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Online attention and mutual fund performance: Evidence from Norway

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ABSTRACT

This paper studies whether flows of funds into and out of equity mutual funds depend on investor attention measured as Google searches for company names and on fund's performance. We find that mutual funds which performed well in the past receive more attention and more inflows. These results hold no matter which measure of past performance is considered. Interestingly, funds which performed well in previous twelve months are also subject to increased outflows, but this relationship is less robust than relationship for inflows. Lastly, longer-term (one year) performance matters more than shorter-term (one month and six months) performance.

1. Introduction

The internet usage has grown tremendously the last decade, and today investors can access a major amount of information through the internet. Google search engine is the most utilized information gathering tool in the world. Since 2005 scholars have argued to use internet search data to forecast economic statistics (Ettredge et al., 2005) and there have been many other studies that have explored internet search data in different fields. Among the first to utilize Google search volume index (SVI) as a measure of internet search frequency is the studies of Choi and Varian (2012). They argue that data from Google trends may be linked to present values of different economic indicators such as automobile sales, unemployment claims, travel destination planning, and consumer confidence and that it may be helpful for short-term economic prediction. Preis et al. (2010) investigate the link between search volume data and market fluctuations. They discover that weekly transaction volumes of S&P 500 firms are positively correlated with weekly search volume of the corresponding company names and that the price fluctuations do affect search volumes for that specific firm in the coming weeks.

Previous literature has suggested a lot of indirect measures of investor attention, such as abnormal returns, trading volume, news headlines, and media coverage. The problem with these measures is the assumption that investors pay attention to funds with higher visibility or marketing efforts. To avoid this problem, many studies have been using SVI as a direct measure of investor attention. Da et al. (2011) was among the first to utilize SVI as a new and direct measure of investor attention. They observe that when there is a higher SVI the stock prices in the following weeks increase, in line with the results of Preis et al. (2010). Another study that uses SVI as a direct measure of investor attention or sentiment is (Joseph et al., 2011). They find that search intensity can predict returns in subsequent periods, confirming the findings in Da et al. (2011). Preis et al. (2013) investigate changes in Google search

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volume for search terms related to finance. They find that Google trend data reflects aspects of the current state of the economy and that it provides insight into future trends in the behavior of economic factors. Challet and Ayed (2013) challenge the claims that data from Google trend contains enough information to predict future index returns, and they find that finance-related keywords do not contain more exploitable predictive information than random keywords. Additionally, they find that other keywords applied on suitable assets gives robust profit strategies, in line with the findings of Preis et al. (2013). Bijl et al. (2016) find that high levels of SVI predict low future excess returns and that the predictive power of SVI is similar both during the financial crisis and in more ordinary market conditions. (Kim et al., 2018) investigate whether Google search activity can explain and predict the Norwegian stock market. They find no relationship between Google searches and stock returns, different from findings from the US market (Bijl et al., 2016; Da et al., 2011). On the other hand, they find that Google searches can predict volatility and trading volume.

(Ippolito, 1992) was one of the first to study mutual fund investor‘s reaction to performance. He suggested that the relationship between flow and performance is nonlinear. Gruber (1996) provides explanation why actively managed mutual funds has grown so fast, despite their performance on average being inferior to that of index fund. Moreover, he finds evidence of the convexity of the flow-performance relationship, meaning that investors rush into funds with high past performance, but are reluctant to withdraw money from funds that have performed poorly. Sirri and Tufano (1998) and Chevalier and Ellison (1997), also provide evidence of the convexity of the flow-performance relationship. Sirri and Tufano (1998) finds that search cost is an important determinant of mutual fund flows. Additionally, they find that funds with high performance usually have high marketing effort and hence higher fees and lower search cost for investors. (Chevalier and Ellison, 1997) portrays the convex flow-performance relationship as an incentive scheme for mutual fund companies by mutual fund investors. They argue that the convex flow-performance relationship can develop incentives for mutual fund companies to increase or decrease the riskiness of their portfolio. Huang et al. (2007) explored the effect of investor‘s participation costs on the response of mutual fund flows to past performance using a simple rational model. This study also provides evidence of the convex flow-performance relationship. Kaniel et al. (2007) investigate the role of media coverage in investment decisions of mutual fund investors, and the effect of media coverage on fund flows. They find that media coverage of mutual funds has a significant impact on investor flows to the fund. Solomon et al. (2014) investigate the same concept as (Kaniel et al., 2007) and find that investors seems to respond only to those funds that were recently featured in the news. On the other hand, they find little evidence that newspaper articles are related to better decision making. Barber and Odean (2007) portray a model of decision making where investors faced with many alternatives consider mainly those alternatives that have attention-attracting qualities. Moreover, they confirm and test the proposition that individual investors are net buyers of attention grabbing stocks, i.e. stocks featured in the news, stocks with high abnormal trading volume, and stocks with extreme one day return. Barber et al. (2016) explore which factors investors care about by analyzing net flows as a function of recent returns decomposed into alpha and factor-related returns. They observe that investors care more about the market risk (beta) when evaluating funds and that more sophisticated investors use more sophisticated benchmarks.

There have been many studies about SVI and the stock market, but not on SVI and the mutual fund industry. Previous research studies volatility (Kim et al., 2018; Bijl et al., 2016), trading volume (Kim et al., 2018; Da et al., 2011; Preis et al., 2010; Joseph et al., 2011; Bijl et al., 2016), economic statistics (Ettredge et al., 2005), economic indicators (Choi and Varian, 2012), and trading strategies (Bijl et al., 2016; Challet and Ayed, 2013; Preis et al., 2013).

(Gallefoss et al., 2015) pointed out that in spite of the fact that the Norwegian economy is one of the most developed economies in the world there are almost no studies of Norwegian mutual funds. Inspired by Kim et al. (2018) and Da et al. (2011) that suggest that SVI may be more pronounced in smaller markets, our paper investigates the Norwegian mutual fund market. There are several reasons for this choice. Most importantly, for Norwegian mutual funds, we have access to inflows and outflows, while many other databases contain only net flows. Consequently, most of the existing studies are based on net flows. Second, internet penetration and use of Google search engine belongs to highest in the world, which makes it particularly suitable to study attention measured by Google searches. Lastly, high faction of population is familiar with, and investing in mutual funds.

We study the relationship between attention and fund performance and flows for open- end equity funds. We find that positive prior performance attracts attention, inflows, and outflows. We do not find attention to be able to improve prediction of inflows or outflows beyond what past performance predicts. We also find that one-year performance is more important than one-month or six-months performance.

The only other study about mutual fund performance, flows and Google search volume index (SVI) we are aware of is (Chen et al., 2021). Chen et al. (2021) study US mutual funds, and, as a result, have larger and more comprehensive dataset. Conclusion that funds with positive prior performance attract attention and inflows (net flows) is common for both (Chen et al., 2021) and our study. Our conclusions about outflows cannot be compared, as dataset of Chen et al. (2021) does not include outflows. Regarding the impact of attention on fund flows, there is a seeming difference between (Chen et al., 2021) and our study. Chen et al. (2021) conclude that investor attention enhances fund inflows, while we do not make such conclusion. However, past performance in Chen et al. (2021) is measured by performance over previous month. In case we use previous month's performance, our conclusion is the same as (Chen et al., 2021). However, we argue that previous year's performance is more relevant, and once performance over previous year is considered, attention does not have impact on fund flows.

Several papers study funds' flows with respect to some variables related to attention. El Ghoul and Karoui (2021) find that changes in funds' names to a sustainability-related appellation resulted in an increase in fund flows, a significant rise in portfolio turnover, and no substantial change in fund betas and alpha. French and Li (2022) find that economic policy uncertainty is strongly negatively related to equity fund flows. Alda (2020) find that a higher environmental, social and governance screening provides larger fund flows. Bazley et al. (2021) show that experiencing investors' happiness is associated with flows to mutual funds.

The rest of this paper is structured as follows. Section 2 describes the data. Section 3 presents the methodology. Section 4 discusses the results. Section 5 concludes.

2. Data

The data was obtained from Google trends, EIKON, Norges Bank, and the Norwegian Fund and Asset Management Association (henceforth VFF). Data spans the period from January 25, 2013 to January 25, 2018). However, in order to standardize some of the variables, data from 2012 was also obtained. VFF provided us with the funds monthly inflow, outflow, net flow, and total net assets (henceforth TNA). EIKON was used to collect daily net asset value (henceforth NAV) for the funds and daily return on the market. Furthermore, daily risk-free rates from Norges Bank were collected. The Google Trends platform was used to collect the monthly SVI.

2.1. Google trends data

Previous research about the stock market utilized company names or tickers from Google trend. Bijl et al. (2016) found evidence that company name search activity has a stronger relationship to stock market returns than tickers searches, hence the full fund names were used. Da et al. (2011) argues that in case of stocks, using a company name as search term could be disturbing and biased, since investors might search for the company name with other intentions than investing. Nevertheless, in mutual funds case this is not a problem because funds exist for the sole purpose of attracting investments. If an investor search for a particular fund, he is likely interested in investing in this fund. Moreover, funds often have long and detailed names, so it would be nearly impossible for an investor to accidentally search for a particular fund.

(Preis et al., 2013) suggests that data filtered according to geographic location can better explain movements in the specific geographic location. Following their example, first we searched for Norwegian funds, and used the filter "Norway". However, this resulted in 13 hits in Google Trend out of the 60 Norwegian funds. Therefore, we decided to check the 388 funds using the world-wide filter in Google Trend and 52 hits were obtained. It was not possible to include all the actively managed open-end equity funds because Google trend does not provide data on search terms with too low search volume. SVI is reported weekly, monthly or not at all for words with low search volume, hence monthly SVI was collected to avoid too many zero occurrences. Funds that had complete data for the full sample period were included. Moreover, funds that have merged, delisted, over 60% zero values in Google trend, and funds with no data in EIKON were excluded. Thus, 36 funds were included in the final sample for the SVI.

For the funds that were chosen to be included in the final sample, 0 values were exchanged with 1, in order to use the logarithm to standardize the data. The formula used was inspired by Da et al. (2011). We calculate the abnormal SVI as the difference between logarithm of Google searches during particular months and logarithm of median Google searches over past 12 months, and we denote this variable as $Attention$.

$$Attention_t = log(SVI_t) - log[Median(SVI_{t-1}, \dots, SVI_{t-12})] \tag{1}$$

2.2. Mutual fund data

VFF was used since they provide not only net flows but also inflows and outflows. Only actively managed open- end equity funds were included in the sample. Equity funds are defined by VFF as a fund where minimum 80% of the assets are invested in the stock market. These funds are further divided into groups depending on which investment universe the funds are placed within, e.g. geography, sector and industry, or a combination of these. We include all funds that were a member of VFF in 2017. We omit funds that have merged, delisted, over 60% zero values in Google trend and funds with no data in EIKON. Thus, 36 funds were included in the final sample. Furthermore, we only include funds with regular flows. Our final sample for the flows consists of 30 funds. Many of the funds in our sample invest internationally, hence we have several benchmarks. The list of the funds with their respective benchmarks is presented in the Appendix. Since these funds are equity funds we expect that the beta on average should be not too far from 1. We checked the betas from the CAPM regressions to ensure that we had selected the appropriate benchmark for each fund.

(Gallefoss et al., 2015) argue that daily data makes it possible to evaluate the performance over short time horizons more reliably, which is essential because the risk exposure of funds can change over time. Inspired by this, daily data were used to estimate monthly alpha. Daily net asset value (NAV) and the benchmark returns were obtained from the financial database EIKON for the sample period 24.01.2013i–25.01.2018.

The daily risk-free rate was obtained from Norges Bank. Three-month Treasury bills' daily quotes divided by 252 (number of trading days in one year) days were used to get daily risk-free rate. There were some days with no quotes, because of holidays or non-trading days. For these instances, the risk-free rate from the previous trading day was used.

Daily returns were calculated as the logarithm of the daily NAV divided by daily NAV of the previous trading day. Monthly returns were obtained by aggregation of daily returns.

$$r_{i,t} = log\left[\frac{NAV_{i,t}}{NAV_{i,t-1}}\right] \tag{2}$$

Inspired by the work of Barber et al. (2016) which argues that the CAPM is the best model to explain the variations in flows across mutual funds, we obtained the monthly alphas by utilizing the single index model (CAPM).

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \epsilon_i \tag{3}$$

Table 1
Descriptive statistics for all variables.

	N	Mean	St. Dev.	Min	Max
Attention	2196	0.055	1.277	−4.256	4.605
α	2135	0.007	0.033	−0.242	0.149
t-Stat(α)	2135	0.174	1.113	−4.853	4.932
Return	2135	0.008	0.035	−0.136	0.177
Sharpe	2135	1.421	3.990	−12.043	16.070
Inflow	1826	0.044	0.093	−0.001	1.822
Outflow	1826	0.033	0.051	−0.014	1.107
Net Flow	1826	0.011	0.091	−0.645	1.809
NAV	2135	8290.4	32865.8	53.8	261887.3
IN	1826	82461.4	221363.5	−301.0	4866766.0
OUT	1826	108624.4	463248.5	−131.0	14903699.0
NET	1826	−26163.0	454846.5	−14597413.0	4832296.0
TNA	1826	4087983.7	8582303.7	6968.0	50036877.0
SVI	2196	23.3	23.7	0	100

Table 2
Correlation matrix for all variables.

	Attention	α	t-Stat(α)	Return	Sharpe	Inflow	Outflow	Net Flow	NAV	IN	OUT	NET	TNA
α	0.04*												
t-Stat(α)	0.03	0.87***											
Return	0.06***	0.65***	0.58***										
Sharpe	0.07***	0.67***	0.67***	0.91***									
Inflow	0.09***	0.07***	0.03	0.08***	0.05**								
Outflow	0.01	0.01	0.00	−0.01	−0.03	0.31***							
Net Flow	0.09***	0.07***	0.03	0.09***	0.07***	0.84***	−0.25***						
NAV	−0.02	0.00	0.01	0.01	0.01	−0.02	0.02	−0.04					
IN	0.01	0.03	0.00	0.02	0.03	0.39***	0.02	0.38***	−0.04*				
OUT	−0.01	0.02	0.01	0.00	−0.01	−0.04*	0.17***	-0.14***	−0.03	0.28***			
NET	0.02	−0.01	−0.01	0.01	0.02	0.23***	−0.17***	0.33***	0.01	0.21***	−0.88***		
TNA	−0.04*	0.01	0.01	−0.01	0.00	−0.11***	−0.07***	−0.07***	−0.08***	0.49***	0.54***	−0.31***	
SVI	0.38***	0.02	0.00	0.04**	0.05**	0.13***	0.08***	0.09***	−0.09***	0.08***	−0.03	0.07***	−0.04*

The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The alpha t-statistic is the regression alpha divided by its standard error.

$$t{-}stat = \frac{\alpha}{\sigma(\alpha)} \tag{4}$$

The Sharpe ratio is the excess return divide by the standard deviation of the excess returns.

$$S_i = \frac{r_i - r_f}{\sigma_i} \tag{5}$$

The monthly fund inflows, outflows, net flows, and TNA were collected from VFF. Since our goal is to study the fund flows, we excluded fund that had too many zero flows. These were mainly funds for institutional investors. Our final sample consists of 30 funds. The flows are defined as a fraction relative to the funds previous months TNA as in Sirri and Tufano (1998). This can be interpreted as the percentage growth in assets over return and reinvested dividend.

$$Inflow_{i,t} = \frac{IN_{i,t}}{TNA_{i,t-1}} \tag{6}$$

$$Outflow_{i,t} = \frac{OUT_{i,t}}{TNA_{i,t-1}} \tag{7}$$

$$Netflow_{i,t} = \frac{NET_{i,t}}{TNA_{i,t-1}} \tag{8}$$

$IN_{i,t}$, $OUT_{i,t}$ and $NET_{i,t}$ is inflow, outflow and net flow for fund i at time t. The $TNA_{i,t-1}$ is last month's total net assets for fund i. Size is defined as a logarithm of TNA:

$$Size_{i,t} = ln(TNA_{i,t-1}) \tag{9}$$

2.3. Summary statistics

Table 1 provides the summary statistics for the variables used in further regression. In order to present all the statistics at the same time scale, monthly alpha was multiplied with 22 trading days.

Table 3
Predictors of investors' attention. Robust standard errors are stated in parentheses. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: $Attention_t$											
	Performance measure:											
	Alpha (α)			Alpha (α) t-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$Performance_{t-1}$	0.088***			0.078**			0.089***			0.120***		
	(0.025)			(0.033)			(0.034)			(0.031)		
$Performance^{6M}_{t-1}$		0.125***			0.111*			0.137**			0.159***	
		(0.044)			(0.064)			(0.056)			(0.042)	
$Performance^{12M}_{t-1}$			0.167***			0.182**			0.213***			0.247***
			(0.055)			(0.076)			(0.075)			(0.063)
$Size_{t-1}$	−0.095	−0.130	−0.262	−0.096	−0.120	−0.232	−0.101	−0.141	−0.307*	−0.086	−0.124	−0.275
	(0.160)	(0.162)	(0.172)	(0.162)	(0.165)	(0.173)	(0.162)	(0.164)	(0.174)	(0.161)	(0.165)	(0.174)
Observations	1,736	1,592	1,419	1,736	1,592	1,419	1,736	1,592	1,419	1,736	1,592	1,419
R^2	0.085	0.086	0.089	0.085	0.083	0.086	0.084	0.085	0.094	0.088	0.091	0.107
Adjusted R^2	0.036	0.035	0.036	0.035	0.031	0.033	0.035	0.034	0.041	0.039	0.040	0.055

Before carrying out the regression, correlation between the variables were checked. Table 2 displays that the correlation of the performance measures with $Attention$ is close to 0, hence they are uncorrelated. Nevertheless, as expected there is correlation between the measures of fund performance.

3. Methodology

The results were obtained in the statistical software R. Panel data regressions were performed with fixed and random effects. Since Hausman test preferred fixed effects models, all the models presented in this paper are panel data models with fund-fixed effects (c_i) and time-fixed effects (γ_t). Control variable $Size$ is also included in all the models.

First, we study the impact of performance on $Attention$.

$$Attention_{i,t} = c_i + b_2 Performance_{i,t-1} + b_3 Size_t + \gamma_t + \epsilon_{i,t} \tag{10}$$

We utilize four different performance measures with different time horizons: performance over previous month, average performance over previous six months and average performance over previous twelve months. The four performance measures are: alpha, alpha t-statistics, returns, and the Sharpe ratio.

Next we study the effect of attention and performance on inflows, outflows and net flows.

$$Inflow_{i,t} = c_i + b_1 Attention_{i,t-1} + b_2 Performance_{i,t-1} + b_3 Size_t + \gamma_t + \epsilon_{i,t} \tag{11}$$

$$Outflow_{i,t} = c_i + b_1 Attention_{i,t-1} + b_2 Performance_{i,t-1} + b_3 Size_t + \gamma_t + \epsilon_{i,t} \tag{12}$$

$$NetFlow_{i,t} = c_i + \beta_1 Attention_{i,t-1} + b_2 Performance_{i,t-1} + b_3 Size_t + \gamma_t + \epsilon_{i,t} \tag{13}$$

4. Results

The Hausman test supported the fixed effects model when we tested the regression model with fixed and random effects. Hence, the results are presented with both time- and fund-fixed effects. To correct for eventual auto-correlation and heteroskedasticity the results are presented with robust standard errors. As the variables have different scales, the results are standardized. The results with estimated coefficients without standardization are reported in Appendix.

4.1. Predictors of attention

Table 3 presents the results of the regressions where the dependent variable $Attention$ is regressed against the control variable $Size_{t-1}$ and past performance as independent variables. There is a positive statistically significant relationship between attention and performance, intuitively indicating that investors search more for the funds with higher performance. This result holds no matter which measure of attention is used in the model. The results indicate that investors generally care more about long-term performance (one year) than short-term performance (one month or six months). Hence, investors are more likely to search for funds that has high long-term performance than short-term performance. This is quite intuitive as long-term performance is a better measure of fund manager skills than short-term performance, which could be a result of luck rather than fund manager skills.

Table 4
Predictors of inflows. Values in columns are for regression outputs for the variables in the respective rows. All are multiple regressions of the dependent variable on independent variables on the respective rows. Robust standard errors are stated in parentheses. Number of observations vary but R (the software program) matches the observations to balance the data. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: $Inflow_t$											
	Performance measure:											
	Alpha (α)			Alpha (α) t-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$Attention_{t-1}$	0.079**	0.034	0.040	0.080**	0.040	0.049	0.073**	0.033	0.034	0.073**	0.028	0.025
	(0.035)	(0.025)	(0.030)	(0.036)	(0.027)	(0.033)	(0.036)	(0.026)	(0.033)	(0.036)	(0.026)	(0.031)
$Performance_{t-1}$	0.125***			0.115***			0.197***			0.167***		
	(0.038)			(0.028)			(0.037)			(0.035)		
$Performance^{6M}_{t-1}$		0.169***			0.144**			0.207***			0.191***	
		(0.044)			(0.064)			(0.049)			(0.043)	
$Performance^{12M}_{t-1}$			0.233***			0.233***			0.280***			0.264***
			(0.050)			(0.072)			(0.063)			(0.055)
$Size_{t-1}$	−0.286	−0.403	−0.628*	−0.287	−0.388	−0.583	−0.284	−0.420	−0.683*	−0.276	−0.396	−0.624*
	(0.234)	(0.286)	(0.371)	(0.233)	(0.286)	(0.367)	(0.239)	(0.285)	(0.371)	(0.239)	(0.289)	(0.372)
Observations	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417
R^2	0.083	0.097	0.114	0.082	0.088	0.104	0.092	0.100	0.118	0.088	0.100	0.120
Adjusted R^2	0.033	0.046	0.061	0.031	0.037	0.051	0.043	0.049	0.066	0.038	0.049	0.068

Table 5
Predictors of outflows. Robust standard errors are stated in parentheses. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: $Outflow_t$											
	Performance measure:											
	Alpha (α)			Alpha (α) t-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$Attention_{t-1}$	−0.023	−0.016	−0.021	−0.023	−0.016	−0.018	−0.024	−0.022	−0.036	−0.023	−0.020	−0.030
	(0.039)	(0.040)	(0.037)	(0.040)	(0.040)	(0.038)	(0.040)	(0.042)	(0.042)	(0.040)	(0.042)	(0.043)
$Performance_{t-1}$	0.026			0.024			0.029			0.005		
	(0.041)			(0.042)			(0.041)			(0.037)		
$Performance^{6M}_{t-1}$		−0.034			−0.049			0.041			0.006	
		(0.038)			(0.044)			(0.049)			(0.046)	
$Performance^{12M}_{t-1}$			0.021			0.001			0.141***			0.073
			(0.052)			(0.050)			(0.059)			(0.054)
$Size_{t-1}$	−0.039	−0.094	−0.107	−0.039	−0.099	−0.099	−0.040	−0.098	−0.170	−0.044	−0.094	−0.122
	(0.348)	(0.424)	(0.541)	(0.343)	(0.427)	(0.540)	(0.351)	(0.424)	(0.542)	(0.350)	(0.426)	(0.540)
Observations	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417
R^2	0.063	0.064	0.063	0.063	0.065	0.063	0.063	0.064	0.072	0.063	0.064	0.066
Adjusted R^2	0.012	0.011	0.008	0.012	0.012	0.008	0.012	0.012	0.017	0.011	0.011	0.011

4.2. Predictors of inflows

Table 4 shows the regression results where inflow is the dependent variable, size as control variable and lagged performance and attention as independent variables.

The table shows that there is a positive and statistically significant relationship between performance and inflows, indicating that past performance can predict inflows. This means that if a fund performs well investors put more money into it. As the table shows this conclusion holds no matter which measure of performance is considered. Again, investors care more about the performance over previous year than about the performance over previous one month or six months. Interestingly, attention is significant only in the models with one-month performance. The likely reason is that one-month performance is not a very relevant measure that investor care about, and therefore, attention provides some additional information in addition to one-month performance. However, once longer-term (six months or one year) performance is included in the model, attention is not significant anymore. This means that attention in not useful in predicting fund inflows once the model includes performance over most recent 12 months.

4.3. Predictors of outflows

Table 5 reports the regression results for outflow as dependent variable, size as a control variable, and lagged performance and attention as independent variables. Altogether, contrary to the inflows, outflows are mainly unpredictable. Neither attention, nor most of the measures of past performance. The only exception is past performance measured by simple return. Positive returns are followed by increased outflows. This relation is insignificant when we consider returns over previous one month and six months, but is significant for return over previous one year. One possible explanation for increased outflows for funds that performed well over

Table 6
Predictors of net flows. Robust standard errors are stated in parentheses. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Net $flow_t$											
	Performance measure:											
	Alpha (α)			Alpha (α) t-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$Attention_{t-1}$	0.094**	0.043	0.053	0.095**	0.050	0.061	0.088**	0.046	0.055	0.087*	0.040	0.043
	(0.044)	(0.033)	(0.037)	(0.045)	(0.035)	(0.040)	(0.045)	(0.037)	(0.043)	(0.045)	(0.035)	(0.039)
$Performance_{t-1}$	0.113***			0.103***			0.184***			0.167***		
	(0.041)			(0.031)			(0.033)			(0.035)		
$Performance^{6M}_{t-1}$		0.192***			0.175***			0.189***			0.192***	
		(0.028)			(0.050)			(0.052)			(0.038)	
$Performance^{12M}_{t-1}$			0.226***			0.238***			0.206***			0.228***
			(0.041)			(0.063)			(0.059)			(0.040)
$Size_{t-1}$	−0.270**	−0.358**	−0.581**	−0.271**	−0.341**	−0.539**	−0.267*	−0.374**	−0.601***	−0.257*	−0.351**	−0.568**
	(0.131)	(0.147)	(0.234)	(0.132)	(0.146)	(0.223)	(0.138)	(0.152)	(0.228)	(0.135)	(0.150)	(0.226)
Observations	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417
R^2	0.066	0.078	0.087	0.064	0.070	0.081	0.074	0.071	0.077	0.072	0.076	0.086
Adjusted R^2	0.014	0.026	0.033	0.013	0.018	0.026	0.023	0.019	0.023	0.021	0.023	0.032

the previous twelve months might be loss aversion. If investors whose funds performed poorly are reluctant to sell (loss aversion), while investors whose funds performed well are not reluctant to sell, then higher outflows will be detected for well-performing funds. However, since the relationship between performance and outflows can be observed only when twelve-month returns are used as a performance measure, and not for alpha, alpha t-stats or Sharpe ratio, this relationship should be further re-investigates on other datasets.

The main conclusion should be that outflows are mainly unpredictable, and investors are probably taking money out for some external reasons, such as liquidity needs.

4.4. Predictors of net flows

Since a large part of previous literature is based solely on net flows, we also include net flows in our study. Table 6 shows the results from the regression where net flow is the dependent variable, size as control variable, and lagged performance and attention as independent variables. The results from this regression is very similar to the results for inflows. The table also shows that there is a positive and statistically significant relationship between past performance and net flows, no matter which performance measure we consider, and this relationship is strongest when longer-term performance is considered.

5. Conclusion

We investigate the relationship between performance of mutual funds, investor attention measured by the Google searches for fund names, and flows in and out of these mutual funds. This study is based on Norwegian data, because in Norway has data not only about net flows, but also about inflows and outflows. We study whether funds with high past performance attract investor attention and whether investors put money into these funds. We are also interested in finding which performance measure that is most important for investors. The four considered performance measures are: alpha, alpha t-statistics, returns, and Sharpe ratio. Furthermore, measures of the past performance are considered over past one month, past six months, and past twelve months in order to evaluate whether investors care more about short-term or long-term performance.

Our results reveal that investors search for information about the funds which performed well in the past. Past performance matters more for inflows than for outflows. Investors put money into funds that performed well in the past. Interestingly, we find some evidence that funds that performed well experience also increased outflows. This conclusion is not possible to observe if analysis is conducted on net flows only. Regarding the time horizon, performance over previous twelve months has stronger impact on flows than performance over previous one months or previous six months. Regarding the performance measures, most of our conclusions remain the same no matter which measure of attention we use.

The main limitation of our study is the limited size of our data sample. One of our findings is that funds which performed well experience not only increased inflows, but also increased outflows. Since the relationship between past performance and outflows was detected only for returns as a measure of past performance, this evidence is not very strong. It should be therefore considered partly as an open question for further research. Moreover, most of the mutual fund flows research has been conducted for net flows. However, some factors might influence inflows and outflows in such way that no impact is observed on net flows. Therefore, additional studies on datasets that contain inflows and outflows are recommended.

CRediT authorship contribution statement

Hamid Cheraghali: Data curation, Formal analysis. **Sofia Aarstad Igeh:** Data curation, Formal analysis, Writing – original draft. **Kuan-Heng Lin:** Writing – review & editing. **Peter Molnár:** Supervision, Conceptualization, Methodology, Writing – review & editing. **Iddamalgodage Wijerathne:** Data curation, Formal analysis, Writing – original draft.

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Appendix

Table A.1
List of funds with their benchmarks.

Fund ID	Fund	Fund Ticker	Benchmark	Benchmark Ticker
1	Delphi Europe	VI-DELEU	STOXX Europe 50 CR (EUR)	STOXX50D
2	Delphi Nordic	VI-DELNC	MSCI Nordic Countries TR ($)	MIND00000PEU
3	Storebrand Vekst	SB-VEKST	Oslo Børs Benchmark Index_GI (OSEBX) (NOK)	OSEBX
4	Skagen m2	ST-M2	MSCI ACWI Real Estate IMI (NTR)	MIWD0REI0PUS
5	SKAGEN Vekst A	ST-VEKST	MSCI World TR ($)	MIWO00000PUS
6	SKAGEN Global A	ST-GLOBA	MSCI World TR ($)	MIWO00000PUS
7	SKAGEN Kon-Tiki A	ST-KONTI	MSCI EM (Emerging Markets) NR ($)	MSCIEF
8	Nordea Stabile Aksjer Global Etisk	KF-SAGE	MSCI World TR ($)	MIWO00000PUS
9	Nordea Global	KF-GLOBL	MSCI World TR ($)	MIWO00000PUS
10	Nordea Norge Verdi	KF-AKPEN	OSE Fund Index (OSEFX) (NOK) TR	OSEFX
11	Nordea Avkastning	KF-AVKAS	OSE Fund Index (OSEFX) (NOK) TR	OSEFX
12	Holberg Norg	HO-NORGE	OSE Fund Index (OSEFX) (NOK) TR	OSEFX
13	Forte Norge	FV-NORGE	OSE Fund Index (OSEFX) (NOK) TR	OSEFX
14	First Generator S	FT-GNRTR	OSE Fund Index (OSEFX) (NOK) TR	OSEFX
15	Eika Norden	EK-NORD	MSCI Nordic Countries TR ($)	MIND00000PEU
16	Eika Spar	EK-SPAR	MSCI Norway TR ($)	MINO00000PNO
17	DNB Navigator (I)	DK-NAVII	MSCI World TR ($)	MIWO00000PUS
18	DNB Miljøinvest	SK-MILJO	WilderHill New Energy Global Innovation	NEXEU
19	DNB Finans	VI-FNANS	MSCI World/Financials TR ($)	MIWO0FN00PUS
20	DNB Health Care	DK-GLHEA	MSCI World/Health Care TR ($)	MIWO0HC00PUS
21	DNB Aktiv 100	VI-DA100	MSCI World TR ($)	MIWO00000PUS
22	DNB Global Indeks	VI-DNBGI	MSCI World TR ($)	MIWO00000PUS
23	DNB Global (I)	VI-GLOBI	MSCI World TR ($)	MIWO00000PUS
24	DNB Fund India	VI-CAIND	MSCI India NR ($)	MIIN00000PIN
25	DNB Norden	AF-NORDE	MSCI Nordic Countries TR ($)	MIND00000PEU
26	DNB Barnefond	DI-BARNE	MSCI World TR ($)	MIWO00000PUS
27	DNB SMB	DI-SMB	MSCI Norway TR ($)	MINO00000PNO
28	Alfred Berg Aktiv	AI-AKTIV	OSE Fund Index (OSEFX) (NOK) TR	OSEFX
29	Alfred Berg Gambak	GA-GAMB	OSE Fund Index (OSEFX) (NOK) TR	OSEFX
30	Parvest Equity Europe Small Cap	PA-EURSC	MSCI Europe Small Cap Index TR ($)	MIEU000S0PEU
31	Parvest Equity India	AI-EINDA	MSCI India 10/40 NR ($)	MIN0000TPUS
32	Parvest Equity World Emerging	AI-EWEMR	MSCI EM (Emerging Markets) NR ($)	MSCIEF
33	PARVEST EQUITY RUSSIA	AI-EREUR	MSCI Russia 10–40 NR ($)	MIRU00005PUS
34	Parvest Equity Turkey	AI-FETC	FTSE Turkey Index TR (TRY)	FTWITURL
35	DNB Norge	DK-PBNOR	Oslo Børs Benchmark Index_GI (OSEBX) (NOK)	OSEBX
36	DNB Norge Indeks	DK-NORIX	Oslo Børs Benchmark Index_GI (OSEBX) (NOK)	OSEBX

Table A.2
Predictors of investors' attention. Values in columns are for regression outputs for the variables in the respective rows. All are multiple regressions of the dependent variable on independent variables on the respective rows. Robust standard errors are stated in parentheses. Number of observations vary but R (the software program) matches the observations to balance the data. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: $Attention_{t-1}$											
	Performance measure:											
	Alpha (α)			Alpha (α) t-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$Performance_{t-1}$	76.173***			0.091**			3.227***			0.038***		
	(21.872)			(0.038)			(1.240)			(0.010)		
$Performance^{6M}_{t-1}$		261.541***			0.278*			11.686**			0.124***	
		(92.890)			(0.160)			(4.790)			(0.033)	
$Performance^{12M}_{t-1}$			471.539***			0.536**			25.679***			0.268***
			(155.479)			(0.223)			(9.035)			(0.068)
$Size_{t-1}$	−0.062	−0.086	−0.173	−0.063	−0.079	−0.153	−0.067	−0.093	−0.202*	−0.057	−0.082	−0.182
	(0.106)	(0.107)	(0.114)	(0.107)	(0.109)	(0.114)	(0.107)	(0.108)	(0.115)	(0.106)	(0.109)	(0.115)
Observations	1,736	1,592	1,419	1,736	1,592	1,419	1,736	1,592	1,419	1,736	1,592	1,419
R^2	0.085	0.086	0.089	0.085	0.083	0.086	0.084	0.085	0.094	0.088	0.091	0.107
Adjusted R^2	0.036	0.035	0.036	0.035	0.031	0.033	0.035	0.034	0.041	0.039	0.040	0.055

Table A.3
Predictors of inflows. Values in columns are for regression outputs for the variables in the respective rows. All are multiple regressions of the dependent variable on independent variables on the respective rows. Robust standard errors are stated in parentheses. Number of observations vary but R (the software program) matches the observations to balance the data. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: $Inflow_t$											
	Performance measure:											
	Alpha (α)			Alpha (α) t-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$Attention_{t-1}$	0.006**	0.002	0.003	0.006**	0.003	0.004	0.005**	0.002	0.002	0.005**	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
$Performance_{t-1}$	7.889***			0.010***			0.515***			0.004***		
	(2.389)			(0.002)			(0.097)			(0.001)		
$Performance^{6M}_{t-1}$		25.735***			0.026**			1.282***			0.011***	
		(6.163)			(0.010)			(0.305)			(0.002)	
$Performance^{12M}_{t-1}$			47.693***			0.050***			2.450***			0.021***
			(10.241)			(0.015)			(0.554)			(0.004)
$Size_{t-1}$	−0.014	−0.019	−0.030*	−0.014	−0.019	−0.028	−0.014	−0.020	−0.033*	−0.013	−0.019	−0.030*
	(0.011)	(0.014)	(0.018)	(0.011)	(0.014)	(0.018)	(0.011)	(0.014)	(0.018)	(0.011)	(0.014)	(0.018)
Observations	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417
R^2	0.083	0.097	0.114	0.082	0.088	0.104	0.092	0.100	0.118	0.088	0.100	0.120
Adjusted R^2	0.033	0.046	0.061	0.031	0.037	0.051	0.043	0.049	0.066	0.038	0.049	0.068

Table A.4
Predictors of outflows. Values in columns are for regression outputs for the variables in the respective rows. All are multiple regressions of the dependent variable on independent variables on the respective rows. Robust standard errors are stated in parentheses. Number of observations vary but R (the software program) matches the observations to balance the data. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: $Outflow_t$											
	Performance measure:											
	Alpha (α)			Alpha (α) t-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$Attention_{t-1}$	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Performance_{t-1}$	0.902			0.001			0.042			0.0001		
	(1.414)			(0.002)			(0.059)			(0.0005)		
$Performance^{6M}_{t-1}$		−2.817			−0.005			0.139			0.0002	
		(3.228)			(0.004)			(0.168)			(0.001)	
$Performance^{12M}_{t-1}$			2.389			0.0001			0.684***			0.003
			(5.925)			(0.006)			(0.284)			(0.002)
$Size_{t-1}$	−0.001	−0.002	−0.003	−0.001	−0.003	−0.003	−0.001	−0.003	−0.004	−0.001	−0.002	−0.003
	(0.009)	(0.011)	(0.014)	(0.009)	(0.011)	(0.014)	(0.009)	(0.011)	(0.014)	(0.009)	(0.011)	(0.014)
Observations	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417
R^2	0.063	0.064	0.063	0.063	0.065	0.063	0.063	0.064	0.072	0.063	0.064	0.066
Adjusted R^2	0.012	0.011	0.008	0.012	0.012	0.008	0.012	0.012	0.017	0.011	0.011	0.011

Table A.5
Predictors of net flows. Values in columns are for regression outputs for the variables in the respective rows. All are multiple regressions of the dependent variable on independent variables on the respective rows. Robust standard errors are stated in parentheses. Number of observations vary but R (the software program) matches the observations to balance the data. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Net flow$_t$											
	Performance measure:											
	Alpha (α)			Alpha (α) t-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Attention$_{t-1}$	0.007**	0.003	0.004	0.007**	0.004	0.004	0.006**	0.003	0.004	0.006*	0.003	0.003
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Performance$_{t-1}$	6.987***			0.008***			0.473***			0.004***		
	(2.530)			(0.003)			(0.084)			(0.001)		
Performance$^{6M}_{t-1}$		28.552***			0.031***			1.143***			0.011***	
		(4.223)			(0.009)			(0.314)			(0.002)	
Performance$^{12M}_{t-1}$			45.303***			0.050***			1.766***			0.018***
			(8.269)			(0.013)			(0.507)			(0.003)
Size$_{t-1}$	−0.013**	−0.017**	−0.027**	−0.013**	−0.016**	−0.025**	−0.013*	−0.018**	−0.028***	−0.012*	−0.016**	−0.027**
	(0.006)	(0.007)	(0.011)	(0.006)	(0.007)	(0.010)	(0.006)	(0.007)	(0.011)	(0.006)	(0.007)	(0.011)
Observations	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417	1,733	1,589	1,417
R^2	0.066	0.078	0.087	0.064	0.070	0.081	0.074	0.071	0.077	0.072	0.076	0.086
Adjusted R^2	0.014	0.026	0.033	0.013	0.018	0.026	0.023	0.019	0.023	0.021	0.023	0.032

Table A.6
Hausman test results for all the model reported in the main text. Each column represents p-values of the Hausman test between the models with fund and time fixed-effects and random effects.

	Dependent variable:			
	Attention	Inflow	Outflow	Net flow
Performance measure				
Alpha (α) 1-month	0.965	0.142	0.216	0.012
Alpha (α) 6-month	0.559	0.096	0.138	0.002
Alpha (α) 12-month	0.010	0.000	0.025	0.000
αt-stat 1-month	0.467	0.056	0.240	0.002
αt-stat 6-month	0.110	0.015	0.148	0.000
αt-stat 12-month	0.000	0.000	0.040	0.000
Return 1-month	0.958	0.002	0.314	0.000
Return 6-month	0.697	0.028	0.396	0.002
Return 12-month	0.010	0.000	0.320	0.000
Sharpe 1-month	0.346	0.003	0.196	0.000
Sharpe 6-month	0.133	0.013	0.190	0.001
Sharpe 12-month	0.000	0.000	0.164	0.000

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