071)
Objective Dollar Volume	0.142***	0.280***
	(0.054)	(0.065)
Family Dollar Volume	0.217***	0.281***
	(0.077)	(0.082)
Objective Tracking Error	0.055	-0.355**
	(0.069)	(0.163)
Objective Expense Ratio	0.129	0.243
	(0.089)	(0.183)
Family Expense Ratio	-0.014	-0.026
	(0.091)	(0.120)
Objective Portfolio Turnover	-0.021	-0.019
	(0.045)	(0.060)
Family Portfolio Turnover	-0.109	-0.053
	(0.081)	(0.103)
Objective Size	0.452***	0.496***
	(0.126)	(0.144)
Family Size	0.186	0.219*
	(0.121)	(0.117)
Family Launched in Prior Year	0.580***	0.410*
	(0.218)	(0.218)
Constant	-5.711***	-6.236***
	(0.307)	(0.357)
Observations	49,075	25,845
Number of Family-Objectives	705	677
Clustered on families	YES	YES
Time Dummy	YES	YES
Regression p-value	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Time-to-Event Analysis on the Lifespan of ETF Offerings

This table reports the results from a time-to-event analysis on the lifespan of the ETF offerings. The dependent variable is the life of an ETF offering, measured in months and right-censored. The specification is an Accelerated Failure Time model with Weibull distribution. All explanatory variables are standardized to have a mean of zero and standard deviation of one.

		Life of ETF	
VARIABLES	(1)	(2)	(3)
Family Flow	-3.033***		-2.611***
	(0.375)		(0.424)
Family Dollar Volume	-1.185***		-0.622
	(0.413)		(0.431)
Family Expense Ratio	2.091***		1.934***
	(0.359)		(0.410)
Family Portfolio Turnover	0.087		0.264
	(0.260)		(0.280)
Family Size	0.304***		0.293***
	(0.038)		(0.039)
Family Launched in Prior Year	-0.257		-0.136
	(0.204)		(0.203)
Family Benchmark-Adjusted Return	0.008*		0.007*
	(0.004)		(0.004)
Objective Flow		0.520**	0.301
		(0.245)	(0.239)
Objective Dollar Volume		-1.075***	-0.452**
		(0.217)	(0.222)
Objective Expense Ratio		-1.146**	-1.624***
		(0.525)	(0.515)
Objective Portfolio Turnover		-1.352***	-0.674*
		(0.281)	(0.345)
Objective Size		-0.135***	-0.035
		(0.040)	(0.042)
Objective Tracking Error		0.076*	0.072*
		(0.042)	(0.041)
Objective Benchmark-Adjusted Return		-0.010	-0.007
		(0.006)	(0.006)
Constant	-0.848	9.876***	0.564
	(0.908)	(0.931)	(1.317)
Observations	1,239	1,468	1,056
Wald chi-square	249.300	63.590	217.000
Regression p-value	0.000	0.000	0.000

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness Check on Determinants of Big Three Launching Decisions

This table presents the results from panel logistic regression models on the likelihood of new ETF launches in the subsample of existing families. The dependent variable is an indicator variable taking a value of one if an existing family launches in a given investment objective during a given month, and zero otherwise. All explanatory variables in Table 3 are included as control variables. The reported coefficients are estimated on the interaction terms of each explanatory variable with the dummy variable indicating a family is within the Big Three. The models assume independence of ETF launching decisions across families, but not within families. Heteroscedasticity robust standard errors are clustered on the fund families. Year dummies are included. All the explanatory variables are standardized to have a mean of zero and a standard deviation of one.

VARIABLES	Existing Families	Existing Family-Objectives
Interaction with the Bigthree Dummy		
Percentage Family Asset in Objective		0.449**
		(0.191)
Objective Flow	0.015	-0.109*
	(0.049)	(0.064)
Family Flow	-0.167	-0.169
	(0.115)	(0.171)
Objective Dollar Volume	0.244***	0.126
	(0.045)	(0.088)
Family Dollar Volume	-0.002	-0.056
	(0.168)	(0.179)
Objective Tracking Error	0.090	0.097
	(0.123)	(0.151)
Objective Expense Ratio	0.170*	0.140
	(0.093)	(0.135)
Family Expense Ratio	0.749***	0.933***
	(0.184)	(0.319)
Objective Portfolio Turnover	-0.129	-0.143**
	(0.100)	(0.072)
Family Portfolio Turnover	0.865	2.306**
	(0.742)	(0.983)
Objective Size	0.465***	0.200
	(0.181)	(0.199)
Family Size	0.453*	1.082**
	(0.253)	(0.429)
Constant	-4.074***	-5.193***
	(0.428)	(0.717)
Observations	67,540	48,061
Number of Family-Objectives	704	669
Control Variables Included	YES	YES
Clustered on Families	YES	YES
Time Dummy	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Multinomial Logistic Regression on Determinants to Incubate

This table presents the results from multinomial logistic regression models on the decision to launch an incubated ETF versus a non-incubated ETF, both relative to no launching. The dependent variable takes a value of one if, in a given month, the family launches an incubated ETF. It takes a value of two if the family launches a non-incubated ETF and zero otherwise. The column “Difference p-value” presents the p-value of a difference test between the coefficients across two model specifications. The models assume independence of ETF launching decisions across families, but not within families. Heteroscedasticity robust standard errors are clustered on the fund families. Year dummies are included. All the explanatory variables are standardized to have a mean of zero and a standard deviation of one. Pseudo R^2 is computed as one minus the log-likelihood ratio at convergence over the log-likelihood ratio at zero.

Variables	Incubated (1)	Non-Incubated (2)	Diffefence p-value (1) - (2)
flowrank_cat_std	0.026	0.138***	0.378
	(0.115)	(0.035)	
flowrank_fam_std	0.223	0.007	0.425
	(0.289)	(0.077)	
dvolrank_cat_std	0.161	0.236***	0.714
	(0.195)	(0.044)	
dvolrank_fam_std	0.523	0.212***	0.479
	(0.433)	(0.071)	
trker_cat_std	-0.019	0.113**	0.325
	(0.121)	(0.055)	
expense_ratio_cat_pr1yr_std	0.211*	0.170**	0.758
	(0.112)	(0.070)	
expense_ratio_fam_pr1yr_std	0.395*	0.116	0.148
	(0.206)	(0.102)	
pturn_cat_pr1yr_std	-0.554***	-0.074	0.011
	(0.192)	(0.056)	
pturn_fam_pr1yr_std	0.242	-0.202**	0.050
	(0.227)	(0.086)	
L.ln_tna_cat_std	0.725***	0.615***	0.508
	(0.097)	(0.138)	
L.ln_tna_fam_std	0.475	0.234**	0.616
	(0.485)	(0.115)	
1.incpt_fam_pr1yr	1.542***	0.523***	0.073
	(0.521)	(0.196)	
alpha_bmk_cat_pr1yr_std	0.092	0.026	0.376
	(0.075)	(0.028)	
alpha_bmk_fam_pr1yr_std	0.023	-0.025	0.771
	(0.157)	(0.058)	
Constant	-4.716***	-4.293***	
	(0.814)	(1.029)	
Observations		71,423	
Incubated/Non-Incubated Launches		124 / 1,423	
Clustered on families		YES	
Time Dummy		YES	
Pseudo R^2		0.058	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1: Default Benchmarks of the Investment Objectives

This table lists the default benchmark for each of the 74 investment objectives in our sample. These are obtained by taking the most commonly used (sorted on the TNA) primary benchmark of ETFs in each Morningstar category. I use the default benchmark to compute the benchmark-adjusted returns where the primary benchmark of an ETF is missing.

Investment Objective	Benchmark	Investment Objective	Benchmark
All-Cap Core	S&P 1500 PR	Large Relative Value	MSCI USA Minimum Volatility (USD) NR U:
All-Cap Growth	Russell 3000 Growth NR USD	Large Valuation-Sensitive Growt	MSCI USA Momentum NR USD
All-Cap Value	NASDAQ US Dividend Achievers 50 PR USD	Latin America	MSCI ALL Argentina 25/50 PR USD
China	MSCI China GR USD	Leveraged	Russell 2000 NR USD
Commodities Agriculture	Rogers Intl Commodity Agriculture TR USD	Leveraged Net Long	Russell 1000 Leverage Long PR USD
Communications	MSCI US IMI/Comm Svc 25-50 NR USD	Materials	Morningstar Gbl Upstm Nat Res PR USD
Consumer Cyclical	S&P Consumer Disc Select Sector PR USD	Micro Cap	Russell Micro Cap PR USD
Consumer Defensive	S&P Cons Staples Select Sector PR USD	Mid Core	S&P MidCap 400 NR
Diversified Emerging Markets	MSCI EM GR USD	Mid Core Growth	S&P MidCap 400 Growth TR USD
Diversified Pacific/Asia	FTSE Dvlp Asia Pacific (US RIC) NR USD	Mid Core Value	Russell 2000 Value NR USD
Domestic Energy	Alerian MLP Infrastructure PR USD	Mid Deep Value	S&P MidCap 400 Value TR USD
Domestic Financial	S&P Financial Select Sector TR USD	Mid High Growth	Morningstar US Mid Growth PR USD
Domestic Real Estate	DJ US Select REIT PR USD	Mid Relative Value	S&P MidCap 400 Equal Weighted TR USD
Emerging Europe	MVIS Russia NR USD	Pacific/Asia ex-Japan	MSCI Korea 25-50 100% Hedged NR USD
Emerging Markets Bond	MSCI Pacific GR USD	Precious Metals	NYSE Arca Gold Miners PR USD
Europe	EURO STOXX 50 PR USD	S&P 500 Tracking	S&P 500 NR USD
Foreign Giant	MSCI EAFE Free Value GR USD	SMID Core	S&P Completion TR USD
Foreign Large Core	MSCI EAFE PR USD	SMID Growth	MSCI ACWI SMID Growth GR USD
Foreign Large Growth	MSCI EAFE Free Growth GR USD	SMID Value	MSCI ACWI SMID Value NR USD
Foreign Large Value	DJ EPAC Select Dividend TR USD	Small Core	S&P SmallCap 600 NR USD
Foreign Real Estate	DJ Gbl Ex US Select RESI NR USD	Small Core Growth	S&P SmallCap 600 Growth TR USD
Foreign Small/Mid Core	MSCI EAFE Small Cap 100% Hedge NR USD	Small Core Value	S&P SmallCap 600 Value TR USD
Foreign Small/Mid Growth	MSCI Israel IMI Capped GR USD	Small Deep Value	Russell 2000 Value PR USD
Foreign Small/Mid Value	WisdomTree Intl SmallCap Dividend PR USD	Small High Growth	Morningstar US Small Growth TR USD
Giant Core	S&P 100 TR	Small Relative Value	S&P SmallCap 600 Equal Weighted TR USD
Giant Growth	S&P 500 Growth TR USD	Small Valuation-Sensitive Growt	Russell 2000 High Momentum TR USD
Giant Value	DJ Industrial Average PR USD	Technology	S&P 500 NR USD
Health Care	S&P Health Care Select Sector TR USD	Utilities	S&P Utilities Select Sector PR USD
India	MSCI India PR USD	World All-Cap	MSCI ACWI Low Carbon Target PR USD
Industrials	S&P Industrial Select Sector TR USD	World Energy	S&P Global 1200 Energy Sector PR USD
Infrastructure	S&P Global Infrastructure TR USD	World Financial	MSCI Europe/Financials GR USD
Japan	MSCI Japan PR USD	World Large Core	MSCI ACWI GR USD
Large Core	S&P 500 NR USD	World Large Growth	Gavekal Knowledge Leaders Dev Wld PR U
Large Core Growth	Russell 1000 Growth PR USD	World Large Value	S&P Global 100 NR USD
Large Core Value	S&P 500 NR USD	World Mid Cap	Solactive Global SuperDividend TR USD
Large Deep Value	Russell 1000 Value PR USD	World Real Estate	FTSE EPRA Nareit Developed TR USD
Large High Growth	S&P 500 Pure Growth PR	World Small Cap	MSCI World Small Cap PR USD

References

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do ETFs Increase Volatility? *The Journal of Finance*, *73*(6), 2471–2535. https://doi.org/10.1111/jofi.12727

Berk, J. B., & Green, R. C. (2004). Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy*, *112*(6), 1269–1295. https://doi.org/10.1086/424739

Box, T., Davis, R., & Fuller, K. (2020). The Dynamics of ETF Fees. *Financial Analysts Journal*, *76*(1), 11–18. https://doi.org/10.1080/0015198X.2019.1694356

Brown, S. J., & Goetzmann, W. N. (1995). Performance Persistence. *The Journal of Finance*, *50*(2), 679–698. https://doi.org/10.1111/j.1540-6261.1995.tb04800.x

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Clifford, C. P., Fulkerson, J. A., & Jordan, B. D. (2014). What Drives ETF Flows? *Financial Review*, *49*(3), 619–642. https://doi.org/10.1111/fire.12049

Evans, R. B. (2010). Mutual Fund Incubation. *The Journal of Finance*, *65*(4), 1581–1611. https://doi.org/10.1111/j.1540-6261.2010.01579.x

Garleanu, N., & Pedersen, L. H. (2019). *Active and Passive Investing* (SSRN Scholarly Paper ID 3253537). Social Science Research Network. https://doi.org/10.2139/ssrn.3253537

Greene, J. T., & Stark, J. (2016). *What's Trending? The Performance and Motivations for Mutual Fund Startups* (SSRN Scholarly Paper ID 2826677). Social Science Research Network. https://doi.org/10.2139/ssrn.2826677

Ippolito, R. A. (1992). Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry. *The Journal of Law and Economics*, *35*(1), 45–70. https://doi.org/10.1086/467244

Khorana, A., & Servaes, H. (1999). The Determinants of Mutual Fund Starts. *The Review of Financial Studies*, *12*(5), 1043–1074. https://doi.org/10.1093/rfs/12.5.1043

Levy, A., & Lieberman, O. (2016). Active Flows and Passive Returns. *Review of Finance*, *20*(1), 373–401. https://doi.org/10.1093/rof/rfu054

Loughran, T., & Ritter, J. R. (2002). Why Don't Issuers Get Upset About Leaving Money on the Table in IPOs? *The Review of Financial Studies*, *15*(2), 32.

Lunde, A., Timmermann, A., & Blake, D. (1999). The hazards of mutual fund underperformance: A Cox regression analysis. *Journal of Empirical Finance*, *6*(2), 121–152. https://doi.org/10.1016/S0927-5398(98)00013-9

Reinganum, J. F. (1985). Innovation and Industry Evolution. *The Quarterly Journal of Economics*, *100*(1), 81–99. https://doi.org/10.2307/1885736

Roll, R. (1986). The Hubris Hypothesis of Corporate Takeovers. *The Journal of Business*, *59*(2), 197–216. JSTOR.

Sirri, E. R., & Tufano, P. (1998). Costly Search and Mutual Fund Flows. *The Journal of Finance*, *53*(5), 1589–1622. https://doi.org/10.1111/0022-1082.00066