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Empirical investigation of the relationship between Google search volume index and mutual fund performance and flows: evidence from Norway

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Empirical investigation of the relationship between Google search volume index and mutual fund performance and flows: evidence from Norway

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Abstract

We investigate the relationship between Google search volume index (SVI) and Norwegian mutual fund performance and flows. We use abnormal SVI (ASVI) and relative fund flows as measures of investor attention. The aim of this thesis is twofold, we focus on past performance as a determinant of investor attention measured by ASVI, and past performance and investor attention as determinants of mutual fund flows. Our results show that performance can predict ASVI, inflows, outflows, and net flows. ASVI can predict inflows and net flows but not outflows. Interestingly, high performance has positive impact not only on inflows but also on outflows. On average, simple returns attract investor‘s attention more than risk-adjusted performance measures and long-term performance is more important than short-term performance.

Keywords: mutual funds, Google searches, fund performance, fund flows

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. Google processes approximately 90% of the internet search activity (Harford, 2017).

In 2017 Norwegians invested more in mutual funds than ever before. The total net assets in Norwegian mutual funds increased by 157 billion to 1,138 billion NOK in 2017, 51% of this amount went to equity funds. This growth in the popularity of Norwegian mutual funds could be explained by the low interest rate together with the launch of new saving schemes (The Norwegian Fund and Asset Management Association (VFF), 2018b).

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 queries 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 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.

Recently, the study of Kim et al. (2018) as the first study in the Norwegian market investigate whether Google search activity can explain and predict the 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.

Mutual fund flows are direct measures of investor attention, as it is expected that if an investor is interested in a fund he will invest (inflow) and if he is not interested he will not invest or if he already owns assets he will sell (outflow). 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 has 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 finds 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) portrays 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). However, the only study about mutual fund performance, flows and Google search volume index (SVI) we are aware of is the unpublished work of Chen et al. (2016). Chen et al. (2016) use SVI as a direct measure of investor attention in order to explore how attention-grabbing information is connected to the fund flows, survivorship and future performance of newly issued funds in the US market. They find that investor attention plays an important role in fund flows, survivorship, and future performance of newly issued funds.

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 suggests that SVI may be more pronounced in smaller markets, our thesis investigates the Norwegian mutual fund market. We study the relationship between ASVI and fund performance and flows for open- end equity funds. We find that past performance predicts ASVI, inflows, and outflows. ASVI can predict inflows but not outflows. On average the simple return seems to be the most important performance measure, and long-term performance is more important than short-term performance.

The rest of the thesis is structured as follows. Chapter 2 is an overview of Google trend. Chapter 3 describes the data. Chapter 4 presents the methodology. Chapter 5 discusses the results. Chapter 6 concludes.

2. Google trends overview

The questions and subjects people search for can provide a lot of information about what people care about (Tamir, 2015). Billions of searches take place on Google every day, making it one of the worlds largest real time data sets. The data is an unbiased random sample and

Google trend filters the data by real time minute by minute data and non-real time. The real time data can be viewed and downloaded in these time ranges: past hour, past 4 hours, past day, and past 7 days. Furthermore, the non- real time data can also be viewed and downloaded in different time ranges: past 30 days, past 90 days, past 12 months, past 5 years, 2004–present, and customized time horizon. Nevertheless, the different time frequencies in the data sets varies with the time range set by the user: hourly data for the past hours up to the past day; daily data for the past seven days up to the past 90 days; weekly data from the past year up to the past 5 years; and monthly data for a time range above 5 years. Moreover, the features of the Google trend interface allow the user to delineate the specific geographic location, category, type of search and to compare different search terms. Google trend also allows for the possibility to view the search interest in a topic or search term according to where its most-searched (interest by region) and what else people search for in connection with it (related topics and queries) (Rogers, 2016).

Trends only view the data for the popular terms, hence search terms with low volume appears as 0 (Google, 2018a). Additionally, Google trends adjust the search data to allow for comparison of terms. The data is normalized and then scaled on a range of 0 to 100, based on a topics proportion to all searches (Google, 2018b).

Google embarked on their data collection of search queries in 2004 and Google search volume index became available to the general public through Google trends in 2006. Since then there have been several improvements and updates. In June 2008 the website was updated with numbers and the ability to download results as a spreadsheet. Moreover, they launched Google insights for search in august 2008 (Claibone, 2008). In September 2012, Google trend and Google insights for search were merged into the current interface (Matias, 2012). In 2015 they introduced the biggest extension since 2012 with real time data on everything. Furthermore, YouTube and Google News were combined and used to better understand what topics that are trending the web. Additionally, this update increased both the coverage and breadth of the data and allowed for in depth research on more niche topics

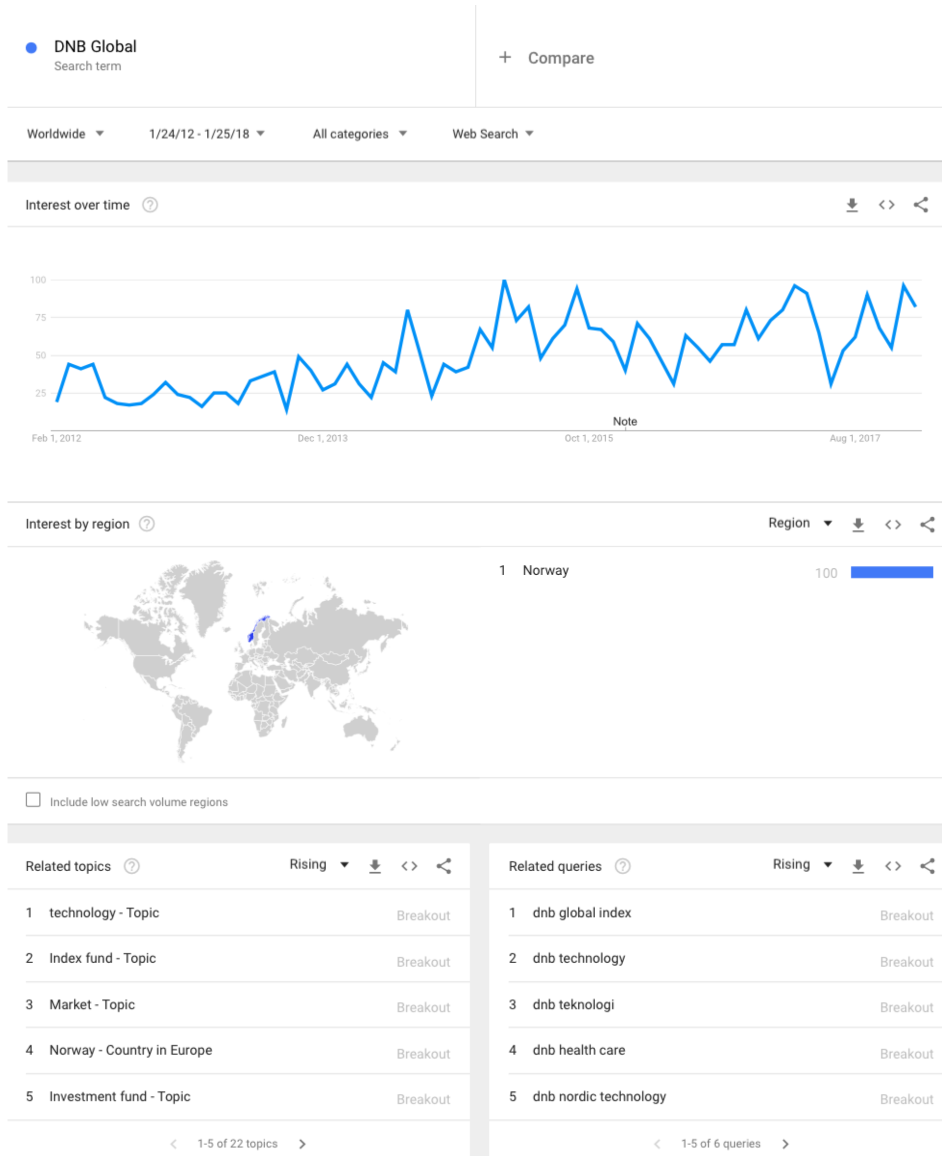

Fig. 1. Google trends output for the search term DNB Global with customized time range from 24.01.12 - 25.01.18 in order to obtain monthly data (Google trend homepage accessed on 10.04.18)

in smaller geographic regions (Tamir, 2015).

3. Data

The data was obtained from Google trends, EIKON, Norges Bank, and the Norwegian Fund and Asset Management Association (henceforth VFF). Following the example of Bijl et al. (2016) and Kim et al. (2018) the last five years were used as the sample period (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.

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 for the SVI. Furthermore, we only include funds with regular flows. Our final sample for the flows consists of 30 funds.

3.1. 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 do 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), where the log of raw weekly SVI is subtracted from log of the median SVI in the past weeks. We calculate the median SVI over the past 12 months.

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

3.2. Mutual fund data

The sample includes all Norwegian mutual funds that were a member of VFF in 2017. VFF was used since they provided 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 (The Norwegian Fund and Asset Management Association (VFF), 2018a). Survivorship bias was not an issue in this study since the main interest is on individual funds, not the fund industry as a whole. 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 appendix 1. 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 reliably, which is essential because the risk exposure of funds can change over time. Inspired by this, daily data from the last five years 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 24.01.2013 - 25.01.2018 (included one extra day to get the first days return).

The daily risk-free rate was obtained from Norges Bank. 3-month Treasury bills daily quotes divided by 252 trading days were used to get daily risk-free rate. There were some days with no quotes, probably because of holidays or non-trading days. For these instances, the closest previously reported 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 converting daily returns into monthly returns in the statistical software R.

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

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).

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

The alpha t- statistic was obtained by dividing the regression alpha by the standard deviation of alpha.

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

The Sharpe ratio was calculated by dividing the excess return by the sigma of the excess returns.

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

The monthly fund inflows, outflows, net flows, and TNA was collected from VFF for the total market. The total market consists of: Norwegian institutional investors, Norwegian retail investors, Pension funds and foreign investors (both retail and institutional) (The Norwegian Fund and Asset Management Association(VFF), 2018). We want to study the funds with regular flows. Our final sample for the flows 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.

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

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

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

Where IN, OUT and NET is inflow, outflow and net flow for fund i at time t. The $TNA_{i,t-1}$ is last months total net assets for fund i.

3.3. *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 and Sharpe ratio multiplied by the square root of 22 trading days.

Table 1: Descriptive statistics for all variables

Statistic	N	Mean	St. Dev.	Min	Max
ASVI	2,196	0.055	1.277	-4.256	4.605
Alpha	2,196	-0.015	0.037	-0.348	0.126
Alpha T-Stat	2,196	-0.531	1.201	-7.991	4.127
Return	2,160	0.012	0.038	-0.193	0.155
Sharpe	2,196	-1.855	1.977	-30.901	1.967
Inflow	1,826	0.044	0.093	-0.001	1.822
Outflow	1,826	0.034	0.06	-0.014	1.107
Net Flow	1,826	0.01	0.097	-1.022	1.809

Table 2: Correlation Matrix for all variables

	ASVI	Alpha	Alpha T-Stat	Return	Sharpe	Inflow	Outflow	Net Flow
ASVI	1	-0.01	-0.01	0.09	-0.03	0.09	0.01	0.08
Alpha	-0.01	1	0.86	0.43	0.58	0.08	0.04	0.05
Alpha T-Stat	-0.01	0.86	1	0.39	0.57	0.09	0.05	0.06
Return	0.09	0.43	0.39	1	0.4	0.1	-0.01	0.1
Sharpe	-0.03	0.58	0.57	0.4	1	0.07	0.04	0.05
Inflow	0.09	0.08	0.09	0.1	0.07	1	0.25	0.8
Outflow	0.01	0.04	0.05	-0.01	0.04	0.25	1	-0.38
Net Flow	0.08	0.05	0.06	0.1	0.05	0.8	-0.38	1

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

4. Methodology

The results were obtained in the statistical software R. Panel data regressions were performed with fixed and random effects. The Hausman test was utilized to identify which of the two methods should be applied. In the coming subsections the models we use are presented.

First, we study the impact of performance on investor attention measured by ASVI.

Model 1.

$$ASVI_t = \alpha + \beta_1 ASVI_{t-1} + \beta_2 Performance_{t-1} + \epsilon_t \tag{9}$$

In order to isolate the effect of performance on ASVI, lagged ASVI is included in the regression model. $ASVI_t$ is the standardized SVI at time t, β are the regression coefficients for one month lagged ASVI and performance. We utilize four different performance measures with different time horizons: lagged by one month, average last six months lagged by one month and average last twelve months lagged by one month. The four performance measures are: alpha, alpha t-statistics, returns, and the Sharpe ratio.

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

Model 2.

$$IN_t = \alpha + \beta_1 IN_{t-1} + \beta_2 ASVI_{t-1} + \beta_3 Performance_{t-1} + \epsilon_t \tag{10}$$

Model 3.

$$OUT_t = \alpha + \beta_1 OUT_{t-1} + \beta_2 ASVI_{t-1} + \beta_3 Performance_{t-1} + \epsilon_t \tag{11}$$

Model 4.

$$NET_t = \alpha + \beta_1 NET_{t-1} + \beta_2 ASVI_{t-1} + \beta_3 Performance_{t-1} + \epsilon_t \tag{12}$$

5. 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 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 2.

5.1. *Regression results for ASVI as dependent variable*

Table 3: **Dependent Variable : ASVI** 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: ASVI											
	Alpha			Alpha T-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$ASVI_{t-1}$	0.250***	0.240***	0.198***	0.250***	0.240***	0.198***	0.241***	0.231***	0.187***	0.248***	0.237***	0.198***
	(0.030)	(0.034)	(0.041)	(0.030)	(0.034)	(0.041)	(0.032)	(0.037)	(0.039)	(0.030)	(0.034)	(0.038)
$Performance_{t-1}$	-0.0002			0.0050			0.057**			-0.011*		
	(0.001)			(0.027)			(0.024)			(0.006)		
$Performance_{t-1}^{6M}$		-0.0004			0.005			0.074***			-0.020	
		(0.002)			(0.038)			(0.024)			(0.014)	
$Performance_{t-1}^{12M}$			0.004***			0.076***			0.079***			-0.012
			(0.001)			(0.026)			(0.024)			(0.013)
Observations	2160	1944	1476	2160	1944	1476	2124	1944	1476	2160	1944	1476
R^2	0.062	0.058	0.048	0.062	0.058	0.046	0.064	0.063	0.046	0.064	0.06	0.041
Adjusted R^2	0.046	0.04	0.024	0.046	0.04	0.021	0.047	0.045	0.022	0.047	0.042	0.016

Table 3 presents the results of the regressions where the dependent variable ASVI is regressed against the control variable lagged ASVI and past performance as independent variables. The table shows that there is a positive relationship between last months ASVI and current months ASVI, and last months ASVI can predict ASVI of the current month. Moreover, there is a positive statistically significant relationship between ASVI and performance, intuitively indicating that investors search more for the funds with higher performance. The simple returns is the performance measure that better can predict ASVI, where all returns variables is highly positively significant. Regarding the different time horizons, the table shows that the magnitude of the returns coefficients is higher for longer time horizons. Alpha t-statistics for the average last 12 months and the alpha for the average last 12 months lagged by one month is also highly significant, while the shorter time horizons for these variables is insignificant.

Results show that mutual fund investors pay attention primarily to simple returns, not risk- adjusted performance measures. Additionally, the results indicate that investors generally care more about long-term performance than short-term performance. 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.

5.2. *Regression results for inflow as dependent variable*

Table 4: **Dependent Variable : Inflow** 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											
	Alpha			Alpha T-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$ASVI_{t-1}$	0.078**	0.047**	0.069***	0.076**	0.045**	0.071***	0.063*	0.034	0.060**	0.078**	0.045*	0.073***
	(0.033)	(0.022)	(0.022)	(0.033)	(0.023)	(0.022)	(0.035)	(0.025)	(0.028)	(0.033)	(0.023)	(0.025)
$Inflow_{t-1}$	0.177**	0.192**	0.171**	0.176**	0.196**	0.179**	0.159**	0.188**	0.255***	0.176**	0.202**	0.276***
	(0.070)	(0.077)	(0.067)	(0.071)	(0.079)	(0.070)	(0.065)	(0.077)	(0.069)	(0.071)	(0.081)	(0.080)
$Performance_{t-1}$	0.002*			0.044			0.121***			0.015**		
	(0.001)			(0.038)			(0.037)			(0.007)		
$Performance^{6M}_{t-1}$		0.004***			0.064**			0.083**			0.005	
		(0.001)			(0.028)			(0.037)			(0.012)	
$Performance^{12M}_{t-1}$			0.005***			0.057*			0.083**			-0.020
			(0.002)			(0.033)			(0.039)			(0.015)
Observations	1793	1614	1226	1793	1614	1226	1764	1614	1227	1793	1614	1227
R^2	0.043	0.051	0.073	0.042	0.048	0.064	0.051	0.052	0.064	0.043	0.044	0.06
Adjusted R^2	0.026	0.032	0.048	0.025	0.029	0.039	0.034	0.032	0.038	0.025	0.025	0.034

Table 4 shows the regression results where inflow is the dependent variable, lagged inflow as control variable and lagged performance and ASVI as independent variables. The results show strong evidence that there is a positive statistically significant relationship between lagged ASVI and inflows. This means that previous months ASVI can predict current months inflows. This makes sense since if an investor is interested in a fund he is more likely to invest in it. Thus, higher investor attention (ASVI) leads to higher fund inflows.

The table also depicts strong persistence in inflows, where last months inflows can predict current months inflows. Moreover, 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 all performance measures matters for the inflows, but again the simple returns seems to be the performance measure that investors care more about and on average long-term performance is more important than short-term performance.

5.3. *Regression results for outflow as dependent variable*

Table 5: **Dependent Variable : Outflow** 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											
	Alpha			Alpha T-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$ASVI_{t-1}$	-0.006	-0.002	-0.022	-0.006	-0.001	-0.021	-0.012	-0.01	-0.023	-0.006	-0.002	-0.002
	(0.022)	(0.024)	(0.033)	(0.021)	(0.023)	(0.033)	(0.022)	(0.024)	(0.035)	(0.021)	(0.023)	(0.033)
$Outflow_{t-1}$	0.074*	0.051	0.057	0.074*	0.051	0.057	0.072*	0.048	0.027	0.073*	0.051	0.04
	(0.039)	(0.035)	(0.045)	(0.039)	(0.035)	(0.045)	(0.039)	(0.034)	(0.035)	(0.039)	(0.035)	(0.037)
$Performance_{t-1}$	-0.0004			-0.003			0.061**			0.003		
	(0.002)			(0.044)			(0.025)			(0.006)		
$Performance^{6M}_{t-1}$		-0.002			-0.037			0.064**			-0.012	
		(0.002)			(0.034)			(0.026)			(0.011)	
$Performance^{12M}_{t-1}$			0.002			0.013			0.124***			-0.011
			(0.001)			(0.031)			(0.026)			(0.013)
Observations	1793	1614	1226	1793	1614	1226	1764	1614	1227	1793	1614	1227
R^2	0.004	0.003	0.004	0.004	0.003	0.003	0.007	0.005	0.015	0.004	0.002	0.002
Adjusted R^2	-0.014	-0.017	-0.022	-0.015	-0.017	-0.023	-0.011	-0.015	-0.011	-0.014	-0.018	-0.025

Table 5 reports the regression results for outflow as dependent variable, lagged outflow as control variable, and lagged performance and ASVI as independent variables. Contrary to the inflows, there is no persistence in outflows and last months ASVI cannot predict current months outflows. This means that investors do not search for funds to take out money from, they only search for funds which they are interested to invest in.

There is a positive and statistically significant relationship between performance and outflows, where only the returns coefficient is significant. This means that high return yields high outflows. This indicates that investors who holds mutual fund shares with high returns might want to sell (share redemption) their shares in order to capitalize their gains.

Additionally, long-term performance is more important than short-term performance, as the magnitude of the coefficients is higher for longer time horizons.

The results from the inflows and outflows regression is in line with the convex flow-performance relationship, as investors rush into funds with high past performance while tend to stay in funds that has performed badly.

5.4. Regression results for net flow as dependent variable

Table 6: **Dependent Variable : Net flow** 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											
	Alpha			Alpha T-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ASVI $_{t-1}$	0.081**	0.049**	0.081***	0.079**	0.047**	0.083***	0.070**	0.041	0.072**	0.081**	0.048**	0.075***
	(0.033)	(0.022)	(0.027)	(0.034)	(0.023)	(0.027)	(0.035)	(0.026)	(0.028)	(0.034)	(0.024)	(0.025)
Net Flow$_{t-1}$	0.148**	0.161**	0.151**	0.148**	0.167**	0.157**	0.133**	0.168**	0.234***	0.149**	0.174**	0.238***
	(0.060)	(0.066)	(0.068)	(0.061)	(0.068)	(0.070)	(0.057)	(0.070)	(0.057)	(0.062)	(0.069)	(0.056)
Performance $_{t-1}$	0.003*			0.047*			0.080**			0.013*		
	(0.001)			(0.028)			(0.034)			(0.007)		
Performance$^{6M}_{t-1}$		0.005***			0.088***			0.044			0.013	
		(0.001)			(0.029)			(0.034)			(0.011)	
Performance$^{12M}_{t-1}$			0.004***			0.049			0.018			-0.011
			(0.002)			(0.031)			(0.043)			(0.011)
Observations	1793	1614	1226	1793	1614	1226	1764	1614	1227	1793	1614	1227
R^2	0.031	0.04	0.058	0.029	0.035	0.053	0.031	0.031	0.042	0.029	0.03	0.043
Adjusted R^2	0.013	0.021	0.033	0.012	0.016	0.027	0.013	0.011	0.017	0.011	0.01	0.017

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, lagged net flow as control variable, and lagged performance and ASVI as independent variables. The results from this regression is very similar to the inflows and the last months net flows can predict the current months net flows. Furthermore, ASVI can also predict net flows. The table also shows that there is a positive and statistically significant relationship between performance and net flows, where all performance measures matters except for the Sharpe ratio. Additionally, on average long-term performance is more important than short-term performance. Contrary to the inflows and outflows, the most important performance measure is the risk-adjusted performance measure alpha. This result is in line with the findings of Barber et al. (2016), who finds that in general the CAPM alpha generated the largest net flow response.

6. Conclusion

In recent years the Norwegian mutual fund industry and the internet usage has grown tremendously. In this master thesis we will therefore investigate the relationship between the Google search volume index (SVI), mutual fund performance, and mutual fund flows. We study whether past performance can predict investor attention measured as abnormal SVI (ASVI) and if past performance and ASVI can predict inflows, outflows and net flows. We are interested in which type of performance and which performance measure that is more important. The four different performance measures are: alpha, alpha t-statistics, returns, and Sharpe ratio. Furthermore, measures of the past performance are considered over past 1 month, past 6 months, and past 12 months.

We find a positive and statistically significant relationship between past performance and ASVI. This indicates that investors search for more information about the funds with higher performance. Furthermore, we find that ASVI can predict inflows and net flows, but not outflows. We also find that past performance can predict inflows, outflows, and net flows. On average simple returns attract investor‘s attention more than risk-adjusted measures of performance, and long-term performance is more important than short-term performance. Interestingly, high performance has positive impact not only on inflows but also on outflows.

The results from the inflows and outflows regressions are in line with the convex flow-performance relationship where investors rush into funds with high past performance but are reluctant to withdraw money from funds that perform badly. Furthermore, the results from the net flows regression where we find that the risk-adjusted performance measure alpha matters more to investors are in line with the findings of Barber et al. (2016).

Future research should aim to include a bigger sample, longer time horizons and different investor groups. Another suggestion for further research is to include mutual fund fees.

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Appendices

Appendix 1. The sample funds with their respective 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

Appendix 2. Tables - Non-standardized

Table 7: **Dependent Variable : ASVI** 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 : ASVI											
	Alpha			Alpha T-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ASVI $_{t-1}$	0.249***	0.239***	0.198***	0.249***	0.239***	0.198***	0.240***	0.230***	0.186***	0.248***	0.237***	0.198***
	(0.030)	(0.034)	(0.041)	(0.030)	(0.034)	(0.041)	(0.031)	(0.037)	(0.039)	(0.030)	(0.034)	(0.038)
Performance $_{t-1}$	-0.131			0.005			1.919**			-0.024*		
	(0.907)			(0.029)			(0.799)			(0.013)		
$\text{Performance}_{t-1}^{6M}$		-0.595			0.004			0.996***			-0.053	
		(2.635)			(0.031)			(0.321)			(0.038)	
$\text{Performance}_{t-1}^{12M}$			6.984***			0.066***			0.730***			-0.031
			(2.209)			(0.023)			(0.219)			(0.036)
Observations	2,160	1,944	1,476	2,160	1,944	1,476	2,124	1,944	1,476	2,160	1,944	1,476
R^2	0.062	0.058	0.048	0.062	0.058	0.046	0.064	0.063	0.046	0.064	0.06	0.041
Adjusted R^2	0.046	0.04	0.024	0.046	0.04	0.021	0.047	0.045	0.022	0.047	0.042	0.016

Table 8: **Dependent Variable : Inflow** 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											
	Alpha			Alpha T-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ASVI $_{t-1}$	0.006**	0.003**	0.005***	0.006**	0.003**	0.005***	0.005*	0.002	0.004**	0.006**	0.003*	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Inflow_{t-1}	0.176**	0.192**	0.171**	0.176**	0.196**	0.178**	0.159**	0.188**	0.255***	0.176**	0.202**	0.276***
	(0.070)	(0.077)	(0.067)	(0.071)	(0.079)	(0.070)	(0.065)	(0.077)	(0.069)	(0.071)	(0.080)	(0.080)
Performance $_{t-1}$	0.136*			0.003			0.295***			0.002**		
	(0.077)			(0.003)			(0.091)			(0.001)		
$\text{Performance}_{t-1}^{6M}$		0.404***			0.004**			0.080**			0.001	
		(0.142)			(0.002)			(0.036)			(0.002)	
$\text{Performance}_{t-1}^{12M}$			0.575***			0.004*			0.056**			-0.004
			(0.171)			(0.002)			(0.026)			(0.003)
Observations	1,793	1,614	1,226	1,793	1,614	1,226	1,764	1,614	1,227	1,793	1,614	1,227
R^2	0.043	0.051	0.073	0.042	0.048	0.064	0.051	0.052	0.064	0.043	0.044	0.060
Adjusted R^2	0.026	0.032	0.048	0.025	0.029	0.039	0.034	0.032	0.038	0.025	0.025	0.034

Table 9: **Dependent Variable : Outflow** 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											
	Alpha			Alpha T-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ASVI $_{t-1}$	-0.0003	-0.0001	-0.001	-0.0003	-0.00005	-0.001	-0.001	-0.0005	-0.001	-0.0003	-0.0001	-0.0001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Outflow$_{t-1}$	0.073*	0.051	0.056	0.073*	0.051	0.057	0.071*	0.048	0.027	0.073*	0.051	0.04
	(0.038)	(0.034)	(0.044)	(0.039)	(0.034)	(0.044)	(0.038)	(0.034)	(0.035)	(0.038)	(0.035)	(0.036)
Performance $_{t-1}$	-0.013			-0.0002			0.097**			0.0003		
	(0.064)			(0.002)			(0.04)			(0.001)		
Performance$^{6M}_{t-1}$		-0.134			-0.001			0.041**			-0.001	
		(0.133)			(0.001)			(0.016)			(0.001)	
Performance$^{12M}_{t-1}$			0.118			0.001			0.054***			-0.001
			(0.104)			(0.001)			(0.012)			(0.002)
Observations	1,793	1,614	1,226	1,793	1,614	1,226	1,764	1,614	1,227	1,793	1,614	1,227
R^2	0.004	0.003	0.004	0.004	0.003	0.003	0.007	0.005	0.015	0.004	0.002	0.002
Adjusted R^2	-0.014	-0.017	-0.022	-0.015	-0.017	-0.023	-0.011	-0.015	-0.011	-0.014	-0.018	-0.025

Table 10: **Dependent Variable : Net flow** 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											
	Alpha			Alpha T-stat			Return			Sharpe		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ASVI $_{t-1}$	0.006**	0.004**	0.006***	0.006**	0.004**	0.006***	0.005**	0.003	0.005**	0.006**	0.004**	0.006***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Net Flow$_{t-1}$	0.148**	0.161**	0.151**	0.147**	0.166**	0.156**	0.133**	0.168**	0.234***	0.148**	0.173**	0.237***
	(0.060)	(0.066)	(0.067)	(0.061)	(0.068)	(0.070)	(0.056)	(0.070)	(0.057)	(0.062)	(0.069)	(0.056)
Performance $_{t-1}$	0.154*			0.004*			0.203**			0.002*		
	(0.079)			(0.002)			(0.086)			(0.001)		
Performance$^{6M}_{t-1}$		0.557***			0.005***			0.045			0.003	
		(0.147)			(0.002)			(0.035)			(0.002)	
Performance$^{12M}_{t-1}$			0.478***			0.003			0.013			-0.002
			(0.178)			(0.002)			(0.03)			(0.002)
Observations	1,793	1,614	1,226	1,793	1,614	1,226	1,764	1,614	1,227	1,793	1,614	1,227
R^2	0.031	0.04	0.058	0.029	0.035	0.053	0.031	0.031	0.042	0.029	0.03	0.043
Adjusted R^2	0.013	0.021	0.033	0.012	0.016	0.027	0.013	0.011	0.017	0.011	0.01	0.017