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Investor attention and short-term return reversals☆

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ABSTRACT

The Google Search Volume Index is proposed as a novel and improved proxy for overreaction as selling winner stocks after they enjoyed a substantial surge in search volume is found to be profitable. It increases the gains of a standard reversal strategy, net of transaction costs, from 17.5 basis points to 34.2 basis points on a weekly basis, corresponding to a 9.1% increase on an annual basis. Furthermore, we report significant alphas in Fama–French-type regressions. The results suggest that most of the reversal profits are made in volatile times, which are typically periods when overreaction is most likely.

1. Introduction

This study examines whether winner stocks are more likely to revert after a surge in Google search volumes. Lehmann (1990) found that portfolios of stocks that performed well in one week ('winner' portfolios) typically had negative returns the next week, while the portfolios of stocks that performed poor in one week ('loser' portfolios) typically had positive returns the following week. While Kaul and Nimalendran (1990), among others, reported that most short-term reversal profits fall within bid-ask bounds, more recent findings of de Groot et al. (2012); Da et al. (2014); Frazzini et al. (2012) and Nagel (2012) are in favor of the return reversal anomaly.

Two possible explanations for short-term reversal profits stand out. The first one is overreaction, suggested by Shiller et al. (1984) and De Bondt and Thaler (1985). As De Bondt and Thaler (1985) pointed out, 'overreaction' implies that some degree of reaction is considered appropriate. However, investors tend to overweight recent information and underweight prior data. This rule of thumb is what Tversky and Kahneman (1973) call 'the representative heuristic'. Investors subject to this heuristic overreact to salient information such as recent past performance. This is confirmed by Barber and Odean (2008), who showed that individual investors are net buyers of attention-grabbing stocks, resulting in price pressure.

A second explanation for short-term reversal profits is based on liquidity. Campbell et al. (1993) conjectured that the returns from price reversals stem from a divergence in the short-term supply and demand curve of stocks, which can lead to higher bid-ask spreads. When liquidity providers eventually absorb these price concessions, this results in price reversals that serve as a reward for those who provide liquidity. In fact, Nagel (2012) used these price reversals as a proxy for the return from liquidity provision.

In terms of the relative importance of these two explanations, Subrahmanyam (2005) noted that "microstructure effects take at least several months to be fully reversed in stock prices", thus giving more weight to the overreaction explanation. Furthermore, de Groot et al. (2012) concluded that "the only explanation that has been put forward in the literature whose projections are not

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inconsistent with our findings is the behavioral explanation that market prices tend to overreact to information". Therefore, the aim of present study is to further examine the impact of overreaction on the reversal strategy.

One of the papers that considers the behavioral explanation comes from Da et al. (2014), who used two indirect measures of investor sentiment that reflect optimism and overvaluation. They observed that stock returns unexplained by 'fundamentals' are more likely to reverse. Most importantly, they found that liquidity shocks explain the reversal on recent losers, whereas investor sentiment drives the reversal on recent winners. The latter is important because the present study focuses on the effect of overreaction on winning stocks. In addition, Miller (1977) argued that the existence of short-sale constraints limits arbitrage to exploit overpricing. The proxies (Da et al., 2014) uses for overreaction are the monthly number of initial public offerings and equity share in new issues. Because these metrics ignore firm-specific overreaction and have a monthly frequency, it is impossible to test for weekly short-term reversals. Therefore, in the present study, a novel direct measure is used to test for overreaction: weekly search frequencies from Google. Following Barber and Odean (2008), we argue that increased investor attention endorses overconfidence and the representative heuristic, leading to a higher overreaction probability.

The objective of this study is to investigate whether winning stocks are more likely to revert when there is overreaction. In a standard reversal strategy, recent losers are bought while recent winners are sold. In our behavioral reversal strategy, losers are also bought, but winners are only sold when there is a surge in investor attention. Using S&P500 stocks from 2004 to 2016, we show that conditioning winners on an increase in investor attention doubles the net profitability of a reversal trading strategy. To the best of our knowledge, we are the first to empirically test the overreaction-based explanation for short-term price reversal using Google Trends data.

2. Data and methodology

This study focuses on S&P500 constituents and uses Thomson Reuters Datastream to retrieve data on returns and market capitalizations. The sample starts in January 2004 and runs until December 2016.

Google Trends provides data on search term frequencies starting from 2004. This metric has several advantages over traditional measures of overreaction. First, Google Trends data measures attention for each individual firm, capturing the idiosyncratic component in investor attention. Moreover, the theory of buyer behavior posits that a consumer's search for information precedes his or her purchase decision (Beatty and Smith, 1987). A third important point is that Google queries account for approximately 71.2% of the searches worldwide,[1] supporting its representativeness of internet search behavior. More specifically, Da et al. (2011) found that Google Trends seems to mainly represent the attention of retail investors, that is, the group of investors who do not have access to any specialist data source such as Bloomberg. This group is actually more likely to suffer from behavioral biases such as overconfidence or the representative heuristic (Barber et al., 2009). In this study, the weekly Search Volume Index (SVI) was used, which is a perfect match to the weekly short-term reversal strategy.

For the identification of a stock in Google, the approach of Da et al. (2011) was followed. They argued that searching for a ticker is less ambiguous than using the company name, since the former more likely measures attention to financial information. Starting from 800 companies, we excluded 16% of the tickers that may have other meanings such as 'ACE', 'COST' or 'DNA', leaving us with 674 unambiguous ticker symbols. Next, we excluded the weeks when Google Trends did not return a valid SVI because a ticker was rarely searched. This left us with 403,046 firm-week observations.

It is important to note that Google scales the data to account for the natural temporal variation in the overall search intensity, for instance, due to holidays. To make inter-temporal comparisons meaningful, we scaled the data appropriately and focused on the abnormal SVI (ASVI), following Da et al. (2011). ASVI was defined as follows:

$$ASVI_t = log(SVI_t) - log[Med(SVI_{t-1}, ..., SVI_{t-8})], \tag{1}$$

where $log(SVI_t)$ is the logarithm of SVI during week t, and $log[Med(SVI_{t-1}, ..., SVI_{t-8})]$ the logarithm of the median value of SVI during the prior 8 weeks (Da et al., 2011). This measure has the advantage that it is robust to recent jumps and low-frequency seasonalities. Therefore, ASVI represents a surge in investor attention and can be compared across stocks in the cross section (Da et al., 2011).

To construct the reversal portfolios, we sorted all available stocks every week based on the past-week returns. As the returns were used to form our portfolios, this is referred to as the 'formation period'. Our base case reversal strategy is long (short) in the ten stocks with the lowest (highest) returns over the past week. To construct our behavioral overreaction portfolio, we only went short in previous winning stocks if they experienced a 20% or more ASVI increase in the week before the formation period. The reason the increased interest was measured before the formation period is that Google Trends reveals the intentions of retail investors mostly 1 or 2 weeks before they act (Da et al., 2011). When the condition of overreaction was not met for any of the winners, we simply shorted the standard winner portfolio. This occurred in 37, or 5%, of the 679 weeks. As motivated in Section 1, we did not filter our losing stocks, and went long in the ten stocks with the lowest returns. The portfolios were equally weighted and rebalanced at a weekly frequency. Implementing this as a trading strategy would result in frequent trading, and thus substantial transaction costs. To account for this, we used transaction cost data as suggested by de Groot et al. (2012), who presented these trading cost schemes in such a way that other researchers could use them in their studies. The cost of a single-trip varies between 4 and 40 basis points, depending on the period and the company size. However, de Groot et al. (2012) only computed transaction costs until 2009, while our dataset runs until 2016. Rather conservatively, we used the average transaction costs over the last 3 years as a proxy for the

[1] Source: https://www.netmarketshare.com/search-engine-market-share.aspx?qprid=4&qpcustomd=0.

Table 1
Profitability of the reversal investment strategy.

	Standard				Behavioral		
	Long (bps) (1)	Short (bps) (2)	Long/short (bps) (3)	t-stat (4)	Cond. short (bps) (5)	Long/Cond. short (bps) (6)	t-stat (7)
Gross return	43.0	6.6	49.6	(2.4)	22.7	65.7	(2.5)
Net return	26.6	−9.1	17.5	(0.8)	7.6	34.2	(1.3)

Table 1 reports the average weekly gross and net returns in basis points of the reversal strategy portfolios using S&P500 constituents from 2004 until 2016. It shows the long portfolio (1), the short portfolio (2), the standard long/short portfolio (3), and the short portfolio conditional on a 20% increase in the Abnormal Search Volumes Index (5) of Da et al. (2011). Column 6 presents the results of the combination of the standard long portfolio (1) and short portfolio conditional on overreaction (5). Net returns are calculated using transaction costs from de Groot et al. (2012). T-statistics of the long/short portfolios are provided in column 4 and 7.

transaction costs from 2010 onwards.

3. Empirical results

3.1. Main empirical results

Table 1 shows the main results of our empirical analysis. We report gross and net returns for the short and long portfolio separately, as well as the returns of the long/short portfolio. In addition, columns 5 and 6 present the returns of the behavioral short portfolio conditional on overreaction, and the returns of the long/conditional short portfolio. To start, we confirm that the standard reversal strategy is still profitable in our sample. Buying ten loser stocks, and simultaneously selling ten winning stocks, yields an average weekly gross return of 49.6 basis points. After transactions costs, this strategy yields an average of 17.5 basis points per week. More interestingly, columns 5 and 6 reveal the returns on the strategy that exploits overreaction. Conditional on a surge in the abnormal search volume by more than 20%, shorting the winner portfolio generates an average gross return of 22.7 basis points, compared to 6.6 basis points for the standard short portfolio. Hence, the average return on a long/short portfolio conditional on overreaction amounts to 65.7 basis points per week, which is 16.1 basis points higher than the standard reversal strategy. The return net of transaction costs rises from 17.5 to 34.2 basis points per week when conditioning on increased attention. We conclude that, on an annual basis, the overreaction strategy adds a non-negligible return of 9.1% to the profitability of the short-term reversal strategy.

3.2. Fama–French regressions

To test whether our results can be attributed to common risk factors, we regressed our reversal portfolio returns on factors for the market, size, value and momentum (Carhart, 1997). Table 2 reports coefficient estimates and R-squared values for equally and value-weighted portfolio returns of both the standard reversal strategy and the strategy conditional on overreaction. Panel A illustrates that the standard strategy generates an alpha of 38 basis points for the equally weighted portfolio. Interestingly, this alpha increases to 52 using the behavioral approach. In addition to the significant alphas, the explanatory power of the risk factors are below 14%, suggesting that our reversal profits do not stem from exposures to the common risk factors. In Panel B of Table 2, we add a risk factor[2] based on the (Amihud, 2002) measure of illiquidity. The alpha of the standard strategy decreases to 25 basis points, showing that the reversal strategy partly originates from liquidity shocks. This is in line with the findings of Da et al. (2014). However, consitent with our overreaction hypothesis, our behavioral strategy still enjoys a higher average return of 38 basis points per week. Similar conclusions hold for value-weighted portfolios.

3.3. Follow-up analysis

A final step in the analysis is to verify whether the results are sensitive to the chosen trading specifications or the time period. Tables 3 and 4 show the results for gross returns and net returns, respectively. In both tables, Panel A refers to the benchmark results of Table 1.

First, the threshold for overreaction is adjusted. Panel B of both Tables 3 and 4 shows that, instead of using 20%, conditioning on a 10% or 30% increase in abnormal search volumes results in an average gross return of 58.0 and 58.1 basis points, respectively. Although this is both lower than the 65.7 basis points when using a 20% threshold, the overreaction strategy still ameliorates the average weekly return with 9 basis points. We argue that our 20% threshold is well chosen, as a more inclusive approach of 10% would fail to select overreacting stocks, while a more rigorous conditioning of 30% would lead to the selection of too few

[2] In line with the methodology suggested on the website of Kenneth French, we use six value-weighted portfolios formed on size and illiquidity to construct our factor. The portfolios, which are formed weekly, are the intersections of 2 portfolios formed on size and 3 portfolios formed on illiquidity. The size breakpoint is the median and the illiquidity breakpoints are the 30th and 70th percentiles. ILLIQ is the average return on the two high illiquidity portfolios minus the average return on the two low illiquidity portfolios.

Table 2
Fama–French regressions.

	Equally weighted				Value weighted			
	Standard		Behavioral		Standard		Behavioral	
Panel A: Fama–French–Carhart model								
Alpha	0.38	(1.99)	0.52	(2.14)	0.46	(2.32)	0.59	(2.36)
Mkt-RF	0.56	(6.08)	0.59	(5.08)	0.61	(6.38)	0.63	(5.33)
SMB	−0.38	(−2.16)	−0.42	(−1.83)	−0.53	(−2.89)	−0.66	(−2.81)
HML	0.68	(4.47)	0.81	(4.16)	0.42	(2.67)	0.40	(1.99)
WML	−0.28	(−3.27)	−0.48	(−4.56)	−0.26	(−2.96)	−0.49	(−4.55)
R^2	0.14		0.14		0.12		0.11	
N	669		669		669		669	
Panel B: Fama–French–Carhart–Amihud model								
Alpha	0.25	(1.27)	0.38	(1.54)	0.34	(1.69)	0.45	(1.79)
Mkt-RF	0.08	(0.44)	0.05	(0.21)	0.18	(0.97)	0.12	(0.54)
SMB	−0.53	(−2.94)	−0.60	(−2.52)	−0.66	(−3.52)	−0.83	(−3.41)
HML	0.55	(3.55)	0.66	(3.32)	0.31	(1.90)	0.26	(1.28)
WML	−0.28	(−3.29)	−0.49	(−4.59)	−0.26	(−2.97)	−0.50	(−4.58)
ILLIQ	0.45	(3.15)	0.51	(2.80)	0.40	(2.70)	0.48	(2.56)
R^2	0.16		0.15		0.13		0.12	
N	669		669		669		669	

Table 2 presents the coefficient estimates and R-squared values of Fama–French regressions using the weekly long/short portfolios over the period 2004–16. In Panel A, we regress the gross reversal portfolio returns on the risk factors for market, size, value (Fama and French, 1993) and momentum (Carhart, 1997). In Panel B, we add a liquidity (ILLIQ) factor based on the Amihud (2002) measure of illiquidity. We focus on gross returns because they are the most suitable to illuminate the relation between risk and returns (Frazzini et al., 2012). We present results using both equally weighted (column 2–5) and value weighted (column 6–9) portfolios. Column 4–5 and 8–9 show us the results of the reversal strategy conditional on overreaction. T-statistics are provided within parentheses.

Table 3
Robustness profitability (gross) of the reversal investment strategy.

	Standard				Behavioral		
	Long (bps) (1)	Short (bps) (2)	Long/short (bps) (3)	t-stat (4)	Cond. short (bps) (5)	Long/Cond. short (bps) (6)	t-stat (7)
Panel A: Benchmark results							
Gross return	43.0	6.6	49.6	(2.4)	22.7	65.7	(2.5)
Panel B: Adjust threshold of 20% ASVI increase							
10% increase	43.0	6.6	49.6	(2.4)	15.0	58.0	(2.6)
30% increase	43.0	6.6	49.6	(2.4)	15.1	58.1	(2.0)
Panel C: Alter portfolio size of 10 stocks							
5 stocks	42.2	3.0	45.2	(1.7)	26.7	68.9	(2.1)
20 stocks	36.9	−5.8	31.1	(1.7)	−2.4	34.5	(2.2)
Panel D: Different portfolio weights							
Value-weighted	46.2	11.3	57.4	(2.7)	24.9	71.1	(2.8)
Panel E: Subsample analysis							
2004–07	5.6	14.8	20.4	(1.1)	34.5	40.1	(1.5)
2008–11	97.2	35.0	132.2	(2.2)	70.6	167.8	(2.3)
2012–16	28.2	−22.4	5.8	(0.3)	−22.0	6.2	(0.2)

Table 3 reports the weekly gross returns in basis points of the reversal strategy portfolios using S&P500 constituents from 2004 until 2016. Panel A holds the benchmark returns similar to the results in Table 1. Panel B until E provide us with results to test the robustness of our trading strategy. Panel B adjusts the threshold of a 20% increase in attention to 10% and 30%. In Panel C, we change the number of stocks in our long and short portfolios. Panel D represents the results using market capitalizations as portfolio weights. Panel E shows the results of a subsample analysis. T-statistics of the long/short portfolios are provided in column 4 and 7.

overreacting winners, which would result in mimicking the standard reversal strategy.

Secondly, the number of stocks included in the portfolios of winners and losers is altered, as reflected in Panel C. When we only take 5 stocks into account, the gross return of the conditional portfolio increases to 68.9 basis points. However, with a larger portfolio of 20 stocks, the profitability of both the standard and the conditional reversal strategy drops to 31.1 and 34.5 basis points, respectively. This tells us that incorporating less extreme winners and losers in the portfolio mitigates the overall reversal effect. Moreover, the smaller additional value of the behavioral strategy suggests that overreaction is less important for moderate winning stocks.

Next, the portfolio weights are changed from equal weighting to weighting based on market capitalization. The value-weighted results presented in Panel D of Tables 3 and 4 reveal slightly higher returns for both the standard and the behavioral strategy. This is

Table 4
Robustness profitability (net) of the reversal investment strategy.

	Standard				Behavioral		
	Long (bps) (1)	Short (bps) (2)	Long/short (bps) (3)	t-stat (4)	Cond. short (bps) (5)	Long/Cond. short (bps) (6)	t-stat (7)
Panel A: Benchmark results							
Net return	26.6	−9.1	17.5	(0.8)	7.6	34.2	(1.3)
Panel B: Adjust threshold of 20% ASVI increase							
10% increase	26.6	−9.1	17.5	(0.8)	2.3	28.9	(1.3)
30% increase	26.6	−9.1	17.5	(0.8)	0.1	26.7	(1.2)
Panel C: Alter portfolio size of 10 stocks							
5 stocks	24.6	−13.2	11.4	(0.4)	17.2	41.8	(1.2)
20 stocks	28.2	−20.4	7.8	(0.4)	−17.5	10.7	(0.7)
Panel D: Different portfolio weights							
Value-weighted	29.7	−10.2	18.7	(1.4)	14.7	44.4	(1.6)
Panel E: Subsample analysis							
2004–07	−13.9	−1.0	−14.8	(−0.8)	19.2	5.3	(0.2)
2008–11	80.8	18.5	99.4	(1.7)	54.8	135.6	(1.9)
2012–16	13.9	−37.3	−23.4	(−1.4)	−35.6	−21.7	(−1.2)

Table 4 reports the weekly net returns in basis points of the reversal strategy portfolios using S&P500 constituents from 2004 until 2016. Net returns are calculated using transaction costs from de Groot et al. (2012). Panel A holds the benchmark returns similar to the results in Table 1. Panel B until E provide us with results to test the robustness of our trading strategy. Panel B adjusts the threshold of a 20% increase in attention to 10% and 30%. In Panel C, we change the number of stocks in our long and short portfolios. Panel D represents the results using market capitalizations as portfolio weights. Panel E shows the results of a subsample analysis. T-statistics of the long/short portfolios are provided in column 4 and 7.

in line with de Groot et al. (2012), as they reported that the largest stocks yield higher reversal profits. In addition, the impact of trading costs is lower for large cap stocks.

Finally, the sample is divided into three subsamples in Panel E. This shows that most of the returns for both the standard and the overreaction strategy stem from the period 2008–11, which is the period of the financial crisis. During this period, 132.2 basis points of net return are generated every week with the standard reversal strategy, and no less than 167.8 basis points with its behavioral counterpart. To a large extent, 97.2 basis points, these returns originate from the long portfolio of previous losers. This is in line with our results in Section 3.2 and confirm the findings of Da et al. (2014) who show that liquidity shocks explain the reversal on recent losers. However, this does not overrule our overreaction hypothesis, as conditioning on overreaction increases the gross return on shorting winners from 35.0 to 70.6 basis points. These results are also in agreement with Michayluk and Neuhauser (2006), who found evidence for short-term return predictability in the aftermath of the 1997 Asian financial crisis. Outside the crisis period, conditioning winners on overreaction also increases the return for the reversal strategy, although the effect is negligible for the most recent period 2012–16. This suggests that price reversals, and the effects of overreaction, are not as important during less volatile periods.

4. Discussion and conclusion

This paper explores whether winner stocks are more likely to revert after a surge in Google search volumes. We show that shorting a portfolio of winner stocks that enjoy an abnormal increase in search volumes improves the short-term reversal strategy profitability. On average, the behavioral winner portfolio adds 16.7 basis points per week, or 9.1% annually. Interestingly, most returns of both the standard and the behavioral reversal strategy stem from the period of the financial crisis. During these crisis years, the added value of the overreaction portfolio increases to more than 35 basis points per week. We conclude that, besides liquidity, overreaction is an important factor that drives price reversals, especially during times of high volatility. These results have important implications for understanding market (in)efficiency and testing asset pricing models, as well as for investors looking for a hedge in times of high turmoil.

Declaration of interest

None to declare.

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