

# ADVERTISING ON FACEBOOK: THE EFFECT ON FUND FLOWS OF FUND FAMILY

by

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## **Abstract**

Using data for the top 100 US mutual fund families for the period between Jan 2009 to Jun 2016, this paper studies the relationship between mutual fund families' advertising on Facebook and their fund flow. In particular, I examine whether advertising via social media helps mutual funds to attract new fund flow. I also include the number of followers to proxy for visibility and past returns to control for performance. In line with previous research, I find that large part of the variation in the mutual fund flows remains unexplained. My findings suggest that the effect of higher attention drawn by social media advertising on the new fund flow (although positive) is weak.

**Keywords:** Advertisement; Facebook; Mutual funds; Fund family; Fund flows

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# 1: Introduction

With the emergence of different kinds of social media, the way people interact with real world has changed, and the way they buy and consume products and services has also been changed. The more popular social media becomes, the more companies focus on marketing on these platforms. The same trend applies to the mutual funds industry. Mutual funds, as one of the most popular investment products for investors, need to market themselves as they have the non-negligible amount of retail investors. As a result, fund families<sup>1</sup> have shifted the way they advertise and have become highly active on social media. It is also a way to compete with other types of investment products such as EFTs, which has gained a lot of attention recently and taken away some investment monies from the mutual funds. Thus, in this paper, I would like to look at the impact of advertising on Facebook and whether it helps to attract new fund flows to the fund family.

In the past, fund family had advertised on traditional platforms such as newspapers and magazines. Recently, as social media became more and more influential, mutual fund families began to be active on the Internet as a way to advertise themselves. I looked at some fund families' website and found out the most popular social media they use are Facebook, Twitter, YouTube and LinkedIn. This paper chooses Facebook as the medium to start with as it appears to be the most relevant one among other platforms.

The reason is that the way each platform achieves visibility is different, which provides ideas for my research. For example, LinkedIn is a relatively more professional platform and more targeted for people looking for a career in a certain industry. So even if a fund family has a lot of followers, this may not indicate more potential customers (which may not be true and can be a future research direction). Since the actual number of viewers for each post on YouTube is difficult to count as it is inflated (people who watched the first five seconds will also be included in the number of viewers) it is not ideal to use YouTube at this point. As for Twitter, it is limited by the length of each posting, which may pose certain restrictions on what the fund families would like to tell. Because of all the limits, it makes Facebook the most ideal social media to start

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<sup>1</sup> Fund Family: a group of mutual funds offered and managed by the same investment or management company. Generally, the constituent funds cover a wide range of fund categories and investment objectives.

with, as it targets to everyone on the Internet, is not career-oriented, and can post various types of files including photos, videos and articles. Perhaps there is some overlap too. So what you find for Facebook will hold for twitter and the other way around. So looking at just one platform is enough.

On the other hand, mutual fund has always been the focus of researchers' and fund managers, and the most important question has been what are the determinants of the flow of funds. As one of the potential reasons, advertisement has also been a popular topic. The reason is that advertisement influences people's way of spending in certain ways. Thus, researchers are curious about whether advertisement helps the growth of fund flows to the fund family. In the past, a large number of studies have looked at fund flows and performance whereas other studies have looked at mutual funds advertising and fund flow. But there has not been much studies on the effects of advertising, fund performance and returns together on fund flows. Thus, I would like bring these factors together and look at the big picture.

Having said that, the ultimate goal of this paper would still be to study the relationship between advertisements on Facebook and total monthly fund net flows to fund family, which focuses on whether social media attracts new fund flows. I select the top 100 largest US fund families, and I hand-collect information on their social media presence such as how long they have been on Facebook and how many followers they have, as well as financial information on their net asset values and performance. I estimate a panel data fixed effects model for the family flow of funds as well as a pooled regression model. The relationship is modelled as a four-factor regression model, similar to Fama-French model.

The remainder of this thesis is organized as follows. The next section presents the literature review. Section 3 provides information on the data sources and discusses some summary statistics. Section 4 presents the methodology and interprets the estimation results. Conclusions and suggestions for future research are in the last section. The next section provides a literature review on the factors that have impact on fund flows.

## 2: Literature Review

As mutual funds represent one of the most popular investment instruments, it has long been a focus on what contributes to the mutual fund flows. As of today, over 60 percent of investment products of US individual investors are mutual funds. Institutional investors also use mutual funds as important investment vehicle among other investment funds such as ETFs, endowments, foundations and pension plans.

For instance, prior research documents a convex relation between past performance and the mutual fund flows. Ippolito (1992) find that investment monies in the mutual fund industry would move toward recent good performers and away from recent poor performers over the period 1965-84. The assumption is that low-quality funds exist so that investment performance residuals convey quality information. Wermers (2003) further shows that at least a portion of the persistence in mutual fund returns can be attributed to the tendency of consumers to aggressively chase mutual funds with high past returns, which results in fund managers chasing stocks with high past returns. Warther (1995) splits fund flows into expected and unexpected components and examines the relationship between unexpected flows and lag market returns. Luo (2003) examines the fund flows from the market volatility side and finds that stock funds react negatively to past market returns, while bond funds show trend-chasing pattern.

Johnson's (2007) paper suggest a flow components perspective by testing whether shareholders continue to respond to returns after they make their initial investment in fund shares. Results show that "new" and "old" shareholders have a similar, positive response to lagged returns when buying fund shares. Frazzini (2008) argues that individual investors are dumb money, meaning that they do the wrong thing by investing their money in mutual fund which own stocks that do poorly over the next few years. On the other hand, institutional investors are smart money and trade in the opposite direction of individual investors. Zheng (1999) argues that the smart money effect exists in small funds, although short-lived with the positive and negative portfolios reversals after 30 months. Also, even when the investors are able to pick good performers, execute timing can be a tricky factor. Friesen and Sapp (2007) find that investors who select the best performing funds also exhibit the worst performance timing of all.

When investigating the relationship between aggregate mutual fund flows and security returns, Warther (1995) find that flows into stock funds are correlated with stock returns, flows into bond funds are correlated with bond returns, and flows into precious metals funds are correlated with gold returns. Cross-correlations between the various groups is negligible. Meantime, mutual fund flows and security prices move together.

From a more systematic perspective, there are studies on factors that may impact mutual fund flows. For example, Barber, Huang and Odean (2016) decomposed the returns of each mutual fund into eight components: a seven-factor alpha and flows associated with market, size, value, momentum factors, and three industry factors and find that flows respond to each of the eight return components, but to varying degrees, where the fund alpha generated the largest flow response. Also, the flows of investors who are likely more sophisticated—direct-sold investors, investors trading during low-sentiment periods, and wealthier investors are more aware that returns are not indicative of the skills of the fund manager.

Investor behavior also has impact on mutual fund companies' incentives with respect to risk. Chevalier and Ellison (1997) note that mutual fund advisor compensation is typically tied to funds under management which implies that investor flows serve as an implicit incentive mechanism. Brown, Harlow and Starks (1996) argue that compensation tied to relative return performance of funds under management that is assessed annually creates incentives for managers to effectively changing managerial objectives from a long-term to a short-term perspective.

By studying the behavioral factor in mutual fund flows, Goetzmann, Massa and Rouwenhorst (2000) show that the difference between stocks and bond fund returns is the major behavioral factor. They also show that rebalancing decisions by investors are closely related to contemporaneous daily returns. They further attribute the result to the existence of behavioral factors per se such as market sentiment, or alternatively, flows and returns may both be correlated with an unidentified additional factor in the economy.

Irrational investor behavior also contributes to the increasing fund inflows when funds change their names to different styles, where the funds experience a significantly negative fund flows over the 6 months before the name change and have not spent much on marketing and advertising (Cooper, Gulen and Rau (2005)). This effect also shows that most individual investors are irrational. Huang, Wei and Yan (2012) eliminates the impact from unsophisticated investors and demonstrates that higher volatility of past performance attenuates sophisticated investors' reaction to past performance, making their fund flows less sensitive to performance. This



reduction in the flow-performance sensitivity may partially mitigate managers' incentive to increase portfolio risk.

Another interesting fact is the impact of the disposition effect on fund flows, a behavioral effect that has been widely documented for individual investors. Cici (2010) concludes that disposition-driven behavior has a negative effect on "winners" funds and could hurt investors by altering their asset allocations.

Other than those aspects, an interesting point of view is whether the brand image brings fund inflows. When testing the effect of advertising on fund flows, Jain and Wu (2000) find that the inflows to the advertised funds are about 20 percent larger than those for the nonadvertised funds with similar characteristics. The advertised funds they chose were advertised in Barron's or Money Magazine and had a superior past performance. Moreover, Cronqvist (2006) finds that fund advertising can arouse certain key positive emotions in investors, which make their attitudes towards a fund more favorable. Following that, Wang and Tsai (2014) demonstrate positive and direct effects of brand image on purchase intention, where delivering a positive brand image is mostly done by advertising and marketing. Sirri and Tufano (1998) demonstrate the contribution of advertising on fund flows by showing the negative impact of investors' search costs on fund flows, while advertisements reduce search costs to some extent because investors believe in the advertisements. . Sirri and Tufano (1998) also point out that garnering a larger share of current media cites is related to faster current growth. In a similar spirit, Barber and Odean (2008) conclude that individual investors display attention-driven buying behavior, while institutional investors do not display attention-driven buying.

Above I reviewed the findings related to the mutual fund flows in order to give an overall idea on what factors might have impact on aggregate fund flows. While institutional investors are sophisticated, individual investors are the major players in the game of trend-chasing and irrational behaving led by advertisements. In the next sections I will describe the data I use for this paper.

### 3: Data and Summary Statistics

For the empirical analysis, I use the Center for Research in Security Prices (CRSP) mutual fund database to obtain information about fund's total net asset value (TNA), fund identifier and the name of the fund family from the entire database. The data sample covers the period between January 2009 and June 2016. The reason the data starts from 2009 is because most fund families began to be active on Facebook in 2009. Non-surviving funds are included to account for survivorship bias.

After obtaining the data, I group the mutual funds together by each fund family and then rank the size of the fund families according to their total net asset value in June 2016. Fund families that are ranked at the top 100 are selected as the sample for this paper. Next step is to collect data from CRSP. As stated above, monthly data for mutual funds belonging to the selected fund families during the period from 2009 to June 2016 are collected. To be more specific, after obtaining the data, I sum monthly TNA for funds that are from the same fund family to get monthly TNA of each fund family. Then I calculate the change of monthly TNA and monthly return for each fund family.

Next, I look up on Facebook website to find out whether the fund families advertise. If that fund family does advertise, I search its profile to mark down when it starts to advertise, and how many followers it has so far. These will later be used to do the regression. Because there are about 90 observations on month and I only have current data on the followers, I assume the number of followers grows at a constant rate since the fund family began to be active on Facebook.

Table I shows the summary statistics for the variables I mentioned above. Panel I is the summary statistics for all families. There is around 8,900 observations. The different between the number of the TNA and  $\ln(\text{TNA})$  is due to some negative values in TNA, where TNA is the total net asset value.  $\ln(\text{TNA})$  is the variable to represent size of the fund family in the regression model in the next section. The fund flow is calculated by  $(\text{TNA}_t - \text{TNA}_{t-1} * (1 + \text{return}_t)) / \text{TNA}_{t-1}$ , where I take size and return into consideration and take those effect out, so the fund flow is presented as a percentage. And the monthly return of each fund family is the percentage change of TNA, denoted by  $R_{t-1}$ . Panel II and III show the summary statistics for fund families with

Facebook and without Facebook respectively. The average TNA for families with Facebook is much higher than families without Facebook. So do fund flows. Although, the average sizes of families with or without Facebook are about the same.

**Table I. Summary Statistics**

<b>Panel I: Summary Statistics - All Fund Families</b>					
	Observations	Mean	Std. Dev	Min	Max
TNA	8,978	135,995.50	319141.8	-13860	3631016
Size, ln(TNA)	8,962	10.65	1.58	-2.3	15.11
Fund Flows	8,977	123.92	10,994.06	0	1,040,400
Returns	8,880	0.162	11.1922	-65.6674	1020
Number of Followers	8,978	8930	57,297.92	0	1891530
Number of FF with FB	100	61			
<b>Panel II: Summary Statistics - Fund Families with Facebook</b>					
	Observations	Mean	Std. Dev	Min	Max
TNA	3,248.00	238,686.00	478,029.30	4,114.50	3,631,016.00
Size, Ln(TNA)	3,248.00	11.33	1.39	8.32	15.11
Fund Flows	3,248.00	0.0143	0.2127	0	7.3501
Returns	3,248.00	0.01	0.12	-0.82	2.71
Number of Followers	3,248.00	168,635.50	320,748.10	89.00	1,891,530.00
<b>Panel III: Summary Statistics - Fund Families without Facebook</b>					
	Observations	Mean	Std. Dev	Min	Max
TNA	5,730	77,786.34	143,927.10	-13,860.00	1,350,970.00
Size, Ln(TNA)	5,714	10.27	1.56	-2.30	14.12
Fund Flows, $\Delta$ TNA	5,279	194.17	13762.02	0	1,040,400
Returns	5,633	0.25	14.05	-65.67	1,020.00

TNA is the Total Net Asset Value for all funds in one family; Size of each family is denoted by ln(TNA); Fund flows are the difference between TNA in two consecutive periods; Returns are calculated by the percentage change of TNA in two consecutive periods; Number of followers is the followers each family has in each period.

Now, let's look at how each component changed over the years.

Table II shows the summary statistics for every single year. One thing to notice is that the average number of followers was only 3 in 2009 and rapidly grew to 65613 in 2016, with the number of fund families with Facebook grew from 8 in 2009 to 61 in 2016. The trend on both the fund families with Facebook and their followers show an increasing importance and popularity of

Facebook. As 2009 was near the end of financial crisis, the average TNA was at a relatively low level, with some fund families had negative TNA and negative fund flows. After 2009, TNA has been grow at a stable pace, with a bit reluctant in 2016. Returns on mutual funds are also worth noting: they were negative in 2010 and 2011, and they recovered in 2012 but have been fluctuating. It shows the overall unstable performance of mutual funds, although the TNA has been growing during this period of time. Overall, data from 2009 to 2016 all show an upward trend except returns are unpredictable. The rapid growth on Facebook and on the number of followers is remarkable.

**Table II: Summary statistics by Year**

<b>Summary Statistics: 2009-2016</b>								
	2009	2010	2011	2012	2013	2014	2015	2016
TNA	93288.8 (203651.7)	108082 (235115.3)	119462.3 (259160.3)	127338.6 (278681.8)	146687.3 (325141.9)	165124.5 (377722.8)	173618.4 (417806.9)	171879.8 (431791.9)
Size	10.07 (2.01)	10.42 (1.61)	10.58 (1.5)	10.64 (1.5)	10.8 (1.47)	10.95 (1.4)	10.97 (1.4)	10.9 (1.43)
Fund Flows	941.0748 (30309.05)	0.5421 (16.10)	0.0536 (10798.6)	0.2676 (8.9043)	0.0047 (0.0305)	0.0036 (0.0207)	0.0093 (0.1669)	0.0166 (0.2545)
Returns	1.2693 (31.9949)	-0.0011 (0.7366)	-0.0062 (0.2314)	0.0267 (0.5168)	0.0202 (0.0655)	0.0085 (0.0592)	0.000023 (0.0693)	0.0056 (0.1289)
Followers	3 (18.00)	22 (113.43)	161 (542)	596 (1776)	2068 (5796)	6804 (18483)	24354.39 (66577)	65613 (187522)
Number of FF with FB	8	20	37	48	51	53	57	61

Number of FF with FB: the number of fund families with Facebook.

Summary statistics of the mean of each variable with standard deviation in brackets.

## 4: Methodology and Results

This section describes the model I use to examine the relationship between fund flows and advertisements, and interpret the results I find for the effects of different factors on fund flows. I also compare my results with related literatures in the aspects of the variables that impact fund flows.

### 4.1 Methodology

I use two regression models to explore the relationship between various factors and the fund flows for a sample of 100 fund families. The model uses monthly data covering the period between January 2009 and June 2016. First, I run a pooled regression model, and then I run a fixed-effect panel regression model to compare and contrast the results of the two regressions.

The pooled regression model I use is:

$$\text{Fund Flow}_t = \alpha_1 + \beta_1 \text{FB}_t + \beta_2 \ln(\text{Followers})_t + \beta_3 \ln(\text{TNA})_t + \beta_4 R_{t-1} + \varepsilon,$$
$$t = 200901, \dots, 201606,$$

where the dependent variable,  $\text{Fund Flow}_t$ , equals to  $[(\text{TNA}_t - \text{TNA}_{t-1} * (1 + \text{return}_t)) / \text{TNA}_{t-1}]$ , at time  $t$ , representing monthly fund flows to each fund family,  $\text{FB}_t$ , represents each fund family's advertisement status on Facebook and I use one to denote active and zero to denote not active at time  $t$ ,  $\ln(\text{Followers})_t$  represents the number of followers at time  $t$ ,  $\ln(\text{TNA})_t$  is the size of the fund families at time  $t$ ,  $R_{t-1}$  is the gross rate of return on fund family  $i$  at time  $t-1$ , calculated by  $[(\text{TNA}_t - \text{TNA}_{t-1}) / \Delta \text{TNA}_{t-1}]$ ,  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$  and  $\beta_4$  are the coefficients of each factor to  $\text{Fund Flow}_t$ , and  $\alpha_1$  is the constant factor that cannot be explained by the variables the model assumed.

The fixed-effect panel regression model I use is:

$$\text{Fund Flow}_{i,t} = \alpha_2 + \gamma_1 \text{FB}_{i,t} + \gamma_2 \ln(\text{Followers})_{i,t} + \gamma_3 \ln(\text{TNA})_{i,t} + \gamma_4 R_{i,t-1} + \varepsilon,$$
$$i = 1, 2, \dots, 100, t = 200901, \dots, 201606,$$

where the dependent variable,  $\text{Fund Flow}_{i,t}$ , equals to  $[(\text{TNA}_t - \text{TNA}_{t-1} * (1 + \text{return}_t)) / \text{TNA}_{t-1}]$ , on fund family  $i$  at time  $t$ , representing monthly fund flows to fund families,  $\text{FB}_{i,t}$ , represents the fund family  $i$ 's advertisement status on Facebook at time  $t$ ,  $\ln(\text{Followers})_{i,t}$  represents the number of

followers on fund family  $i$  at time  $t$ ,  $\ln(\text{TNA})_t$  is the size of the fund family  $i$  at time  $t$ ,  $R_{i,t-1}$  is the gross rate of return on fund family  $i$  at time  $t-1$ , calculated by  $[(\text{TNA}_{i,t} - \text{TNA}_{i,t-1})/\Delta\text{TNA}_{i,t-1}]$ ,  $\gamma_1$ ,  $\gamma_2$ ,  $\gamma_3$  and  $\gamma_4$  are the coefficients of each factor to  $\text{Fund Flow}_{i,t}$ , and  $\alpha_2$  is the constant factor that cannot be explained by the variables the model assumed.

The purpose of the two regressions is to get the coefficients and the alphas, which reveals how the fund flows are affected by each of the variables. A pooled regression has the advantage of using all the variation in the data, while a fixed-effect panel regression enables us to more complicated behavioural models and can also minimise the bias that might result if we aggregate individuals or firms into broad aggregates.<sup>2</sup> A fixed effects model is a statistical model that represents the observed quantities in terms of explanatory variables that are treated as if the quantities were non-random. In panel data analysis, the term fixed effects estimator (also known as the within estimator) is used to refer to an estimator for the coefficients in the regression model. If we assume fixed effects, we impose time independent effects for each entity that are possibly correlated with the regressors<sup>3</sup>. The results of the two test are presented in below.

**Table III**

<b>Pooled Regression: 200901-201606 on Top 100 Fund Families</b>		
	Coefficient	p-value
Whether on FB	0 (omitted)	
Number of Followers	-0.0002	0.843
Size	0.0057	0.020
Returns, R	-0.2833	0.000
$\alpha$	-0.0600	0.030

**Table IV**

<b>Panel Regression: 200901-201606 on top 100 fund families</b>		
	Coefficient	p-value
Whether on FB	0 (omitted)	
Number of Followers	-0.0180	0.000
Size	0.2360	0.000
Returns, R	-0.2915	0.000
$\alpha$	-2.5439	0.000

<sup>2</sup> Panel Regression in Stata: An introduction to type of models and tests, Gunajit Kalita, Rio Tinto India, STATA Users Group Meeting, 1<sup>st</sup> August, 2013, Mumbai

<sup>3</sup> Source: Wikipedia

The hypothesis test is whether the coefficient equals to zero. The p-values indicate whether we reject the hypothesis that the factors are correlated to monthly fund flows. At the 95% Confidence Interval, p-values that are smaller than 0.05 will be rejected, meaning that the coefficient does not equal to zero and thus correlated to fund flows. Through the test I would like to find out whether  $\beta_1$  and  $\beta_2$  are significant, and whether  $\alpha$  equals to zero, meaning that the models have correctly assumed all the factors that determine fund flows. Next part I will interpret and analyze the results.

## 4.2 Results

The two regressions give somewhat different results. The coefficient of FB is omitted due to collinearity. So we cannot tell whether advertising on Facebook helps fund flows in this model, which can be a future research direction done by a different model. From the pooled regression results we can see, the p-values of followers is higher than 0.05, meaning the results are insignificant at a 95% Confidence Interval. And the p-values of the number of followers, size, returns and  $\alpha_1$  are smaller than 0.05, meaning the hypotheses are rejected and the results are significant at a 95% Confidence Interval. On the other hand, all the p-values from the panel regression results are smaller than 0.05, which means the results are rejected and are significant at the 95% Confidence Interval.

As I could not get the result on Facebook in this model, I can focus on the result of the number of followers to have an estimation. Because the two factors are somehow connected inside. If the number of followers have a whatever impact on fund flows, it will certainly reveal some relationship between advertising on Facebook and fund flows. Looking at the results given by the two models, the difference mainly lies with the results on the number of followers, where it is insignificant in the pooled regression and significant in the panel regression. As I stated above, a pooled regression uses all the variation in the data, so it solves the problem as a whole without distinguish each fund family. In theory, if the data are ideal, fixed-effects regression is supposed to produce the same coefficient estimates and standard errors as ordinary regression when indicator (dummy) variables are included for each of the groups<sup>4</sup>, while in fact we get different results. The pooled regression is biased due to the inclusion of dummy variables.

So, as the pooled regression gives a p-value of the number of followers higher than 0.05, it could be flawed due to the inefficiency of the model. For example, if we eyeball the number of followers' data, we will observe that there is considerable variation (“action”) from one row to

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<sup>4</sup> <http://www.stata.com/support/faqs/statistics/intercept-in-fixed-effects-model/>

the next. This variation comes in two “flavors”. One is inter-family (across fund family) variation: variation in the average number of followers from one family to the next. Another is intra-family (within family) variation: variation within each family over time. The pooled regression offered only inter-family (across) variation. And regressions relying on inter-family variation are problematic due to potential omitted variable bias. The solution is to focus on intra-family (within) variation<sup>5</sup>, which comes to the point of using the panel regression. Because panel data structure makes it possible to deal with certain types of endogeneity without the use of exogenous instruments<sup>6</sup>. Since the effect of advertisements can be categorized as behavioural factor, it is reasonable to believe that the panel regression is more possible to provide a better estimation and results for our data sample.

As this paper’s main goal is to find out whether advertisements help fund flows, let’s first look at that aspect from the number of followers. Combining the two models, the p-value of the number of followers indicate a weak correlation between the number of followers and fund flows. Surprisingly, the coefficient suggests a negative impact of an increasing number of followers, which means that the more popular a fund family’s Facebook page is, the less fund flow it has. It contradicts with the common sense held by most people that advertising helps the sales of products. The more active a fund family is on Facebook, the lower the fund flows. On the other hand, the negative impact of the number of followers reveals the impact of advertising on Facebook. Because the existing of followers drag down fund flows, advertising on Facebook place a downward pressure on fund flows as well.

Next, let’s look at the result on the number of followers given by the pooled regression. The p-value means the effect of advertisement is insignificant, and the coefficient shows no correlation between advertisements and fund flows. The result conflicts with the panel regression. And the reason is as explained above: the pooled regression does not take into consideration of the variation within the fund families, and is more likely to give inaccurate results. As we are studying a behavioural model, a panel regression will provide a better solution.

So, if the coefficient given by the panel regression holds, it means that advertisements on Facebook and accumulating more followers would actually make a negative contribution to the fund families’ net flows. Does it make sense? The answer is yes. There are several possible explanations.

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<sup>5</sup> <http://www.jblumenstock.com/files/courses/econ174/FEModels.pdf>

<sup>6</sup> <http://faculty.washington.edu/ezivot/econ582/introductionpaneldata.pdf>



First of all, advertising incurs costs, which may be too high to be overcome by the new fund flows. It could be that the inflows to funds are not enough to cover the costs (outflows) on advertisements. For example, to maintain a Facebook page, a fund family needs to have a marketing team, delivering positive public image, and even pay advertisement fees to Facebook. All these activities require extra expenses, which would otherwise be saved if choose not to advertise. And then the high costs result in negative fund net flows, while the fund inflows might already get improved. More importantly, we do not know whether higher spending is needed to attract more followers. This could contribute to the negative correlation.

Bearing the cost effect in mind, other explanations will give more ideas. For example, it is possible that Facebook is not the right place to advertise mutual funds, as investors who purchase mutual funds may view Facebook advertisement in a different way than advertisements on a professional platform because Facebook is seen more as a social networking media. Thus the advertisements on Facebook pose a non-important image on the fund family's brand name. This cannot reach a conclusion without further research, and it could be done by looking at the relationship between advertisements on professional platforms, such as Morningstar and Investopedia, and fund flows.

Moreover, it could be due to investors' rational behaviour. Sirri and Tufano (1998) point out a positive contribution of advertising on fund flows, because it reduces investors' search cost and they believe in advertisements. The assumption is investors are irrational. However, as our result shows, it may not be the case. What if investors as whole are rational? It is possible that the advertisements on Facebook do reach to investors. It is just that they do not believe in the advertisements and would rather spend time searching for their needs.

Besides, as the investors are constituted by individual and institutional investors, where individual investors show attention-driven buying behaviour and institutional investors do not (Barber and Odean (2008)), it could be that the buying behaviour of individual investors are offset by the rational institutional investors, who do not believe in advertisements but do their own researches. So even the amount of followers is increasing, there are more educated institutional investors. Thus, the fund families incur costs without having more inflows. Moreover, even it is not because of the different character between individual and institutional investors, it could be due to the different mindset of the two kinds of investors, as the way they interpret advertisements are different, resulting in negative fund flows. To find out whether my guesses hold, further studies can be done by splitting the fund net flows into fund inflows and outflows,

and look into advertisement effects on fund inflows while taking costs on advertisements into consideration.

One last possible explanation is that the amount of postings on Facebook are not high enough to make the quantity change. So even the fund families spend all the money, time and energy, their fund inflows are not high enough to cover costs. All the guesses provide ideas on future research direction. At this moment, we can conclude that advertising on Facebook is negatively correlated with fund flows to fund families using monthly data of the largest 100 fund families in the US.

Back to the result on the number of followers. If it is true, what does it imply? Because the number of followers will not make a negative growth on fund flows, the fund families will have no incentive to attract new followers. The purpose of advertisements is to increase followers and thus incur more buying behaviour as the beginning. But if the model gives the right answer, then there is no reason for fund families to keep active on Facebook. The entire efforts the fund families put are not effective, since the followers they have would not help the sales record. Other than the conclusion we can get the test results, it worth thinking why the number of followers has this negative impact on fund flows. For example, is it possible that the followers that would buy the products are the ones have not seen the advertisements on Facebook? For an advertisement to display on a user's Facebook page, the fund family needs to pay certain amount of fees to Facebook. So, it could be that, although the fund families input expenses, it is not enough to let most people see the advertisement. In this way, the fund families do not successfully attract their target investors. Again, this can be attributed to that the Facebook may not be an ideal platform for fund families to advertise, as it is more like a place for amusement and entertainment. Because when looking at a celebrity's Facebook page, such as Justin Bieber and Taylor Swift, they are so popular and the followers they have would actually copy their apparels or styles. But we do not see this kind of influence on the advertisements of fund families. On the other hand, as the celebrities are already famous in the real world, the reason their followers are being enthusiastic is because they have known them before they follow them. This rule can be applied to fund families, where some families have a huge number of followers such as Fidelity, their followers are already buying their products. Then it will not make a difference on fund flows when they follow it on Facebook. Because of all that, it is also worth thinking what is the right form of advertisements for fund families.

If the above explanations do not correspond to the reality, the model may be flawed in a way that it does not reveal the true relationship between advertisement and fund flows, which will

need further studies. Comparing to the literature I mentioned in Section 2, I cannot conclude whether result is inconsistent with Cronqvist (2006), where the paper shows that the advertised funds are more favourable by investors, since I cannot tell from the results whether it is because the costs are too high or because the fund inflows are too low. In this case, the effect of being active on Facebook arouse the same outcome in the fund families who advertise than those who don't. As Wang and Tsai (2014) shows positive and direct effects of brand image on purchase intention, it is hard to tell whether it shows the same effect in our case.

All I mentioned above are based on that the regression model is correct, and I did not discuss the possibility that it is flawed. Now, recall the Data section, I explained that I assume the number of followers grows at a constant rate because I do not have the data for the number of followers the fund families had in the past. Thus, this can be a false assumption and cause the model gives wrong results. If the followers do not increase at a presumed rate, or even has some fluctuations in the middle years, the results can be different. But to do this test at this moment, this is no better way. To improve the model, one could assume different growth rates for different time of period and run several simulation test, then analyze each result based on different scenarios. Another better way to solve this problem is to collect data on followers from now on, and run the test a few years later. I believe it will give a more accurate results.

The result on the size of the fund family is not surprising. Both the pooled and panel regression give the same results with different coefficients. The p-value are smaller than 0.05 and the hypothesis is rejected so that the test result is significant. It indicates that the size of a fund family is correlated with its fund flows. Also, as the coefficient is positive, the correlation between size and fund flows is positive. It makes sense because big firms have more customers and business in reality. The same rule apply to mutual funds. The big firms have the most customers, which in turn bring up their revenue. Also, as big companies are more likely to realise economic scale, their costs would be lower than small firms. For mutual funds, as they are also products, investors have the incentive to choose a big fund family. Because a big fund family may let the investors believe it is more experienced, more secure, and more trustworthy, even though it may not be true.

The result on gross returns is a bit surprising, as it states negative correlation between gross returns and fund flows. It conflicts with the findings in Ippolito (1992), which finds investment monies moving toward recent good performers. If the result holds, it implies that investors as a whole are rational, and they do not try to interpret future performance based on past returns. But it only means the investors as whole are rational and knowledgeable. To find out the

difference between individual investors and institutional investors, we need to separately study the reaction of the two types of investors. Because as Frazzini (2008) and Zheng (1999) show, individual investors are dumb money and institutional investors are smart money. Linking to our case, I cannot conclude if the overall rational behaviour of the investors is due to the higher portion of institutional investors than individual investors.

One last estimation is the constant component  $\alpha$ . It constitutes a negative part to fund flows and cannot attribute to other components in the model. It should raise our attention and further studies need to be done to find out the exact factors. As suggested by Warther (1995) and Chevalier and Ellison (1997), the factors may include security prices and mutual fund advisor compensation. These factors have been proved to be correlated to fund flows. In the case of the panel regression, all fund flows are explained by this unknown component, which gives researchers more incentive to further look at the factors inside it.

As a whole, the model provides an estimation on the effects of advertisements and followers, and gives a rough idea on what affects fund flows. The results suggest a negative but weak effect of advertising on fund flows. To explore the more detailed relationship, many aspects can be improved in this paper, such as a larger sample size, a long time frame, and a more complicated model. Due to the limitation of the model and the data, this is the best result I can provide at this moment.

## 5: Conclusion

The main goal of this paper is to find whether advertising on Facebook has an impact on monthly net flows to fund family. The sample fund families I use are the top 100 fund families in the US, ranked by the size of the fund family. The test period covers between January 2009 and June 2016. Reason for that is because most fund families start to be active on Facebook in 2009. Besides testing the relationship between advertisements and fund flows, I also include the number of followers, the size of the fund family, and the gross returns as independent variables in the regression model.

To provide better estimation, I use a pooled regression model and a fixed-effect panel regression model respectively and look at the difference between the two regressions. Both regression models have their advantages. A pooled regression has the advantage of using all the variation in the data. A fixed-effect panel regression is more suitable for a complicated behavioral model and gets rid of the impact of dummy variables, thus providing a better estimation in this case.

The results of the two regressions are similar except the results on the number of followers, which is the most important variable in this paper. The result of advertising on Facebook is not available because of collinearity, which may be tested by a different model in the future. The pooled regression shows no correlation between the number of followers and fund flows, while the panel regression shows a negative correlation. As a pooled regression is somewhat flawed for the data used in this paper, the result of the panel regression has the potential to provide the most appropriate result. The explanation for the relationship could be that the costs spent on advertising are too high, Facebook is not an ideal advertising platform for Facebook, or other reasons explained in previous section. The result does not mean that advertisements do not increase fund inflows and thus useless. This paper is limited in that I only look at the fund net flows. For future research direction, it might be a good idea to split the fund flows into inflows and outflows, and look at the relationship between the number of followers and fund inflows. One thing to notice is that I assume the number of followers grows at a constant rate since the fund families are active on Facebook. However, this assumption can be flawed and cause an inaccurate estimation. A further study can be done by assume various ways of growth and analyze the results based on those different scenarios.

The size of a fund family is positively correlated with fund flows, which seems reasonable as big firms have more customers and business. As long as big firms realised economic scale, costs can be low and profit can be high. The gross returns of the fund family show a negative correlation with fund flows. It implies that investors as a whole are rational and believe that past returns do not indicate future returns. This result conflicts with Ippolito (1992), which finds the investment monies move toward recent good performers. Since I do not separate the individual investors from the institutional investors, future studies can look at the effect of past returns on individual investors, which is proved to be correlated in other papers (Frazzini (2008), Zheng (1999)). Furthermore, there exists a negative constant ( $\alpha$ ) in the model, which causes a large portion of negative fund flows. This unexplained component should raise our attention and look for possible explanations.

Overall, this paper finds that higher amount of followers on Facebook has a negative impact on monthly net flows to fund family and other factors also contribute to fund flows to different extent, while an explained constant component has the highest contribution to fund flows. Future studies can be focused on the number of followers and split the fund inflows from fund outflows.

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