

In Search of Alpha—trading on limited Investor Attention

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Abstract

In this study we develop a trading strategy that exploits limited investor attention. Trading signals for US S&P 500 stocks are derived from Google Search Volume data, taking a long position if investor attention for the corresponding security was abnormally low in the past week. Our strategy generates 19% average annual return and thereby outperforms a simple market buy-and-hold strategy. After controlling for the well-known risk factors, a significant alpha (abnormal return) of 10% p.a. remains. Returns are sufficiently large to cover transaction costs.

JEL classification: G02, G12, G14

Keywords: investor attention, search engine volume, trading strategy

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1 Introduction

Researchers as well as investment professionals are continuously searching for promising trading strategies. While academia is primarily interested in understanding the dynamics of capital markets and the behavior of its acting investors, investment professionals like hedge fund managers rather yearn for abnormal returns and desire to outperform relevant benchmarks.

Goals of trading strategies are multifarious. While some simply aim at diminishing portfolio risk, e.g. by shifting into certain asset classes at the occurrence of predefined events, others seek to better diversify an existing portfolio by adding securities or varying portfolio weights according to certain signals. Some other strategies advance more aggressively and actively select under-priced stocks.

There are almost countless sources of trading signals. Popular examples include past returns, which are applied in momentum trading (e.g. Jegadeesh and Titman, 1993; Chan et al., 1996) or contrarian strategies (e.g. De Bondt and Thaler, 1985, 1987).¹ Also market news or investor sentiment are proven sources of trading signals (e.g. Uhl et al., 2015; Da et al., 2015; Tetlock, 2007). And truly extraordinary triggers like Super Bowl results (Krueger and Kennedy, 1990) or weather forecasts (Hirshleifer and Shumway, 2003) have been successfully applied in the never ending attempt to beat the market.

In this study we focus on a novel and by now little considered source of trading signals. The behavior of internet users, who conduct online searches for certain key words, contains valuable information and often has direct implications for real world developments. Fortunately, Google makes such behavior of its users publicly available and provides data on when and how often certain terms are searched for. The power of this “Google Trends” data and its correlation with real world phenomena has been shown in many studies. For instance, Google Search Volume (GSV) data can be used to predict the diffusion of influenza in the US (Polgreen et al., 2008; Ginsberg et al., 2009) or to forecast car sales (Varian and Choi, 2009). For a financial application, Da et al. (2011) propose GSV as a reliable measure of retail investor attention. They highlight that if users search certain stocks on the internet, they definitely pay attention to it, which has implications for the return of those stocks. Building on these insights, Vozlyublennaia

¹Momentum trading, on the one hand, exploits return continuation resulting from under-reaction of investors to certain news or events. Contrarian strategies, on the other hand, prey upon investor over-reaction, typically leading to reversal of returns. Both strategies, although being of contradictory nature, can be applied, as time horizons are different. While momentum trading works short-term, typically with 1-12 months past returns as decision criterion, contrarian strategies are rather long-term, i.e., 3-5 years of historic returns for stock selection (Balvers and Wu, 2006, for a summary).

(2014) and further Storms et al. (2015) emphasize that low retail investor attention as measured by GSV is associated with less efficient asset prices. When investor attention is low, firm related information is not sufficiently incorporated into security prices. As a consequence, stocks experiencing low investor attention should be suitable for an active stock selection strategy, as they can be expected to be inefficiently priced.

Indeed, few studies successfully apply GSV in order to detect trading signals. Preis et al. (2013) suggest a GSV approach, for which search terms related to financial turmoil like “debt” or “risk” can be used as a warning indicator of declining stock markets. As the authors emphasize, their approach can be applied in a trading strategy in order to shift asset classes whenever Google searches warn of a crisis. The study, however, does not provide tools for active stock selection. Kristoufek (2013) develops a trading strategy for US Dow Jones securities based on GSV. Main focus of his study is yet on risk diversification. His strategy alternates portfolio weights of the 30 Dow Jones stocks depending on past attention. Weight is increased if attention was low in the last week, as risk is hypothesized to be lower for these stocks. But also this study does not give explicit guidance for stock picking and does not adjust for the known risk factors. Hence it lacks an assessment regarding the strategy’s ability to create abnormal return (alpha). Bank et al. (2011) develop an active stock selection strategy based on GSV for German stocks. However, the authors receive trading signals from “large or low signed changes” in Google Search Volume, and, therefore, do not explicitly focus on the low attention stocks. Also their search term approach using firm name is rather noisy when capturing investor attention.

Our study fills this gap and develops a new trading strategy with the goal of exploiting limited investor attention. Thereby, focus is not on portfolio insurance or diversification but on actively picking under-priced stocks. We identify individual under-valued stocks from the S&P 500 index based on low past investor attention measured by GSV, using a modified search term approach as proposed by Storms et al. (2015). We take a long position in the security whenever past week’s attention was abnormally low. Performance of our strategy is assessed in broad detail through exhaustive portfolio measures as well as risk adjustments. The presented strategy generates 19% average annual return over a period from March 2004 until October 2014. Thereby, it outperforms the S&P 500 by 14%. After controlling for the Fama and French risk factors (Fama and French, 1992, 1993), a significant alpha (abnormal return) of 10% p.a. remains. Returns are sufficiently large to cover cost of trading.

Our findings are of interest for both academia and practitioners with twofold contri-

bution. First, we provide further evidence that low retail investor attention is associated with mispricing and hence market inefficiency. Second, we present a strategy which can be applied in order to exploit these inefficiencies in a very practical approach. We present a novel and active stock selection strategy based on a large sample of US stocks. Performance is evaluated through relevant portfolio performance measures and based on more than 10 years of trading. To stress robustness of our findings, we further distinguish different sub periods, apply alternative re-balancing periods (monthly, weekly and daily) as well as search term approaches (including firm name and ticker) and do not ignore cost of trading.

The remainder of this study is organized as follows. First, we explain our strategy and the applied performance measures in the methodology part. We continue with a data and sample description and provide detailed performance evaluation in the results part. Finally, findings are summarized in the conclusion.

2 Methodology

2.1 Google Search Volume as source of trading signals

On its “Trends” website², Google provides data on how often certain terms have been searched by its users over time. Da et al. (2011) explore Google Search Volume (GSV) for stock ticker as powerful measure of retail investor attention. The authors emphasize that searching the internet is a definite sign of paying attention to the corresponding stock. The selection of the adequate search term in that context seems crucial. Search terms applied in recent research include ticker (Da et al., 2011) and firm name (e.g. Bank et al., 2011; Aouadi et al., 2013).

Following Storms et al. (2015) we use a modified approach consisting of firm name in combination with the word “stock” as search term. Google Trends data allows us to investigate, whether attention on a certain stock was high or low, relative to average levels of search volume for that stock. Instead of showing the actual number of searches, Google provides a scaled score, ranging from 0 to 100, with 100 representing the maximum search volume over the selected period. Based on Da et al. (2011), we calculate abnormal search volume (ASV) of week t relative to median (Med) search volume of the past 8 weeks with:

²www.google.com/trends

$$ASV_t = \ln [GSV_t] - \ln [Med(GSV_{t-1}, \dots, GSV_{t-8})] \quad (1)$$

If $ASV > 0$ we receive a signal that attention for the individual stock is abnormally high, for $ASV \leq 0$ we conclude that attention is abnormally low or unchanged.

2.2 Development of a trading strategy

After having defined a methodology for receiving trading signals based on Google Search data, we need to codify, what kind of positions in the corresponding stocks these signals should trigger. Therefore, we establish a main strategy with two amendments, as summarized in Table 1 and described below.

Table 1: Summary of trading strategies

Strategy	Rationale/hypothesis	Application
Low attention ("Main")	Low attention stocks relatively under-priced (Fang and Peress, 2009) and low attention associated with lower volatility/risk (Kristoufek, 2013)	Long in week t if $ASV_{t-1} \leq 0$
Low Attention Loser ("Loser")	Past negative returns increase probability of under-pricing	Long in week t if $ASV_{t-1} \leq 0$ and $r_{t-1} < 0$
Low Attention Fear ("Fear")	Past market fear increases probability of under-pricing	Long in week t if $ASV_{t-1} \leq 0$ and $VIX_{t-1} > VIX_{t-2}$

Notes: ASV_{t-1} is abnormal search volume in past week, r_{t-1} is stock return in past week, VIX_{t-1} and VIX_{t-2} is level of the CBOE volatility index lagged by one and two weeks respectively.

Low Attention ("Main")

Fang and Peress (2009) demonstrate that stocks with low media coverage and hence low attention, experience higher abnormal returns. In that same logic, we expect stocks with low Google measured attention to experience higher returns as well. For this relation, we propose the following rationale: if attention in one week is low, we expect a stock to be relatively under-priced compared to weeks in which the stock experiences high attention for two reasons. First, news about positive changes in fundamentals are not adequately priced, triggering an appreciation of the stock price in the future, if attention rises.³

³Even if attention never rises, the investor could still benefit from the fundamental value, i.e., dividend payments. Dividends should be higher than implied by the current price of the under-valued stock. But

Second, Barber and Odean (2008) demonstrate that retail investor attention creates positive buying pressure. If attention on the low attention stock rises in the following weeks, the stock should tend to increase in value as retail investors will tend to buy rather than sell securities, once they pay attention. Consequently, buying low attention stocks should on average generate positive returns.

The low attention strategy can further be motivated from a risk perspective. Kristoufek (2013) argues that high attention is associated with risk and volatility, while low attention implies more stable returns. Based on Google Search volume he demonstrates how increasing the portfolio weight of Dow Jones 30 stocks in case attention on that stock as measured by GSV is low, can outperform a passive index buy-and-hold strategy. Therefore, it should be reasonable to buy low attention stocks, as the return of the resulting portfolio should be relatively stable and less volatile.

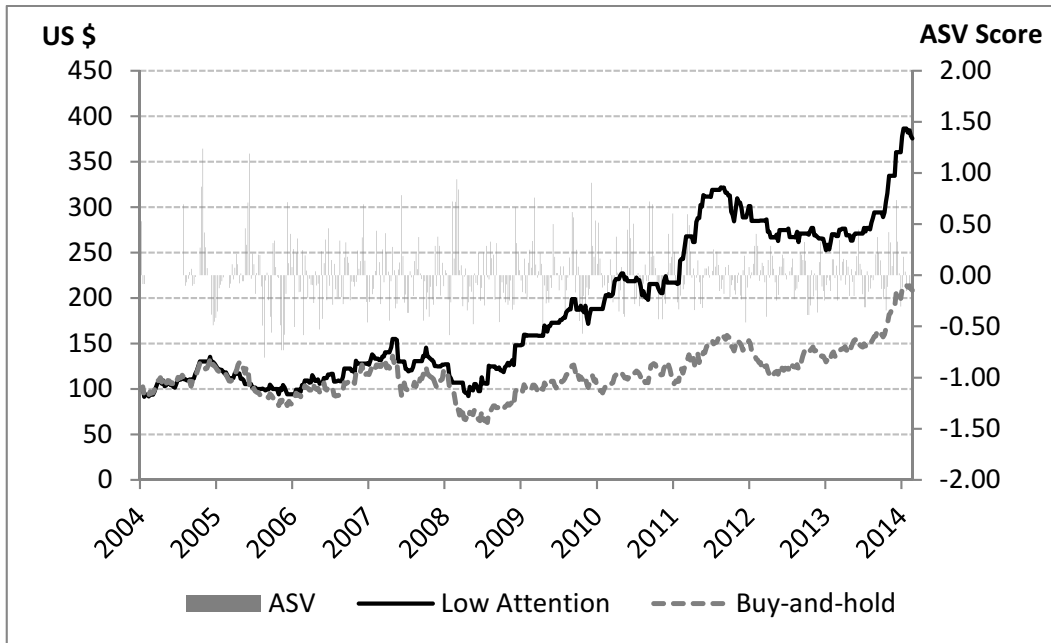


Figure 1: Illustration of strategy for “Intel Stock”

Figure 1 illustrates our strategy for an individual stock, namely for Intel Incorporated. Google provides weekly search volume scores comprising searches from Sunday to Saturday. Investment decisions are made every Monday morning and positions are closed Friday night. Whenever last week’s ASV was zero or below (based on searches from Sunday to Saturday of last week), as indicated by the gray bars, we hold the stock this approach would require to hold the stock for a long time period.

of Intel in the current week. Investing 100\$ into this strategy in August 2004 would have yielded a final wealth of about 376\$ in September 2014, compared to a \$209 outcome, which could be achieved in a simple buy-and-hold approach for the Intel stock. Also in terms of risk this strategy is more favorable as it yields a 21.1% annualized standard deviation of weekly returns compared to 27.8% for the buy-and-hold approach.

Low Attention Loser (“Loser”)

The main strategy relies on the assumption that low attention results in under-pricing. On average, this assumption might hold. However, in order to increase probability that the stock we buy is truly under-priced, we introduce a second, slightly modified strategy. Thereby, we only go long in the low attention stock, if it additionally experienced a price decline in the past week (i.e., it is a “loser” stock with past week’s return $r_{t-1} < 0$). This approach is somehow similar to a contrarian strategy, albeit time horizons for this kind of strategies are typically more long-term (i.e., years rather than weeks). We expect this strategy to perform even better than the main strategy, as the under-pricing effect should be more pronounced for the low attention “loser” stocks.

Low Attention Fear (“Fear”)

In addition, we introduce a second amendment whereby we take a long position in the low attention stocks only if we faced fearful or turbulent market conditions in the last week, as measured by the market volatility index (VIX). The VIX, often referred to as the “investor fear gauge” (Whaley, 2000), expresses the consensus view of the market about volatility and hence risk. In fearful market conditions (i.e., the level of the VIX increased with $VIX_{t-1} > VIX_{t-2}$), we expect under-pricing to be more pronounced for two reasons. First, investors could refrain from trading as outcomes are uncertain. This leads to even less incorporation of news about positive changes in fundamentals. Second, if investors trade, they could base decisions on negative sentiment and market fear, which would further enhance under-pricing due to irrational selling of stocks.

2.3 Performance measures and risk adjustment

In order to assess the success of our trading strategy, we rely on a potpourri of performance measures. First, we apply a t-test in order to assess, whether the average weekly portfolio return $\mu_r = \frac{1}{T} \sum_{t=1}^T r_t$, consisting of the equally weighted returns of past week’s low attention stocks, over the investment horizon of T weeks is statistically different from

zero. We verify that the time series of returns is stationary by applying an Augmented Dickey-Fuller test (ADD) and as additional robustness check apply Dewey-West standard errors in order to correct for heteroscedasticity and autocorrelation of returns. We apply the same test for portfolio returns in excess of market returns in order to assess market out performance.

Additionally, we calculate the Sharpe ratio (SR) of the portfolio excess return, i.e., portfolio return minus risk-free rate (rf), and divide the mean μ_{r-rf} of this expression by its standard deviation with:

$$SR = \frac{\mu_{r-rf}}{\sigma_{r-rf}} \quad (2)$$

Furthermore, we compute the Omega ratio (Rudolf and Baedorf, 2011; Keating and Shadwick, 2002) for each portfolio by dividing the sum of weekly portfolio returns r_t from week $t=1$ until T , which are greater than threshold τ (for which we choose $\tau = 0$) by the absolute value of the sum of returns smaller than threshold τ with:

$$\Omega(\tau) = \frac{\sum_{t=1}^T \max(0, r_t - \tau)}{\sum_{t=1}^T \max(0, \tau - r_t)} \quad (3)$$

Finally, we conduct risk adjustments following the Fama French factor model (Fama and French, 1992, 1993, 1996) including the momentum factor (Carhart, 1997) using OLS regression with:

$$r_{it} - rf_t = \alpha_i + \beta_i mktrf_t + h_i HML_t + s_i SMB_t + u_i UMD_t + \epsilon_{it} \quad (4)$$

Thereby, rf_t is the return of the risk-free asset, $mktrf_t$ is market return minus return of the risk-free asset, i.e., “excess market return”, HML_t is the return of the “high-minus-low” portfolio, SMB_t is the return of the “small-minus-big” portfolio and UMD_t is the return of the momentum or “up-minus-down” portfolio. If this regression yields a significant positive intercept α we can conclude that the strategy generates a positive abnormal return.

3 Data

We focus our analyses exclusively on the United States, using a large pool of stocks with available Google Search Volume data.

Google search volume

We manually downloaded weekly Google Search data from the Google Trends website⁴ in the end of October 2014. Google only provides weekly search volume data, if a certain threshold is reached. Therefore, we can calculate weekly ASV scores for 122 US stocks out of the original sample of the S&P 500 stocks considered, providing 36,287 firm weeks with an ASV score available. For those 122 stocks we additionally download daily GSV scores by limiting the request period to three months. For 66 stocks we find daily data as well, providing us with 61,114 firm days with available ASV data. As Google scales daily search volume relative to the maximum volume within this three month period, the daily data requires rescaling. Thus, we calculate a daily scaled score by making use of the weekly GSV score with:

$$GSV_{Scaled}^{Daily} = \frac{GSV_{Unscaled}^{Daily} \times GSV^{Weekly}}{100} \quad (5)$$

Market data

We retrieve all stock market data, i.e., return index (RI), bid price (PB) and ask price (PA) from Thomson Reuters Datastream. We use arithmetic returns with:

$$r_{it} = \frac{RI_{it} - RI_{it-1}}{RI_{it-1}} \quad (6)$$

The Fama and French risk adjustment factors including momentum are retrieved from Wharton Research Data Services (WRDS). The respective portfolios are constructed following Fama and French (1992, 1993, 1996) and Carhart (1997), risk-free rate (rf) is the return on US T-bills.

⁴www.google.com/trends

4 Results

In order to evaluate our trading strategy, we first compare its performance to a simple market buy-and-hold strategy, which passively invests into the S&P 500 index. Then, we assess if the generated return stems from loading on well-known risk factors or whether it is rather of abnormal nature, which implies that our strategy generates compensation in excess of the borne risk, i.e., it creates alpha.

4.1 Performance comparison

We begin our first investment in the second week of March 2004. Google provides data starting January 2004 and we consume 8 past weeks for calculating abnormal search volume for each stock. Hence, in the 9th week of 2004 we have the first abnormal search volume (ASV) score available, allowing for the first stock selection decision in the next week, i.e., week 10. We assume equal weights of the selected stocks in the strategy portfolio each week.

Figure 2 illustrates the performance of our main strategy and the two amendments.

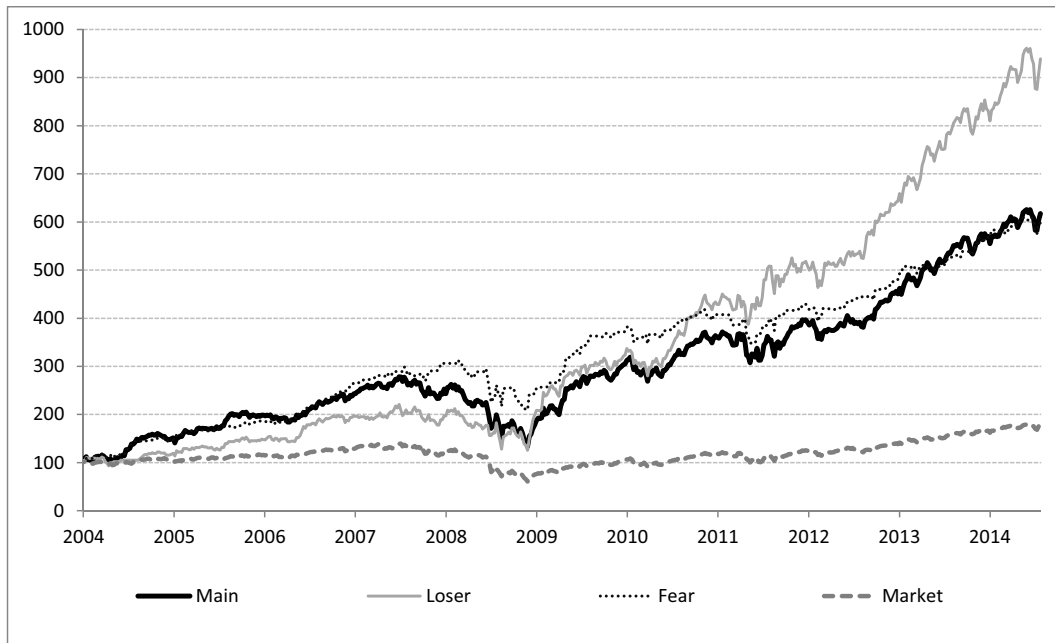


Figure 2: Performance comparison

The black line shows the performance of investing 100\$ into the “Main” strategy vs. a pure market buy-and-hold of the S&P 500 index, displayed by the gray dashed line.

After 556 weeks at the end of October 2014, the “Main” strategy investment of \$100 will increase to a total of \$617, while the market increases to \$180 at the same time. The figure also reveals that at any point in time, the low attention strategy yields a higher wealth than the market buy-and-hold.

The gray line represents the strategy with the amendment of only buying the low attention stock, if it had a negative return in the last week. This “Loser” strategy leads to a final wealth of \$939, which is 50% higher than the outcome of the main strategy. Except for few weeks in 2004, its wealth path is constantly superior to the one of the market buy-and-hold approach. This shows us that the under-pricing effect of low attention stocks is indeed more pronounced, if combined with a “buying a loser” amendment.

The black dotted line shows the last amendment of only going long in the low attention stock, if we face fearful market conditions, i.e., the level of the VIX index increased. This “Fear” strategy generates a final wealth of 598\$ and thereby just \$19 less than our “Main” strategy. However, the wealth path seems to be more stable and less volatile. This effect potentially originates from the fact that this strategy only takes positions in 262 out of the 556 weeks at all. In the remaining 294 weeks market conditions were unafraid in the last week as measured by the volatility index and hence we do not take any position. Remarkably, the outcome is almost as favorable as for the “Main” strategy, implying that the under-pricing effect is particularly present in fearful markets. This could be because investors potentially refrain from trading in fearful markets and hence under-react to positive news. This leads to positive returns in the following week, when the under-reaction gets corrected. Or, if they trade albeit fearful market conditions, their actions could lead to more pronounced under-pricing of the corresponding securities, due to irrational selling of the stocks.

Let us now compare our strategy to the market based on some additional performance measures. As table 2 shows, all three strategies indeed generate statistically significant annual average returns of 19.3%, 23.6% and 18.1% for the “Main”, “Loser” and “Fear” strategy respectively. At the same time, the market only yields a return of 5.2% annually, which is not even statistically different from zero over the 556 weeks. Therefore, it is not astonishing that all three strategies significantly outperform the market buy-and-hold strategy (as seen in line “Portfolio minus Market p.a.”).

While the “Main” strategy produces 14.1 percentage points more return than the market, it only adds additional 3.4 percentage points standard deviation to achieve its return. Hence, the Sharpe ratio of annually 0.83 is higher than the Sharpe ratio of a pure market buy-and-hold strategy, which yields only 0.21 units of return per unit of

risk the investor accepts.

Table 2: Performance comparison (weekly re-balancing)

	Main	Loser	Fear	Market
Average portfolio return p.a.	19.3%	23.6%	18.1%	5.2%
t-test	2.94***	3.27***	3.56***	0.94
Standard deviation p.a.	21.4%	23.6%	16.6%	18.0%
Sharpe p.a.	0.83	0.94	1.00	0.21
Omega ratio	1.43	1.51	1.94	1.12
Portfolio minus Market p.a.	14.1%	18.4%	12.9%	
t-test	4.67***	4.01***	3.03***	
Avg. trades per week	71.0	33.0	33.0	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Average weekly portfolio return annualized with factor 52. T-test based on weekly returns with $T=556$ weeks or 10.7 years. Returns are stationary according to ADF test and results are robust to applying Newey-West standard errors correcting for heteroscedasticity and autocorrelation.

The most favorable Sharpe ratio, however, is achieved through the “Fear” strategy with $SR=1.00$. For this strategy we only invest if market conditions were fearful in the last week. Hence, we do not take positions in every week, which leads to a much smoother return profile and, hence, lower standard deviation. And indeed, the “Fear” strategy only requires on average 33 trades (or 16.5) positions per week (buying on Monday, selling on Friday), while the “Main” strategy requires 71 trades or 35.5 positions each week. Also the Omega ratios for all three strategies are higher than that of the market. An Omega of 1.94 for the “Fear” strategy indicates that total positive returns outweigh negative returns by 94%, which is very relevant to a loss averse investor.⁵

To sum up, all our strategies outperform a pure market buy-and-hold. An investor, who purely seeks highest return, could combine the main strategy with a “buying a loser” approach and invest into the “Loser” portfolio, as return is even higher. A mean-variance investor who seeks to maximize the relation of risk and return, i.e., the Sharpe ratio, is better off with only trading if the market was fearful. The return of this “Fear” strategy is slightly lower, but standard deviation and, hence, Sharpe ratio is most favorable for this approach. Also the relation of gains to losses (Omega ratio) is highest for this strategy and therefore most favorable to a loss averse investor.

⁵Omega is calculated relative to a threshold of 0 return.

Robustness checks

As a first check of robustness, we split the sample into three periods. We distinguish the financial crisis (2008-2011) with the Lehman break-down in 2008, a pre-crisis period (2004-2007) and an after-crisis period which marks financial recovery (2012-2014). Table 3 presents the performance comparison for these three sub samples.

Table 3: Performance comparison (sub samples)

2004-2007	Main	Loser	Fear	Market
Average portfolio return p.a.	25.3%	18.6%	28.0%	5.2%
t-test	2.91***	2.00**	4.32***	0.89
Standard deviation p.a.	17.0%	18.2%	12.7%	11.4%
Sharpe p.a.	1.28	0.83	1.93	0.15
Omega	1.73	1.49	3.58	1.18
Portfolio minus Market p.a.	20.1%	13.4%	22.8%	
t-test	3.36***	1.79*	3.68***	
Avg. trades per week	19.0	8.0	9.0	
2008-2011				
	Main	Loser	Fear	Market
Average portfolio return p.a.	12.2%	27.4%	11.5%	-2.9%
t-test	0.84	1.71*	1.00	-0.23
Standard deviation p.a.	29.1%	32.0%	22.9%	25.6%
Sharpe p.a.	0.40	0.84	0.48	-0.13
Omega	1.18	1.42	1.35	0.96
Portfolio minus Market p.a.	15.1%	30.3%	14.4%	
t-test	2.8***	3.25***	1.59	
Avg. trades per week	84.0	41.0	38.0	
2012-2014				
	Main	Loser	Fear	Market
Average portfolio return p.a.	21.1%	25.0%	14.1%	16.6%
t-test	2.92***	2.92***	2.61**	2.57**
Standard deviation p.a.	12.2%	14.4%	9.1%	10.9%
Sharpe p.a.	1.73	1.73	1.55	1.52
Omega	1.81	1.83	2.26	1.71
Portfolio minus Market p.a.	4.5%	8.3%	-2.5%	
t-test	2.01**	1.83*	-0.53	
Avg. trades per week	121.0	55.0	60.0	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Average weekly portfolio return annualized with factor 52. T-test based on weekly returns with $T=200$ weeks or 3.8 years for 2004-2007, $T=208$ weeks or 4.0 years for 2008-2011 and $T=148$ weeks or 2.8 years for 2012-2014. Returns are stationary according to ADF test and results are robust to applying Newey-West standard errors correcting for heteroscedasticity and autocorrelation.

In 2004-2007 and 2012-2014, all three strategies produce returns that are signifi-

cantly different from 0 and substantially outperform the market, except for “Fear” from 2012-2014. During the financial crisis of 2008-2011, all returns are positive but not significantly different from zero, presumably due to augmented volatility. But as the market performed badly during the crisis and lost 2.9% p.a., the strategies at least significantly outperform the market, with exception of the “Fear” amendment. When considering Sharpe and Omega ratio a mixed picture emerges. While in 2004-2007 also the “Fear” strategy was most favorable to the mean-variance optimizer, in 2008-2011 it is the “Loser” strategy. In that period the return of this strategy is exceptionally high with 27.4% as compared to only 12.2% of the “Main” strategy. This shows us that during the crisis there was a strong ultra-short-term mean-reversal effect which caused last week’s loser stocks to appreciate in the following week. This effect, however, cannot be explained with low attention but rather with irrational over-reaction during the crisis, which gets corrected in the following week. In 2012-2014 “Fear” is most favorable according to Omega, but Sharpe ratio would favor the “Main” strategy.

Remarkably, in 2012-2014 the “Fear” strategy cannot outperform the market. As the overall stock market performs exceptionally well with 16.6% p.a., it is almost impossible for the “Fear” strategy to catch up, as it only takes positions in about half of the weeks, i.e., when the level of the VIX increased. To conclude, results are overall robust towards splitting the sample into sub periods.

Table 4: Performance comparison (monthly re-balancing)

	Main	Loser	Fear	Market
Average portfolio return p.a.	16.8%	33.4%	6.0%	5.6%
t-test	2.85***	1.65	1.44	1.17
Standard deviation p.a.	19.2%	65.9%	13.5%	15.7%
Sharpe p.a.	0.80	0.48	0.34	0.27
Omega	1.95	2.63	1.68	1.32
Portfolio minus Market p.a.	11.2%	27.8%	0.4%	
t-test	3.92***	1.45	0.09	
Avg. trades per month	71	30	26	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Average monthly portfolio return annualized with factor 12. T-test based on monthly returns with $T=128$ months or 10.7 years. Returns are stationary according to ADF test and results are robust to applying Newey-West standard errors correcting for heteroscedasticity and autocorrelation.

In a next step we alternate the holding period. First, we increase it from one week to one month. We use our weekly GSV scores and calculate the average GSV score

each month from the weekly data. Then we again calculate abnormal search volume by dividing the current month’s average GSV score by the median of the last two months (i.e., 8 weeks). Table 4 contains the results.

With annual return of 16.8% monthly re-balancing produces slightly less return than weekly re-balancing but at least statistically significant for the main strategy. Hence, we conclude that the low attention underpricing effect is rather of short-term nature. Also the “Main” strategy significantly outperforms the market. Remarkably, the “Loser” approach generates an extremely high return of 33.4%, although not significant due to high volatility. And this effect needs to be rather attributed to a mean-reversion than a low attention effect.

Additionally, we decrease the holding period to one day and make use of our daily GSV scores with results presented in Table 5.

Table 5: Performance comparison (daily re-balancing)

	Main	Loser	Fear	Market
Average portfolio return p.a.	32.0%	33.9%	12.5%	6.6%
t-test	2.30**	2.48**	1.58	0.70
Standard deviation p.a.	36.3%	35.6%	20.7%	24.6%
Sharpe p.a.	0.82	0.89	0.50	0.18
Omega	1.21	1.31	1.15	1.05
Portfolio minus Market p.a.	25.4%	27.3%	5.9%	
t-test	2.12**	2.02**	0.72	
Avg. trades per day	16.0	5.0	10.0	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Average daily portfolio return annualized with factor 365. T-test based on daily returns with $T=2484$ days or 6.8 years. Returns are stationary according to ADF test and results are robust to applying Newey-West standard errors correcting for heteroscedasticity and autocorrelation.

The average annualized return of 32.0% for the main strategy is higher than for weekly re-balancing and statistically significant. This again shows us that the low attention under-pricing effect seems to be highly short-term. However, in terms of Sharpe and Omega ratio, weekly re-balancing still is superior. And in addition, daily re-balancing incurs substantial transaction costs. Consequently, daily re-balancing needs to generate a lot more return in order to compensate the investor for significantly higher cost of trading (see following section).

As a last robustness check we apply alternative search terms including ticker as well as firm name in order to grasp GSV trading signals. Table 8 in the appendix shows

the performance comparison for firm name and for ticker as alternative search terms. With 15.7% and 16.2% annual average return for firm name and ticker respectively, those alternative search term strategies also generate significantly positive returns, but lower than for our proposed search term approach. Also market out-performance as well as Sharpe and Omega ratio are less favorable for all three strategies. And, with up to 488 trades per week, these approaches require substantially more trading as they chose from a much larger pool of stocks, for which Google data is available.

4.2 Risk adjustment

For risk adjustments, we regress weekly annualized return of our trading strategy portfolio in excess of risk free rate on the common risk factors including excess market return ($mktrf$), high-minus-low (HML), small-minus-big (SMB) and momentum (UMD). Thereby, we investigate, whether returns of our strategy can be justified by taking on structural risk into the portfolio, or if true mispricing/underpricing was identified. Table 6 reports results of this analysis.

Table 6: Risk adjustment (weekly re-balancing)

Portfolio	(1) Main	(2) Loser	(3) Fear
Dependent	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$
$mktrf_t$	0.984*** (0.0584)	0.909*** (0.121)	0.584*** (0.0487)
HML_t	0.0529 (0.0597)	0.0693 (0.0874)	0.153 (0.0998)
SMB_t	0.103 (0.105)	0.153 (0.201)	-0.0183 (0.0690)
UMD_t	-0.133*** (0.0331)	-0.207*** (0.0557)	-0.0367 (0.0581)
Constant	0.100*** (0.0292)	0.149*** (0.0471)	0.118*** (0.0365)
Observations	556	556	556
Adjusted R ²	0.820	0.639	0.480

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Ordinary Least Square regression is applied. r_t is annual arithmetic return of respective portfolio, r_f is the return of the risk-free asset, $mktrf_t$ is market return minus return of the risk free asset, i.e., excess market return, HML_t is the return of the high-minus-low portfolio, SMB_t is the return of the small-minus-big portfolio and UMD_t is the return of the momentum or up-minus-down portfolio.

Indeed, all three strategies generate a positive and significant annual alpha of 10%,

14.9% and 11.8% for the “Main”, “Loser” and Fear” strategy respectively. Hence, the return of our strategy is higher than justified from a risk perspective, i.e., the strategy generates alpha.

Robustness checks

As a robustness check, we again split the sample into three periods, i.e., 2004-2007, 2008-2011 and 2012-2014 with results presented in Table 9 in the appendix. For 2004-2007 all three strategies generate significantly positive alphas. For 2008-2011, only the “Main” and “Loser” strategies alphas are significant. For the sample of 2012-2014, the alphas are positive but not significant. The lacking of significance could be attributed to the relatively smaller sample size of only 148 weeks. With 2.0%, 3.8% and 2.7%, alphas are yet much smaller than in the preceding sub samples. The market performed exceptionally well in 2012-2014 with annual return of 16.6%. As the portfolio has a factor loading on the market excess return ($mktrf_t$) of $\beta \approx 1.1$, the intercept (alpha) decreases roughly in the proportion 1:1 for each unit of additional market excess return. If the market performs very well, as it was the case 2012-2014, the alpha is a lot smaller. This implies that our strategy is not necessarily suitable in times of highly favorable market conditions. At least not, if investors seek to generate returns in excess of fair compensation for the borne risk.

For monthly re-balancing, results are presented in Table 10 in the appendix. The alpha for the “Main” strategy is 7.4% and hence lower than for weekly re-balancing. For the “Loser” and “Fear” strategy, alphas are insignificant. Hence, we can again conclude that the under-pricing effect is rather short-term and returns are more favorable if weekly re-balancing is applied. Results of daily re-balancing are shown in Table 11 in the appendix. The alpha of 21.9% is higher than for weekly re-balancing and statistically significant at the 10% level. However, we need to recall that daily re-balancing results in substantially larger trading costs. Risk adjustment results for the alternative search terms consisting of firm name and ticker are presented in Table 12 in the appendix. Alphas are positive and significantly different from zero, but persistently lower than for our proposed search term of firm name and “stock”.

4.3 Transaction costs

Due to the high frequency of portfolio re-adjustments, transaction costs cannot be ignored. For weekly re-balancing, the investor needs to open a position on Monday morning

and close it on Friday night (ignoring that some stocks might be held for more than one week). When buying the security the difference between ask and average price is paid as trading costs. When selling the stock the delta between bid and average price is incurred. Hence, every week the bid-ask spread in percent of average price needs to be deducted from the weekly return as trading costs. Over the period of 2004-2014, the average bid-ask spread of the 122 stocks in our sample was 0.1054%. If we multiply this spread with 52 weeks of trading per year, we get annual trading costs of 5.5%, which needs to be subtracted from our average annual return. A summary of net return and net alpha after transaction costs is shown in Table 7.

Table 7: Net performance after transaction costs

Re-balancing	Main			Loser			Fear		
	Monthly	Weekly	Daily	Monthly	Weekly	Daily	Monthly	Weekly	Daily
Return p.a.	16.8%***	19.3%***	32.0%**	33.4%	23.6%***	33.9%**	6.0%	18.1%***	12.5%
Transaction cost p.a.	1.3%	5.5%	26.4%	1.3%	5.5%	26.4%	1.3%	5.5%	26.4%
Net return p.a.	15.5%***	13.8%**	5.7%	32.1%	18.1%**	7.6%	4.7%	12.6%**	-13.9%*
Alpha p.a.	7.4%**	10.0%***	21.9%*	23.6%	14.9%***	26.6%**	0.2%	11.8%***	5.4%
Transaction cost p.a.	1.3%	5.5%	26.4%	1.3%	5.5%	26.4%	1.3%	5.5%	26.4%
Net alpha p.a.	6.1%**	4.5%	-4.5%	22.3%	9.4%**	0.3%	-1.1%	6.3%*	-20.9%***

*** p<0.01, ** p<0.05, * p<0.1

Notes: "Main" is performance of buying last week's low attention stocks, "Loser" is performance of buying last week's low attention stocks having a negative return in the past week, "Fear" is performance of buying past week's low attention stocks only if CBOE volatility index (VIX) increased in last week, "Market" is performance of investing into the S&P 500 index.

If we recall that our "Main" strategy generated a yearly return of 19.3%, profits are sufficiently large in order to compensate for transaction costs in the case of weekly re-balancing. For monthly re-balancing, transaction costs amount to 1.3% (0.1054% x 12 months). This implies that after cost of trading, monthly re-balancing is more favorable, although its gross performance is worse. If we consider daily re-balancing, the strategy incurs 26.4% trading costs p.a. (0.1054% x 250 trading days). Recalling a return of 32.0% for the main strategy, the return in excess of transaction costs is only 5.7% and insignificant. Although gross returns are higher compared to weekly and monthly re-balancing, they are off-set by disproportionately larger cost of trading. From a cost perspective, monthly re-balancing is most favorable for the "Main" strategy. For the "Loser" and "Fear" approach weekly re-balancing is superior. The bid-ask spread is the relevant transaction cost for institutional and large scale investors. If we consider retail investors, willing to follow our strategy, additional trading fees would occur. If we remember that we need to execute on average 70 trades per week or 3,640 trades p.a. and assuming that every trade costs about \$10, the investor would need to invest at least \$264k into the strategy each year in order to break-even after trading fees, considering

an average of 13.8% annual net return after bid-ask spread. Hence, for a private and small-scale investor, monthly re-balancing definitely seems more reasonable to pursue, as it requires substantially less trades and a smaller stake to break even. After adjusting for the main risk factors, also the alpha needs to be adjusted for cost of trading. With an alpha of 10% the strategy produces abnormal return in excess of trading costs, but the net alpha is insignificant. For daily re-balancing, the alpha of 22% does not compensate for annual trading costs of 26%. But again, monthly re-balancing, although having a lower alpha, is more favorable than weekly re-balancing. The net alpha is 6.1% and statistically significant.

The choice of re-balancing hence depends on the individual transaction cost situation of the investor. If we ignore cost of trading, daily and weekly re-balancing clearly dominate a monthly portfolio reallocation. But as costs for these approaches are proportionally larger compared to monthly re-balancing, this conclusion changes quickly.

5 Conclusion

In this study we present a trading strategy based on signals received from Google Trends data in order to exploit limited investor attention. From a large sample of US S&P 500 stocks we buy a security if last week's Google Search Volume for that security was abnormally low. We expect the corresponding stock to be under-priced due to lacking attention towards positive changes in fundamentals. Our strategy produces a significant average annual return of 19.3%, which represents an out-performance of a pure market buy-and-hold strategy by 14.3 percentage points. After controlling for risk, a significant alpha (abnormal return) of 10% remains. The strategy can be combined with a "buying a loser" approach in order to further push returns. If the investor seeks to maximize Sharpe or Omega ratio, the strategy can be enhanced by investing in "fearful" market conditions only, as measured by the market volatility index. Generated returns are sufficiently large to cover trading costs. Depending on the individual cost situation of the investor, monthly re-balancing can be shown to be more favorable than weekly and daily re-balancing.

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Appendix

Table 8: Performance comparison (based on GSV for alternative search terms)

GSV for firm name	Main	Loser	Fear	Market
Average portfolio return p.a.	15.7%	21.6%	12.6%	5.2%
t-test	2.57**	3.25***	2.63***	0.94
Standard deviation p.a.	20.0%	21.7%	15.6%	18.0%
Sharpe p.a.	0.71	0.93	0.71	0.21
Omega	1.37	1.50	1.65	1.12
Portfolio minus Market p.a.	10.5%	16.4%	7.4%	
t-test	7.94***	7.68***	2.05**	
Avg. trades per week	438.0	197.0	206.0	

GSV for ticker	Main	Loser	Fear	Market
Average portfolio return p.a.	16.2%	23.0%	12.6%	5.2%
t-test	2.61***	3.43***	2.60***	0.94
Standard deviation p.a.	20.2%	22.0%	15.9%	18.0%
Sharpe p.a.	0.73	0.98	0.71	0.21
Omega	1.38	1.53	1.65	1.12
Portfolio minus Market p.a.	10.9%	17.8%	7.4%	
t-test	8.11***	8.03***	2.07**	
Avg. trades per week	488.0	219.0	231.0	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Average weekly portfolio return annualized with factor 52. T-test based on weekly returns with $T=556$ weeks or 10.7 years. Returns are stationary according to ADF test and results are robust to applying Newey-West standard errors correcting for heteroscedasticity and autocorrelation.

Table 9: Risk adjustment (sub samples)

Portfolio	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Main	Loser	Main	Loser	Fear	Main	Loser	Main	Loser	Fear	Main	Loser	Main	Loser	Fear	Main	Loser	Fear
Period	2004-2007	2004-2007	2004-2007	2004-2007	2004-2007	2008-2011	2008-2011	2008-2011	2008-2011	2008-2011	2008-2011	2008-2011	2012-2014	2012-2014	2012-2014	2012-2014	2012-2014	2012-2014
Dependent	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$
$mkt_r f_t$	0.927*** (0.0736)	0.841*** (0.0952)	0.425*** (0.0754)	0.925*** (0.0843)	0.425*** (0.0754)	0.840*** (0.171)	0.925*** (0.0843)	0.425*** (0.0754)	0.840*** (0.171)	0.571*** (0.0692)	1.038*** (0.0199)	1.087*** (0.0432)	1.038*** (0.0199)	1.087*** (0.0432)	0.571*** (0.0692)	1.038*** (0.0199)	1.087*** (0.0432)	0.571*** (0.0692)
HML_t	-0.574*** (0.130)	-0.466** (0.234)	-0.499*** (0.154)	0.188** (0.0779)	-0.499*** (0.154)	0.180 (0.120)	0.188** (0.0779)	-0.499*** (0.154)	0.180 (0.120)	0.284** (0.136)	0.0220 (0.0603)	0.0524 (0.109)	0.0220 (0.0603)	0.0524 (0.109)	0.284** (0.136)	0.0220 (0.0603)	0.0524 (0.109)	0.0606 (0.114)
SMB_t	0.250** (0.123)	0.136 (0.163)	0.157 (0.124)	0.0613 (0.176)	0.157 (0.124)	0.187 (0.331)	0.0613 (0.176)	0.157 (0.124)	0.187 (0.331)	-0.0596 (0.117)	-0.0606 (0.0522)	-0.0131 (0.109)	-0.0606 (0.0522)	-0.0131 (0.109)	-0.0596 (0.117)	-0.0606 (0.0522)	-0.0131 (0.109)	-0.171** (0.0691)
UMD_t	0.104 (0.0847)	0.0522 (0.147)	0.164** (0.0822)	-0.144*** (0.0412)	0.164** (0.0822)	-0.233*** (0.0752)	-0.144*** (0.0412)	0.164** (0.0822)	-0.233*** (0.0752)	-0.0161 (0.0698)	-0.109*** (0.0332)	-0.0835 (0.0632)	-0.109*** (0.0332)	-0.0835 (0.0632)	-0.0161 (0.0698)	-0.109*** (0.0332)	-0.0835 (0.0632)	-0.0573 (0.0843)
Constant	0.193*** (0.0575)	0.129* (0.0730)	0.232*** (0.0553)	0.0756* (0.0446)	0.232*** (0.0553)	0.216*** (0.0797)	0.0756* (0.0446)	0.232*** (0.0553)	0.216*** (0.0797)	0.0956 (0.0762)	0.0102 (0.0204)	0.0378 (0.0450)	0.0102 (0.0204)	0.0378 (0.0450)	0.0956 (0.0762)	0.0102 (0.0204)	0.0378 (0.0450)	0.0274 (0.0407)
Observations	200	200	200	208	200	208	208	200	208	208	148	148	148	148	208	148	148	148
Adjusted R ²	0.584	0.372	0.298	0.906	0.298	0.720	0.906	0.298	0.720	0.560	0.924	0.727	0.924	0.727	0.560	0.924	0.727	0.482

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Ordinary Least Square regression is applied. r_t is annual arithmetic return of respective portfolio, r_f is the return of the risk-free asset, $mkt_r f_t$ is market return minus return of the risk free asset, i.e., excess market return, HML_t is the return of the high-minus-low portfolio, SMB_t is the return of the small-minus-big portfolio and UMD_t is the return of the momentum or up-minus-down portfolio.

Table 10: Risk adjustment (monthly re-balancing)

Portfolio	(1) Main	(2) Loser	(3) Fear
Dependent	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$
$mktrf_t$	1.038*** (0.0630)	0.812*** (0.294)	0.531*** (0.0999)
HML_t	0.0184 (0.136)	1.911 (1.698)	0.0464 (0.156)
SMB_t	-0.0937 (0.106)	-0.202 (0.396)	0.0760 (0.120)
UMD_t	-0.104** (0.0452)	-0.503 (0.394)	0.0252 (0.107)
Constant	0.0735** (0.0298)	0.236 (0.189)	0.00177 (0.0334)
Observations	128	128	128
Adjusted R ²	0.790	0.152	0.399

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Ordinary Least Square regression is applied. r_t is annual arithmetic return of respective portfolio, r_f is the return of the risk-free asset, $mktrf_t$ is market return minus return of the risk free asset, i.e., excess market return, HML_t is the return of the high-minus-low portfolio, SMB_t is the return of the small-minus-big portfolio and UMD_t is the return of the momentum or up-minus-down portfolio.

Table 11: Risk adjustment (daily re-balancing)

Portfolio	(1) Main	(2) Loser	(3) Fear
Dependent	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$
$mktrf_t$	0.710*** (0.0541)	0.465*** (0.0509)	0.451*** (0.0408)
HML_t	0.0970 (0.185)	0.189 (0.186)	-0.00356 (0.0684)
SMB_t	0.0970 (0.0812)	0.0287 (0.0864)	-0.0218 (0.0673)
UMD_t	-0.184*** (0.0438)	-0.0902 (0.0716)	-0.0885** (0.0449)
Constant	0.219* (0.120)	0.266** (0.130)	0.0543 (0.0648)
Observations	2,484	2,484	2,484
Adjusted R ²	0.295	0.134	0.327

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Ordinary Least Square regression is applied. r_t is annual arithmetic return of respective portfolio, r_f is the return of the risk-free asset, $mktrf_t$ is market return minus return of the risk free asset, i.e., excess market return, HML_t is the return of the high-minus-low portfolio, SMB_t is the return of the small-minus-big portfolio and UMD_t is the return of the momentum or up-minus-down portfolio.

Table 12: Risk adjustment (based on GSV for alternative search terms)

Portfolio	(1) Main	(2) Loser	(3) Fear	(4) Main	(5) Loser	(6) Fear
Search term	Firm name	Firm name	Firm name	Ticker	Ticker	Ticker
Dependent	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$	$r_t - r_f$
$mktrf_t$	1.027*** (0.0162)	1.085*** (0.0235)	0.636*** (0.0579)	1.034*** (0.0125)	1.094*** (0.0187)	0.647*** (0.0610)
HML_t	0.0546** (0.0220)	0.0627 (0.0430)	0.115 (0.0841)	0.107*** (0.0199)	0.0748* (0.0446)	0.131 (0.0832)
SMB_t	0.103*** (0.0256)	0.108*** (0.0417)	-0.0359 (0.0765)	0.102*** (0.0207)	0.109*** (0.0419)	-0.0423 (0.0834)
UMD_t	-0.0768*** (0.0113)	-0.0892*** (0.0250)	-0.00511 (0.0515)	-0.0636*** (0.0114)	-0.0876*** (0.0262)	0.000413 (0.0514)
Constant	0.0600*** (0.00892)	0.114*** (0.0179)	0.0594* (0.0312)	0.0631*** (0.00886)	0.128*** (0.0184)	0.0587* (0.0317)
Observations	556	556	556	556	556	556
Adjusted R ²	0.980	0.933	0.594	0.980	0.929	0.597

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Ordinary Least Square regression is applied. r_t is annual arithmetic return of respective portfolio, r_f is the return of the risk-free asset, $mktrf_t$ is market return minus return of the risk free asset, i.e., excess market return, HML_t is the return of the high-minus-low portfolio, SMB_t is the return of the small-minus-big portfolio and UMD_t is the return of the momentum or up-minus-down portfolio.