Why do Fund Managers Trade So Much and Cost You Money?

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(Bachelor of Business (Honours)

Certificate of Original Authorship

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text. I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Contents

Abstract

My study is the first to reconcile the negative association between trading and performance by analysing the fund family's product offering and investor flows. Specifically, I explore the impact of a fund family's degree of asset-based concentration in the active management segment (ACF) on the trading levels of subsequent fund offerings. Among active funds, I find that those offered by families with a higher degree of assets invested in active products are traded more frequently. My findings are not explained by the heterogeneity of fund, time, and family characteristics. I document that those families with a higher ACF, on average, are more likely to have their active funds ranked in the top performance bands based on their end-of-year performance. Thus, my results suggest that actively focused fund families justify their high-risk aggressive trading strategies by attempting to create lottery-like funds to generate stellar fund performance. The benefits of engaging in such a strategy are enjoyed only by the fund family in the form of investor flows, while investors endure the costs by way of inconsistent and overall underperformance. Thus, understanding the causes and implications of such heterogenic trading strategies at the fund family level has direct economic implications for shareholder returns.

Keywords: ACF, trading frequency, active funds, stellar fund performance, investor flows

JEL classifications: C33, G12, G24

Section 1. Introduction

In the fund management setting, fund managers trade their portfolios to meet liquidity provisions, rebalance their portfolios to take advantage of information and trade based on speculation (Barber and Odean, 1999). But such motives for trade do not seem to explain the magnitudes of trade or the high transaction costs incurred by investors when they make such trades. The trading volume in the fund industry is vast. Throughout 2005-2021, the average quarterly turnover for U.S. funds was 88%, namely, 78% for diversified domestic equity mutual funds (Morningstar (2021). These high trading levels are troubling, especially when the outcome of the overtraded portfolio generates suboptimal net performance[2]. Studies have shown that investors who trade too frequently tend to underperform (see, e.g., Carhart ,1997[3]; Odean, 1999; Barber et al., 2000)). To quantify this in economic terms, a ten basis point (after-fee)[4] underperformance of high trading funds relative to low-trading funds accrues to an average yearly investor loss (-0.001*1.1billion) of $1.1 million.

This issue raises a number of important questions: Why are fund managers allowed to trade in such great volumes incurring high transaction costs and hindering performance? What are the motives behind a fund's high portfolio turnover? I believe it is unlikely that the theories on rational trading motives of fund managers explain the high trading volumes we observe. In this study, I provide an explanation for the reasons behind the excessive trading of mutual funds and their fund families. Specifically, I show that families offering predominately active funds tend to encourage their fund offerings to engage in excessive trading strategies hoping that one or a few funds will top the ranking in performance. I refer to this as a fund family's lottery-like strategy.

Given the large competition in the mutual fund industry, mutual funds and their affiliated fund families are looking to differentiate themselves and exploit investors heterogeneity to attract investor flows. Thus, following the literature which documents that

[2] This issue can be better described by a visual representation of turnover, net returns and gross returns which depicts that funds with high turnover have the lowest net return (Daniel, et al. (2015), Figure 1, p.65)).
[3] Carhart, finds that active funds have high portfolio turnover rates, which hurts their net performance. In addition, he suggests that this underperformance is due to the high transaction costs incurred by managers when they trade frequently. He finds that mutual funds pay 0.21% to buy shares and 0.63% to sell which is close to the bid ask spread of trading costs.
[4] Yearly average performance (alpha) of funds in the highest quintile according to their yearly turnover minus the average alpha of the funds in the lowest quintile. (-0.000783-0.000063).

investors use the performance rank order as a quick tool to make investment decisions, fund families are looking to set up "top-tier funds" to distinguish themselves from competing companies. However, to produce stellar funds, fund families must take a lot of risks (Nada, Wang, and Zheng, 2004). Therefore, to generate star performance, it is instrumental to trade excessively as only by engaging in such trading risk across all the fund offerings you're more likely to generate stellar performance. Consequently, I propose that actively oriented fund families encourage aggressive trading and high turnover in search of top-tier performance. This strategy by which fund families push their active funds to trade a lot can be described as a lottery-like behaviour. For illustrative purposes, for a fund family which offers ten active funds, they push all ten funds to engage in high-risk trading strategies to give them a better chance of exploiting mispricing's in the market, with the hopes of generating top decile performance.

Alternatively, operating funds with a lottery-like behaviour by encouraging high trading strategies, on average, generate negative net performance. Why do we observe this? Why do fund families keep the underperforming funds? To achieve a lottery-like outcome, fund families need to keep many funds as by having a plethora of offerings, the family has a better chance of producing star funds. However, an unintended consequence of this action is that performance is not persistent, as shown by Jensen (1969). Specifically, engaging in such risky strategies generates a lot of noise in performance, where a top-performing fund in one year is unlikely to continue its streak the following year (Jensen, 1969). Therefore, in the process of developing stellar performing funds, the majority of funds that active families push to take a lot of risk by trading frequently and don't hit the top performance bands generate lousy performance. This underperformance by the majority of funds weighs down substantially on the average net performance of the fund family. Consequently, the costs implied by the detrimental strategy of aggressive trading are endured by investors. In contrast, all the benefits are enjoyed only by the fund family in the form of investor flows.

On the other hand, my results also examine why passively oriented fund families don't engage in such high trading levels. Passive fund families do not try and beat the market by their nature. This is transparent through their active fund offerings, which are based around the philosophy of minimising transaction costs and fees. Therefore, their active funds are constrained from trading freely because they incur transaction costs when stocks are bought and sold. So rather than engaging in the lottery-like game, passive families prefer to take a more cautious strategy that is more fine-tuned with their philosophy of being conservative in terms of fees and turnover. Consequently, passively oriented fund families don't push their active funds to trade frequently as they believe they can produce high-performing funds at lower cost and risk.

This depicts the aggressive vs. conservative trading strategies implemented by the active vs. passive families, respectively. This idea is illustrated through the objectives of Vanguard Vs. Fidelity. Vanguard is a passive-oriented fund family whose marketing message states, "it is all about costs," whereas Fidelity, which offers mainly active products, is all about generating performance. Therefore, does Fidelity allow their active funds to trade frequently and engage in high active risk to produce stellar performance? Does Vanguard restrict their active funds to trade often due to their cost minimisation philosophy? If so, are the active funds of Fidelity more likely to hit the top performance band vs. the active funds of Vanguard? What are the implications of such risky strategies?

My thesis focuses on the driving factor behind high trading levels observed in the mutual fund industry. Specifically, I focus on the degree of a fund family's assets invested in active products as the key factor contributing to the high trading levels observed. Following this intuition, I look into the mechanics and implications behind the high trading strategies implemented by mutual fund families.

In this thesis, I raise the concern surrounding high trading frequency by mutual funds by exploring the trading-performance relationship. Using the fund duration measure developed by Cremers and Pareek (2015) as a proxy for a funds trading frequency, I show that funds that hold onto their stocks for shorter durations underperform peer lower trading funds. Thus, a one standard deviation increase in the fund duration reduces net performance by 190[5] basis points per year on average. The performance of funds is derived from the alpha of the Carhart four-factor model from 2006 to 2020. These findings remain consistent when I use the Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) holding-based model as an alternative measure of fund performance. The results also survive when controlling for a host of fund and family affiliated characteristics, consistent with Cremers and Pareek (2016).

[5] 2.24*0.071*12= 190 basis points.

Next, I evaluate the impact of the degree of fund family's specialisation in the active management segment on the trading levels of subsequent active fund offerings. I use the proportion of the fund family's assets invested in the active products (ACF) as a measure of expertise in that segment. My evidence indicates that active funds offered by fund families offering predominately active products are traded more frequently. In economic terms, a one standard deviation increase in the ACF (21%) reduces the duration of a fund's yearly stock holdings by 344[6] basis points. These findings remain consistent when using the fund turnover ratio (CRSP) and the fund holdings turnover (Gaspar, Massa, and Matos, 2005) as alternative proxies capturing a funds trading frequency. The findings also survive after incorporating fund, family, and time fixed effects and various fund and family affiliated control variables.

After that, I explore the motive behind why fund families with a higher ACF implement such aggressive trading strategies. I investigate whether fund families with a higher ACF are more likely to generate stellar performing funds. By identifying the top 1%,5%, and 10% of performing funds and simultaneously sorting funds into quintiles based on their ACF, I discover a monotonic increase in the average hit rate of families from the lowest to highest ACF quintiles. I support the fund family's decision to implement such high trading strategies' by providing evidence on the investment flows (Kubrik et al., 2004) experienced by funds and their family siblings. I find that the star performance of one fund doesn't just attract flows to that fund but to all sibling funds in the family.

Overall, my results are consistent with the evidence that highly actively focused fund families engage in a lottery-like game by encouraging their active funds to trade a lot to top the ranking with one or a few of their active funds. Consequently, engaging in such high trading frequency to produce top-tier funds benefits the entire family in terms of net flows.

Due to the large size and high fees charged in the mutual fund industry, understanding the problem of strategies implemented at a family level in terms of product offering and trading frequency is essential. However, this is still something that is still not clear in the literature. For instance, do active funds offered by families with a higher active asset-based concertation trade more frequently? What is the strategy that justifies their aggressive trading strategy? Is the strategy of generating star funds homogenous across families? And this is not the case;

[6] 0.21*1.3660*12=344 basis points.

what are the costs and benefits of different methods of generating star funds in terms of performance, fees, and flows? How do different families approach the problem and issue of generating star funds if they have different philosophies regarding active vs. passive management? This thesis will provide the first empirical evidence addressing these concerns. The importance of the study is reinforced by the belief when an investor selects a mutual fund to invest in, they first identify the fund family (see, e.g., Gruber et al., 2006 and Massa, 2003). Therefore, a fund family's product offering decisions in the respective active vs. passive segments affect an investor's wealth and exposure to risk.

More generally, the trading activity of fund managers is essential to fund investors because funds incur transaction costs whenever their portfolios are bought and sold. Therefore, expenses arising from high trading levels reduce returns to investors if the trades do not add value. Existing studies have found that high trading costs exceed the value added by the trades and, therefore, reduce overall returns (Reid and Millar, 2004). Consequently, shareholders bear a large portion of the costs of the underperforming fund, ultimately ending up worse off. Since excessive trading harms shareholder returns, studying the high trading frequency by funds is intuitive for investors. Furthermore, following the adverse impacts on fund performance, investors could potentially lose confidence in mutual funds. Consequently, capital flight could be observed where investors prefer to invest their capital into other asset classes. This bears detrimental implications for the growth and development of the mutual fund industry. Ultimately, through my study, investors will incorporate the factors contributing to excessive trading in deciding where to invest their capital. This could potentially lead to newfound confidence in mutual funds and improve the industry's growth and development.

In addition, excessive trading by mutual funds is a systematic issue caused by the structure of the mutual fund industry. More importantly, mutual funds and affiliated families operating this way represent an agency issue that regulators should pay attention to. Specifically, operating funds with a lottery-like behaviour possess a large risk to investors, given such an approach leads to greater volatility, higher expenses, and overall underperformance. This particular problem continues to occur since fund families operate with investors' capital rather than their own. Thus, the fund family bears all the benefits of a successful lottery strategy in the form of investor capital while investors take on all the costs of the underperforming and inconstant approach. Therefore, my study brings such an issue to the regulator's attention, acting as a catalyst for improved transparency and regulations.

From the trustee's and practitioners' perspectives, the study notably advances the understanding of the extent to which fund families impose their respective investment philosophies on the fund managers. This inference is based on whether fund families imply stronger or weaker binding restrictions on the portfolio management of funds. On this note, the study also provides an enhanced understanding of the operational processes within fund families. Following my analysis on the differential strategic behaviour by active vs. passive fund family's investors will be able to make more informed decisions regarding their strategic presences. This improved transparency also benefits practitioners and funds alike by providing a more efficient market to operate within.

The layout of this paper is as follows; Section 2 describes the current literature on excessive trading by funds and affiliated family strategies. Section 3 outlines the structure of the data and computation of key variables. Section 4 discusses the main results of the study. Lastly, Section 5 concludes, providing guidance for future research.

Section 2. Literature review

Theoretical models suggest that rational investors maximise their returns while minimising their risk. Furthermore, theories on trading activity state that rational investors only trade when the benefit is greater than or equal to the cost of trading (Grossman and Stiglitz, 1980). However, in reality, investors behave differently, where in many cases, they trade excessively based on speculation (Phan, Rieger, and Wang, 2018). This is evident in the mutual fund industry, as the financial times report that "some funds generate turnovers of 500% annually" (Alice Ross, 2011). The high trading levels become a concern following the literature, which documents a negative association between trading frequency and subsequent net performance. Carhart (1997) studies the relationship between fund turnover and fund performance. Through a sample of diversified mutual funds from 1962 to 1993, Carhart (1997) discovers that trading reduces performance by about 0.95%. Carhart suggests that this underperformance is due to the high transaction costs incurred by investors when they trade frequently. Similarly, Wermers (2000) reinforces Carhart's (1997) findings as he also discovers that funds that trade frequently tend to underperform. Compared to Carhart (1997), by eliminating survival and survivorship bias through merging the CRSP and CDA mutual fund databases, Wermers (2000) suggest that high trading funds incur substantially higher transaction costs and charge higher expenses. Like Carhart, Wermers links this underperformance of high turnover funds to the transaction costs funds incur from trading. Contrastingly Jan and Hung (2003) use a stochastic dominance approach to study the interaction between mutual fund characteristics and performance. They also report a negative loading of portfolio turnover on a fund’s net performance.

However, another strand of literature that studies the trading-performance relationship focuses on the overconfidence of investors. Bloomsfield (1999) discovers that the overconfidence behaviour by investors increases their error, which leads to unfavourable trading where investors buy stocks that are too expensive and sell too cheap. This idea is further apparent through Gervais and Odean (2001), who, through a multivariate model, proclaim that an increase in trading volume will reduce investor returns. However, the overconfidence literature only includes retail investors in their samples while excluding institutional traders; therefore, their results are limited. More recently, Cremers and Pareek (2016) incorporate institutional traders in their study, analysing the impact of fund trading levels on fund performance. Cremers and Pareek (2016) use a fund duration measure as a proxy for the trading frequency of their sample of active mutual funds. The fund duration measure calculates the average length in time stocks in a fund's portfolio were held by looking back at the previous five years of holdings report. By sorting funds into quintiles based on their duration and activeness, they report that funds that trade infrequently outperform their high trading counterparts. These results are consistent and robust when they incorporate a multivariate performance regression. By regressing fund performance, derived by Carhart's alpha, on fund duration, they report a positive and statistically significant loading on the fund duration. Therefore, funds that hold onto their stocks for more extended periods tend to outperform inpatient funds. Since excessive trading harms fund net performance, investors have become increasingly concerned about the driving factors contributing to the high trading levels by mutual funds.

The current literature has only considered fund level factors in their search to help determine the driving forces behind the high trading levels observed in the mutual fund industry. My study differs from the existing literature as it looks up the chain of command and considers the fund family as the main force behind the excessive trading levels. My study evaluates the impact of a fund family's specialisation in the active vs. passive management segments on the subsequent trading levels of active funds. This is extremely important given the extraordinary diverseness in the degree to which fund families operate across the segments of active and passive fund management (Cassevecchia and Ge, 2015). However, there is still considerable ambiguity surrounding whether a fund family's decision to offer mainly active products would encourage consistent mutual funds to trade more frequently. However, there are grounds to suggest this may be the case.

For fund families offering performantly active products, one could expect to see trades arising from the rebalancing of their portfolio to take advantage of information from factor-based strategies. This gives insight into the aggressive culture of active fund families, which establish a philosophy of generating performance at all costs to beat the market in gross terms. Therefore, active funds constantly shift around stock holdings to boost their returns which translates into higher fees charged (Wermers (2000)). Thus, to justify the high fees, active fund managers are always looking to trade to say as if they are "simply not doing nothing" (Dow and Gorton, 1997). In addition, Wermers (2000) suggests that the nature of active investment philosophy is to trade a lot, such that funds can exploit mispricing's and generate alpha. Thus, fund families offering predominately active products are likely to have higher trading levels.

Nonetheless, the average mutual fund and affiliated fund family embracing a high trading culture underperforms in comparison to their more conservative counterparts (see, e.g., Carhart, 1997; Wermers, 2000; Bloomsfield, 1999; Barber and Odean, 2001; Cremers and Pareek, 2016). Therefore, what is the strategy that justifies why fund families specialising in active management push their active funds to trade frequently?

Nanda Wang and Zheng (2004) emphasise the importance to fund families in generating stellar performing funds. Their study analyses the effect of different strategies in a fund family's attempt to produce star-performing funds. They begin by highlighting the importance of producing top-tier funds by showing that investment flows for stellar families are substantially higher than those for families with no stellar funds. They propose that for a fund family to produce star performance, they must engage in increased risks. Specifically, by incorporating logistic regressions, their study reports that increasing the number of funds and adopting a higher cross-fund variance increases the family's chance of producing top-tier funds. However, increasing the variance in the cross-fund investment strategies reduces the likelihood of generating a top-ranking fund. Ultimately, fund families need to engage in high-risk trading strategies if they want to develop star performers. Following Nanda, Wang, and Zheng (2004), I predict that fund families specialising in active management are engaging in a lottery-like behaviour by encouraging their active funds to trade a lot. The ultimate objective of such a strategy is to hit the jackpot by having a few of their funds ranked in the top performance bands.

Section 2.1. Performance-flow relationship

However, engaging in such risk can come at a substantial cost. The literature studying the trading-performance relationship finds that, on average, high-risk trading strategies generate underperformance (see, e.g., Carhart, 1997; Wermers, 2000; Bloomsfield, 1999; Barber and Odean, 2001; Cremers and Pareek, 2016). In addition, Nanda, Wang, and Zheng (2004) discover an inconsistency among families with star performers, where a star performer in one period is unlikely to generate star returns in the following period. Blake and Morey (2000) also support this idea as they discover that the five-star Morningstar ratings fail to forecast stellar future performance. This underpins the findings of Jensen (1997), who suggest that past performance is not a good predictor of future performance. Specifically, Jensen (1997) finds a lack in performance persistence among funds engaging in high-risk strategies where funds who hit the top rank one year are likely to be ranked in the bottom in the next year-round. The inconsistency and overall average underperformance of the high trading strategy come at a cost to the investor.

On the other hand, following the performance-flow literature, the fund family endures all the benefits of engaging in a successful lottery-like strategy. This intuition is based on the findings which document that investors chase past performance. Smith (1978) analyses the relationship between performance and subsequent mutual fund growth from 1966 to 1975. Smith (1978) reports that new investor capital is positively related to improved risk-adjusted fund performance. Similarly, Kane et al. (1991) and Patel et al. (1994) document a similar relationship where mutual fund flows are positively related to past fund performance. More importantly, by incorporating a behavioural model solely based on performance, they discover that mutual fund flows appear better related to performance ranks than absolute performance. This has opened the door to a more modern strand in the literature that looks at the relationship between performance rank, and subsequent investor flows rather than just considering absolute performance. Gruber (1996) studies the flow of money in and out of mutual funds. By sorting funds into ten equal groups based on their performance, Gruber (1996) finds that investors act rationally and invest money into the best-performing funds. However, a considerable limitation of Gruber's (1996) research is his limited sample which only includes 200 funds. Contrastingly to Gruber (1996), Chevalier and Ellison (1997) use a semiparametric model to predict the relationship between performance and subsequent fund flows for a larger sample of 500 funds. They discover a positive performance-flow relationship consistent with the literature. Specifically, they interpret the flow-performance relationship as an incentive given to mutual funds by investors. Through multiple regressions, they show mutual fund managers respond to this incentive scheme by adjusting their portfolios at the end of their reporting period.

More closely related to my study, the papers by Sirri and Tufano (1998) and Nanda, Wang, and Zheng (2004) study the relationship between performance rank and subsequent fund flows in greater depth by considering the implications on fund families. By purchasing data on 690 funds and 288 unique fund families from Investment Company Data Institute (ICDI), Sirri and Tufano (1998) study the factors contributing to the flow of capital in and out of equity mutual funds. After sorting funds into quintiles according to their lagged performance, they discover that the funds in the top quintiles are associated with economically and statistically significantly higher inflows. Moreover, Sirri and Trufano (1998) further elaborate on their findings by looking at the search costs investor incur in their process of deciding where to invest their capital. The research discovers that investors would invest in funds that are easier or less costly to identify. They find that low search costs are associated with more prominent fund families, which engage in marketing strategies, and attract greater media attention. Thereby, a star-performing fund automatically attracts media attention, which generates cash inflows for the affiliated fund family. However, Nanda, Wang, and Zheng (2004) take a different approach by considering the stellar performance of one fund in a family and analysing subsequent flows to all other sibling funds. The study begins by replicating the literature and showing the positive performance flow relationship. Using this as a foundation, Nanda, Wang, and Zheng (2004) suggest that the positive effects of star performers can have an amplified impact on all funds if the funds are a part of a family. By integrating multivariate regression models, they discover that in a family-like structure, a star performer brings investor capital to all funds in the family. These findings are consistent with Khorana and Servaes (2000), who report that a stellar performing fund has a positive and significant impact on the market share of the entire fund family. However, compared to Nanda, Wang, and Zheng (2004), my study focuses on a more concentrated sample on only U.S. domestic diversified equity mutual funds. Brown and Wu (2016) further elaborate on Nanda, Wang, and Zheng's (2004) findings by studying the implications of family star performance on member funds' inflows. The study extends the work of Berk et al. (2004) by developing a framework that allows for cross-fund learning within fund families. Through a novel test Brown and Wu (2016) question whether the performance of all funds in a family is used by investors rather than assessing each fund individually. They discover a positive effect of the star performance of one fund on fund flows to all other member funds. Brown and Wu (2016) attribute this to the fact that the star family performance of one fund contains information about the skill of the whole family for investors. The study highlights the overall spill over effect of the performance of one fund in the evaluation process of all funds in a family. These findings are consistent with Berk and Green (2004), who find that investors evaluate the skill of a fund by analysing the returns of all funds in the family. Evidently, in the case where the lottery behaviour generates a star performer, the fund family endures all benefits in the form of investor flows. This underpins the rationale in my study behind the fund family's decision to encourage their active offerings to trade frequently. In particular, my work contributes to the performance-flow literature by considering the implications of the incentives generated by the star performance flow-relationship on active vs. passive fund families. Specifically, my study adds another strategy implemented at the fund family level to generate cash flows. I provide empirical evidence on the heterogeneous mix of trading strategies implemented by active and passive fund families to maximise investor flows.

Section 2.2. Fund manager outperformance: luck or skill?

My project is also connected to the research by Kosowksi et al. (2005), who study whether fund managers posses' stock-picking skills or whether the high returns by some funds reflect the luck of a few fund managers. The research is the first in the literature to analyse mutual fund performance while controlling for luck. Specifically, using several bootstrap approaches, the study examines the significance of the alphas of the best-performing funds. By implementing the DGTW (1997) model to measure the performance of funds, the study's evidence suggests that the performance of good and bad managers is not just based on luck or differences in expenses and trade costs but rather due to differences in skills in picking stocks. These findings implicate the importance of active-management skills in producing star performance and not just cost strategies. This supports the decision by highly actively focused fund families in my study who, rather than taking a conservative cost approach, implement aggressive trading strategies to generate top-tier performance.

Section 2.3. Factors contributing to high trading levels by mutual funds

My study is also related to the literature examining the factors behind the high trading levels observed among investors. The literature looks to the theories of behavioural finance to better understand the mechanic rationale behind an investor's decision to trade frequently. This area in the literature believes that investors are overconfident and therefore trade excessively. This idea first came about by arguing that the critical behavioural component needed to understand the trading maze is overconfidence (De Bondt et al., 1995). This is based on the belief that investors overestimate their knowledge when evaluating stocks (Odean, 1998). This leads to differences in opinions that cause trading (see, e.g., Varian, 1989 and Harris, 1993). However, overconfident investors trade too much as they have unrealistic beliefs regarding the returns of securities. One of the first papers to target this theory was Oden (1998), studying what happens when overconfident in financial markets. However, instead of looking at only one type of trader, which he believes will provide a misleading picture, Oden (1998) analyses the overconfidence level of price takers, market makers, and strategic trading insiders. The study's findings suggest that the level of trading increases when price takers, market makers, and insiders are overconfident. Shortly after, Benos (1998) tests the same theory through auction markets to show that overconfident investors trade too much. He discovers that investors with high confidence tend to overestimate their information's accuracy as they believe they have superior skills compared to other investors when it comes to evaluating information. Therefore, Benos (1998) finds that higher trading volumes are associated with more confident investors. Oden (1999) tests his overconfidence theory of excessive trading (Oden, 1998) by analysing the trading behaviour of discount brokerage customers. He adds to the literature by discovering that overconfident discount brokerage customers trade too much, but they trade even when the gains from trading do not offset trading costs. However, the paper "Boys will be Boys" (Barber and Odean, 2000) takes a different approach where they believe gender differences play a role in an investors' overconfidence. They assume that since men are more overconfident than women (Lundeber et al., 1994), men are likely to trade more. By using data on households, the paper analyses the stock investments of men and women during the 1990s. The study documents that men trade 45% more than women, which suggests their hypothesis. However, gender is linked to several other characteristics that might affect trading. For example, males are more common among males, thrill-seeking, a measurable proxy for gambling, dangerous driving, alcohol abuse, and many other behaviours. These variables not mentioned in the study could account for some differences in trading levels between genders. Therefore, the lack of consideration for endogeneity and omitted variable bias leads to questioning the accuracy of the results.

Another potential explanation for the relationship between overconfidence and excessive trading is depicted through the learning-to-be-confidant model (Gervais et al. 2001). This is based on the assumption that investors might falsely credit past positive returns to their skills and become overconfident. Consequently, this increases their trading volume. This assumption was studied by Glaser and Weber (2003) in their paper, who hypothesise that investors who are more confident on average trade more than the average investor. They test this by correlating individual investor confidence scores to a host of trading volume measures of investors, such as turnover and number of trades complemented. The study found that investors who have generated positive past returns believe they are above the average investor in terms of skill and thus tend to trade more excessively. Similarly, Statman, Thorley, and Vorkink (2003) also hypothesise that a higher level of overconfidence by investors leads to higher trading levels. Likewise, they also base their assumption on the belief that investors' overconfidence is motivated by past performance (Gervais and Odean, 1997). They test this through a multivariate analysis on turnover and returns using VAR and other impulsive response metrics. The study ultimately finds that as investors generate positive portfolio returns, they become overconfident and consequently trade more. Statman (2006) improves his previous findings of 2003 by incorporating more robust measures and using more accurate data. He still finds past positive returns prompt overconfident investors to trade more. More recently, Hoffmann and Post (2014) show that investors with higher past performance wrongly interpret this as a reflection of their investment skill, which leads them to trade excessively.

However, a significant limitation among these studies is that a lot of the data used to link behavioural traits and excessive trading is experimental and aggregated only across retail investors. Therefore, when trades are analysed on individual investors, the results are likely generated from self-reported surveys and brokerage trading records. For illustrative purposes, this is evident in the study of Glaser et al. (2003). They asked a sample of online broker investors to answer a set of questions designed to measure the investors' overconfidence. Along with this, Barber and Odean (2000) use large brokerage firms as the primary data source for their study. More recently, Hoffman and Post (2014) use a combination of survey data and trading records from a brokerage firm to generate their results. These few examples which use surveys are based on a restricted number of people and often have timing issues where performance and turnover can affect an investor's willingness to respond to the survey. This exposes the studies to sample selection bias. Moreover, these studies fail to include variables which might mitigate the effects of omitted variable bias and potential endogeneity issues. These flaws in the studies have questioned the validity of their results. In addition, most studies are only on retail traders, which raises questions about whether the relationship between investors' overconfidence and subsequent excessive trading is also prevalent among institutional traders. This exclusion of institutional traders such as fund managers from their samples (Statman and Thorley, 2003) has opened the door to studying other factors contributing to the excessive trading by fund managers.

In addition, another strand of new literature looks at the unique skill set of fund managers as the potential driving force behind the trading levels by funds. Specifically, the paper by Cremers and Pareek (2016) studies the causes of the high trading volume by institutional managers. The paper suggests that in informationally efficient markets, information is quickly incorporated into the price. Therefore, managers containing superior information need to trade excessively to benefit from it. Thus, the fund managers skilled in exploiting mispricing opportunities (Da et al., 2011) need to trade excessively to benefit from their unique skill set. This suggests that the excessive trading by fund managers could be motivated by the unique skill set that managers have.

As portrayed, some research targets the motivation behind the excessive trading by investors, but this is still very scant. Most studies targeting these factors only include retail investors in their sample while excluding institutional investors such as fund managers. Therefore, whether their results stand among institutional traders is still unknown. Moreover, the literature appears outdated, where markets and their subsequent retail and institutional traders have changed dramatically (see, e.g., Almazan, et al., 2004; Barber, et al., 2000). Along with this, the use of surveys and discount brokerage data in studies has questioned the accuracy of their findings (Oden 1998; Hoffman and Post 2014 and Glaser and Weber 2003). There appears to be a significant gap in the literature that needs to get addressed. Thus, my study contributes greatly to the literature. It is the first to empirically analyse the impact of decisions at the fund family level on the subsequent trading frequencies of affiliated funds. This encourages a plethora of further research that could consider the effects of other family-level factors on a funds trading decision.

Section 2.4. Fund family restrictions

My study is also related to the literature, which looks at the constraints and restrictions imposed by fund families. In particular, Almazan (2004) is one of the few papers examining the causes and consequences of various mutual fund restrictions. Through a sample of equity funds, the research considers the economic determinates of implementing restrictions. The study's findings suggest the objective behind implementing constraints is to mitigate the effects of agency problems between shareholders and fund managers. In comparison, my study considers the constraints imposed on mutual funds by fund families as a direct consequence of their respective active vs. passive product offering. My study contributes to the literature by identifying the fund family as another factor impacting the degree of restrictions imposed on affiliated mutual funds. Precisely, in my research, I discover that fund families who predominantly specialise in active management, as reflected by a high active product offering, tend to impose fewer trading constraints on their mutual funds. I attribute this to the fact that these fund families encourage high trading levels because of their active culture, as they are more concerned with generating star funds rather than containing costs.

Section 2.5. Fund family strategies in generating performance

My paper is also connected to the literature, which explores various fund family strategies to generate performance. Massimo Massa (1998) provides a framework to explain mutual funds' market segmentation and fund proliferation strategies. The study finds that due to the increase in the size of the mutual fund industry, fund managers have turned to marketing strategies to differentiate themselves. Such methods are implemented to exploit investors' heterogeneity and limited information. Specifically, the study believes that in an investor's decision-making process, the performance of all funds belonging to a family is essential. This is because the managing skills displayed in managing a particular fund can also be shown through the management of all other funds run by the same fund family. This reinforces the idea in my study that fund families attempt to produce stellar performing funds by trading excessively to attract investors' attention to the family and thereby their capital. However, my analysis differs from Masaa's (1998). Rather than looking at fund families as a whole, I differentiate between active and passive fund families and analyse the different trading strategies they engage in to generate star performance and attract flows. Thus, understanding the impact of the specialisation's decisions by a fund family further elaborates on the findings of Massa (1998) in understanding the strategic behaviour by fund families.

Contrastingly to Massa (1998), Bhattacharya, Lee, and Pool (2013) analyse the investment behaviour of affiliated mutual funds, defined as funds that can only invest within sibling funds belonging to the same family. They begin their analyses by questioning that in a family structure, could wealthy funds provide capital to sibling's funds who are suffering from large redemption requests? By law, they cannot, the family benefits, but shareholders bear the cost, and the mutual funds only owe a duty to their shareholders, not the fund family. By dividing funds into deciles according to investor flows, funds in the lowest group have a higher average inflow from their affiliated family funds than the other nine groups. This shows that funds strategically offset serve cash flow problems of corresponding funds in the family.

However, compared to Massa (1998) and Bhattacharya et al. (2013), other papers believe in some cases that family interest among funds comes before the shareholder. Evans (2010) states that fund families strategically set their fees to chase their objectives and market only good-performing funds. In addition, through his sample of domestic equity mutual funds obtained through CRSP, Evans (2010) proclaims that fund incubation is another family strategy to increase performance and attract flows. The study finds that start-up funds outperform older funds by 3.5% while also attracting more cash flows. In addition, through a sample of target-date funds between 2001 to 2008, Sandhya (2010) finds that, when funds are a part of a family-like structure, they tend to allocate their capital to bottom-performing or high fee funds. By distinguishing between active vs. passive funds families and analysing their strategic behaviour, my study adds another dimension to the diversified mix of strategies implemented by fund families.

Finally, my study also contributes to the literature concerned with agency issues in delegating portfolio management. Some problems analysed in the literature are risk shifting (see, e.g., Chevalier et al., 1997; Hu et al., 2010), window dressing (see, e.g., Lakonishok et al., 1991; Carhart et al., 2002; He et al., 2004), career concerns (see, e.g., Chevalier et al., 1999) and rotating of portfolios (see, e.g., Gorton et al., 1993; Dow et al., 1998). In my study, the observed lottery-like behaviour by fund families also falls into this category. Specifically, I find that families operating funds in this way pose large risks to investors in the form of higher fees, inconsistency in performance, and overall net underperformance. However, any benefits from the lottery-like outcome are borne by the family itself. Therefore, fund families implementing such strategies represent an agency problem between the fund family and its shareholders that needs to be addressed by regulators. Thus, my study brings to the regulator's attention such an issue encouraging the implementation of regulations and greater control over the actions of fund families.

Section 2.6. Hypotheses

As limited literature addresses the factors contributing to the high trading levels observed in the mutual fund industry, I address this research by first formulating a hypothesis identifying the issue surrounding the high trading frequency by equity mutual funds. I then formulate two hypotheses addressing why funds and affiliated fund families trade excessively by analysing the driving force behind the high trading levels observed in the industry.

Hypothesis 1: High trading frequency by mutual funds has a negative effect on their net performance.

Hypothesis 2: Active funds offered fund families with a high degree of assets invested in active products are traded more frequently.

Hypothesis 3: Fund families offering mainly active products engage in high-risk trading strategies as they attempt to generate star-performing funds to attract investor flows.

Section 3. Data and Methodology

In this section, I describe the main dependent, independent and various control variables used in my study.

Section 3.1. Dependent variables

1. Fund net performance

To evaluate the net fund performance using net fund returns after all costs obtained by the investor, I rely on the results from the Carhart four-factor model (Carhart 1997) (Carhart-4-factor) as shown in the model below:

$$R_{i,t} - R_{F,t} = a_i + \beta_{i,M}\left(R_{M,t} - R_{F,t}\right) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \varepsilon_{i,t}\,, \quad (1)$$

where $R_{i,t} - R_{F,t}$ refers to the difference between net return of fund *i* and the risk-free rate at time *t* respectively. The key independent variable of interest, alpha (a_i), is used to measure the fund's performance following Jensen (1968). The other independent variables in the model denote the returns of four factor portfolios. These include the following $R_{M,t} - R_{F,t}$, which represents the difference in market return and the risk-free rate, SMB denotes the difference between the returns of small and large capitalisation stocks, HML is the difference in returns of high and low book-to market stock's, MOM is the difference in returns between stocks with high and low past performance. To estimate the fund performance and factor loadings I take the last 36 months of observations requiring a minimum of 30 months of available fund holdings data to alleviate issues surrounding potential look-ahead bias.

In addition, I turn to an alternative measure of fund net performance to ensure robustness, developed in Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW). This particular model captures the changes in a fund's exposure to a specific style or stock characteristic. For each stock in a fund's portfolio, the DGTW stock returns are calculated by taking the difference between the stock return at time *t* and an equally weighted portfolio with similar stock characteristics (value, size, and momentum). After that, I calculate the average weight of each DGTW stock return to arrive at the DGTW return of the fund.

The DGTW model is better described by the following equation:

$$CS_t = \sum_{j=1}^{N} w_{j,t-1}(R_{j,t} - R_t^{b_{j,t-1}}), \qquad (2)$$

where $w_{j,t-1}$ is the weight of stock *j* in the fund at the quarter prior to *t*, $R_{j,t}$is the return of stock *j* at quarter *t* and $R_t^{b_{j,t-1}}$ is the return of a value-weighted portfolio which is matched to stock *j* based on particular characteristics at the beginning of the quarter.

2. Fund trading frequency proxies

2.1 Fund Duration

The first proxy for trading frequency, Fund Duration, measures each stock's ownership duration in a fund's portfolio by calculating the stock's buys and sells, weighted by the average length in time the fund held onto the stock. This is determined by looking back over a period and measuring the length of time a particular stock has been held in a fund's portfolio. This measure, known as the fund duration, developed in Cremers and Pareek (2016), was used in the study to analyse the relationship between the average length in time funds held onto their stocks and their subsequent performance.

I calculate the length in time a stock *i* included in the fund portfolio *j* at time *T-1*(quarters) was held continuously, for all stocks i=1…. I by using the following formula:

$$Duration_{i,j}T - 1 = d_{i,j}T - 1 = \sum_{t-T-W}^{T-1} \left(\frac{(T-t-1)a_{i,j,t}}{H_{i,j}+B_{i,j}}\right) + \frac{(W-1)H_{i,j}}{H_{i,j}+B_{i,j}}, \qquad (3)$$

$B_{i,j}$ = Percentage of shares outstanding fund *j* bought of stock *i* between *T-W* and *T*

$H_{i,j}$ = Percentage of total shares held by fund *j* of stock *i* at time *T-W*

$\alpha_{i,j,t}$ =Percentage of shares outstanding in the market that fund *j* bought or sold of stock *i* between *t-1* and *t* (quarter), where $a_{i,j,t}$ is positive for buys and negative for sales.

Thus, the weighted average of the duration, $d_{i,j}T-1$, for all stock's *i* held in the fund's portfolio, using the fund's portfolio as weights is taken to arrive at the fund duration of fund *j* at time *T-1*. However, if a stock is not included in the fund at the time of calculation, then that stock's duration is 0. The fund duration measure accounts for the purchases and sells of stocks for tax reasons and other temporary alterations in the portfolio because immediate purchases cancel immediate sales. In addition, following Cremers and Pareek (2015), I require funds to have a minimum of two years of holdings reports to be included in the sample. Similar to Cremer's and Pareek (2016), I choose to look back on the past 16 quarters of a fund's holdings(W=16) because, beyond four years, any informational or behavioural effects would seem to be insignificant.

The following example can better describe the computation of the fund duration. Assume a fund's portfolio consists of two stocks, Tesla, Apple. The portfolio owns 4% of the total shares of Tesla, having bought 3% four quarters back and the other 1%, two quarters back. The weighted average duration of Tesla now in the fund's portfolio would be (3%/4% x 4 quarters + 1%/4% x 2 quarters) 3.5 quarters. Also, suppose the fund now owns 2% of shares in Apple, where 6% it purchased seven quarters back and sold 4% two quarters back. Therefore, the duration of Apple over the past four years is (6%/6% x 7 quarters – 4%/6% x 2 quarters) 5.67 quarters. Therefore, the fund duration would be the average of the duration of the two stocks weighted by their loadings in the fund's portfolio. Thus, the measure depicts the weighted length in time that a fund has held each stock in its portfolio. However, a limitation of the fund duration measure is that it does not capture the round-trip trades within each quarter. This refers to the opening and closing of a position in a security. For illustrative purposes, they have completed the round trip if a fund manager buys a stock and then sells it. Therefore, next to Fund Duration I employ, the fund turnover ratio.

2.2. Fund turnover ratio

The fund turnover is an annual ratio declared by the fund to CRSP-MFDB. This is calculated by dividing the aggregated dollar buys or sells of stocks in the previous year by the average total net assets of the fund. This particular metric has the advantage over the fund duration proxy as it incorporates the round-trip trade of fund managers. The below equation can better describe this specific measure:

$$Turnover\ ratio = \frac{Aggregated\ dollar\ buys\ and\ sells}{Total\ Net\ Assets\ (TNA)}, \qquad (4)$$

2.3. Fund Holdings Turnover

For my last proxy of trading frequency, I relied on the integrated model of asset buying and selling, the fund holdings turnover. This was first formulated in Gaspar, Massa, and Matos (2005) as they examine the impact of investors' investment horizons on the corporate control of firms. Thus, they develop a model to measure how often institutional investors turnover their portfolios. The study centred the model around the logic that a long-term investor is expected to hold onto their positions for longer periods while a short-term investor frequently buys and sells securities. Therefore, using this logic, they calculate the turnover rate for each institutional investor, which is done by measuring how often the investors rotate the positions of the stocks in their portfolios. After that, the total portfolio turnover rates of the investors are weighted averaged over four quarters to determine the investor turnover of a firm.

However, in my study I apply the same logic at the fund level where for each portfolio I measure how frequently the portfolio rotates the positions on all stocks they hold. If I denote the set of stocks Q held by fund i then the holdings turnover of fund i at quarter t is as follows:

$$CR_{i,t} = \frac{\sum_{j \epsilon Q} |N_{j,i,t}P_{j,t} - N_{j,i,t-1}P_{j,t-1} - N_{j,i,t-1}\Delta P_{j,t}|}{\sum_{j \epsilon Q} \frac{N_{j,i,t}P_{j,t} + N_{j,i,t-1}P_{j,t-1}}{2}}, \qquad (5)$$

where $CR_{i,t}$ represents the portfolio turnover of fund *i* at quarter *t*, where *j* is the stock issued. $P_{j,t}$ and $P_{j,t-1}$ is the price of the stock *j* at time *t* and the quarter before *t* respectively. $N_{j,i,t}$ and $N_{j,i,t-1}$ is is the number of stocks *j* held by the fund *i* in their portfolio at quarter *t* and the quarter before *t*, respectively. $\Delta P_{j,t}$ is the change in the price of stock *j* in quarter *t* compared to the quarter before *t*. Thus, the denominator and numerator's weighted sum is calculated using the market value of the stock held in the fund's portfolio as weights. Finally, the two values are divided, which returns a positive value depicting the total movement of stocks in a fund's portfolio at each quarter. This procedure follows the theories developed by Carhart (1998) and Barber, et al. (2001) while also integrating the logic of Gaspar, Massa, and Matos (2005), where a long-term investor is expected to hold onto their positions for more extended periods compared to a short-term investor who frequently trades.

Section 3.2. Key Independent/Control Variables

1. ACF

My proxy for the fund family's specialisation in the active management segment (ACF) is calculated as one minus the proportion of the fund family's assets under management invested in index and ETF products. This particular model developed by Casavecchia and Ge (2016) was used in their study to analyse the impact of a fund family's specialisation decisions in the respective active vs. passive segments on the performance of their subsequent fund offerings. The following equation can better describe this calculation:

$$ACF = 1 - \left(\frac{Sum\, TNA\, of\, index\, \&\, etf\, porducts}{sum\, total\, family\, TNA}\right) \qquad (6)$$

To precisely identify index and ETF products, I use the index and ETF flags, provided by CRSP-MFDB. I also complement these two flags by conducting a fund name search based on the following vocabulary: "Index", "Idx", "Nasdaq", "Dow", "Jones", "Mkt", "Market", "Composite", "S&P", "Barra", "Russell", "Wilshire", "100", "400", "500", "600", "1000","1500", "2000", "3000", "5000", "SPDR", "ishares", "StreetTRACKS", "HOLDRs", "ETF", and "Exchange". This further helps identify the passive products offered by fund families ensuring a more precise measure. Ultimately family's with a higher active pedigree (ACF), closer to one, offer mainly active products and therefore specialise predominately in the active management segment.

2. Fund activeness

The fund activeness is calculated using the one minus r-squared model developed in Amihud and Goyenk (2013). This particular measure is used as a proxy to capture the cross-sectional variation of activeness among funds in my sample. This measure is derived from the funds r-squared, which is estimated by regressing a funds returns on the returns of a multifactor benchmark model. Amihud and Goyenko (2013) propose various benchmark models, but following Casavecchia and Ge (2019), Carhart's Four factors seem most appropriate for my study. Thus, the fund's returns are regressed on the Rm-Rf, SMB, HML, and MOM return factors over the past 24 months to get an accurate r-squared. Using the past 24 months of returns and return factors is justified as one can argue that the fund's activeness is an ergodic process that changes smoothly over time rather than instantly. Ultimately, the regression leaves an r-squared that determines the percentage of the funds return explained by the four factors. Therefore, a higher r-squared demonstrates the fund tracks the factors closely. Thus, the activeness of a fund is obtained by taking one minus the r squared. The below formula can better describe this model:

$$1 - R^2 = \frac{RMSE^2}{Systematic\, risk^2 + RMSE^2} \qquad (7)$$

This particular variable is expected to have a positive relationship with the funds trading proxies since, by nature of the industry, active funds trade more in an attempt to beat the market.

3. Herfindahl-Hirschman Index (HHI)

The Herfindahl-Hirschman Index (HHI) is a measure commonly used to determine the level of competitiveness amongst firms in the market. This measure can also be applied in the fund management setting to measure the concentration level of a fund's portfolio. Precisely, the measure captures the loadings of a fund's portfolio on the stock holdings. This measure is described by the equation below:

$$\sum_{i=1}^{N} s^2 i \ , \qquad (8)$$

where $s_i$is the market value weight invested in stock *i* by the fund. Thus, a higher HHI would indicate a highly concentrated fund portfolio that is not closely related to the market index. For illustrative purposes, say a fund has three stocks, Tesla, Apple and Facebook, and the following respective portfolio weights 0.2,0.2,0.6. Thus, the HHI of the fund would equate to 0.44 $(0.2^2 + 0.2^2 + 0.6^2)$. Hence the high loading of the portfolio on Facebook is captured by the high HHI. In addition, this suggests the highly concentrated portfolio is not closely related to the market and is, therefore, more active. Consequently, the HHI index is expected to positively correlate with the fund trading frequency proxies since more active funds are likely to trade more.

4. Fund Characteristics

A. **Fund TNA** refers to the fund's total net assets under management which are expressed in millions. The coefficient of the estimator is expected to be negative, as smaller funds are expected to engage in more risk, translating into high trading frequency. This is consistent with the findings of Evans (2010). The fund TNA variable is obtained from the CRSP-MFDB database.

B. **Fund Age** denotes number of years since the fund’s inception. Fund age is expected to be negatively associated with a funds trading frequency as start-up funds by nature engage in more risk (Evans, 2010).

C. **Fund Operating expenses**: refers to the total expense’s investors pay for a funds operating costs. The relationship between operating expenses and fund trading levels are studied extensively in the literature (Carhart, 1997). Funds that trade more incur higher transaction costs which increase their annual operating expenses. Therefore, a positive loading of operating expenses on fund trading levels is expected to be observed.

5. Mutual Fund Family affiliated characteristics

A. **Family TNA** denotes to the total net assets managed by the fund family, expressed in millions. Similarly, to Fund TNA the family's value of assets under management is also predicted be negatively related to fund turnover. This is congruent with the idea that smaller fund families are likely to implement high-risk strategies in line with excessive trading levels.

Section 3.3. Data

My study is concerned with mutual funds and their affiliated fund families. To obtain this data, I use the Survivorship Bias-Free Mutual Fund database (CRSP-MFDB). The following procedure is used to identify mutual funds and link them to their affiliated fund families. Firstly, data on the fund families are gathered directly from the CRSP-MFDB. During this process, fund family names are verified to consider any variations in names and account for a different segment within the fund family. However, even though CRSP-MFDB offers the fund family names, it is often not consistent across time. Therefore, as a precautionary measure, the Investment Adviser Public Disclosure (IAPD)[7] database is used as a robustness check to gather all previously registered names of fund families (Chen et al., 2013). This check will verify the names of fund families and eliminate the chances of incorrect and misleading data. After gathering and ensuring all the data on the fund families is accurate, it is necessary to match the fund families with their mutual fund offerings. Mutual funds are matched to their affiliated fund families via the management company codes derived from the CRSP-MFDB. Lastly, to refine the legitimacy of the fund and affiliated fund family identification procedure, I use SEC letters [8]and FACTIVA to look through all the fund family names and their

[7] the Investment Adviser Public Disclosure provides information about the registration documents filled by investment firms.
[8] SEC have information about fund family mergers

subsequent fund offerings. The results from this matching procedure leaves 721 unique fund families and 9397 fund offerings.

In addition, my study only focuses on active U.S. domestic diversified equity mutual funds. Therefore, I use the following sample selection criteria. First, the fund's investment objectives are identified through the CRSP objective codes. I require that these codes indicate that the fund is a U.S. domestic diversified equity mutual fund[9]. Second, active ETF's and hybrid funds are excluded from the study as implied by CRSP since the study is only focused on actively managed U.S. equity mutual funds. Thirdly, I verify that the mutual funds included in the sample are primarily focused on U.S. equities by requiring each fund to have at least 80% of their total net assets (TNA) under management invested in U.S. common shares. Forth, I require funds to have a total net of at least $10 million under management at any given month following Elton, at el. (1996) who find it necessary to eliminate reporting bias. Therefore, funds with less than $10 million total monthly TNA are excluded from the dataset. In addition, I also preclude observations before CRSP first reported the fund following Evan's (2010) remark about incubation bias. Finally, funds with missing family codes (management codes) or unique fund identifiers (fundnos) are automatically eliminated from the sample to ensure an accurate data set.

As a result, of the selection criteria, 447 unique fund families and 5766 subsequent funds are left in the data sample, with 3797 being active equity mutual funds over the sample period from January 2006 to December 2020 (15 years)[10].

To compute the holding-based performance and trading frequency measures, fund holdings data is also derived from the CRSP-MFDB. Fund holdings are reported quarterly, where funds with no unique portfolio identifies (portnos) are removed from a dataset. In addition, funds with 20% of missing unique stock identifiers (permnos) are excluded from the data set to ensure more accurate results.

[9] The codes are created based on information from different sources including the Lipper codes (1998–2015), Weisenberger (1962–1993) and the Strategic Insight (1993–1998).)
My sample of funds only includes large, small, micro-cap funds, growth, growth and income funds and equity income funds.
[10] For further data transformations refer to figures 1 to 8 in the appendix 1A

Section 3.4 Descriptive Statistics/Correlations

Table 1 contains the summary statistics for the key-dependent and independent variables for my sample of mutual funds. Equity mutual funds in my sample, on average, turnover 55.92% of their portfolios a year. This can better be described as 55.92% of the holdings in the fund's portfolio have been changed over one year. Similar to Milan et al. (2015), who, through their sample of U.S. domestic diversified equity mutual funds, report an average holdings turnover of 15.34% compared to my average of 12.23%. This can be interpreted as, on average, funds change 12.23% percent of their holdings from quarter to quarter. On average, funds in my sample continuously hold onto their stocks for about 6.85 quarters, with a maximum duration of 38.14. This result is consistent with Cremer and Pareek (2015), who report very similar statistics in their study.

Due to the large sample of funds and relatively long period, my study's fund and affiliated family variables have a large dispersion. For this reason, I analyse the stationarity characteristics of the time series components in my data; otherwise, the findings of my study maybe be unreliable (Cevik and Jalles, 2020). I use the Augmented Dicky-Fuller (ADF) test to distinguish if a unit root is present and the Kwiatkowski, Phillip, Schmidt, and Shin (KPSS) test to locate trends. Fund age, Fund TNA, and Family TNA indicated non-stationarity in both tests. To control for the variation in the fund age, TNA and family TNA, I take the natural logarithm as shown by the last three columns of Table 1. The average mutual fund has existed for about nine years (Fund Age) and controls about $1065 million (Fund TNA) worth of assets. The average fund turnover (Turnover Ratio) of 55.92% translates into total operating expenses of 1.21%.

Furthermore, funds on average have a HHI of 2.23%, which suggests that they have a relatively low level of concentrated portfolios. Thus, mutual funds in my sample, on average have an activeness of 58.42%. In addition, the average mutual fund family manages assets of $14477 million and offers about 15 fund portfolios. In addition, 60.28% of a fund family's assets on average are invested in active mutual fund products, varying between 30.96% and 71.26%. Thus, fund families appear to have a highly diversified product offering across the active and passive segments.

Table 2 provides the Spearman rank correlation matrix of the key-dependent mutual fund variables. All the trading level measures appear to be high correlated as expected. The two holdings-based measures, holdings turnover and fund duration have the highest correlation rank of minus 53% as expected following Cremers and Pareek (2015). This is because funds that hold onto their stocks less obviously turnover their portfolios more. Holdings turnover and turnover ratio are positively correlated at 45.2%, whereas turnover ratio and fund duration are negatively correlated at 44.1%. These results are consistent and follow the logic described by Cremers and Pareek (2015) and Gaspar and Matos (2005).

Table 3 reports the Spearman rank correlation matrix among the independent variables, with family ACF being the key variable. ACF is not highly correlated with any of the variables above apart from the fund activeness, with the highest correlation rank of 51.2%. In addition, other variables with potentially high correlation include the fund and family TNA at 29.3%, HHI, and fund activeness at 25%, and fund TNA and expense ratio at -24.8%, which is all consistent with past studies. However, the family TNA and number of portfolios have the highest correlation with 79.3%. This underscores the importance of my decision to remove the number of portfolios as a control variable from the model.

Table 4 displays the averages of my sample of U.S. diversified equity mutual funds over two-year intervals to evaluate the time-series variation in fund and affiliated fund family characteristics. These statistics are reported every two years starting from the beginning of the sample, 2006 to 2020. Regarding the key-dependent variables in my study, the turnover ratio rose from 62% to 66% from 2006 to 2012 and then dropped to 46% in 2020. This is consistent with the recent literature that studies the recent increase in competition in the mutual fund industry due to the rise in active ETF products. They find that the competition of cheap active ETF's has pushed many active funds to trade less in order to reduce the costs and fees and become more competitive (Archana et al., 2021) The holdings turnover ratio also rose from 16% in 2006 to 20% in 2012 and subsequently fell in 2020 back to 11.34%. The fund duration measure fell from 2006 to 2012 from 3.93 quarters to 5.27 quarters, rising to 7.11 quarters in 2020. In addition, over time, a fund's total assets under management grew from $725 million in 2006 to $2686 million in 2020, with the affiliated fund family's total assets under management also increasing from $7256 million in 2006 to $28265 million in 2020. This is in accordance with the rise in the size of the industry from $1611524 million to $4878789 million.

This evidence is consistent with Fernando et al. (2019), who find that the mutual fund industry has been rapidly rising, attributing it to the development of investor confidence in the market.

Table 1 This table reports the descriptive statistics for the dependent and independent variables in my sample of mutual funds over the period from January 2006 to December 2020. The three main dependent variables reported, capturing the trading frequency of funds are: **Turnover Ratio**, **Holdings Turnover** (Gaspar, Massa and Matos, 2005) and **Fund Duration**, (Cremers and Pareek, 2016). The key independent variable of concern, **ACF**, measures the degree of a fund family's asset-based concentration invested in the active management segment, TNA weighted (**ACF**)**.** In addition, the table reports fund and affiliated fund family characteristics which include: the fund's annual operating expenses **(Expense Ratio)**, the number of years since the fund was offered **(Fund Age)**, family's total number of assets under management measured in millions ($M) (**Family TNA)** , the funds' assets under management also measured in $M (**Fund TNA**), the activeness of the fund itself measured by one minus R-squared derived by regressing the funds returns against Carhart's four factors (**Fund Activeness**)(Amihud and Goyenko, 2013), the concertation level of the fund's portfolio (Herfindahl-Hirschman Index (**HHI**)), the logarithm of the number of years since the fund was first offered and the logarithm of the funds and fund family's total assets under management respectively (**LFAGE,LFAMTNA,LFTNA**).

Table 1: Descriptive Statistics of Dependent Variables

	Mean	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
Turnover Ratio	55.92%	45.25%	0.00%	27.02%	44.20%	73.50%	922.0%
Holdings Turnover	12.23%	13.00%	0.00%	5.38%	9.21%	15.18%	457.12%
Fund Duration	6.85	2.24	0.00	5.13	6.91	8.55	38.14
ACF	60.28%	21.38%	0.00%	30.96%	46.44%	71.26%	100%
Expense Ratio	1.21%	0.004%	0.05%	0.09%	1.11%	1.41%	3.41%
Fund Age	8.59	3.31	0.01	6.00	8.50	11.25	14.51
Family TNA	14477.04	10961.16	10.10	1111.98	60021.25	18743.10	1600836
Fund TNA	1065.87	4386.63	10.03	11.30	336.94	1041.08	109373
Fund Activeness	58.41%	52.80%	0.00%	26.29%	44.26%	72.50%	99.89%
HHI	2.23%	1.13%	0.00%	1.01%	2.21%	3.59%	98%
NO. Portfolio	15.21	17.57	1.00	5.00	10.00	17.00	76.00
LFAGE	5.70	1.57	1.746	4.50	5.60	6.78	11.60
LFAMTNA	9.42	2.21	2.30	8.34	9.71	10.50	14.28
LFTNA	1.90	0.57	0.00	1.61	2.01	2.35	2.69

Table 2 Reports the Spearman's correlation matrix between the dependent variables in my sample of equity mutual funds from 2006 to 2020. The table includes the following variables: the fund-reported turnover provided by CRSP (**Turnover Ratio)**, how often a fund rotates its positions on all the stocks it holds in its portfolio (**Fund Holdings Turnover**) (Gaspar, Massa and Matos, 2005) and the average length in time stocks were held in a fund's portfolio by looking at the past 4 years of holdings report (**Fund Duration**) (Cremers and Pareek, 2016).

Table 2: Spearman's rank Correlation Matrix- Dependent Variables

	Turnover ratio	**Fund Holdings Turnover**	**Fund Duration**
Turnover Ratio	1	0.452	-0.441
Holdings Turnover	0.452	1	-0.503
Fund Duration	-0.441	-0.503	1

Table 3 Reports the Spearman's correlation matrix between the independent variables in my sample of equity mutual funds from 2006 to 2020. The table includes the following variables: the fund's annual operating expenses (**Expense Ratio**) expressed as a percentage, the number of years since the fund was first offered (**Fund Age**), the fund family's total assets under management (**Family TNA**), the fund's total assets under management (**Fund TNA**), the activeness of the fund itself measured as one minus the r-squared derived by regressing the funds returns on Carhart's four factor benchmark model (Amihud and Goyenko 2013) (**Fund Activeness**), the concentration level of a fund's portfolio (**HHI**), the number of unique portfolios offered by fund families (**No.Portfolios**) and the key independent variable of concern, **ACF**, measures the degree of a fund family's asset-based concentration invested in the active management segment, TNA weighted (**ACF**).

Table 3: Spearman's rank Correlation Matrix- Independent Variables

	Expense Ratio	**Fund Age**	**Family TNA**	**Fund TNA**	**Fund Activeness**	**HHI**	**No. Portfolios**	**ACF**
Expense Ratio	1	-0.098	-0.230	-0.248	0.068	0.047	-0.144	0.069
Fund Age	-0.098	1	0.141	0.060	0.158	0.088	0.021	0.142
Family TNA	-0.230	0.141	1	0.293	-0.048	-0.093	0.793	-0.145
Fund TNA	-0.248	0.060	0.293	1	0.005	-0.025	0.164	-0.021
Fund Activeness	0.068	0.158	-0.048	0.005	1	0.250	-0.102	0.512
HHI	0.047	0.088	-0.093	-0.025	0.250	1	-0.117	0.183
No. Portfolios	-0.144	0.021	0.793	0.164	-0.102	-0.117	1	-0.155
ACF	0.069	0.142	-0.145	-0.021	0.512	0.183	-0.155	1

Table 4 outlines the summary statistics by time intervals of my sample of U.S. diversified active equity mutual funds during January 2006 to December 2020. It displays the time-series averages of my mutual fund and affiliated family sample every 2 years. The averages of reported fund and fund family characteristics are described below, the funds turnover as declared by CRSP, (**Turnover Ratio**), the average length in time stocks were continuously held in a fund's portfolio (**Fund Duration**), how frequently a fund rotates its positions on all the stocks of their portfolio (**Fund Holdings Turnover**) the funds' total assets under management (**Fund TNA**) , the fund family's total assets under management (**Family TNA**), the number of years since the funds inception (or number of years since the fund became offered) (**Fund Age**), the fund's annual operating expenses (**Expense Ratio**), the activeness of the funds measured by one minus the r-squared derived by regressing a funds returns on the return of Carhart's four factors(Amihud and Goyenko, 2013) (**Fund Activeness**), the fund family's degree of asset invested in active products (**ACF**), total size of the industry in millions (**Industry Size**)($m), the unique number of portfolios managed by the mutual fund family (**NUM PORT**) and the total number of fund families in the sample (**NUM FAM**).

Table 4: Descriptive Statistics by Time Intervals of Dependent Variables

	2006	**2008**	**2010**	**2012**	**2014**	**2016**	**2018**	**2020**
Turnover Ratio	62.13%	60.17%	65.23%	66.22%	60.71%	58.15%	49.01%	46.28%
Fund Duration	3.93	5.83	5.79	5.27	6.83	6.84	6.97	7.11
Fund Holdings Turnover	15.97%	15.73%	19.21%	20.64%	15.33%	14.38%	11.98%	11.34%
Fund TNA	724.61	895.93	1016.52	1039.26	1598.27	1789.48	2081.00	2685.59
Family TNA	7256.41	5115.95	7617.67	7878.66	11802.29	13179.05	15331.84	28265.37
Fund Age	0.74	2.22	4.26	6.23	8.10	10.10	12.10	13.10
Expense Ratio	1.13%	1.13%	1.09%	1.08%	1.04%	1.02%	1.27%	1.29%
Fund activeness	67.34%	63.16%	69.55%	70.86%	77.13%	70.49%	61.06%	60.62%
ACF	64.70%	63.80%	60.90%	64.40%	67.80%	63.20%	61.90%	61.20%
Industry Size	1611524.10	2126128.80	2424460.10	2478482.48	3849467.80	3848380.17	4357216.77	4878789.43
NUM PORT	6.41	6.16	7.22	7.25	8.72	9.21	9.25	10.02
NUM FAM	293	311	318	320	321	325	342	343

Section 4. Main Results

My study evaluates the relationship between the degree of a fund family's asset-based concentration in the active management segment and the subsequent trading frequency of their active fund offerings. In addition to this, I sort funds based on their end-of-year family affiliated ACF and performance to analyse the implications and underlying rationale behind implementing high trading strategies. In **Section 4.1**, I identify the issue concerning the high trading frequency by mutual funds by examining the relationship between trading frequency and performance. I find that funds that trade frequently and therefore have lower fund durations suffer from significant underperformance. Performing several robustness tests, I find that this result is not driven by the heterogeneity in fund and family characteristics. **Section 4.2** studies the effects of a fund family's specialisation in the active management segment on the subsequent trading frequencies of affiliated active fund offerings. Through the analysis, active funds offered by families offering predominately active products are traded more frequently. The result is robust to inclusions of fund, family, and time-fixed effects. **Section 4.3** studies the strategy that justifies why fund families specialising in active management implement such aggressive trading strategies, which on average generate underperformance. By sorting funds into quintiles, my analysis in **Section 4.3** suggests that families with a high ACF on average produce more top-ranking funds, suggesting that these families are pursuing star performance. I provide a rational explanation of why fund families would engage in such a risky trading strategy by presenting evidence indicating that one fund's star performance subsequently attracts investor flows to all funds in the family in **Section 4.4**.

Section 4.1 Pooled panel performance regression

My study begins with the assumption that high trading frequency by mutual funds generates suboptimal net performance. Therefore, it is necessary to replicate past studies to show the negative relationship between fund trading levels and subsequent net performance. Following Cremer's and Pareek's (2016) research, which analyses the relationship between fund duration and subsequent fund performance, I conduct a series of pooled panel regressions at quarterly and yearly frequencies. Precisely, I regress the net performance of funds on the lagged fund duration. I control for several fund and affiliated fund family characteristics, including the logarithm of the fund size and age, respectively, and the expense ratio. Specifically, I estimate the following pooled panel regression:

$$PER\ F_{i,t} = \beta_0 + \beta_1 FDURATION_{i,t-1} + CONTROLS_{i,t-1} + \epsilon_{i,t} \ , \qquad (9)^{11}$$

where $PER\ F_{i,t}$, is the variable (in percentage terms) for performance, represented by the alpha derived from Carhart's four factor model and the DGTW (1997) holdings-based model, $FDURATION_{i,t-1}$, is a proxy capturing the trading frequency of funds which measures the average length in time stocks are held in the fund's portfolio at time *t-1* , $CONTROLS_{i,t-1}$ refers to the following control variables: the logarithm of the funds' assets under management (LFTNA), the logarithm of the number of years since the fund was first issued (LFAGE) and funds annual operating expenses (OPEX). My leading coefficient of interest is β_1, which quantifies the sensitivity of mutual fund performance to the fund duration.

In Table 5, I document the results of the regression specification illustrated in Eq. (9) by using funds net returns derived from the Carhart (1997) four-factor model. The fixed effects regression is implemented with clustered standard errors and robust to entity and time effects to help control for endogeneity. Column 1 reports the results from the first estimated regression at a quarterly frequency. The model in column (1) regresses a fund's net performance derived by the alpha obtained from Carhart's four-factor model on the key independent variable of concern, the fund duration while controlling for the logarithm of the fund's age and size. The estimated loading of 0.071 on the key independent variable, the FDURATION, is economically and statistically significant with a t-statistic of 9.651. Its economic significance can be better described as one standard deviation (2.24) increases in FDURATION results to 190 basis points (2.24*0.071*12) increase in performance for the average fund. The economic and statistical significance remains consistent when I turn to alternative models in columns (2) and (3). Since the operating expenses for a fund are calculated yearly, columns (2) and (3) re-estimate the model in Eq. (9) by re-calculating the variables at yearly frequencies. In column (2), the key independent variable of concern shows a positive (0.070) and statistically significant coefficient (t-statistic of 9.276). This indicates that increasing the fund duration by

[11] Refer table 1B in appendix for a better description of the model

one quarter leads to an increase in the average net performance by 0.070 percentage points. However, following Carhart (1997), who finds that funds that trade a lot generate higher annual operating expenses, which translates into subsequent underperformance, I find it necessary to capture loading of the relationship between fund duration and operating expenses on fund performance. Thus, after the inclusion of the interaction term between fund duration and operating expense in column (3), the positive loading on FDURATION is consistent with the evidence in columns (1) and (2), suggesting that more patient funds outperform funds that hold onto stocks for short periods.

The results in Columns (1) to (3) are robust when using the alpha derived from Daniel, Grinblatt, Titman, and Wermers's (1997) holdings-based model as a measure of fund performance. Columns (4) to (6) report the re-estimated results of the pooled panel regression specification illustrated in Eq. (9) using the DGTW (1997) model as a proxy for a fund's performance. The DGTW (1997) model has an advantage over Carhart's (1997) model as it captures the funds change in loadings on the size, book to market, and momentum factors. Column (4) reports the results from the base estimated regression generated at a quarterly frequency. The positive factor loading of 0.048 on FDURATION is economically and statistically significant (3.311). Thus, if you increase the fund duration by one quarter, the average net fund performance increases by 0.048 percentage points. After including other control variables in column (5), such as the expense ratio, which is calculated at the end of the year, all variables are re-calculated at yearly frequencies. FDURATION still has a positive (0.047) and statistically significant coefficient as indicated by the t-statistic of 3.337. The results remain consistent in column (6) after incorporating an interaction between the fund duration and operating expenses. Therefore, funds engaging in high trading strategies are likely to underperform more conservative peer funds. My findings that a fund's performance is negatively related to the fund size are congruent with Chen et al. (2004).

Overall, the results support hypothesis one and are congruent with the past literature (see, e.g., Cremers and Pareek, 2016 and Carhart, 1997), which finds that funds hold onto their stocks for shorter periods and subsequently trade more, generate suboptimal net performance. This is likely because high trading levels come with high transaction costs, which in turn deflates performance substantially.

Table 5 Relationship between fund duration and fund performance. This table represents the estimates of the pooled panel regressions estimated at both quarterly and yearly frequencies over the period of 2006 to 2020. The dependent variable, in columns (1) to (3) is the funds' performance estimated by using **Carhart's** (1997) four factor benchmark model. The alpha from Carhart's model is derived by regressing the funds net returns on the factor returns of size (big minus small), book to market (value minus growth or growth minus value) and momentum (high past returns minus low past returns) is used as a proxy for the fund's performance. The performance measure from columns (3) to (6) is obtained from the alpha derived from Daniel, Grinblatt, Titman and Wermers (1997) holdings-based model (**DGTW 1997**). The main independent variable of concern is the fund duration (**FDURATION**) developed in Cremer's and Pareek (2016). It measures the weighted average length in time that a stock was continuously held in a fund's portfolio by looking back at the last 4 years of holdings. Lagged control variables include the logarithm of the fund's total assets under management (**LFTNA**), the logarithm of the number of years since the fund was first offered (**LFAGE**), the total annual operating expenses (**OPEX**) and an interaction term between the fund duration and operating expense variables (**FOPEX*FDURATION**). Column (1) and (4) report the estimated results at a quarterly frequency while column (2), (3), (5) and (6) report result at an annual frequency. Table 7 denotes the estimated coefficients of the pooled panel regressions with clustered standard errors. T-statistics reported in brackets with one, two and three starts indicate a statistical significance at the 10%,5% and 1% levels, respectively.

Table 5: Pooled panel performance regression

Dependent Variable:		**Carhart (1997)**			**DGTW (1997)**	
	(1)	(2)	(3)	(4)	(5)	(6)
INTERCET	-0.043 ***	-0.036***	-0.035 **	-0.009	-0.019 **	-0.014
	(-5.359)	(-3.020)	(-2.104)	(-1.146)	(-2.003)	(-1.004)
FDURATION	**0.071 *****	**0.070*****	**0.070 *****	**0.048 *****	**0.047 *****	**0.0068**
	(9.651)	**(9.276)**	**(3.365)**	**(3.311)**	**(3.337)**	**(1.550)**
FOPEX		-0.4110***	-0.3914***		-0.7633 ***	-0.1856 ***
		(-9.280)	(-3.651)		(-5.486)	(-5.019)
LFTNA	-0.006	-0.004***	-0.004 ***	-0.0005 ***	-0.0004 ***	-0.0004 ***
	(-1.198)	(-3.914)	(-3.897)	(-4.659)	(-3.058)	(-3.172)
LFAGE	0.004 ***	0.004 ***	0.004 ***	0.0007 **	0.0007 **	0.0006 **
	(14.492)	(15.159)	(15.155)	(2.648)	(2.599)	(2.433)
FOPEX*FDURATION			0.034			0.063 ***
			(0.187)			(4.685)
N-OBS	24,528	24,528	24,528	19,187	19,187	19,187
R-SQUARED	26.54%	26.87%	27.11%	9.26%	9.31%	9.52%

Section 4.2. Relationship between an Active Funds Trading Frequency and its affiliated Fund Family's ACF

In this section, I provide evidence on the impact of the degree of a fund family's specialisation in the active management segment on the subsequent trading frequency of affiliated active funds. I aim to explore the results of Table 5 by looking into the driving factors behind why funds trade so much. I use three different measures to calculate a funds trading frequency used previously in the literature (see, e.g., Gaspar, Massa, and Matos, 2005 and Cremers and Pareek, 2016) and quantify directly the percentage of a fund family's asset base concentrated in the active management segment.

My main proxy for the trading frequency comprises the following dependent variable: the fund's duration, which is computed by looking back four years into the fund's holdings and determining how long each stock has been continuously held in the fund's portfolio (Cremers and Pareek (2016). My proxy for the fund family's specialisation in active management is estimated as a TNA weighted percentage of the proportion of a fund family's assets invested in active products.

Several studies in the literature which explore the factors impacting a funds trading levels only incorporate one measure of trading frequency (Milan et al., 2015 and Champagne et al., 2018). Thus, many academics and industry practitioners have questioned the robustness of their findings as to whether their proxies of trading frequency capture the accurate trading levels of equity mutual funds. For this reason, I complement the fund duration measure by including two other proxies which capture the fund's trading frequency. My first alternative proxy is the funds turnover as declared by the fund in the CRSP-MFDB, which also has the advantage over the fund duration measure as it captures the round-trip trades by funds. The second alternative proxy is the fund's holdings turnover as estimated in Gaspar, Massa, and Matos (2005), which measures how often stocks in a fund's portfolio have been rotated. These two measures provide robustness and ensure my findings capture the precise trading levels of funds.

Specifically, I estimate the following panel regression:

$$TRADEFREQ_{i,t} = \beta_0 + \beta_1 ACF_{i,t} + \beta_2 CONTROLS_{i,t} + \epsilon_{i,t}, \qquad (10)[12]$$

where $TRADEFREQ_{i,t}$represents the following three proxies used to capture a funds trading frequency; fund duration, holdings turnover and fund turnover ratio, $ACF_{i,t}$is the key independent variable of interest which measures the proportion of a fund families assets invested in active products, TNA weighted, and $CONTROLS_{i,t}$represents the following set of controls variables to account for some of the variability in my results, the fund investment objective codes (CRSP- OBJ), the fund's portfolio asset concentration (Herfindahl-Hirschman Index (HHI)), the fund-level activeness, obtained by the R-squared derived from Carhart's four factor model (Fund activeness) (Amihud and Goyenko, 2013[13]), the logarithm of the fund family's total assets under management (LFAMTNA), the logarithm of the fund's total assets under management (LFTNA), the logarithm of the number of years since the fund was first offered (LFAGE), and an interaction term between the fund family's total assets under management and their degree of active product offering (FAMACF). The inclusion of the mentioned control variables is consistent with past studies (see e.g., Cremers and Pareek , 2016; Gaspar, Massa and Matos, 2005; Wermers, 2000; Carhart, 1997). All model specifications include fund, family and time fixed effects.

Table 6 illustrates the results of multiple regressions as illustrated in Eq. (10) at both quarterly and yearly frequencies with clustered standard error. The estimated coefficients of the key independent variable, ACF, are consistent in all three model variations with the hypothesis that funds affiliated with higher-ACF families engage in higher trading levels. Column (1) reports an estimated coefficient of -1.366 on family affiliated ACF variable, which is statistically significant with a t-statistic of -4.452. The economic magnitude of such a

[12] Refer to table 2B in appendix for a more visual representation of the model
[13] Refer section 3.2 in data and methodology, for a better description of the model developed by Amihud and Goyenko (2013)

relationship can be described as one standard deviation (21%) increase in ACF results to a 344 basis points (0.21*1.3660*12) decrease in the average quarterly duration for a fund.

In the study, an active fund family is defined as predominately invested in active products. However, these families are expected to have a wide-ranging mix of active products in their offering where some active funds could be very active, and others could be less. This point was discussed by Cremers and Petajisto in 2009, who found that a large amount of actively managed US equity funds have holdings that are very close to their benchmarks. They state that it is vital to differentiate between active funds that truly justify their activeness and those that are closet-indexing. They support their argument by discovering a substantial number of closet-indexing among active funds where a large portion of active funds have similar holdings relative to their benchmark. In the context of my study, this suggests that if two families have the same ACF, one could have a greater percentage of closet indexing funds than the other. In addition to this, when comparing the trading level of funds that are equally as active but are offered by fund families with different styles and ACF levels on average, it would be that the funds in less active families would, by construction, be less active and have less turnover due to this. Therefore, provided the two issues, it is essential to control for the fund's activeness itself. Thus, the model specification in column (2) includes a measure of the fund's activeness itself. In addition, the model also incorporates the HHI index as a measure of asset concentration of the fund and the logarithm of the family TNA as independent variables. The estimated loading of -1.355 on ACF in column (2) is economically and statistically significant with a t-statistic of -3.440. In addition, my evidence in column (2) that fund activeness itself has a negative (-1.307) and statistically significant coefficient (t-statistic of -4.493) is consistent with the literature which characterises active funds with lower durations and thus high trading levels (Wermers, 2000). After including additional control variables in Column (3), such as fund investment objectives as well as an interaction term to capture the loading of family TNA and ACF on the duration of fund holdings, the results remain consistent with columns (1) and (2). ACF has a negative coefficient of -1.083, suggesting that active funds offered by high actively oriented fund families are traded more frequently.

However, since the operating expenses of the fund are calculated annually, the estimated regression result's in columns (1) to (3) are re-estimated at yearly frequencies as shown in columns (4) and (5). The results in columns (4) and (5) remain consistent with the findings in columns (1) through to (3) after controlling for the operating expenses of the fund.

The estimated results computed at yearly frequencies report negative (-0.769 and -0.751) and statistically significant coefficients (t-statistics of -2.079 and -2.027) respectively for the key independent variable of concern, ACF. The results remain congruent to the hypothesis that active funds offered by fund families specialling in the active management segment, as reflected by their high active product offerings, likely generate higher trading frequencies.

To ensure robustness, I employ two other trading frequency proxies, the fund holdings turnover and the fund turnover declared by the fund. Table 7 displays the results of multiple panel regressions where the fund holdings turnover capturing the funds trading frequency is regressed on the key independent variable ACF.

Table 7 illustrates the estimates of the regression model illustrated in Eq. (10) at quarterly and yearly frequencies with clustered standard errors. The estimated coefficients of the key independent variable, ACF, are positive and statistically significant across all model variations. This suggests in favour of the prediction that mutual funds offered by families highly focused in the active management segment are likely to turnover over their portfolios more often. The base model in column (1) displays a positive coefficient of 0.185 for the key independent variable, ACF, with a high t-statistic of 5.452. In economic terms, a one percentage point increase in the ACF would increase the average fund holdings turnover by 0.1852. The economic and statistical significance remains relatively stable in columns (2) and (3) after controlling for various extra fund and family affiliated characteristics consistent with the literature.

However, since the operating expenses are computed annually, the regression results in columns (1) to (3) are re-estimated at yearly frequencies in columns (4) and (5). The findings in columns (4) and (5) remain harmonious with the evidence found at the quarterly frequency (column (1) to (3)) that fund families with a higher ACF encourage their active offerings to trade more. This is portrayed in all three columns by the positive loading on the key independent variable ACF, which is significant in all columns.

Interestingly, my evidence that fund holdings turnover declines with an increase in the size and age of the fund run contrary to the results of Milan and Junior (2015), who study the determinates of a fund holdings turnover by considering fund and managerial characteristics. This is because their sample is limited to only 47 stock investment funds in Brazil from 2007 to 2011. Along with this, they fail to take the logarithm of the fund age and TNA, which further accounts for the variation in results. In my study, the fund age and TNA both report negative coefficients, suggesting younger and smaller funds on average trade more. This is in accordance with Evans (2010), who finds that start-up and smaller active funds engage in higher-risk strategies in their search for alpha.

Finally, Table 8 displays the last set of regression results where the fund turnover as declared by the fund to CRSP-MFDB is used as a proxy to capture the trading frequency of funds. The reported coefficients of the panel regression as indicated by Eq. (10) are computed at yearly frequencies since the fund turnover is calculated yearly. The t-statists displayed in parathesis are robust to clustered standard errors. The base model in column one exhibits a positive coefficient of 0.558 for the fund turnover, suggesting that funds offered by families with a higher ACF turnover their portfolios substantially more. The finding remains consistent in columns (2) and (3), which report positive loadings of 0.293 and 0.130 respectively on the key independent variable, ACF. In addition, as expected, the high positive coefficient of the expense ratio suggests that higher costs are associated with increased trading levels (Carhart, 1997).

Table 6 Relationship between trading frequency and fund family ACF. This table reports the estimated coefficients of quarterly (columns (1) to (3)) and year panel regression (columns (4) & (5)) capturing the relationship between the trading frequency of funds (**FDURATION**) and the affiliated fund family specialisation in the active management segment (**ACF**) between 2006 to 2020. My dependent variable is a proxy for the funds trading frequency which measures the average length in time funds hold onto their stocks (**FDURATION**) as proposed by (Cremers and Pareek, 2016). The key independent variable of concern is the degree of a fund family's assets invested in active products (**ACF**). Other lagged control variables include, the fund investment objective codes (**CRSP OBJ**), the fund's portfolio asset concentration (Herfindahl-Hirschman Index, (**HHI**)), the fund-level activeness, obtained by one minus the R-squared derived from Carhart's four factor model (**FUND ACTIVNESS)** (Amihud and Goyenko 2013), the logarithm of the fund family's total assets under management (**LFAMTNA**), the logarithm of the fund's total assets under management (**LFTNA**), the logarithm of the number of years since the fund was first offered (**LFAGE**), and an interaction term between the fund family's total assets under management and their asset based specialisation in the active management segment (**FAMACF**). The regression estimates all include fund, family and time fixed effects.

Table 6: Relationship between an Active Funds Trading Frequency and its affiliated Fund Family's ACF

Dependent Variable: FUND DURATION

	1	2	3	4	5
ACF	**-1.366 *****	**-1.355 *****	**-1.083 *****	**-0.769 ****	**-0.751 ****
	(-4.452)	**(-3.440)**	**(-3.436)**	**(-2.079)**	**(-2.027)**
HHI		-0.286 ***	-0.290 ***	-0.377 ***	-0.381***
		(-5.402)	(-5.449)	(-6.329)	(-6.403)
FUND ACTIVNESS		-1.307 ***	-1.369 ***	-1.137***	-1.202 ***
		(-4.493)	(-6.279)	(-3.205)	(-3.384)
LFAMTNA		0.289 ***	0.289 ***	0.262 ***	0.263 ***
		(8.993)	(9.072)	(7.753)	(7.8010)
LFTNA	0.311 ***	0.244 ***	0.242***	0.253***	0.249 ***
	(12.892)	(9.382)	(9.339)	(8.729)	(8.570)
LFAGE	0.929 ***	0.832 ***	0.833 ***	0.903***	0.910***
	(16.229)	(14.653)	(14.708)	(13.071)	(13.235)
FOPEX				-19.736	-24.207
				(-1.137)	(-1.387)
LFAMTNA* ACF			-1.168 **		-0.494
			(-2.3658)		(-0.823)
CRSP OBJ	NO	NO	YES	NO	YES
FUND/FAMILY/TIME FIXED EFFECTS	YES/YES/YES	YES/YES/YES	YES/YES/YES	YES/YES/YES	YES/YES/YES
R-SQUARED	54.65%	55.03%	55.13%	55.27%	55.42%
N-OBS	91,786	91,876	91,876	28,875	28,875

Table 7 Relationship between fund holdings turnover and fund family ACF. This table reports the estimated coefficients of quarterly columns (1) to (3)) and year panel regression (columns (4) & (5)) capturing the relationship between the fund trading proxy (**FHOLDT**) and the affiliated fund family specialisation in the active management segment (**ACF**) between 2006 to 2020. My dependent variable is a proxy for the funds trading frequency which captures how frequently stocks in a fund's portfolio are turned over (**FHOLDT**) as proposed by Gaspar, Massa and Matos, 2005) The key independent variable of concern is the fund family's asset-based concentration in the active management segment (**ACF**). Other lagged control variables include, the fund investment objective codes (**CRSP OBJ**), the fund's portfolio asset concentration (**HHI**), the fund-level activeness, obtained by one minus the R-squared derived from Carhart's four factor model (**FUND ACTIVNESS**) (Amihud and Goyenko, 2013), the logarithm of the fund family's total assets under management (**LFAMTNA**), the logarithm of the fund's total assets under management (**LFTNA**), the logarithm of the number of years since the fund was offered (**LFAGE**), funds annual operating expenses (**FOPEX**) and an interaction term between the fund family's total assets under management and their asset based concentration in the active management segment (**LFAMTNA* ACF**). The regression estimates all include fund, family and time fixed effects. All estimated coefficients pooled panel regressions include clustered standard errors', t-statistics reported in brackets with one, two and three asterisks indicate a statistical significance at the 10%,5% and 1% levels, correspondingly.

Table 7: Relationship between an Active Funds Trading Frequency and its affiliated Fund Family's ACF

Dependent Variable: FUND HOLDINGS TURNOVER

	1	2	3	4	5
ACF	**0.185*** (5.452)**	**0.146*** (4.291)**	**0.145 *** (4.285)**	**0.195 *** (4.092)**	**0.190* (1.894)**
HHI		0.013*** (3.9600)	0.014*** (3.974)	0.011 * (1.937)	0.011* (1.932)
FUND ACTIVNESS		0.079*** (4.179)	0.078*** (4.158)	0.057 *** (2.215)	0.054 ** (2.071)
LFAMTNA		-0.007** (-3.465)	-0.007 *** (-3.651)	-0.001 (-0.3271)	-0.001 (-0.523)
LFTNA	-0.017 *** (-12.790)	-0.013*** (-9.691)	-0.013 *** (-9.719)	-0.015 *** (-6.377)	-0.014 *** (-6.455)
LFAGE	-0.013 *** (-5.930)	-0.009 *** (-4.219)	-0.009*** (-4.233)	-0.011 *** (-3.752)	-0.011*** (3.399)
FOPEX				6.7400 *** (3.409)	6.7320*** (7.592)
LFAMTNA* ACF			0.071 (1.248)		0.162 ** (2.196)
CRSP OBJ	NO	NO	YES	NO	YES
FUND/FAMILY/TIME FIXED EFFECTS	YES/YES/YES	YES/YES/YES	YES/YES/YES	YES/YES/YES	YES/YES/YES
R-SQUARED	22.73%	23.15%	24.29%	26.29%	29.63%
N-OBS	103895	103895	103895	37205	37205

Table 8 Relationship between fund turnover and fund family ACF. This table reports the estimated coefficients of yearly panel regression capturing the relationship between the funds turnover ratio and the affiliated fund family specialisation in the active management segment (**ACF**) between 2006 to 2020. My key dependent variable is a ratio between the dollar buys and sells in the previous year and the total assets under management for a fund (**TURNOVER RATIO**) as declared by the fund in the CRSP-MFDB. The main independent variable of interest is the fund family's asset-based concentration in the active management segment (**ACF**). Other lagged control variables include, the fund investment objective codes (**CRSP OBJ**), the fund's portfolio asset concentration (**HHI**), the fund-level activeness, obtained by one minus the R-squared derived from Carhart's four factor model (**FUND ACTIVNESS**) (Amihud and Goyenko, 2013), the logarithm of the fund family's total assets under management (**LFAMTNA**), the logarithm of the fund's total assets under management (**LFTNA**), the logarithm of the number of years since the fund was first offered(**LFAGE**), funds annual operating expenses (**FOPEX**) and an interaction term between the fund family's total assets under management and their asset based specialisation in the active management segment (**LFAMTNA* ACF).** The regression estimates all include fund, family and time fixed effects. All estimated coefficients of the pooled panel regressions include clustered standard errors, with t-statistics reported in brackets with one, two and three starts indicate a statistical significance at the 10%,5% and 1% levels, correspondingly.

Table 8: Relationship between an Active Funds Trading Frequency and its affiliated Fund Family's ACF

Dependent Variable: TURNOVER RATIO	1	2	3
ACF	**0.558 ****	**0.293 ****	**0.130 ****
	(2.049)	**(2.587)**	**(2.303)**
HHI		0.025	0.024
		(1.235)	(1.338)
FUND ACTIVNESS		0.120	0.099
		(0.120)	(1.098)
LFAMTNA	-0.035***	-0.035 ***	-0.033***
	(-3.208)	(-4.498)	(-3.238)
LFTNA	-0.014 **	-0.025 ***	-0.013 **
	(-2.075)	(-4.844)	(-2.029)
LFAGE	-0.012	-0.002	-0.001
	(-1.124)	(-0.045)	(-0.074)
FOPEX	21.040 ***	20.978 ***	8.407 **
	(5.212)	(5.189)	(2.360)
LFAMTNA* ACF			0.170
			(1.218)
CRSP OBJ	NO	NO	YES
FUND/FAMILY/TIME FIXED EFFECTS	YES/YES/YES	YES/YES/YES	YES/YES/YES
R-SQUARED	28.91%	33.56%	33.67%
N-OBS	29274	29274	29274

Section 4.3. Heterogeneity in fund family strategies to produce stellar performing funds

In **Section 4.3**, I provide empirical evidence addressing the issue of why fund families highly concentrated in the active management segment engage in a detrimental aggressive trading strategy which has found to be suboptimal for fund performance. More importantly, following Nanda, Wang, and Zheng (2004), I analyse whether fund families with a higher ACF operate funds with a lottery-like behaviour to generate star performance. Overall, my objective is to investigate the economic mechanism that drives the results in Tables 6 to 8.

Previously in **Section 4.1**, I provide evidence indicating that funds that hold onto their stocks for shorter periods and, therefore, trade frequently underperform peer funds with higher fund durations. So why do funds trade so frequently? Following on, in **Section 4.2**, I consider the fund family as the driving factor behind the high trading levels generated by equity mutual funds. More importantly, I provide evidence suggesting that funds offered by families with a predominant active product offering generate higher trading frequency levels. However, the results in **Section 4.1** still stand that, on average, high trading frequently causes underperformance. So, what strategy justifies why families with a higher ACF engage in such aggressive trading strategies? Why are fund families pushing their active funds to trade a lot? Following Nanda, Wang, and Zheng (2004), fund families must generate stellar performing funds by engaging in high risks. They provide evidence that producing stellar performance attracts fund flows to the star performing fund and all the funds in the family. Thus, I predict that fund families with a higher ACF engage in aggressive trading as they attempt to create top-tier funds to attract investor flows. Therefore, **Section 4.3** examines whether funds offered by families with a higher ACF on average hit the top performance rank more than funds of affiliated lower ACF families.

I address this intuition by first sorting funds into quintiles according to their family affiliated ACF, with funds in quintiles one and five belonging to the families with the lowest and highest ACF, respectively. After that, funds are sorted according to their end-of-year performance following the work by Chelaiver and Ellison (1997). The performance of the funds is determined by the alpha obtained from the four-factor benchmark model (Carhart, 1997). Specifically, a dummy variable is created at the end of each year regarding whether the fund was ranked in the top 1%,5%, and 10% groups based on performance. After that, the average number of times that funds in each quintile have been ranked in the top 1%, 5%, and 10% performance bands, respectively, is calculated to examine the prediction that the funds offered by families with a higher ACF are more likely to generate top rank performance. In addition, time-series averages between 2006 to 2020 of the fund and affiliated family characteristics for each ACF quintile are calculated to further examine the findings.

Table 9 reports the average number of times funds in each quintile are ranked in the top 1%,5%, and 10% performance bands. The results display a monotonic increase in the hit rate from quintile one to five. This suggests funds offered by families with a higher ACF are more likely to generate top-tier performance. This evidence is complemented by the findings in Table 10, which report the percentage of funds in each quintile that are ranked in the top performance bands. Table 10 reinforces the findings of Table 9 as it also demonstrates a monotonic increase in the percentage hit rate. Therefore, fund families with a higher ACF appear to be pushing their active funds to trade a lot as they attempt to top the rank in performance. The significance of the results is verified by a standard two-sided t-test between quintiles one and five, which demonstrates statistical significance among all performance bands.

However, following the inception literature, one can argue that funds ranked in the higher quintiles are just younger, start-up funds that naturally take a lot more risk and therefore are more likely to produce stellar performance. Evans (2010) explores incubation as a performance-enhancing strategy for fund families. He finds that funds in their starting years outperform funds in the non-incubation period by 3.5%. Evans states that this is because the fund family implements more risky strategies for younger funds. Evans (2010) also provides evidence showing that when the incubated funds are opened to the public, they attract high flows. Therefore, it could be that my results are driven by the incubation strategy, where funds in higher quintiles are just younger start-up funds. I address this concern by computing time-series averages of fund and family affiliated characterises for each quintile and performance band individually.

Table 11 displays the time-series averages of fund and family affiliated characteristics of funds in the top 1% performance rank. Evidently, my results are not driven by the inception literature as the age of funds has no monotonic trend. This is consistent with Tables 12 and 13, which also display no trend in the average age of funds in each quintile. In addition, the monotonic increase in both the average turnover and expense ratio reinforces the belief that active funds offered by families with a higher ACF engage in high trading strategies. Thus, if families with a higher ACF truly engage in lottery-like behaviour through high trading strategies, we should observe a lack of consistency in their performance ranks. Therefore, I take the volatility of the residuals from Carhart's four-factor model to explore the consistency in performance among the top-ranking funds. As displayed in Tables 11 to 13, the volatility of funds increases steadily from quintile to quintile. I complement the volatility measure by conducting a Kruskal Wallis test. For funds in the highest and lowest quintiles, I compare the consistency in their performance rank from one year to another, respectively. Specifically, I test the null hypothesis that the mean rank of the performance of funds in quintiles 1 and 5 is not the same from one year to the next. On average, funds in the lowest quintile have a P-value of -0.1225, whereas funds in the highest quintile report a P-value of -0.064. The average P-value of funds in the lowest quintile is substantially higher compared to the highest quintile. This indicates that the performance rank of funds with higher affiliated family ACF is less consistent. Thus, it must be that the funds in the highest quintiles take a lot of risks to generate star performance, and that risk causes noise in their performance, making it unlikely that the fund is still a top-ranking fund next year-round. Overall, the evidence presented in Tables 9 to 13 suggests that fund families are engaging in a risky lottery-like strategy by pushing their active funds to trade frequently with the objective of generating top-tier performance.

Table 9 Relationship between ACF and top performance rank. This table presents the average number of times funds in each ACF quintile have been ranked in the top 1%,5%, and 10% performance bands. Statistical significance at the 10%, 5%, and 1% levels are represented by one, two, and three asterisks correspondingly.

Table 9: Average Number in Each Quintile Funds Rank in The Top Performance Bands

	1	2	3	4	5
TOP 1 %*** (4.93)	0.36	0.90	1.45	2.09	8.18
TOP 5 %*** (4.42)	9.09	10.36	12.72	13.36	22.82
TOP 10 %*** (4.61)	20.27	22.54	27.27	27.27	40.00

Table 10 Relationship between ACF and top performance rank. This table presents the percentage of funds in each ACF quintiles ranked in the top 1%,5%, and 10% performance bands, respectively. One, two, and three asterisks represent statistical significance at the 10%, 5%, and 1% levels, correspondingly.

Table 10: Percentage of Funds in Each Quintile Who Rank in The Top Performance Bands

	1	2	3	4	5
TOP 1 %	0.12%	0.33%	0.54%	0.07%	3.01%
TOP 5 %	2.98%	3.77%	4.91%	4.93%	7.41%
TOP 10 %	6.76%	8.30%	10.01%	10.56%	14.76%

Table 11, 12, and 13 The tables report the time-series averages of fund and family affiliated characteristics from 2006 to 2020. The averages are taken for each quintile one through to five, containing funds with the lowest and highest family affiliated **ACF**. More importantly, the averages are only taken of the funds which have been ranked in the top 1% (Table 11),5% (Table 12), and 10% (Table 13) based on their end-of-year performance. The averages of the fund and family affiliated characteristics are computed as: the number of years since the fund's inception (**Fund Age**), the funds size of assets under management (**Fund TNA**), the fund families size of assets under management (**Family TNA),** the funds turnover ratio displayed as a percentage, declared by CRSP-MFDB (**Fund Turnover Ratio**), funds annual operating expenses reported as a percentage (**Fund Expense Ratio**), the volatility of the return residuals obtained from the Carhart four-factor model (1997) (**Volatility**), the fund and fund families size of assets under management for the whole sample including funds not being ranked in the top bands ((**All Family TNA**), (**All Fund TNA**)), the average number of funds per family and per quintile that have been ranked in the top 1%,5% and 10% bands based on end of year performance respectively (**Percentage per fam, Percentage per quintile**)).

Table 11: Time Series Averages of Fund and Family Affiliated Characteristics (Top 1%)

	1	2	3	4	5
Fund Age	6.42	8.66	9.74	7.15	8.44
Fund TNA	251.30	467.93	1015.22	1605.81	1887.05
Family TNA	7422.91	8185.97	8731.33	10739.94	12781.03
Turnover Ratio	49.17%	58.04%	60.12%	58.38%	62.55%
Expense Ratio	0.88%	1.15%	1.53%	1.57%	1.59%
Volatility	0.010	0.013	0.017	0.017	0.020
All Family TNA	11899.20	11551.37	8424.74	8101.17	3196.03
All Fund TNA	1962.09	1058.25	905.66	1274.55	889.62
Percentage per fam	26.07%	14.61%	18.01%	23.13%	33.08%
Percentage per quintile	0.10%	0.30%	0.50%	0.70%	3.00%

Table 12: Time Series Averages of Fund and Family Affiliated Characteristics (Top 5%)

	1	2	3	4	5
Fund Age	8.46	8.49	8.26	8.35	8.37
Fund TNA	1226.89	1480.16	1255.26	1873.24	2291.02
Family TNA	5366.92	6663.75	6659.28	8648.50	10182.24
Turnover Ratio	38.94%	55.52%	51.86%	59.86	64.47%
Expense Ratio	1.02%	1.12%	1.15%	1.16%	1.18%
Volatility	0.010	0.012	0.013	0.014	0.017
Percentage per fam	19.21%	12.28%	16.88%	21.48%	35.09%
Percentage per quintile	2.98%	3.77%	4.91%	4.92%	8.41%

Table 13: Time Series Averages of Fund and Family Affiliated Characteristics (Top 10%)

	1	2	3	4	5
Fund Age	8.34	8.16	8.29	8.20	8.30
Fund TNA	1001.75	1582.20	1017.02	1792.01	1913.64
Family TNA	4342.24	5945.38	7791.36	9844.57	9555.62
Turnover Ratio	46.28%	52.72%	56.51%	57.13%	63.71%
Expense Ratio	1.02%	1.12%	1.22%	1.26%	1.27%
Volatility	0.010	0.011	0.011	0.013	0.016
Percentage per fam	19.97%	15.91%	23.33%	23.70%	37.63%
Percentage per quintile	6.76%	8.30%	10.00%	10.56%	14.76%

Section 4.4. Stellar performance-flow relationship

This section presents evidence on the implications of the lottery-like strategy in line with the high trading frequency implemented by funds and their associated fund families. More importantly, I aim to explore the effects of such strategies on the flow of investor capital to the star performing funds and their sibling funds within the family across the five quintiles established in **Section 4.3**. Specifically, **Section 4.4** explores the relationship between the end of year net cash flows experienced by funds based on their lagged performance rank. The literature has reported that mutual fund investors chase past performance when deciding where to invest their money across funds (see, e.g., Sapp et al., 2004 and Chevalier et al., 1997). More importantly, past performance generates flows to the best-performing fund and all other funds within the fund family (Nanda, Wang, and Zheng, 2004). Therefore, I expect to observe that funds in the highest quintiles that hit the top rank the most on average should also attract the most investor capital.

Precisely, I calculate the average net cash flows of funds that rank in the top 1%,5%, and 10% performance bands and their affiliated sibling funds. To measure the net cash flows, I use the model developed in Berk and Green (2004), which looks at the change in the TNA for a fund from one year to the next while also capturing the lagged fund return. This model is illustrated as shown below:

$$FLOWS_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} + (1 + R_{i,t})}{TNA_{i,t-1}}, \qquad (12)$$

where $FLOWS_{i,t}$ refers to the cash flows experienced by fund *i* at time t, $TNA_{i,t}$ and $TNA_{i,t-1}$ denote the total net assets under management (TNA) by fund *i* at time *t* and *t-1* and $R_{i,t}$ represents the net return of fund *i* at time *t* obtained from the alpha derived from the Carhart (1997) four factor model. However due to mergers and fund splits, outliers have appeared in the data and therefore I winsorised the fund flows at the 5^{th} and 95^{th} percentiles.

Table 14 reports the time-series averages of the cash flows experienced by star performing funds (flows) and all the other funds in the family which do not hit the top performance rank (sibling flows). The results indicate an upward trend in fund flows for all three top-rank groups. This evidence is consistent with the literature, which reports a positive relationship between past performance and subsequent fund flows. More importantly, the positive cash flows experienced by sibling funds of star performers coincide with the findings of Nanda, Wang, and Zheng (2004), who document that the star performance of one fund generates inflows for the whole family. The results portray the implications of stellar performance, which highlights the rationale and benefits of fund families operating funds with a lottery-like behaviour by encouraging them to trade frequently.

Overall, my results first show that funds that trade a lot generate suboptimal net performance. After that, I provide evidence attributing the high trading levels to the fund family. I find that active funds offered by families who specialise in active management are traded more frequently. However, on average high trading strategies generate suboptimal performance for the family, so why do they engage in such high trading strategies. I show that among active funds, those offered by families with a higher active product offering are more likely to produce star performance. This is consistent with these families on average experiencing positive net cash flows from investors. Thus, it must be that these families are operating funds with a lottery-like behaviour by encouraging them to trade frequently in the hopes of generating star performance and thereby attracting fund flows.

Table 14 This table displays the time series averages of the net cash flows experienced by star performing funds and their affiliated sibling funds from 2006 to 2020. **Net cash flows** are measured by the model developed by Berk and Green (2004). All values are represented in percentage terms with one, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Significance levels are determined by a standard two-sided t-test of quintile 1 and 5.

Table 14: Relationship Between Stellar Performance and Investor Flows

	1	2	3	4	5
Flows (1%) ***	8.83%	8.99%	9.92%	11.34%	16.67%
Sibling flows (1%) **	13.51%	7.87%	9.15%	14.36%	10.79%
Flows (5%) ***	8.83%	7.07%	8.69%	11.59%	14.65%
Sibling flows (5%) ***	13.51%	7.87%	9.15%	14.36%	10.79%
Flows (10%) ***	8.84%	8.99%	10.15%	11.59%	12.97%
Sibling flows (10%) ***	9.70%	12.78%	8.80%	17.36%	9.50%

Section 4.5. Limitations

The study has some limitations, which due to the limited time and lack of accessibility to data, could not be addressed. The study doesn't account for the heterogenic managerial characteristics, which could account for some variability in the results. Specifically, it could be that the high trading frequency by active funds is driven by the fund manager's own desire linked to their specific characteristics, such as age, gender, university, past performance, etc. However, this particular alternative intuition could not be addressed due to the lack of access to fund manager-level data. Data limitations also extend to the CRSP-MFDB. At times, past returns are doubled in the database; for example, if a fund is split into three share classes, each of the classes will inherit the entire return history of the fund. This creates bias surrounding the averaging of returns for mutual funds. Moreover, selection bias is also present as there could be cases where only successful data on private funds are included in the database. However, the CRSP-MFDB is still preferred to other databases such as Morningstar used in other studies (Elton, Gruber, and Blake, 2000) as it has some significant advantages. The CRSP database is more recent and includes data on funds that merge and liquidate. Therefore, it contains information that does not exist anymore, thus controlling for survivorship bias (Elton, Gruber, and Blake, 2000). Even though CRSP-MFDB has some limitations to its dataset, it still has significant advantages over other databases and thus is used as the primary data source for my study.

On the other hand, the limited amount of time has restricted my analysis in Section 4.3, which looks at the heterogenic fund family strategies in generating star funds. Specifically, the study doesn't implement a multivariate model to study the relationship between the performance rank of funds and their affiliated fund families ACF. Thus, future studies could potentially employ a logit or probit regression model to further elaborate on my results on the likelihood that funds offered by families with a higher ACF are more likely to be ranked in the top performance bands.

On another note, potential endogeneity issues arising from my study have been addressed, given the limited time and data accessibility. Specifically, I use various measures to capture the trading frequency and performance of funds and incorporate different model specifications to ensure the results are robust. In addition, the inclusion of lagged variables ensures that the causation can only go one way. However, the optimal solution to mitigate endogeneity concerns would be through the implementation of an instrumental variable. Namely, using fund mergers or fund family sponsorship acquisitions as the key instrumental variable to study the effects of family ACF on subsequent trading frequency could potentially mitigate the effects of endogeneity. Thus, I encourage future studies to implement this method to enhance the validity of my findings.

Section 4.6. Implications for further research

Future extensions of my work could look into analysing the relationship between the trading frequency of funds and an alternative measure capturing a fund family's specialisation in the active vs. passive management segments. Specifically, academics could use the weighted average activeness of the fund themselves as a proxy of the fund family's specialisation in the active division. Furthermore, it would be worthwhile to include more periods in the analysis, such as every month, if CRSP were to release this data.

In addition, future academics could consider another dimension in analysing the effects of fund family-level decisions on the turnover of active funds. Precisely, looking at the impact of a fund family's cooperate governance structure on the trading levels of funds would seem interesting. Academics could consider the boards, size, gender and diversity as potential factors which could impact the fund manager's decision to trade.

Section 5. Conclusion

Trading levels in the fund industry are extreme. In 2011 Alice Ross reported in the "Financial Times" that some funds have an annual turnover of over 500%. These extraordinary trading levels by some funds translate into extra costs for investors, which negatively impact their net performance. Thus, in this thesis, I exploit this issue surrounding the high trading levels by funds by investigating the relationship between the trading frequency and subsequent net fund performance. Specifically, I regress the performance of a fund derived by the alpha from the Crahrat (1997) four-factor model on the fund duration (Cremers and Pareek, 2016) measure, which captures the trading frequency of funds. I find that funds that hold onto stocks for shorter periods and thereby trade a lot generate suboptimal net performance. This result is robust when incorporating the alpha derived from DGTW (1997) holding-based model as an alternative measure of fund performance.

Especially since the discovery that high trading strategies have a detrimental impact on fund performance, investors have sought a better understanding of the underlying factors contributing to the high trade levels observed in the mutual fund industry. The limited literature currently considers the overconfidence of investors (Barber and Odean, 1999), fund managers unique skill set (Cremers and Pareek, 2016) and their career concerns (Brown et al., 2001) as the key driving factors behind a fund managers decision to trade frequently. This research fills an important gap in the literature, as it studies the impact of a fund family's specialisation in the respective active vs. passive management segments on the subsequent trading frequencies of affiliated active fund offerings. Namely, I quantify a fund family's specialisation by measuring the degree of assets invested in active products while simultaneously implementing three proxies to capture the trading frequency of funds (i.e., fund duration, fund holdings turnover, and turnover ratio). Through a variety of panel variations, I regress the fund trading frequency proxies on the family ACF variable for my sample of mutual funds between 2006 to 2020. Through the analysis, I find evidence suggesting that active funds offered by families highly concentrated in the active management segment are traded more frequently. The result is robust to inclusions of fund, family, and time-fixed effects. After that, I explore the strategy that justifies why fund families specialising in active management implement such aggressive trading strategies, which generate net underperformance on average. Specifically, I test the hypothesis that active funds offered by families with a higher ACF are more likely to generate top-tier performance. By sorting funds into quintiles, my analysis suggests that families with a high ACF, on average, produce more top-ranking funds, indicating that these families are pursuing star performance. I provide a rational explanation of why fund families would engage in such a risky strategy by presenting evidence that indicates that one fund's star performance subsequently attracts investor flows to all funds in the family.

Thus, fund families with a high ACF are pursuing a lottery-like strategy as they encourage their funds to trade a lot, hoping that one or a few of their funds will be ranked at the top and thereby attract investor capital for the fund family.

The importance of such a study is reinforced by the belief that during an investor's decision-making process, they first recognise the fund family and then select among the funds offered Massa (2003). Thereby understanding the implications of a fund family's expertise in the active vs. passive segments has direct economic implications on an investor's wealth across family funds. After analysing the detrimental consequences of star-performing strategies implemented at the family level, investors can better incorporate their risk preferences when allocating their capital across funds. However, as mentioned earlier, the benefits of a successful high trading strategy are enjoyed solely by the fund family. In contrast, the investor bears the costs in the form of higher fees, inconsistency in performances, and overall underperformance of such an approach. Thus, such an issue represents an agency problem which regulators must pay attention to. Therefore, my study evokes change, encouraging stricter regulations to mitigate such an issue from continuing to occur. Consequently, such benefits following my research led to the overall improvement in the transparency and development of the mutual fund industry.

Appendix

1.A

After gathering all the necessary data there appeared to be some issues concerning the normality and skewness of some variables. Specifically, this is the case for the fund turnover, fund duration, fund holdings turnover and the family ACF, variables as shown by the below graphs.

Figure 2 Turnover ratio

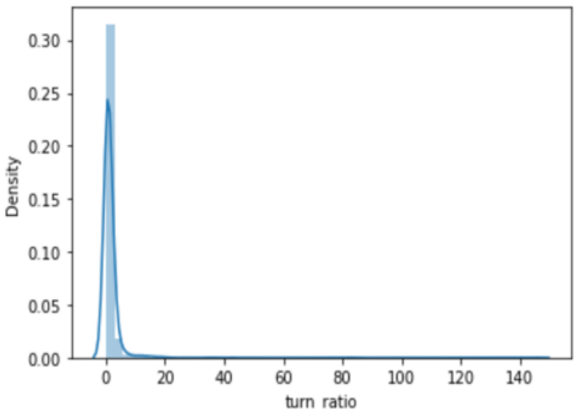


Figure 1 ACF

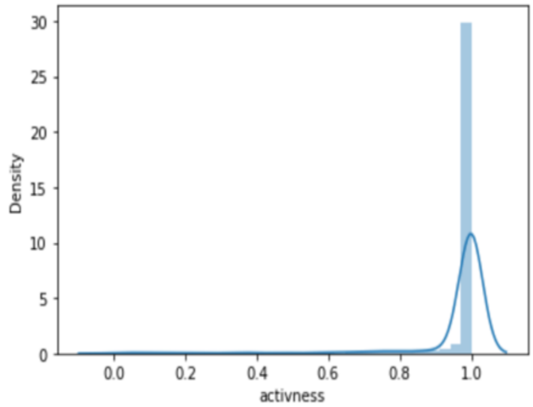


Figure 3 Turnover ratio Winsorised

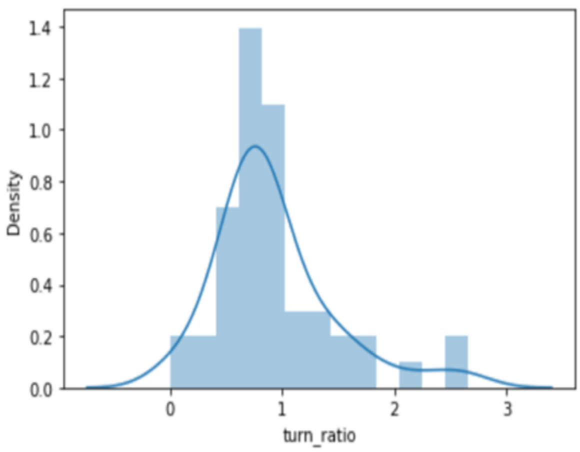


Figure 4 ACF Winsorised

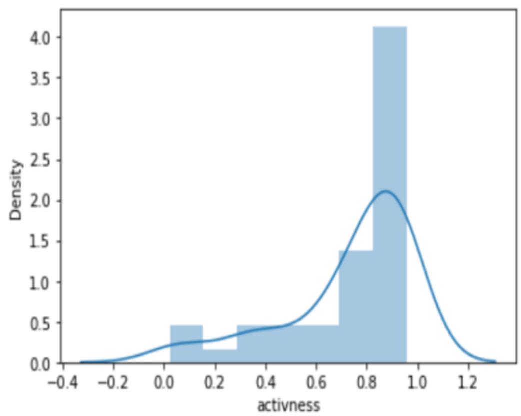


Figure 6 Fund Duration

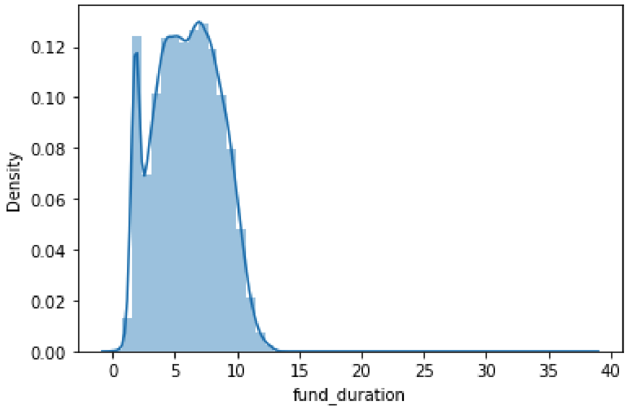


Figure 5 Fund Holdings Turnover

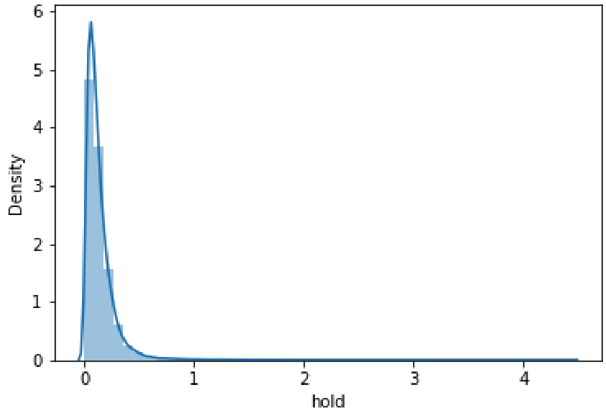


Figure 8 Fund Duration Winsorised

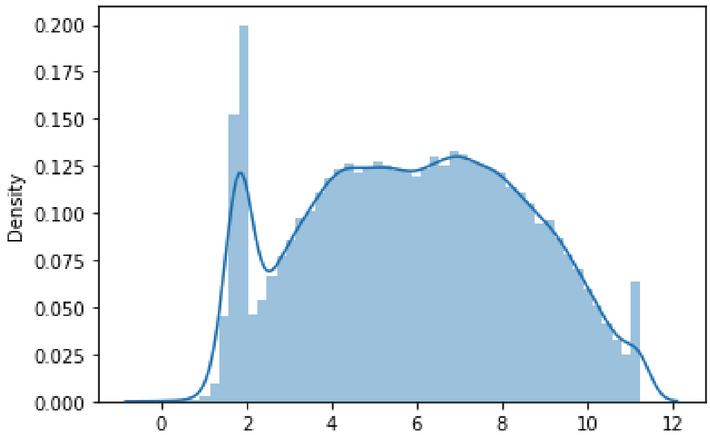
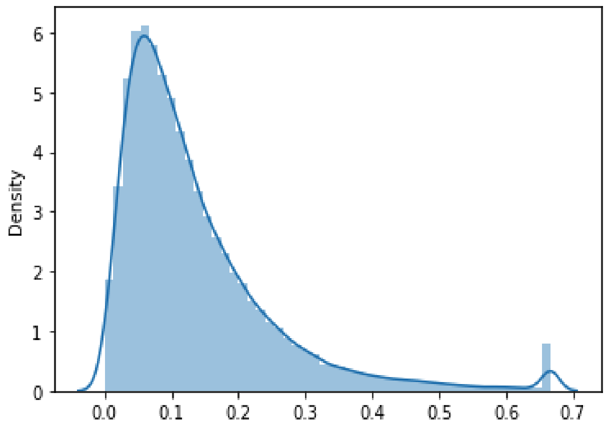


Figure 7 Fund Holdings Turnover Winsorised



As indicated by the following transformations, after winsorisng the data, the variables follow more closely a normal distribution.

Table 1B Pooled Panel regression: Fund trading frequency vs Fund net performance

Dependent Variable	Performance (alpha): 1) Carhart (1997) 4 factor model 2) Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW)
Independent variable	Fund Duration (Cremers and Pareek, 2015)
Controls	$\beta 1$* ln (Fund TNA) β2 * Operating Expenses β3 * ln (Fund Age) $\beta 4 *$Operating expenses * Fund Duration

$$Duration_{i,j}T-1 = d_{i,j}T-1 = \sum_{t-T-W}^{T-1} \left(\frac{(T-t-1)a_{i,j,t}}{H_{i,j}+B_{i,j}} + \frac{(W-1)H_{i,j}}{H_{i,j}+B_{i,j}} \right.$$

Table 2B Panel Regression: Fund trading frequency vs. Family active asset base concentration

Dependent Variable	Trading Frequency: 1) Fund Duration (Cremers and Pareek, 2015) 2) Fund Holdings Turnover (Gaspar,et al. 2005) 3) Fund Turnover Ratio (CRSP-MFDB**)**	$CR_{i,t} = \frac{\sum_{j\epsilon Q} \lvert N_{j,i,t}P_{j,t} - N_{j,i,t-1}P_{j,t-1} - N_{j,i,t-1}\Delta P_{j,t}\rvert}{\sum_{j\epsilon Q} \frac{N_{j,i,t}P_{j,t} + N_{j,i,t-1}P_{j,t-1}}{2}}$
Independent variable	Family activeness (ACF)	$ACF = 1 - (\frac{Sum\ TNA\ of\ index\ \&\ etf\ porducts}{sum\ total\ family\ TNA})$
Controls	β1* ln (age) $\beta 2$ * ln (Fund TNA) $\beta 3$* ln (Family TNA β4 * ln (Operating Expenses) β5 ∗ Activeness of fund (Amihud and Goyenko, 2013) β6 ∗ ln(Asset concentration (HHI)) β7 ∗ ln(Family TNA)* activeness of fund D1* Fund style (CRSP OBJ CD)	$1 - R^2 = \frac{RMSE^2}{Systematic\ risk^2 + RMSE^2}$ $\sum_{i=1}^{N} s^2 i$
Fixed Effects	Fund Family Time	

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