Retail investors’ attention and momentum strategies

- Evidence from the S&P 500 -

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Abstract

Relying on Google Trends search data for the S&P 500 stocks between 2004 and 2015, we find that investing in momentum in a portfolio of stocks with increasing search activity minus a portfolio of stocks facing a decreasing search activity does not exhibit, *ceteris paribus*, significant positive momentum returns. Furthermore, we show that retail investors' attention creates volatility. For that reason, investing in stocks with stable retail investors' attention decreases significantly momentum volatility. The momentum effect has a negative relationship with the market tone and does not significantly impact the long-term reversal effect. For those reasons, while general investors overreact to information as shown by Hillert et al. (2014), we conclude that retail investors underreact to information.

1 Introduction

Many papers have documented that average stock returns are related to past performance. Trading strategies that bought past winners and sold past losers realize significant abnormal returns in the US over the 1965 to 1989 period (Jegadeesh and Titman, 1993) and in Europe between 1980 and 1995 (Rouwenhorst, 1998). More in detail, Jegadeesh and Titman (1993) show that stocks in the US that realized the best returns over the past 3 to 12 months continue to perform well over the subsequent 3 to 12 months. Even if the existence of the momentum effect has been shown in different time periods, countries, indices, and asset classes, a central issue is far from being resolved (Hillert, Jacobs, and Sebastian, 2014): what are the underlying causes of momentum?

The magnitude of momentum profits is about 12% per year in the United States and Europe, and such an amount is unlikely to be explained by risk-based theories or rational asset pricing models. Indeed, most of the focus in the academic research has been on behavioral explanations for this phenomenon (Chui, Titman, and Wei, 2010). Some studies conclude that the market underreacts to information, while others find evidence of overreaction. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) show how the momentum effect can be generated by investors' overconfidence and self-attribution bias. Their theory implies that investors overreact to private information signals and underreact to public information signals.

Media coverage directly affects the way in which investors collect, process, and interpret information (Engelberg and Parsons, 2011). Hillert, Jacobs, and Müller (2014) argue that investors' attention and information processing play a crucial role in prominent behavioral finance theories of momentum. They find that firms specifically covered by the media exhibit, *ceteris paribus*, significantly stronger momentum. This effect is higher if the articles have a positive tone or contain positive content. However, in the long run, they notice the reversal of the momentum return, which is more pronounced for stocks with high uncertainty and in states with high investor individualism. They conclude by supporting the overreaction-based explanation for the momentum effect.

More recent papers study the number of internet users looking for information about a company or stock market. The analysis of internet search queries can be interpreted as a measure of retail investors' attention to the stock market. In contrast, most professional investors probably don't use a search engine to obtain information about the leading stock market index (Da, Engelberg, and Gao, 2011). After searching for the stock market index, some individuals might be inclined to act and trade immediately or the following day; the overall trading volume of the stocks comprising the Dow Jones Industrial Average (Dow Jones) rises after an increase in search queries for the index (Dimpfl and Jank, 2015). A rise in investors' attention is followed by higher volatility.

Retail investors are often considered to be uninformed noise traders. Empirical evidence shows that retail investors lose money with their trading decisions. For example, Grinblatt and Keloharju (2000) analyze Finland's unique data set to understand whether differences in investor sophistications drive the performance of various investor types. They find that foreign investors outperform domestic households.

In this paper, we study the relationship between the retail investors' market attention and the returns of momentum strategies on the S&P 500 in the period from 2004 to 2015. The idea is to partially replicate the analysis of the media coverage effects on momentum returns conducted by Hillert, Jacobs, and Müller (2014). However, the main difference is that, instead of using newspaper articles, we define the media coverage as growth in the residual Google searches for a single stock. According to Latoeiro, Ramos, and Veiga (2013), Google is a good representative of web search queries on the Internet due to its leading market share. While Hillert et al. (2014) study both retail and sophisticated investors, with this study we can contribute to the literature by focusing on the effect of retail investors' attention to the momentum returns. The main assumption of this paper is that most sophisticated investors are not looking for data on Google, but they do use other information providers, as shown by Da et al. (2011).

Furthermore, we aim to understand if it's possible to explain the future media-based momentum return by analyzing the retail investors' confidence in the stock markets. One important disadvantage of Google search queries is that they don't allow for research on the tone of the articles. It is not possible to understand if users' increased attention is due to negative or positive information. For that reason, we use six Google Trend indicators of the investors' confidence in the stock markets, following Preis, Moat, & Stanley (2013). Our hypothesis is the following: if investors search information on a stock in a period in which the confidence indicator queries are high, they will judge more confidently the information they get.

We show three main results. First, contrary to the results shown by Hillert et al. (2014) with media coverage, investing in momentum in a portfolio of stocks with increasing search activity minus a portfolio of stocks facing a decreasing search activity does not exhibit, *ceteris* *paribus*, significant positive momentum returns. However, we notice positive but not statistically significant returns by investing in a portfolio of firms with stable residual Google searches and selling at the same time stocks that had either high increase or decrease in residual Google search during the previous six months.

Secondly, we conclude that a momentum strategy which invests in a portfolio of stocks with high retail investors' attention and sells a portfolio of stocks with low investors' attention has a statistically significant lower volatility than a classical momentum strategy. However, it has a higher volatility than the strategy which invests in a portfolio of stock with stable Google searches. The latter result shows that retail investors' attention creates volatility, as shown by Dimpfl and Jank (2015).

Thirdly, the analysis of the tone of the market and of the long-run reversal effect don't show that investors overreact to information. For those reasons, while the general investors overreact to information as shown by Hillert et al. (2014), we conclude that the retail investors underreact to information.

Section 2 of this paper describes the data sample and the research method. In section 3, we present the empirical results, and, in section 4, we show the analysis of the market tone and long-run reversal effect. Section 5 concludes the research.

2 Data and Empirical Setup

2.1 Data sample

Our initial sample consists of all S&P 500 constituents as of April 2016, which are shown in Appendix A. The monthly prices for those stocks are retrieved from Thomson Eikon for the period beginning January 2004 and ending December 2015. We eliminate all constituents without analyzed prices for the whole period in order to avoid the survivorship bias. After this adjustment, the sample consists of 435 constituents. We compute monthly continuously-compounded returns for the whole period.

The data on search queries are obtained through Google Trends.[1] We decide to use Google Trends for two main reasons. First, according to Latoeiro, ,Ramos and Veiga (2013), Google is a good representative of web search queries on the Internet due to its leading market share, which

[1] Source: Google Trends (www.google.com/trends)

is about 88% worldwide.[2] For that reason, Google Trends data represent the majority of the US population searches. Additionally, Google provides free data, collected on a regular basis beginning in 2004, which is easy to access and to analyze.

One of the main challenges in analyzing Google Trend data is the choice of the search terms. For example, by searching the term "APPLE," it is impossible to understand if the internet user was searching information about "APPLE, Inc" or about fruits. In the previous literature, two main methods are used (Latoeiro et al., 2013). One possible solution is to look for the complete name of the firm; in the Apple example, this would be "APPLE INC." An alternative solution is to use the ticker of the company; in this example: "AAPL." Following Da et al. (2011), we decide to use the ticker of the company as the search term. By searching the ticker of the company, investors show their intention to look for information on the share price of this company and not, for example, to find the new products sold by the firm. We interpret the search of the ticker as a strong signal of investors' interest and attention to a stock.

We download weekly data on search volume from January 2004 to the end of 2015; Google provides weekly indexed data for each search term. The index measure is based on the number of searches within the USA, following Dimpfl and Jank (2015). We define the monthly search volume as the average of the weekly search index provided by Google for each month. We calculate the month-to-month percentage increase or decrease in the index of Google searches for each query. However, for 35 search queries, it was not possible to obtain search information. For that reason, we exclude them from the data set, which, after this correction, is composed of 400 components of the S&P 500. We download data from Google Trends using the gtrendsR package, as shown in Appendix A.

2.2 Calculation of residual Google searches

The advantage of indexed data is that we don't have to control for the size of the company, as suggested by Hillert et al. (2014). They argue that bigger firms could have greater media coverage than smaller ones; for that reason, they use a two-step regression model to correct media coverage data for the size effect. However, we have to account for the effect that high returns for a stock at month t could lead to more Google searches for the same stock at time $t + 1$. For that reason, for the construction of momentum portfolios, we use both the total month-to-month

[2] According to Netmarketshare.com (www.netmarketshare.com), as of January 2016.

percentage change of Google searches and also the month-to-month percentage residual change of Google searches by applying a two-step regression model.

First of all, we estimate for each stock i the constant and the β of the simple regression model (1):

(1) $Actual\ Google\ search\ \%\ change_{t,i} = cons + \beta * Stock\ Return_{t-1,i}$

After estimating the parameters of the regression model for each stock, we can estimate the expected Google search for each stock at time t, given the actual stock return at $t-1$. Using these two parameters, we can estimate the expected Google search percentage change as follows (2):

(2) $Estimated\ Google\ search\ \%\ change_{t,i} = cons_i + \beta_i * Stock\ Return_{t-1,i}$

The residual Google search percentage change is then defined as follows (3):

(3) $$Residual\ Google\ search\ \%\ change_{t,i} = Actual\ Google\ search\ \%\ change_{t,i} - Estimated\ Google\ search\ \%\ change_{t,i}$$

2.3 Construction of momentum portfolios

After downloading data, the second important step in this paper is the construction of momentum portfolios. Consistent with Hillert et al. (2014), returns are given as percentages per month and are based on overlapping equally-weighted portfolios, as in Jegadeesh and Titman (1993). In order to present a clear and transparent methodology for the construction of the momentum portfolios, we follow the subsequent steps.

Firstly, at the beginning of every month t, we rank the 400 stocks based on their cumulative residual Google search growth over the previous six months. Secondly, we sort the stocks into five equal-weighted portfolios. Portfolio 1 contains the 80 stocks with the worst growth (or higher decrease) in Google search. Portfolio 2 contains the next 80 stocks, and so on, until the highest searched stocks are included in Portfolio 5. Thirdly, for each of the five portfolios, we create three sub-portfolios "Winner," "Mid," and "Loser." In other words, we rank the 80 stocks of each of the five portfolios, based on their cumulative stock returns in the last six months. The Winner portfolio includes the 24 best performing stocks inside the portfolio. This represents the best 30% of the 80 stocks included in each of the five main portfolios. The Loser portfolio includes the worst 24 performing stocks, and the Mid portfolio includes the remaining ones. The five portfolios (including the three sub-portfolios for each portfolio) are created at each month t. Returns for each portfolio are calculated monthly for the next six months, or until $t+6$. The return of each sub-portfolio at time t is the average of the return of the sub-portfolio at time t, $t-1$, $t-2$, and so on through $t-5$. This is the overlapping portfolio presented by Jegadeesh and Titman (1993). To conclude, the momentum return for each of the five portfolios is the difference between the Winner and Loser sub-portfolios.

3 Empirical Results

3.1 Analysis of the momentum returns

Following the standard in the literature, we construct momentum portfolios using a formation and holding period of six months, as explained in the previous section. Since we divide the 400 stocks analyzed by ranking them in five different portfolios of 80 stocks each, we show in **Table 1** the 20th average percentiles for the choice of the stocks. Portfolio 1 has, on average, stocks with cumulative residual Google searches during the previous six months between -78% and - 14%. Portfolio 2 has, on average, constituents with cumulative residual Google searches during the formation period between -14% and -3%, and so on through Portfolio 5, which includes the tickers with the highest growth in Google searches during the formation period.

Variable	Obs	Mean	Std. Dev.
min	138	-78.0%	0.2313573
20%	138	-14.3%	0.0561727
40%	138	-3.4%	0.0398342
60%	138	4.6%	0.0385512
80%	138	15.7%	0.0538438
max	138	83.7%	0.1923182

Table 1. Descriptive statistics. The table shows the average percentiles of the growth in Google searches during the six-month formation periods. For that reason, when constructing Portfolio 1, we consider on average changes between -78% and -14%. Portfolio 2 considers on average changes in Google search between -14% and -3%, and so on.

The baseline effect of Google searches on momentum profits is shown in **Table 2**. This analysis is conducted using residual Google searches in order to account for the possible relationship between past stock returns and future growth in Google searches, as shown in the previous section. The results for the raw growth in Google searches are presented in Appendix B. However, the statistical and economic significance of the results is very similar to this case.

Panel A shows the returns of all portfolios. In all five portfolios, there are positive momentum returns, ranging from 0.05% of the low residual Google search for Portfolio 1 to the 0.20% momentum return of Portfolio 3, which includes on average stocks with residual Google search growth between -3% and 5%. In other words, if we go long in each sub-portfolio "Winner" and we short the sub-portfolio "Loser," we have positive momentum returns.

Now we consider the momentum returns between different portfolios. What happens if we go long in the momentum strategy of Portfolio 5 and we short the momentum strategy of Portfolio 1? This is shown in the table in the row "Return 5-1." The return if we invest in a momentum strategy constructed in the high cumulative residual Google search growth portfolio and we sell the low cumulative residual Google search growth one (i.e. Portfolio 5 minus Portfolio 1) equals 0.01%. Even if the results are positive, they are not statistically significant at 10% confidence level since all t-values are very low. It is not possible to state that stocks with high growth in Google searches over the formation period either overperform or underperform stocks with high search decrease. Furthermore, the returns of the Winner, Mid, and Loser sub-portfolios are higher for the low-growth residual Google search portfolios. In this case, the results are statistically insignificant.

Panel A: Double sorts and raw returns

	Loser Return	Mid Return	Winner Return	Mom Return	*t-stat*
1	0.64%	0.58%	0.70%	0.05%	0.19
2	0.45%	0.56%	0.52%	0.06%	0.23
3	0.36%	0.52%	0.56%	0.20%	0.67
4	0.38%	0.47%	0.48%	0.10%	0.33
5	0.51%	0.52%	0.57%	0.07%	0.17
Return 3-1	-0.29%	-0.06%	-0.14%	0.15%	0.95
Return 4-1	-0.26%	-0.11%	-0.21%	0.05%	0.28
Return 3-5	-0.15%	0.00%	-0.02%	0.14%	0.75
Return 5-1	-0.13%	-0.06%	-0.12%	0.01%	0.06
t-stat	-0.67	-0.79	-0.88		

Panel B: Risk Adjusted returns for media-based momentum, Return 5-1

Factor Model	1F	3F
Intercept	0.0005	0.0002
Intercept t-stat	0.21	0.09
R^2	0.01	0.15

Panel C: Risk Adjusted returns for media-based momentum, Return 3-1

Factor Model	1F	3F
Intercept	0.0018	0.0017
Intercept t-stat	1.15	1.09
R^2	0.02	0.08

Table 2. Residual Google search and momentum. This table presents momentum returns for stock portfolios sorted first by residual Google search growth. We calculate the residual Google search growth with a two-step regression model which controls for the correlation between past returns and future Google search growth. We use a formation and a holding period of six months each. For 138 periods, we rank the 400 constituents of the S&P 500 basing on the growth of Google searches during the previous six months. In other words, we create at each month, for 138 months, five portfolios of 80 different stocks each. Furthermore, for each portfolio, we create three sub-portfolios: "Loser," "Mid," and "Winner." The Winner (Loser) portfolio consists of all stocks with a formation period return above the 70th percentile (below the 30th percentile). In each portfolio, the Winner and Loser sub-portfolios are composed of 24 stocks (30% of 80 stocks). Momentum returns (reported in % per month) are based on overlapping portfolios that are equally weighted as in Jegadeesh and Titman (1993) and Hillert et al. (2014). Panel A shows raw returns, while Panels B and C show risk adjusted returns. 1F is the CAPM model, while 3F is the Fama and French (1993) model. Panel B shows the risk-adjusted returns for the difference between the momentum return for the high and the low residual Google search

growth portfolios (5-1). Panel C shows the risk-adjusted returns for the difference between the momentum return for the third quintile and the low residual Google search growth portfolios (3-1).

However, interesting results come from the analysis of the momentum returns between Portfolio 3 and the two extreme portfolios, Portfolios 1 and 5. By investing in Portfolio 3 and selling Portfolio 1 (or 5), it was possible to achieve 0.15% (0.14%) monthly return over the 138 months analyzed. Those returns are higher compared to the other ones. However, even if the t-statistics in this case are higher, both results remain statistically insignificant.

Panels B and C show the risk-adjusted returns. Also, in this case, both with the CAPM and the Fama and French (1993) models, it is not possible to identify positive and significant abnormal returns resulting neither from the 5-1 momentum portfolio, nor from the 3-1 momentum portfolio. However, the significance of the 3-1 momentum portfolio is higher compared to the 5-1 portfolio.

Generally, the results show that the analysis of Google searches does not lead to clear and statistically significant results in the case of media coverage, as shown by Hillert et al. (2014), who have not only economically but also statistically significant results. However, a first interesting – even if not significant – result from this analysis reveals that investing in a strategy which buys a momentum portfolio on stocks that were stable[3] in terms of residual Google searches during the previous six months and sells a momentum portfolio on stocks that had a high increase [Portfolio 5] or decrease [Portfolio 1] in residual Google searches, leads to higher momentum returns. As shown in the Appendix, we obtain similar results by analyzing the raw, rather than residual, Google search growth.

We test now whether the returns obtained from the strategy which buys a momentum portfolio on stocks that were stable in terms of residual Google searches [Portfolio 3] and sells the momentum portfolio on extreme search increase or decrease stocks [Portfolio 1 and 5] generate statistically higher mean returns than investing in the momentum portfolio 5-1, which invests in momentum on high attention stocks and sells momentum on low attention ones. For that reason, we conduct a two-sample t-test. The results are shown in Appendix B. Even if Portfolios 3-5 and 3-1 have higher mean returns compared to Portfolio 5-1, those differences are not statistically significant.

[3] Or, to provide more detail, stocks that on average had a residual Google search growth between -3% and 5%, as shown in Table 1.

3.2 Analysis of the momentum variances

As shown in the introduction of this paper, Dimpfl and Jank (2015) document that the overall trading volume of the stocks comprising the Dow Jones rises after an increase in search queries for the index. They argue that a rise in investors' attention is followed by higher volatility. Based on this result, we test the variances of the momentum returns shown in **Table 1**. For this analysis, we focus on three main momentum strategies.

Firstly, we introduce a classical momentum strategy. Instead of ranking the stocks based on the past residual Google searches, we simply rank them by their past cumulative returns over the same time period. Secondly, we analyze the momentum 3-1 and 3-5 strategies. Both strategies buy stocks that were stable in terms of residual Google search during the previous six months, and they sell stocks with an extreme increase or decrease in residual Google search. On average, those stocks have a search growth between 16% and 84% (Momentum Portfolio 5) or a search decrease between -78% and -14% (Momentum Portfolio 1).[4] Thirdly, we analyze the momentum 5-1 strategy. This strategy buys stocks with an extreme increase in Google searches and sells the ones with the highest decrease. In other words, this strategy buys stocks with an increased investors' attention and sells stocks with a decreased investors' attention.

We choose these three strategies to compare portfolios which invest in momentum based on high investors' attention, stable investors' attention, and not caring about investors' attention (classical momentum). We show graphically the returns of each of the three[5] strategies in **Figure 1**. Some strategies have higher return volatilities than others. In order to prove statistically those differences, we conduct a F-test for the variances of the different momentum strategies.

[4] Please refer to Table 1 for further information about average growth in Google search.

[5] Please note that we refer to three strategies, even if in fact they are four. The reason is that we show Portfolios 3-1 and 3-5 in the same category, since they both invest in stable investor attention momentum, and they sell extreme changes in investor attention.

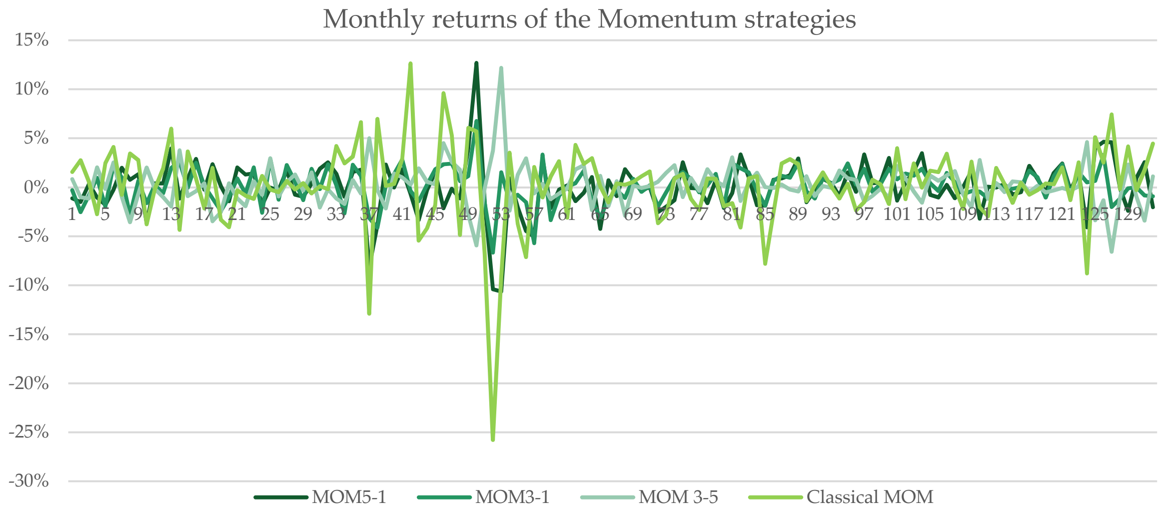

Figure 1. Monthly returns of the momentum strategies. MOM 3-1 (MOM 3-5) is the strategy that buys the momentum strategy on stocks that were stable in terms of residual Google search during the previous six months and sells the momentum strategy on stocks with an extreme decrease (increase) in residual Google search. MOM 5-1 is the portfolio that buys the momentum strategy on stock with an extreme increasing investors' attention during the last six months and sells the momentum strategy on stocks with an extreme decreasing investors' attention. Classical MOM is a classical momentum strategy which ranks the stocks basing on their past cumulative returns.

The results of the F-test of the variances between the different momentum strategies are shown in **Table 3**. If, instead of ranking the stocks basing on the past residual Google searches, we simply rank them by their past cumulative returns over the same time period, we get a 0.14% monthly return with 4.2% standard deviation. Model 1 shows the F-test between the variances of the momentum 3-1 portfolio and the classical momentum portfolio. With high statistical significance, we can conclude that the momentum 3-1 strategy has a lower variance compared to the classical momentum strategy. We obtain similar results if we compare the variance of the 3-5 momentum strategy with the classical momentum (Model 3). In other words, if we buy a momentum portfolio that avoids stocks with extreme growth in residual Google searches and we sell a momentum portfolio with extreme increase or decrease in residual Google searches (or, investors' attention), we can significantly reduce the volatility of the classical momentum strategy. Model 2 shows the F-test between the variances of the momentum 3-1 portfolio and the momentum 5-1 strategy. The mean return of the momentum 3-1 portfolio is, as shown previously, statistically insignificantly higher than the momentum 5-1 portfolio. Furthermore, the variance of the 3-1 portfolio is significantly lower than the variance of the 5-1 portfolio. Similar results are shown in Model 4, which compares the 3-5 portfolio with the 5-1 portfolio. Also in this case, the variance of the portfolio which invests in momentum based on stable investors' attention and sells momentum based on decreased investors' attention is higher compared to the 3-5 portfolio.

F-Test Two-Sample for Variances	1		2		3		4	
	MOM3-1	*Classical MOM*	*MOM3-1*	*MOM5-1*	*MOM3-5*	*Classical MOM*	*MOM3-5*	*MOM5-1*
Mean	0.15%	0.14%	0.15%	0.01%	0.14%	0.14%	0.14%	0.01%
Variance	0.0003	0.0018	0.0003	0.0007	0.0004	0.0018	0.0004	0.0007
Std	1.8%	4.2%	1.8%	2.7%	2.1%	4.2%	2.1%	2.7%
Observations	132	132	132	132	132	132	132	132
df	131	131	131	131	131	131	131	131
F	0.1888		0.4699		0.2527		0.6291	
P(F<=f) one-tail	0.0000		0.0000		0.0000		0.0042	
F Critical one-tail	0.7494		0.7494		0.7494		0.7494	

Table 3. F-Test for the variances of different momentum strategies. MOM 3-1 (MOM 3-5) is the portfolio that buys the momentum strategy on stocks that were stable in terms of residual Google search during the previous six months and sells the momentum strategy on stocks with an extreme decrease (increase) in residual Google search. MOM 5-1 is the portfolio that buys the momentum strategy on stocks with an extreme increased investors' attention during the last six months and sells the momentum strategy on stocks with an extreme decreasing investors' attention. Classical MOM is a classical momentum strategy which ranks the stocks basing on their past cumulative returns. Each of the four models compares the variance of the variable on the left hand side with the variance of the other variable in the model. In other words, Model 1 compares the variance of the MOM3-1 variable with the one of the Classical MOM variable, and so on.

3.3 Findings

In this section, we show the results of the analysis of strategies that invest in momentum portfolios constructed based on the growth of residual Google searches for each stock during the formation period of six months. Firstly, following Hillert et al. (2014), we conduct the analysis of the returns of those strategies. Counter to the results exhibited by Hillert et al. (2014) with media coverage, it is not possible to achieve positive returns by investing in momentum in a portfolio of high residual Google search increase stocks and by selling momentum based on a portfolio which contains stocks that had high residual Google search decrease in the previous six months. However, we notice positive but not statistically significant returns by following the strategy of investing in momentum in a portfolio with firms with stable residual Google searches and selling at the same time a momentum strategy constructed using stocks that had either high increase or decrease in residual Google search during the previous six months.

Secondly, following Dimpfl & Jank (2015), we test the differences between the variances of three momentum strategies. The momentum strategy 5-1, which invests in momentum in a portfolio of stocks with high investors' attention and sells momentum in a portfolio of low investors' attention has a statistically significantly higher volatility than the portfolios 3-5 and 3-1, which invest in momentum in a portfolio of stock with stable Google searches. Since the volatility of the returns of the portfolio momentum 5-1 is significantly higher than that of the momentum 3-1 and 3-5 portfolios, in the next section we aim to understand if overconfidence, as shown by Hillert et al. (2014), is a driver of those returns.

4 Investors' attention and overconfidence-driven overreaction

In the previous section, we showed that investing in a momentum strategy based on a portfolio of stocks with increased investors' attention and at the same time selling a momentum strategy based on a portfolio of decreased investors' attention leads to lower returns (not statistically significant) and higher volatility (statistically significant). Higher volatility means that more extreme returns are possible. For that reason, we aim to understand which factors lead to higher or lower returns of the momentum strategy 5-1. Individuals tend to be particularly overconfident and overreactive in settings in which more judgment is required to evaluate ambiguous information, according to Daniel and Titman (2006). In order to understand if momentum returns are driven by the investors' overreaction to information, following Hillert et al. (2014), we test both the tone of the market and the long-run reversal of momentum strategies.

4.1 Tone of the market

Hillert et al. (2014) argue that if overconfidence-driven overreaction was the force behind media-based momentum, then not only the intensity of media coverage mattered but also its content. They show that the momentum effect is particularly pronounced for stocks for which the article tone matches the formation period return. The problem with Google search data is that it is impossible to understand if users are searching for positive or negative information about a company. For that reason, it is not possible to replicate the analysis presented by Hillert et al. (2014). However, instead of understanding the tone of each individual article or of single pieces of information, we try to quantify the tone of the entire market of players. In other words, if the tone of the market is positive, the momentum effect should be more pronounced. The question is now how to analyze the tone of the market players.

By analyzing changes in Google query volumes for search terms related to finance, Preis et al. (2013) find patterns that can be interpreted as early signals of stock market moves. They notice that important drops in the financial markets are preceded by periods in which investors may search for more information about the market before eventually deciding to buy or sell. They analyze the performance of 98 search terms, including terms related to the concept of stock markets but also other terms suggested by the Google Sets, a tool which identifies semantically-related keywords. Their approach is simple: they invest in the Dow Jones if the search for a given query increases, and they sell if it decreases. As a result, they show the performances of their strategies for each search query analyzed, finding that some queries can anticipate the market better than others.[6]

In order to understand the tone of the market, we use the search queries analyzed by Preis et al. (2013). We choose the three variables with the highest (lowest) performances of investment strategies based on search volume data as indicators of the positive (negative) tone of the market. Preis et al. (2013) note that if they invest in the market when Google searches increase for the queries "debt," "color," and "stocks," their strategy achieves high returns. However, they show the worst performances if they invest in the market when Google searches for the queries "ring," "environment," and "fun" increase. For that reason, we argue that the queries "debt," "color," and "stocks" represent the good tone of the market, while the search terms "ring," "environment," and "fun" represent the negative tone.

In order to understand the relationship between each of these variables and the returns generated by the momentum strategy 5-1, we use them as the independent variables of a multiple linear regression model. The results are shown in the **Table 4**. Model 2 shows all queries, while Model 1 considers only the best- and worst-performing queries shown by Preis et al. (2013), respectively "debt" and "ring."

We obtain opposite results from the ones discovered by Preis et al. (2013). Firstly, we notice a negative relationship between the variables "ln_debt," "ln_color," and "ln_stocks" and the returns of the momentum strategy 5-1. However, those relationships are statistically insignificant. In other words, if the tone of the market is positive at the end of the formation period of the momentum portfolio (represented by the queries "debt," "color," and "stocks"), the returns in the momentum 5-1 portfolio are expected to be lower.

Secondly, we obtain a positive relationship between the variables "ln_ring," "ln_environment," and "ln_fun" and the returns of the momentum strategy 5-1. In this case, only the variable "ln_ring" is statistically significant at level 10%; in Model 1, the significance level is 5%. The other two variables are statistically insignificant.

Dependent: MOM 5-1	1			2		
	Coef.	t	P>t	Coef.	t	P>t
ln_debt	-0.0150	-1.58	0.116	-0.0096	-1.03	0.304
ln_color				-0.0129	-0.61	0.541
ln_stocks				-0.0197	-1.52	0.130

[6] Preis et al. (2013), Figure 3.

ln_ring	0.0446**	1.97	0.051	0.0572*	1.71	0.090
ln_environment				0.0066	0.56	0.575
ln_fun				0.0056	0.22	0.829
_cons	-0.1349	-1.35	0.179	-0.1339	-0.66	0.512
N	126			126		
R-Squared	0.05			0.07		
F	3.54			1.44		
Prob > F	0.03			0.20		

Table 4. The results of the multiple regression analysis. The dependent variable is the momentum strategy 5-1. MOM 5-1 is the self-financing portfolio that buys the momentum strategy on stocks with extreme increasing investors' attention during the last six months and sells the momentum strategy on stocks with extreme decreasing investors' attention. The independent variables are the logarithm of the level of the Google Trend search indexes at the end of each formation period. The queries are "debt," "color," "stocks," "ring," "environment," and "fun," following the results of Preis et al. (2013). Two models are presented. Model 2 considers all queries. Model 1 considers only the best and worst performing queries shown by Preis et al. (2013). * indicates the significance at 10% level, and ** indicates the significance at 5% level.

These results do have economic significance. If the market tone is positive, investing in momentum in a portfolio of stocks with increased investors' attention leads to lower returns, and vice versa. In both regression models, only the "ring" query leads to statistically significant results. For that reason, we can only conclude that if the tone of the market is negative at the end of the formation period, the momentum 5-1 portfolio has higher returns during the following month.

If we assume that the queries presented by Preis et al. (2013) are good indicators of the general market tone at a given time, then investor overconfidence doesn't influence the magnitude of Google search-based momentum. If the market tone is positive, investors should be more confident about the information they get and thus more willing to trade and increase the demand of a stock. For that reason, we support an underreaction-based explanation of momentum across retail investors.

4.2 Long-run reversal

Tests based on long-run reversal help distinguish between overreaction-based versus underreaction-based explanations of momentum (Hillert et al., 2014). We show graphically the long-term returns of the strategies discussed in Section 3. Assume that an investor would invest $1,000 in all strategies at the beginning of our sample. **Figure 2** shows the development of the investment over time.

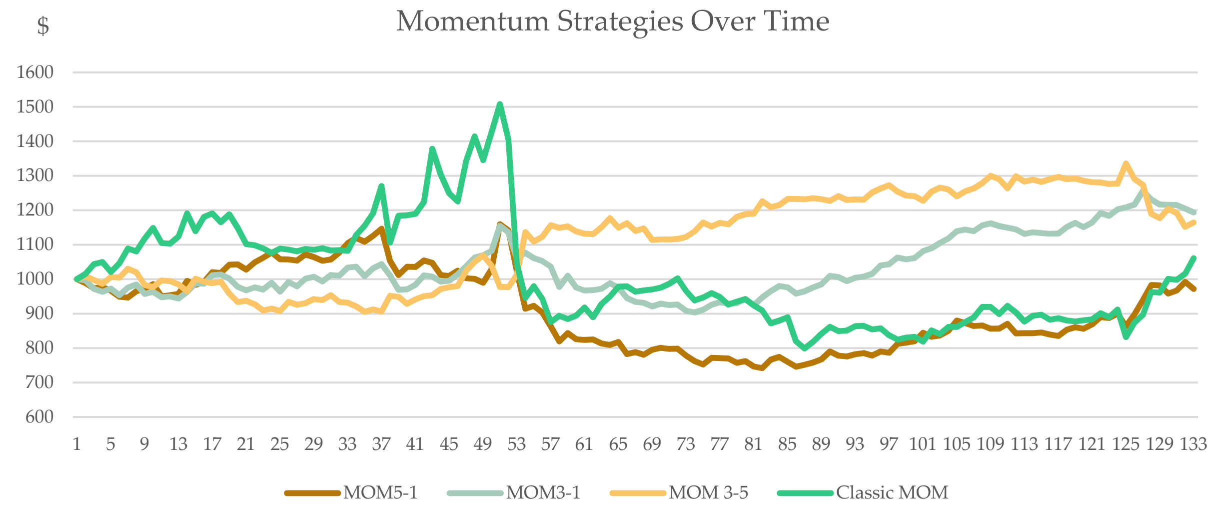

Figure 2. The momentum strategies over time, monthly. MOM 3-1 (MOM 3-5) is the portfolio that buys the momentum strategy on stocks that were stable in terms of residual Google search during the previous six months and sells the momentum strategy on stocks with an extreme decrease (increase) in residual Google search. MOM 5-1 is the portfolio that buys the momentum strategy on stocks with extreme increasing investors' attention during the last six months and sells the momentum strategy on stocks with extreme decreasing investors' attention. Classical MOM is a classical momentum strategy which ranks the stocks basing on their past cumulative returns.

The classical momentum strategy, based only on previous stock returns, has the highest return during the first 50 months of the sample analyzed. However, the chart shows a drop in returns between the periods 51 and 54. The momentum strategy 5-1 is constantly below the classical momentum strategy. The chart shows a drop, also, for this strategy at the same time as the classical one but with a lower magnitude.

Interestingly, the graph shows the low variances of the momentum 3-1 and 3-5 strategies.[7] Before the drop in the classical momentum strategy occurs, those strategies are below the other ones. However, the big difference is that neither momentum 3-1 nor 3-5 strategies are affected by the clear drop between the periods 51 to 54. If the classical momentum strategy loses about 40% in three months, the momentum 3-1 and 3-5 strategies grow continuously. We interpret the clear drop of the classical momentum strategy as the long-term reversal shown in the literature.

In order to prove the interpretation of **Figure 2**, we calculate the momentum returns for the strategies 3-1, 3-5, 5-1 and classical at different times.[8] The results are shown in **Table 5**.

[7] As shown in Section 3.

[8] We split the whole time period into three equal sub-periods of 44 months each.

Panel A: Momentum effect in t+1 to t+44					
	Loser Return	Mid Return	Winner Return	Mom Return	*t-stat*
Return 3-1	-0.27%	-0.11%	-0.26%	0.01%	0.17
Return 3-5	0.05%	0.10%	0.01%	-0.04%	-0.11
Return 5-1	-0.32%	-0.21%	-0.28%	0.04%	0.24
Return Classic	0.20%		0.78%	0.58%	0.97
Panel B: Momentum effect in t+45 to t+88					
Return 3-1	-0.21%	0.02%	-0.15%	0.06%	0.05
Return 3-5	-0.56%	-0.12%	-0.02%	0.54%	1.38*
Return 5-1	0.35%	0.14%	-0.21%	-0.48%	-0.99
Return Classic	0.70%		-0.03%	-0.73%	-0.89
Panel C: Momentum effect in t+89 to t+132					
Return 3-1	-0.38%	-0.08%	0.01%	0.40%	2.49***
Return 3-5	0.05%	0.02%	-0.06%	-0.11%	-0.42
Return 5-1	-0.43%	-0.10%	0.12%	0.50%	1.89**
Return Classic	0.47%		1.03%	0.56%	1.41*

Table 5. Momentum returns at different time periods. Return 3-1 (Return 3-5) is the return of the portfolio that buys the momentum strategy on stocks that were stable in terms of residual Google search during the previous six months, and sells the momentum strategy on stocks with an extreme decrease (increase) in residual Google search. Return 5-1 is the portfolio that buys the momentum strategy on stocks with an extreme increasing investors' attention during the last six months and sells the momentum strategy on stocks with an extreme decreasing investors' attention. Panel A shows the momentum effect over the first 44 periods analyzed, Panel B shows the momentum effect between the period 45 and 88, and Panel C shows the last 44 periods.

Panel A shows the momentum returns over the first 44 periods. The classical momentum strategy has higher monthly returns compared to the other strategies. No results are statistically significant. Panel B shows the reversal effect of the classical momentum strategy, as the monthly return drops from 0.58% to -0.73%. The strategy 5-1 has a reversal effect, too, but not in a higher magnitude compared to the classical strategy. The strategy 3-1 does not show significant changes. However, the table shows that the returns of the strategy 3-5 are positive with 10% confidence. Panel C shows the last 44 periods analyzed. Strategy 3-1 has a positive and statistically significant return; additionally, the classic and 5-1 strategies have significant positive returns.

In summary, we notice a long-term reversal only for the classic and 5-1 strategies, but not for the 3-1 and 3-5 strategies, which perform well in the long term. However, the magnitude of the reversal of the 5-1 strategy is not significantly higher than the classical one. Hillert et al. (2014) show that the reversal effects are more pronounced for firms with high media coverage. They argue that investor overreaction appears to be the driving force behind media-based momentum, suggesting their findings can be best reconciled with models such as those of Daniel, Hirshleifer, and Subrahmanyam (1998). In this case, it is not possible to notice a clear reversal trend for the momentum 3-1 and 5-3 portfolios. However, the momentum 5-1 portfolio shows a reversal pattern with a lower magnitude compared to the pattern from the classical momentum portfolio.

For that reason, we cannot state that the reversal effects are more pronounced for firms with high retail investors' attention. The investors' overreaction doesn't appear to be the driving force behind Google search-based momentum. For that reason, our results support an underreaction-based explanation of momentum.

4.3 Findings

In this section, we analyze the market tone at the end of the formation period by using the queries suggested by Preis et al. (2013). We notice a negative relationship between the market tone and the return of the momentum 5-1 strategy. For that reason, we cannot confirm the result obtained by Hillert et al. (2014), because, in this case, investor overconfidence doesn't influence the magnitude of Google search-based momentum. Furthermore, we analyze the returns of the momentum strategies over time. We notice that the magnitude of the long-term reversal of the classical momentum strategy is higher than the one of the momentum 5-1 strategy. This is a second indicator that shows how investor overreaction doesn't appear to be the driving force behind Google-search based momentum. For that reason, we support the underreaction-based explanation of momentum.

However, recall the main assumption of this paper. Following Da et al. (2011), we assume that the most sophisticated investors are not looking for data on Google but using other information providers, following Da et al. (2011). For that reason, it is also possible that sophisticated investors trade on other stocks, leading the investment of retail investors to poor returns. In order to understand the role of sophisticated investors, it would be crucial to analyze the information they use to base their investment decisions.

5 Conclusion

Even if the momentum effect is one of the most prominent return anomalies shown in the empirical evidence, its drivers are far from being understood. In this paper, we study the effect of Google search growth on the construction of momentum strategies. We analyze the S&P 500 constituents between 2004 and 2015 to produce three relevant results. We assume that the growth in Google search is a good signal of increasing retail investors' attention on a stock. Retail investors are often considered to be uninformed noise traders.

Firstly, we don't show positive returns by investing in momentum in a portfolio of increasing minus decreasing residual Google search stocks. This result is consistent with the fact that empirical evidence shows retail investors losing money with their trading decisions.[9] However, we notice that the strategy of investing in momentum in a portfolio of firms with stable residual Google searches and simultaneously selling a momentum strategy constructed using stocks that had either high growth or a decrease in residual Google searches during the previous six months has positive but statistically insignificant monthly returns. Those results are significant in the long term.

Secondly, we conclude that the strategy which invests in momentum in a portfolio of stocks with high investors’ attention and sells momentum in a portfolio of low investors’ attention has a statistically significantly lower volatility than a classical momentum strategy. However, it has higher volatility than the portfolios which invest in momentum in a portfolio of stocks with stable Google searches. This shows that retail investors’ attention creates volatility, as noted by Dimpfl and Jank (2015). For that reason, in order to decrease momentum volatility, we suggest investing in stocks with stable investors’ attention. Thirdly, contrary to the idea that investor overconfidence should strengthen the momentum effect, we document lower Google search-based momentum profits among strategies started when the tone of the market is positive. Furthermore, we don’t notice a significant increase in the long-term reversal. For those reasons, while general investors overreact to information as shown by Hillert et al. (2014), retail investors underreact to information.

To conclude, we think that three topics should be covered by future research. The analysis of the internet search growth on channels other than Google may help to better understand the reactions of professional or sophisticated investors. Transaction costs should be also considered to understand the real return of momentum strategies. It may also be useful to study an approach to understand the tone of the internet search, similar to the approach used by Hillert et al. (2014) for the analysis of newspaper articles.

[9] see Grinblatt & Keloharju, 2000

6 References

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Appendix A.1: S&P 500 constituents

Name	RIC	Name	RIC
Apple Inc	AAPL.O	Roper Technologies Inc	ROP
Alphabet Inc	GOOGL.O	WEC Energy Group Inc	WEC
Alphabet Inc	GOOG.O	CenturyLink Inc	CTL
Microsoft Corp	MSFT.O	Vornado Realty Trust	VNO
Exxon Mobil Corp	XOM	Amphenol Corp	APH
Berkshire Hathaway Inc	BRKb	Eversource Energy	ES
Facebook Inc	FB.O	International Paper Co	IP
Johnson & Johnson	JNJ	St. Jude Medical Inc	STJ
Amazon.com Inc	AMZN.O	Marriott International Inc	MAR.O
General Electric Co	GE	Royal Caribbean Cruises Ltd	RCL
Wells Fargo & Co	WFC	Willis Towers Watson PLC	WLTW.O
AT&T Inc	T	Ameriprise Financial Inc	AMP
JPMorgan Chase & Co	JPM	Northern Trust Corp	NTRS.O
Procter & Gamble Co	PG	Dr Pepper Snapple Group Inc	DPS
Wal Mart Stores Inc	WMT	Ingersoll-Rand PLC	IR
Verizon Communications Inc	VZ	Expedia Inc	EXPE.O
Pfizer Inc	PFE	Stanley Black & Decker Inc	SWK
Visa Inc	V	Clorox Co	CLX
Coca-Cola Co	KO	Newmont Mining Corp	NEM
Chevron Corp	CVX	Nucor Corp	NUE
Oracle Corp	ORCL.K	HCP Inc	HCP
Home Depot Inc	HD	Republic Services Inc	RSG
Walt Disney Co	DIS	Mead Johnson Nutrition Co	MJN
Merck & Co Inc	MRK	DTE Energy Co	DTE
Bank of America Corp	BAC	Tyco International PLC	TYC
Philip Morris International Inc	PM	Freeport-McMoRan Inc	FCX
Intel Corp	INTC.O	Realty Income Corp	O
Comcast Corp	CMCSA.O	DaVita HealthCare Partners Inc	DVA
PepsiCo Inc	PEP	J M Smucker Co	SJM
Cisco Systems Inc	CSCO.O	SanDisk Corp	SNDK.O
International Business Machines Corp	IBM	Parker-Hannifin Corp	PH
Citigroup Inc	C	C R Bard Inc	BCR
Gilead Sciences Inc	GILD.O	Rockwell Automation Inc	ROK
UnitedHealth Group Inc	UNH	Noble Energy Inc	NBL
Amgen Inc	AMGN.O	Viacom Inc	VIAB.O
Altria Group Inc	MO	Mohawk Industries Inc	MHK
Bristol-Myers Squibb Co	BMY	FirstEnergy Corp	FE
McDonald's Corp	MCD	Concho Resources Inc	CXO
Schlumberger NV	SLB	Essex Property Trust Inc	ESS
CVS Health Corp	CVS	Whirlpool Corp	WHR
Medtronic PLC	MDT	Vulcan Materials Co	VMC
MasterCard Inc	MA	Genuine Parts Co	GPC
3M Co	MMM	Dentsply Sirona Inc	XRAY.O
Nike Inc	NKE	Fifth Third Bancorp	FITB.O
AbbVie Inc	ABBV.K	Hershey Co	HSY
Kraft Heinz Co	KHC.O	Williams Companies Inc	WMB
United Parcel Service Inc	UPS	Henry Schein Inc	HSIC.O
Allergan plc	AGN	W W Grainger Inc	GWW
Starbucks Corp	SBUX.O	Equifax Inc	EFX
United Technologies Corp	UTX	Alcoa Inc	AA

Honeywell International Inc	HON	Red Hat Inc	RHT
Walgreens Boots Alliance Inc	WBA.O	Skyworks Solutions Inc	SWKS.O
Eli Lilly and Co	LLY	Agilent Technologies Inc	A
Boeing Co	BA	Loews Corp	L
Celgene Corp	CELG.O	Chipotle Mexican Grill Inc	CMG
Qualcomm Inc	QCOM.O	Starwood Hotels & Resorts Worldwide Inc	HOT
Accenture PLC	ACN	Invesco Ltd	IVZ
U.S. Bancorp	USB	Entergy Corp	ETR
Union Pacific Corp	UNP	Autodesk Inc	ADSK.O
Reynolds American Inc	RAI	Fastenal Co	FAST.O
Goldman Sachs Group Inc	GS	Motorola Solutions Inc	MSI
Lockheed Martin Corp	LMT	Verisk Analytics Inc	VRSK.O
Lowe's Companies Inc	LOW	Lam Research Corp	LRCX.O
Mondelez International Inc	MDLZ.O	Alliance Data Systems Corp	ADS
Costco Wholesale Corp	COST.O	Macys Inc	M
Priceline Group Inc	PCLN.O	Ulta Salon Cosmetics and Fragrance Inc	ULTA.O
Danaher Corp	DHR	American Water Works Company Inc	AWK
Abbott Laboratories	ABT	CA Inc	CA.O
American International Group Inc	AIG	Principal Financial Group Inc	PFG
Simon Property Group Inc	SPG	Universal Health Services Inc	UHS
Colgate-Palmolive Co	CL	Citrix Systems Inc	CTXS.O
American Express Co	AXP	Rockwell Collins Inc	COL
BlackRock Inc	BLK	Citizens Financial Group Inc	CFG
Broadcom Ltd	AVGO.O	Laboratory Corporation of America Holdings	LH
Texas Instruments Inc	TXN.O	Coca-Cola Enterprises Inc	CCE
Time Warner Inc	TWX	Tractor Supply Co	TSCO.O
ConocoPhillips	COP	Church & Dwight Co Inc	CHD
Dow Chemical Co	DOW	Newell Brands Inc	NWL
Biogen Inc	BIIB.O	Ametek Inc	AME
Thermo Fisher Scientific Inc	TMO	McCormick & Company Inc	MKC
Twenty-First Century Fox Inc	FOXA.O	Marathon Oil Corp	MRO
Twenty-First Century Fox Inc	FOX.O	Xilinx Inc	XLNX.O
Occidental Petroleum Corp	OXY	Symantec Corp	SYMC.O
Time Warner Cable Inc	TWC	Kimco Realty Corp	KIM
Chubb Ltd	CB	Regions Financial Corp	RF
E we du Pont de Nemours and Co	DD	Macerich Co	MAC
Ford Motor Co	F	Advance Auto Parts Inc	AAP
Duke Energy Corp	DUK	D.R. Horton Inc	DHI
NextEra Energy Inc	NEE	Host Hotels & Resorts Inc	HST
Morgan Stanley	MS	Ameren Corp	AEE
EMC Corp	EMC	Discovery Communications Inc	DISCA.O
TJX Companies Inc	TJX	Discovery Communications Inc	DISCK.O
Salesforce.com Inc	CRM	Eastman Chemical Co	EMN
Metlife Inc	MET	KLA-Tencor Corp	KLAC.O
Target Corp	TGT	Xerox Corp	XRX
General Motors Co	GM	Mattel Inc	MAT.O
Kimberly-Clark Corp	KMB	Coach Inc	COH
PayPal Holdings Inc	PYPL.O	CMS Energy Corp	CMS
Adobe Systems Inc	ADBE.O	Cabot Oil & Gas Corp	COG
Caterpillar Inc	CAT	Micron Technology Inc	MU.O
Express Scripts Holding Co	ESRX.O	Waters Corp	WAT
Southern Co	SO	Linear Technology Corp	LLTC.O
Phillips 66	PSX	Extra Space Storage Inc	EXR
Public Storage	PSA	HanesBrands Inc	HBI

FedEx Corp	FDX	EQT Corp	EQT
American Tower Corp	AMT	Martin Marietta Materials Inc	MLM
PNC Financial Services Group Inc	PNC	C.H. Robinson Worldwide Inc	CHRW.O
Dominion Resources Inc	D	Masco Corp	MAS
EOG Resources Inc	EOG	Federal Realty Investment Trust	FRT
Bank of New York Mellon Corp	BK	National Oilwell Varco Inc	NOV
Kinder Morgan Inc	KMI	Hasbro Inc	HAS.O
General Dynamics Corp	GD	Cincinnati Financial Corp	CINF.O
Regeneron Pharmaceuticals Inc	REGN.O	Textron Inc	TXT
Netflix Inc	NFLX.O	XL Group PLC	XL
Stryker Corp	SYK	Best Buy Co Inc	BBY
Automatic Data Processing Inc	ADP.O	Ball Corp	BLL
Monsanto Co	MON	Stericycle Inc	SRCL.O
McKesson Corp	MCK	Quest Diagnostics Inc	DGX
Aetna Inc	AET	Hologic Inc	HOLX.O
Capital One Financial Corp	COF	Carmax Inc	KMX
LyondellBasell Industries NV	LYB	Dover Corp	DOV
Charles Schwab Corp	SCHW.K	Nasdaq Inc	NDAQ.O
Anthem Inc	ANTM.K	Kansas City Southern	KSU
Carnival Corp	CCL	Cimarex Energy Co	XEC
Raytheon Co	RTN	Lincoln National Corp	LNC
Illinois Tool Works Inc	ITW	Airgas Inc	ARG
General Mills Inc	GIS	CBRE Group Inc	CBG
Cognizant Technology Solutions Corp	CTSH.O	SL Green Realty Corp	SLG
Northrop Grumman Corp	NOC	Columbia Pipeline Group Inc	CPGX.K
Cigna Corp	CI	Pentair plc	PNR
Delta Air Lines Inc	DAL	Sealed Air Corp	SEE
Yahoo! Inc	YHOO.O	Wynn Resorts Ltd	WYNN.O
Estee Lauder Companies Inc	EL	Microchip Technology Inc	MCHP.O
The Kroger Co	KR	Western Digital Corp	WDC.O
Emerson Electric Co	EMR	KeyCorp	KEY
Alexion Pharmaceuticals Inc	ALXN.O	WestRock Co	WRK
Prudential Financial Inc	PRU	J B Hunt Transport Services Inc	JBHT.O
Halliburton Co	HAL	Tesoro Corp	TSO
Praxair Inc	PX	Western Union Co	WU
Ecolab Inc	ECL	Mosaic Co	MOS
Travelers Companies Inc	TRV	Whole Foods Market Inc	WFM.O
Becton Dickinson and Co	BDX	Lennar Corp	LEN
Yum! Brands Inc	YUM	Harris Corp	HRS
Marsh & McLennan Companies Inc	MMC	Verisign Inc	VRSN.O
Air Products and Chemicals Inc	APD	SCANA Corp	SCG
HCA Holdings Inc	HCA	Cintas Corp	CTAS.O
CME Group Inc	CME.O	L-3 Communications Holdings Inc	LLL
American Electric Power Company Inc	AEP	Gap Inc	GPS
Exelon Corp	EXC	UDR Inc	UDR
Constellation Brands Inc	STZ	International Flavors & Fragrances Inc	IFF
PPG Industries Inc	PPG	Under Armour Inc	UA
Southwest Airlines Co	LUV	Under Armour Inc	UAc
Hewlett Packard Enterprise Co	HPE	Affiliated Managers Group Inc	AMG
Crown Castle International Corp	CCI	Total System Services Inc	TSS
PG&E Corp	PCG	Interpublic Group of Companies Inc	IPG
Intercontinental Exchange Inc	ICE	Snap-On Inc	SNA
Cardinal Health Inc	CAH	TripAdvisor Inc	TRIP.O
BB&T Corp	BBT	Michael Kors Holdings Ltd	KORS.K

Aflac Inc	AFL	Cablevision Systems Corp	CVC
Eaton Corporation PLC	ETN	Nordstrom Inc	JWN
Valero Energy Corp	VLO	Tiffany & Co	TIF
Aon PLC	AON	Akamai Technologies Inc	AKAM.O
eBay Inc	EBAY.O	Expeditors International of Washington Inc	EXPD.O
Baxalta Inc	BXLT.K	Juniper Networks Inc	JNPR.K
Sherwin-Williams Co	SHW	Garmin Ltd	GRMN.O
McGraw Hill Financial Inc	MHFI.K	CenterPoint Energy Inc	CNP
VF Corp	VFC	Signet Jewelers Ltd	SIG
Kellogg Co	K	Wyndham Worldwide Corp	WYN
Intuit Inc	INTU.O	Goodyear Tire & Rubber Co	GT.O
Boston Scientific Corp	BSX	Harley-Davidson Inc	HOG
Deere & Co	DE	Kohls Corp	KSS
O'Reilly Automotive Inc	ORLY.O	BorgWarner Inc	BWA
Sysco Corp	SYY	Foot Locker Inc	FL
Anadarko Petroleum Corp	APC	Huntington Bancshares Inc	HBAN.O
Humana Inc	HUM	Varian Medical Systems Inc	VAR
Activision Blizzard Inc	ATVI.O	Scripps Networks Interactive Inc	SNI.O
Johnson Controls Inc	JCI	CF Industries Holdings Inc	CF
Monster Beverage Corp	MNST.O	Pinnacle West Capital Corp	PNW
Equity Residential	EQR	Unum Group	UNM
Synchrony Financial	SYF	Darden Restaurants Inc	DRI
Sempra Energy	SRE	Ralph Lauren Corp	RL
General Growth Properties Inc	GGP	Bed Bath & Beyond Inc	BBBY.O
CSX Corp	CSX.O	AGL Resources Inc	GAS
Pioneer Natural Resources Co	PXD	PVH Corp	PVH
Waste Management Inc	WM	Seagate Technology PLC	STX.O
CBS Corp	CBS	Xylem Inc	XYL
Allstate Corp	ALL	AES Corp	AES
PPL Corp	PPL	Iron Mountain Inc	IRM
American Airlines Group Inc	AAL.O	Comerica Inc	CMA
Norfolk Southern Corp	NSC	NiSource Inc	NI
State Street Corp	STT	Fluor Corp	FLR
AvalonBay Communities Inc	AVB	News Corp	NWSA.O
Welltower Inc	HCN	News Corp	NWS.O
Intuitive Surgical Inc	ISRG.O	ONEOK Inc	OKE
Weyerhaeuser Co	WY	Newfield Exploration Co	NFX
Franklin Resources Inc	BEN	Centene Corp	CNC
Zoetis Inc	ZTS	Staples Inc	SPLS.O
Applied Materials Inc	AMAT.O	E*TRADE Financial Corp	ETFC.O
Baxter International Inc	BAX	NetApp Inc	NTAP.O
Dollar General Corp	DG	ADT Corp	ADT
Prologis Inc	PLD	Mallinckrodt Plc	MNK
Discover Financial Services	DFS	Torchmark Corp	TMK
Mylan NV	MYL.O	Helmerich and Payne Inc	HP
Public Service Enterprise Group Inc	PEG	F5 Networks Inc	FFIV.O
Autozone Inc	AZO	FMC Technologies Inc	FTI
Tyson Foods Inc	TSN	PulteGroup Inc	PHM
Corning Inc	GLW	Frontier Communications Corp	FTR.O
Ross Stores Inc	ROST.O	TECO Energy Inc	TE
Edwards Lifesciences Corp	EW	Avery Dennison Corp	AVY
Zimmer Biomet Holdings Inc	ZBH	Range Resources Corp	RRC
Archer Daniels Midland Co	ADM	Leggett & Platt Inc	LEG
TE Connectivity Ltd	TEL	Endo International PLC	ENDP.O

Edison International	EIX	First Solar Inc	FSLR.O
Equinix Inc	EQIX.O	Qorvo Inc	QRVO.O
L Brands Inc	LB	Apartment Investment and Management Co	AIV
Fiserv Inc	FISV.O	Leucadia National Corp	LUK
HP Inc	HPQ	Allegion PLC	ALLE.K
Fidelity National Information Services Inc	FIS	Harman International Industries Inc	HAR
Consolidated Edison Inc	ED	Flowserve Corp	FLS
Spectra Energy Corp	SE	Robert Half International Inc	RHI
Delphi Automotive PLC	DLPH.K	FMC Corp	FMC
United Continental Holdings Inc	UAL	PerkinElmer Inc	PKI
Ventas Inc	VTR	Zions Bancorporation	ZION.O
Marathon Petroleum Corp	MPC	United Rentals Inc	URI
Molson Coors Brewing Co	TAP	Murphy Oil Corp	MUR
Vertex Pharmaceuticals Inc	VRTX.O	H & R Block Inc	HRB
AmerisourceBergen Corp	ABC	Jacobs Engineering Group Inc	JEC
Apache Corp	APA	Tegna Inc	TGNA.K
Baker Hughes Inc	BHI	Assurant Inc	AIZ
Illumina Inc	ILMN.O	People's United Financial Inc	PBCT.O
Hormel Foods Corp	HRL	AutoNation Inc	AN
Electronic Arts Inc	EA.O	FLIR Systems Inc	FLIR.O
Xcel Energy Inc	XEL	Patterson Companies Inc	PDCO.O
Brown-Forman Corp	BFb	NRG Energy Inc	NRG
SunTrust Banks Inc	STI	Navient Corp	NAVI.O
Omnicom Group Inc	OMC	Chesapeake Energy Corp	CHK
Cummins Inc	CMI	CSRA Inc	CSRA.K
NVIDIA Corp	NVDA.O	Southwestern Energy Co	SWN
Cerner Corp	CERN.O	Pitney Bowes Inc	PBI
PACCAR Inc	PCAR.O	Dun & Bradstreet Corp	DNB
ConAgra Foods Inc	CAG	Transocean Ltd	RIG
Boston Properties Inc	BXP	Legg Mason Inc	LM
Moody's Corp	MCO	Quanta Services Inc	PWR
Progressive Corp	PGR	Urban Outfitters Inc	URBN.O
T. Rowe Price Group Inc	TROW.O	Ryder System Inc	R
Hess Corp	HES	GameStop Corp	GME
Level 3 Communications Inc	LVLT.K	Teradata Corp	TDC
Dollar Tree Inc	DLTR.O	Diamond Offshore Drilling Inc	DO
Paychex Inc	PAYX.O	Owens-Illinois Inc	OI
M&T Bank Corp	MTB	Devon Energy Corp	DVN
Nielsen Holdings PLC	NLSN.K		
Campbell Soup Co	CPB		
Hartford Financial Services Group Inc	HIG		
Perrigo Company PLC	PRGO.K		
Analog Devices Inc	ADI.O		

Appendix A.2: R code for downloading data from Google Trends

```
#GOOGLE TRENDS CONNECTION
library(gtrendsR)
library(foreign)
usr <- "x.y@gmail.com"
psw <- "Password"
gconnect(usr, psw)
#GOOGLE TRENDS DATA


#Vector with all tickers of the S&P500
tickers<-c("AAPL", "MSFT", "XOM", "BRK.B", "JNJ", "AMZN", "GE", "WFC", "T", "JPM", "PG", "WMT",
"VZ", "PFE", "KO", "CVX", "ORCL", "HD", "DIS", "MRK", "BAC", "INTC", "CMCSA", "PEP",
"CSCO", "IBM", "C", "GILD", "UNH", "AMGN", "MO", "BMY", "MCD", "SLB", "CVS", "MDT",
"MMM", "NKE", "UPS", "AGN", "SBUX", "UTX", "HON", "WBA", "LLY", "BA", "CELG", "QCOM",
"ACN", "USB", "UNP", "RAI", "GS", "LMT", "LOW", "MDLZ", "COST", "PCLN", "DHR", "ABT",
"AIG", "SPG", "CL", "AXP", "BLK", "TXN", "TWX", "COP", "DOW", "BIIB", "TMO", "FOXA",
"FOX", "OXY", "CB", "DD", "F", "DUK", "NEE", "MS", "EMC", "TJX", "MET", "TGT",
"KMB", "ADBE", "CAT", "ESRX", "SO", "PSA", "FDX", "AMT", "PNC", "D", "EOG", "BK",
"GD", "REGN", "NFLX", "SYK", "ADP", "MON", "MCK", "AET", "COF", "SCHW", "ANTM", "CCL",
"RTN", "ITW", "GIS", "CTSH", "NOC", "CI", "YHOO", "EL", "KR", "EMR", "ALXN", "PRU",
"HAL", "PX", "ECL", "TRV", "BDX", "YUM", "MMC", "APD", "CME", "AEP", "EXC", "STZ",
"PPG", "LUV", "CCI", "PCG", "CAH", "BBT", "AFL", "ETN", "VLO", "AON", "EBAY", "SHW",
"MHFI", "VFC", "K", "INTU", "BSX", "DE", "ORLY", "SYY", "APC", "HUM", "ATVI", "JCI",
"MNST", "EQR", "SRE", "GGP", "CSX", "PXD", "WM", "CBS", "ALL", "PPL", "NSC", "STT",
"AVB", "HCN", "ISRG", "WY", "BEN", "AMAT", "BAX", "PLD", "MYL", "PEG", "AZO", "TSN",
"GLW", "ROST", "EW", "ZBH", "ADM", "EIX", "EQIX", "LB", "FISV", "HPQ", "FIS", "ED",
"VTR", "TAP", "VRTX", "ABC", "APA", "BHI", "ILMN", "HRL", "EA", "XEL", "BF.B", "STI",
"OMC", "CMI", "NVDA", "CERN", "PCAR", "CAG", "BXP", "MCO", "PGR", "TROW", "HES", "LVLT",
"DLTR", "PAYX", "MTB", "CPB", "HIG", "PRGO", "ADI", "DVN", "ROP", "WEC", "CTL", "VNO",
"APH", "ES", "IP", "STJ", "MAR", "RCL", "WLTW", "NTRS", "IR", "SWK", "CLX", "NEM",
"NUE", "HCP", "RSG", "DTE", "TYC", "FCX", "O", "DVA", "SJM", "SNDK", "PH", "BCR",
"ROK", "NBL", "MHK", "FE", "ESS", "WHR", "VMC", "GPC", "XRAY", "FITB", "HSY", "WMB",
"HSIC", "GWW", "EFX", "AA", "RHT", "SWKS", "A", "L", "HOT", "IVZ", "ETR", "ADSK",
"FAST", "MSI", "LRCX", "ADS", "M", "CA", "PFG", "UHS", "CTXS", "COL", "LH", "CCE",
"TSCO", "CHD", "NWL", "AME", "MKC", "MRO", "XLNX", "SYMC", "KIM", "RF", "MAC", "AAP",
"DHI", "HST", "AEE", "EMN", "KLAC", "XRX", "MAT", "COH", "CMS", "COG", "MU", "WAT",
"LLTC", "EQT", "MLM", "CHRW", "MAS", "FRT", "NOV", "HAS", "CINF", "TXT", "XL", "BBY",
"BLL", "SRCL", "DGX", "HOLX", "KMX", "DOV", "NDAQ", "KSU", "XEC", "LNC", "ARG", "SLG",
"PNR", "SEE", "WYNN", "MCHP", "WDC", "KEY", "JBHT", "TSO", "WFM", "LEN", "HRS", "VRSN",
"SCG", "CTAS", "LLL", "GPS", "UDR", "IFF", "AMG", "TSS", "IPG", "SNA", "CVC", "JWN",
"TIF", "AKAM", "EXPD", "JNPR", "GRMN", "CNP", "SIG", "GT", "HOG", "KSS", "BWA", "FL",
"HBAN", "VAR", "PNW", "UNM", "DRI", "RL", "BBBY", "GAS", "PVH", "STX", "AES", "IRM",
"CMA", "NI", "FLR", "OKE", "NFX", "CNC", "SPLS", "ETFC", "NTAP", "TMK", "HP", "FFIV",
"FTI", "PHM", "FTR", "TE", "AVY", "RRC", "LEG", "ENDP", "QRVO", "AIV", "LUK", "HAR",
"FLS", "RHI", "FMC", "PKI", "ZION", "URI", "MUR", "HRB", "JEC", "TGNA", "PBCT", "AN",
"FLIR", "PDCO", "NRG", "CHK", "SWN", "PBI", "DNB", "RIG", "LM", "PWR", "URBN", "R",
"GME", "DO", "OI")

data<-matrix(0,642,length(tickers))
for (j in 1:length(tickers)) {
stock <- gtrends(tickers[j],geo=c("US"))$trend[3]
data[,j]<-stock[,1]
}


library(xlsx)
write.xlsx(data, "google.xlsx”) #export data to excel
```

Appendix A.3: R code for the construction of the momentum portfolios

```
#LOAD DATA

library(XLConnect)
library(xlsx)

stock_r<- read.xlsx("2016_RS_Data_R.xlsx",
        sheetIndex = 1,
        startRow=1)
google_r<- read.xlsx("2016_RS_Data_R.xlsx",
         sheetIndex = 2)
n<-dim(stock_r)[1]
tickers <-c("AAPL", "MSFT", "XOM", "JNJ", "AMZN", "GE", "WFC", "T", "JPM", "PG", "WMT", "VZ",
        "PFE", "KO", "CVX", "ORCL", "HD", "DIS", "MRK", "BAC", "INTC", "CMCSA", "PEP", "CSCO",
        "IBM", "C", "GILD", "UNH", "AMGN", "MO", "BMY", "MCD", "SLB", "CVS", "MDT", "MMM",
        "NKE", "UPS", "AGN", "SBUX", "UTX", "HON", "WBA", "LLY", "BA", "CELG", "QCOM", "ACN",
        "USB", "UNP", "RAI", "GS", "LMT", "LOW", "COST", "PCLN", "DHR", "ABT", "AIG", "SPG",
        "CL", "AXP", "BLK", "TXN", "TWX", "COP", "DOW", "BIIB", "TMO", "FOX", "OXY", "CB",
        "DD", "F", "DUK", "NEE", "MS", "EMC", "TJX", "MET", "TGT", "KMB", "ADBE", "CAT",
        "SO", "PSA", "FDX", "AMT", "PNC", "D", "EOG", "BK", "GD", "NFLX", "SYK", "ADP",
        "MON", "MCK", "AET", "COF", "SCHW", "ANTM", "CCL", "RTN", "ITW", "GIS", "CTSH", "NOC",
        "CI", "YHOO", "EL", "KR", "EMR", "PRU", "HAL", "PX", "ECL", "TRV", "BDX", "YUM",
        "MMC", "APD", "CME", "AEP", "EXC", "STZ", "PPG", "LUV", "CCI", "PCG", "CAH", "BBT",
        "AFL", "ETN", "VLO", "AON", "EBAY", "SHW", "VFC", "K", "INTU", "BSX", "DE", "ORLY",
        "SYY", "APC", "HUM", "ATVI", "JCI", "MNST", "EQR", "SRE", "GGP", "CSX", "PXD", "WM",
        "CBS", "ALL", "PPL", "NSC", "STT", "AVB", "HCN", "WY", "BEN", "AMAT", "BAX", "PLD",
        "MYL", "PEG", "AZO", "TSN", "GLW", "ROST", "EW", "ADM", "EQIX", "LB", "HPQ", "FIS",
        "ED", "VTR", "TAP", "VRTX", "ABC", "APA", "BHI", "HRL", "EA", "XEL", "STI", "OMC",
        "CMI", "NVDA", "CERN", "PCAR", "CAG", "BXP", "MCO", "PGR", "TROW", "HES", "LVLT", "PAYX",
        "MTB", "CPB", "HIG", "ADI", "DVN", "ROP", "WEC", "CTL", "VNO", "APH", "ES", "IP",
        "STJ", "MAR", "RCL", "WLTW", "NTRS", "IR", "SWK", "CLX", "NEM", "NUE", "HCP", "RSG",
        "DTE", "TYC", "FCX", "O", "DVA", "SJM", "SNDK", "PH", "BCR", "ROK", "NBL", "FE",
        "ESS", "WHR", "VMC", "GPC", "XRAY", "FITB", "HSY", "WMB", "GWW", "EFX", "AA", "RHT",
        "A", "L", "HOT", "ETR", "ADSK", "FAST", "MSI", "ADS", "M", "CA", "PFG", "UHS",
        "CTXS", "COL", "LH", "CCE", "TSCO", "CHD", "NWL", "AME", "MKC", "MRO", "XLNX", "SYMC",
        "KIM", "RF", "MAC", "AAP", "DHI", "HST", "AEE", "EMN", "KLAC", "XRX", "MAT", "COH",
        "CMS", "COG", "MU", "WAT", "LLTC", "EQT", "MLM", "CHRW", "MAS", "FRT", "NOV", "HAS",
        "TXT", "XL", "BBY", "BLL", "DGX", "KMX", "DOV", "KSU", "LNC", "ARG", "SLG", "PNR",
        "SEE", "WYNN", "MCHP", "WDC", "KEY", "TSO", "WFM", "LEN", "HRS", "VRSN", "SCG", "CTAS",
        "LLL", "GPS", "UDR", "IFF", "AMG", "TSS", "IPG", "SNA", "CVC", "JWN", "TIF", "AKAM",
        "JNPR", "GRMN", "CNP", "SIG", "GT", "HOG", "KSS", "BWA", "FL", "VAR", "PNW", "UNM",
        "DRI", "RL", "BBBY", "GAS", "PVH", "STX", "AES", "IRM", "CMA", "NI", "FLR", "OKE",
        "NFX", "CNC", "NTAP", "TMK", "HP", "FFIV", "FTI", "PHM", "FTR", "TE", "AVY", "RRC",
        "LEG", "AIV", "LUK", "HAR", "FLS", "RHI", "FMC", "PKI", "ZION", "URI", "MUR", "HRB",
        "JEC", "AN", "FLIR", "NRG", "CHK", "SWN", "PBI", "DNB", "RIG", "LM", "PWR", "URBN",
        "R", "GME", "DO", "OI")
colnames(stock_r)<-tickers
colnames(google_r) <-tickers

lag<-6

past_returns_stock<-matrix(0,144,400)
past_returns_google<-matrix(0,144,400)
colnames(past_returns_stock) <-tickers
colnames(past_returns_google) <-tickers

winners_stock<-matrix(0,n,6)
loosers_stock<-matrix(0,n,6)

google_returns_1<-matrix(0,n,18)
colnames(google_returns_1)<-
c("W1","W2","W3","W4","W5","W6","M1","M2","M3","M4","M5","M6","L1","L2","L3","L4","L5","L6")
google_returns_2<-matrix(0,n,18)
colnames(google_returns_2)<-
c("W1","W2","W3","W4","W5","W6","M1","M2","M3","M4","M5","M6","L1","L2","L3","L4","L5","L6")
google_returns_3<-matrix(0,n,18)
colnames(google_returns_3)<-
c("W1","W2","W3","W4","W5","W6","M1","M2","M3","M4","M5","M6","L1","L2","L3","L4","L5","L6")
google_returns_4<-matrix(0,n,18)
```

```
colnames(google_returns_4)<-
c("W1","W2","W3","W4","W5","W6","M1","M2","M3","M4","M5","M6","L1","L2","L3","L4","L5","L6")
google_returns_5<-matrix(0,n,18)
colnames(google_returns_5)<-
c("W1","W2","W3","W4","W5","W6","M1","M2","M3","M4","M5","M6","L1","L2","L3","L4","L5","L6")

for(k in 1:400) {

for(j in 1:n) {

 past_returns_stock[j,k]<-sum(stock_r[j:(j+lag-1),k])
 past_returns_google[j,k]<-sum(google_r[j:(j+lag-1),k])
}

}

for(i in 1:138) {

 #1) Momentum without considering google
w_names<-names(sort(past_returns_stock[i,], decreasing = TRUE, na.last = NA))
l_names<-names(sort(past_returns_stock[i,], decreasing = FALSE, na.last = NA))
winners_stock[i,1]<-sum(1/80*(stock_r[i+lag,w_names[1:80]]))
winners_stock[i,2]<-sum(1/80*(stock_r[i+lag+1,w_names[1:80]]))
winners_stock[i,3]<-sum(1/80*(stock_r[i+lag+2,w_names[1:80]]))
winners_stock[i,4]<-sum(1/80*(stock_r[i+lag+3,w_names[1:80]]))
winners_stock[i,5]<-sum(1/80*(stock_r[i+lag+4,w_names[1:80]]))
winners_stock[i,6]<-sum(1/80*(stock_r[i+lag+5,w_names[1:80]]))

loosers_stock[i,1]<-sum(1/80*(stock_r[i+lag,l_names[1:80]]))
loosers_stock[i,2]<-sum(1/80*(stock_r[i+lag+1,l_names[1:80]]))
loosers_stock[i,3]<-sum(1/80*(stock_r[i+lag+2,l_names[1:80]]))
loosers_stock[i,4]<-sum(1/80*(stock_r[i+lag+3,l_names[1:80]]))
loosers_stock[i,5]<-sum(1/80*(stock_r[i+lag+4,l_names[1:80]]))
loosers_stock[i,6]<-sum(1/80*(stock_r[i+lag+5,l_names[1:80]]))




 #2) Momentum considering google
google_names<-names(sort(past_returns_google[i,], decreasing = FALSE, na.last = NA))
winners_google_1<-names(sort(past_returns_stock[i,google_names[1:80]], decreasing = TRUE, na.last = NA))
winners_google_2<-names(sort(past_returns_stock[i,google_names[81:160]], decreasing = TRUE, na.last = NA))
winners_google_3<-names(sort(past_returns_stock[i,google_names[161:240]], decreasing = TRUE, na.last = NA))
winners_google_4<-names(sort(past_returns_stock[i,google_names[241:320]], decreasing = TRUE, na.last = NA))
winners_google_5<-names(sort(past_returns_stock[i,google_names[321:400]], decreasing = TRUE, na.last = NA))


for (x in 1:6) {

#Portfolio 1
google_returns_1[i,x]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_1[1:24]]))
google_returns_1[i,x+6]<-sum(1/32*(stock_r[i+lag+x-1,winners_google_1[25:56]]))
google_returns_1[i,x+12]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_1[57:80]]))
```

```
#Portfolio 2
google_returns_2[i,x]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_2[1:24]]))
google_returns_2[i,x+6]<-sum(1/32*(stock_r[i+lag+x-1,winners_google_2[25:56]]))
google_returns_2[i,x+12]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_2[57:80]]))

#Portfolio 3
google_returns_3[i,x]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_3[1:24]]))
google_returns_3[i,x+6]<-sum(1/32*(stock_r[i+lag+x-1,winners_google_3[25:56]]))
google_returns_3[i,x+12]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_3[57:80]]))

#Portfolio 4
google_returns_4[i,x]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_4[1:24]]))
google_returns_4[i,x+6]<-sum(1/32*(stock_r[i+lag+x-1,winners_google_4[25:56]]))
google_returns_4[i,x+12]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_4[57:80]]))

#Portfolio 5
google_returns_5[i,x]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_5[1:24]]))
google_returns_5[i,x+6]<-sum(1/32*(stock_r[i+lag+x-1,winners_google_5[25:56]]))
google_returns_5[i,x+12]<-sum(1/24*(stock_r[i+lag+x-1,winners_google_5[57:80]]))

}


}

write.xlsx(google_returns_1, "G12.xlsx")
write.xlsx(google_returns_2, "G22.xlsx")
write.xlsx(google_returns_3, "G32.xlsx")
write.xlsx(google_returns_4, "G42.xlsx")
write.xlsx(google_returns_5, "G52.xlsx")
write.xlsx(past_returns_google, "GOOGLE PAST.xlsx")
write.xlsx(winners_stock, "NOGOW.xlsx")
write.xlsx(loosers_stock, "NOGOL.xlsx")
```

Appendix B.1: Results for raw google search increase

Panel A: Double sorts and raw returns

	Loser Return	Mid Return	Winner Return	Mom Return	*t-stat*
1	0.64%	0.58%	0.66%	0.02%	0.06
2	0.53%	0.56%	0.53%	0.00%	0.02
3	0.33%	0.47%	0.57%	0.24%	0.76
4	0.38%	0.52%	0.46%	0.08%	0.27
5	0.45%	0.53%	0.60%	0.15%	0.38
Return 3-1	-0.30%	-0.11%	-0.08%	0.22%	1.19
Return 4-1	-0.26%	-0.06%	-0.19%	0.07%	0.36
Return 5-1	-0.19%	-0.06%	-0.05%	0.14%	0.53
t-stat	-0.88	-0.66	-0.37		

Panel B: Risk Adjusted returns for media-based momentum, Return 5-1

Factor Model	1F	3F
Intercept	0.0013	0.0015
Intercept t-stat	0.49	0.60
R^2	0.00	0.07

Panel C: Risk Adjusted returns for media-based momentum, Return 3-1

Factor Model	1F	3F
Intercept	0.0022	0.0024
Intercept t-stat	0.17	1.26
R^2	0.00	0.05

Appendix B.2: Test of the mean between different momentum strategies

Mean return test between Momentum 3-1 and Momentum 3-5

Two-sample t test with unequal variances

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
mom35	126	.001195	.0018991	.0213168	-.0025635	.0049534
mom31	126	.0017706	.0016246	.0182365	-.0014447	.004986
combined	252	.0014828	.0012472	.0197991	-.0009736	.0039392
diff		-.0005757	.0024992		-.0054984	.004347

diff = mean(mom35) - mean(mom31) t = -0.2303
Ho: diff = 0 Satterthwaite's degrees of freedom = 244.148

Ha: diff < 0 Pr(T < t) = 0.4090
Ha: diff != 0 Pr(|T| > |t|) = 0.8180
Ha: diff > 0 Pr(T > t) = 0.5910

Mean return test between Momentum 3-1 and Momentum 5-1

Two-sample t test with unequal variances

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
mom31	126	.0017706	.0016246	.0182365	-.0014447	.004986
mom51	126	.0005757	.0024101	.0270537	-.0041943	.0053456
combined	252	.0011731	.0014509	.023032	-.0016843	.0040306
diff		.001195	.0029066		-.0045335	.0069234

diff = mean(mom31) - mean(mom51) t = 0.4111
Ho: diff = 0 Satterthwaite's degrees of freedom = 219.157

Ha: diff < 0 Pr(T < t) = 0.6593
Ha: diff != 0 Pr(|T| > |t|) = 0.6814
Ha: diff > 0 Pr(T > t) = 0.3407

Mean return test between Momentum 3-5 and Momentum 5-1

Two-sample t test with unequal variances

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
mom35	126	.001195	.0018991	.0213168	-.0025635	.0049534
mom51	126	.0005757	.0024101	.0270537	-.0041943	.0053456
combined	252	.0008853	.0015313	.0243082	-.0021305	.0039011
diff		.0006193	.0030684		-.0054256	.0066641

diff = mean(mom35) - mean(mom51) t = 0.2018
Ho: diff = 0 Satterthwaite's degrees of freedom = 237.031

Ha: diff < 0 Pr(T < t) = 0.5799
Ha: diff != 0 Pr(|T| > |t|) = 0.8402
Ha: diff > 0 Pr(T > t) = 0.4201