Investor Attention and Short-Term Price Reversals*

Dries Heyman[1] Michiel Lescrauwaet[2] Hannes Stieperaere[3]

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Abstract

In this paper we revisit the short-term return reversal anomaly and test for the overreaction-based explanation by using a new and more advanced proxy for overreaction: aggregate search frequencies from Google Trends. First, we find that the standard short-term reversal is still apparent in recent years for stocks in the S&P 500 index before transaction costs, but decreases substantially when we account for these frictions. In contrast, going short on winner stocks conditional on a significant increase in search volume for these winner stocks in the week before the formation period, improves returns considerably. When combining this 'behavioral' winner portfolio with the traditional loser portfolio, the average weekly excess return for our behavioral short-term reversal strategies in our base case scenario amounts to 41 basis points, net of transaction costs.

JEL Classification: G02. G11. G12. G14

Keywords: Price Reversals, Investor Attention, Investor Overreaction, Google Trends

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[1] Department Financial Economics. Ghent University. E-mail: Dries.Heyman@UGent.be

[2] Department Financial Economics. Ghent University. E-mail: Michiel.Lescrauwaet@UGent.be

[3] Department Financial Economics. Ghent University. E-mail: Hannes.Stieperaere@UGent.be

1 Introduction

For more than half a century, researchers have been stymied over the information efficiency of the stock market. As more and more economists observed market anomalies, the validity of the Efficient Market Hypothesis has been called into question.

One of the most pervasive anomalies that has been around for more than 40 years is the short-term return reversal phenomenon. Using weekly returns, Lehmann (1990) found that portfolios of stocks that performed very well in one week ('winner' portfolios) typically had negative returns the next week (-0.35 to -0.55 percent per week on average), while the portfolios of stocks that performed extremely poor in one week ('loser' portfolios) typically had positive returns in the subsequent week (0.86 to 1.24 percent per week on average). Using monthly returns, Jegadeesh (1990) found that 'loser' stocks over the last month achieve significantly higher returns than portfolios of stocks that performed very well over this period. By going long on the loser portfolio and short on the winner portfolio, Jegadeesh (1990) documented profits of 2% a month. More recent findings of De Groot et al. (2012), Da et al. (2013), Frazzini et al. (2012) and Nagel (2012) are also in favor of the return reversal anomaly, while Kaul and Nimalendran (1990), Ball, Kothari and Wasley (1995) and Conrad, Gultekin and Kaul (1997) report that most short-term reversal profits fall within bid-ask bounds. Since the empirical finding of significant short-term reversal profits contradicts the notion that stock prices follow a random walk, this anomaly deserves a deep understanding by finance researchers.

Two possible explanations for short-term reversal profits stand out. The first explanation is overreaction of stock prices, as suggested by Shiller (1984), Black (1986), Poterba and Summers (1987), De Bondt and Thaler (1985, 1987), and Subrahmanyam (2005)

As De Bondt and Thaler (1985) point out, the term "overreaction" carries with it an implicit comparison to some degree of reaction that is considered appropriate. It is generally accepted that Bayes' rule prescribes the correct reaction to new information. According to Bayes' rule, investors update their beliefs, given prior evidence. Kahneman and Tversky (1974), however, found that many of the decisions concerning the likelihood of uncertain events are based on heuristics rather than Bayes' rule. In revising their beliefs, investors tend to overweight recent information and underweight prior data. This rule-of-thumb is what Kahneman and Tversky (1974) call the representative heuristic. Investors subject to this heuristic overreact to salient and similar information about a firm's past performance. Another popular overreaction-based explanation is based on the overconfidence model of Daniel, Hirshleifer, and Subrahmanyam (1998). In their model, investors are likely to be overconfident about the private information they have worked hard to generate. Their theory implies that investors “Overreact to private information signals and underreact to public information signals” (DHS, 1998). It should be stressed that their aim was to explain momentum for time periods between one and six months, rather than short-term reversals for one week. However, this does not change their finding that overconfidence can lead to overreaction; only the time period considered is different. Barber and Odean (2008), among others, show that attention greatly influences individual investor purchase decisions. Individual investors face a huge search problem when choosing stocks to buy and only have a limited amount of attention they can devote to investing. Directing too little attention to important information can result in a delayed reaction to important information. On the other hand, devoting too much attention to perhaps stale or irrelevant information can lead to an overreaction. Since most individual investors own only a small number of stocks and only sell stocks that they own, selling poses less of a search problem and is less sensitive to attention effects and hence overreaction.

A second explanation is the liquidity-based explanation. Campbell at al. (1993), among others, 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 price concessions. 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 for the reversal effect, Subrahmanyam (2003) notes that “microstructure effects take at least several months to be fully reversed in stock prices”, thereby giving more weight to the overreaction explanation. Furthermore, De Groot et al. (2012), who took another look at the short-term reversal, concluded that “The only explanation that has been put forward in the literature whose projections are not inconsistent with our findings is the behavioral explanation that market prices tend to overreact to information in the short run”. We therefore devote our attention to further examining the impact of overreaction on the reversal strategy.

In recent years however, only limited light has been shed on the overreaction-based explanation. This is not entirely surprising, as scholars face a substantial challenge: it is very hard to find a direct measure of overreaction.

One of the few papers that does consider the behavioral explanation comes from

Da et al. (2013) who use two indirect measures of investor sentiment that reflect optimism and overvaluation. They find that stock returns unexplained by "fundamentals" are more likely to reverse in the short run than those linked to fundamental news. Most importantly, liquidity shocks always seem to be explaining the reversal on recent losers, whereas investor sentiment always seems to be driving the reversal on recent winners. The proxies they use for overreaction are the monthly number of initial public offerings (IPOs) and the monthly equity share in new issues. A major shortcoming of these market-based measures is that the outcome can be the result of many different economic forces other than investor sentiment (Da et. al, 2013). Indeed, these metrics only take into account the overall market sentiment and ignore idiosyncratic factors that might cause overreaction to stocks. This could be one of the reasons why they did not find significant results for these variables on the standard short-term reversals. In addition to that, these indirect metrics are only available on a monthly basis, making it impossible to test for weekly short-term reversals. Other standard metrics for overreaction are related to turnover or closed-end fund discounts. However, within the framework of the short-term return reversals, these proxies cannot be used as they are arguably too closely related to liquidity.

Therefore, inspired by Da, Engelberg and Gao (2011), we will use a novel direct measure of investor overreaction: aggregate search frequencies in Google. This new metric has several advantages over traditional measures of overreaction. First, search-based sentiment measures from Google Trends are available on a weekly basis, which makes it a perfect match for the weekly short-term reversal strategy. Second, Google Trends data allow us to measure sentiment for each individual firm, meaning that we can observe the idiosyncratic component in investor sentiment. Next. with millions of people using Google every day, and Google queries accounting for approximately 71.2 percent over the globe[1], the search volume reported by Google is probably representative of Internet search behavior of the general population. More specifically, Da et. al (2011) find that Google Trends is most likely to represent the attention of retail investors. Beyond the empirical evidence, the intuition behind this finding is also fairly convincing. Since institutional investors have access to more sophisticated information services such as Reuters or Bloomberg Terminals, the participants who use Google to search for security information are more likely those who do not have access to any specialist data sources, a group often described as retail investors. Perhaps the most interesting aspect of the data

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

is the fact that it reveals the intentions of these retail investors, often long before they act. By employing a Vector Autoregression (VAR) model, Da et. al (2011) find that "an increase in the Search Volume Index predicts higher stock prices in the next two weeks and an eventual price reversal within the year."[2] This is consistent with other literature (Barber and Odean, 2011) that has documented the tendency of retail investors to be influenced by various behavioral biases that contribute to such short-term overreaction. Beer et al. (2012), for example, found evidence for similar dynamics of short-term overreaction in the French market and provide additional proof of the ability of Google Trends to capture retail investor interest by studying the relationship between the Search Volume Index (Henceforth, SVI) and mutual fund flows. Throughout this paper, we employ these key insights from the academic literature in our exploration of its potential relevance to the short-term reversal anomaly.

Our main hypothesis states that winner stocks are more likely to revert when there is overreaction. We define overreaction as a significant increase in the SVI in the week before the formation period. The reason we measure the increased interest 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). For loser stocks, however, we do not expect that overreaction is at play in the formation period. The reason for this is the existence of short-sale constraints, which limit the ability of rational traders to exploit overpricing immediately (Miller, 1977). Following Shawn et. al (2014), we refer to the situation where the SVI is falling while the price is moving in a steep uptrend as a "sustainable price trend" driven by investors with access to more sophisticated sources of information. Such interest is likely to be more informed, less subject to the biases, and thus we expect such a trend to be more sustainable than a similar price movement characterized by short-term retail interest. Therefore, our empirical approach aims at examining the difference in profitability between the standard reversal strategy, and the reversal strategy based on overreaction in the winners. In our standard reversal strategy, recent losers are bought whereas recent winners are sold. In our reversal strategy based on overreaction, losers are also bought but winners are only sold when there is evidence of overreaction. To the best of our knowledge, we are the first to empirically test the overreaction-based explanation with Google Trends data.

Our empirical analysis firstly shows that the standard short-term reversal profitability is still present for the data in our sample. Before transaction costs, the

[2] The Search Volume Index measures the intensity of searching a keyword in Google. Section 3.2 elaborates on this.

basic scenario in which the portfolio we buy and sell contain ten stocks, a weekly performance of 41 basis points is generated. This diminishes to 11 basis points once transaction costs are taken into account. Secondly, and more important, a portfolio conditional on a significant (20%) increase in the search volume for winner stocks in the week before the formation period improves the overall returns substantially. More specifically, we find that the average weekly returns on this reversal strategy increase to 58 basis points, before transaction costs. The weekly returns still amount to 39 basis points once we count in transaction costs.

We deem that our study contributes to the existing literature in at least two important ways. First and foremost, our findings strengthen the explanation that reversals are induced by overreaction on recent winners, consistent with the findings of Da et al. (2013) and in line with the conjectured hypothesis of De Groot et al. (2012). Second, the finding that our reversal investment strategies yield significant returns net of transaction costs presents a serious challenge to standard rational pricing models. The key lesson is that investors striving to earn superior returns by engaging in reversal trading are more likely to realize their objectives by conditioning their winner positions on overreaction. This comes with an additional advantage of a lower turnover rate, which means lower transaction costs.

The rest of this paper is organized as follows. Section 2 discusses the data and methodology. Section 3 contains the empirical results. Section 4 concludes.

2 Data and Methodology

2.1 Data

The sample starts in January 2004 and runs till December 2016. We use Thomson Reuters Datastream to retrieve data on returns, market capitalizations and volumes of all stocks that have been a constituent of the S&P500 in this period. Next, we use transaction cost data for all the S&P 500 stocks, as reported by De Groot et al. (2012). These trading cost schemes were presented in such a way that other researchers could use them in their studies. However, we should mention that they only computed transaction costs till 2009, while our dataset runs till December 2015. Rather conservatively, we will use the average transaction costs of the last three years as a proxy for the transaction costs from 2009 onwards.

As stated in the introduction, empiricists face a substantial challenge when testing for overreaction: there is no direct measure of investor overreaction. In the next paragraphs, we will argue why the search volume on companies' ticker symbols can be correlated with stock-specific investor overreaction, and thus serve as a direct measure of investor overreaction.

First, the theory of buyer behavior posits that a consumer's search for information precedes his or her purchase decision (Beatty & Smith, 1987). Interestingly, today's digital environment provides previously unavailable measures of consumer search behavior, and recently scholars are coming to recognize that what individuals are searching for on Google leaves a trail of "What we collectively think" and "What might happen in the future" (Rangaswamy, Giles and Seres, 2009, p.58).

Second, as shown by Da et al. (2011), the Search Volume Index (SVI) is a direct measure of individual investor attention. The literature on behavioral finance in general agrees that retail investors are more likely to suffer from behavioral biases such as overconfidence (Barber, Odean & Zhu, 2009; Lee, Shleifer & Thaler, 1991). Now, since paying attention is a necessary condition for behavioral biases to affect trading and asset prices, it can be expected that when more retail investors are paying attention to a stock, their biases are more likely to affect the price of a security and hence generate greater overreaction.

Third, the Internet has recently become an important place for individual investors to gather information and Google continues to be their favorite search engine. With a market share of approximately 71.2 percent over the globe, the search volume reported by Google is probably representative of Internet search behavior of the general population. Many psychological studies find that people feel more confident when they have more information or expertise (Gilovich, Griffin and Kahneman, 2002). After investors spend hours researching the stock on Google, they may feel that they have more expertise and thus become more overconfident about it. In turn, this could lead these investors to think that the information they find online is representative for the company. All in all, both the overconfidence bias and representative heuristic might be at play when we look at Google Trends data.

Fourth, after searching for a stock in Google, investors are often led to the same information and may reach similar assessments about the stock. Barber, Odean and Zhu (2009) reported that assessments of less sophisticated individual investors are likely to be highly correlated, which ties in with the third assumption for behavioral biases to affect stock prices. Following Da et al. (2011), we contend that these correlated private signals will generate a stronger price overreaction.

These motivations strengthen our conviction that using search volume on Google is a relevant proxy for overreaction.

Google Trends (www.google.com/trends/) provides data on search term frequencies from January 2004 onwards. For the purposes of this thesis, we first download the weekly Search Volume Index (SVI) of all companies in the S&P 500, and focus on the period January 2004 - December 2016. For the identification of a stock in Google, we follow the approach of Da et al. (2011). They argue that searching for a stock using its ticker is less ambiguous than using the company name. Indeed, identifying search frequencies by company name can be problematic for three reasons.

First, the company name might be searched for reasons other than investors' interest. For example, one might search for 'Microsoft', just because they want to visit Microsoft's website. This problem is even more problematic when the company name has more meanings (e.g. Apple or Amazon).

Second, Google Trends does not allow non-alphabetical terms, meaning that companies such as "7-eleven" would be missing.

Third, different investors may search the firm using different variations of its name, making it hard for researchers to decide which name to use.

On the other hand, when an investor is searching the ticker symbol of a company (e.g. NFLX for Netflix Inc.), it is more likely that this investor is only interested in financial information about the stock. Since we are mostly interested in the search interest of retail investors, this is exactly the type of data we would like to capture. Moreover, a company's ticker is always alphabetical and uniquely assigned meaning that identifying a stock using its ticker also avoids the other two problems associated with using company names.

Furthermore, we exclude tickers that may have other meanings, such as "ACE", "COST" or "DNA". These tickers are usually associated with abnormally high SVIs that may have nothing to do with attention paid to stocks with these ticker symbols. While we report the results using all ticker symbols to avoid subjectivity in sample construction, we confirm that our results are robust to the exclusion of the noisy tickers we identified. Next, it is important to note that Google scales the data to account for the natural temporal variation. That is, if the overall search intensity for all keywords is low in a given week due to holidays, the data are scaled appropriately to make inter-temporal comparisons meaningful.

Following Da et al. (2011), we will mainly focus on the abnormal SVI (ASVI) when we look for a significant increase in investor attention. In this paper, ASVI is defined as the log SVI in the current week minus the log SVI in the previous week. The reason we focus on ASVI (rather than SVI), is because relative differences are much more sensitive when we take the log of two numbers. This makes more sense when you look for significant or abnormal changes in the SVI, which is our aim. To collect our data, we employ a web-scraping algorithm in Python that inputs each ticker and uses Google Trends' option to download the SVI into a CSV file. We do this for all the 791 ticker symbols in our sample (we have about 9 ambiguous ticker names). Lastly, we exclude the weeks where Google Trends does not return a valid SVI. If a ticker is rarely searched, Google Trends will return a zero value for that ticker's SVI. This makes it impossible for us to capture the relative increase in interest in the next week, as this would always be an infinite increase. Finally, we are left with 413 tickers and 334,703 firm-week observations.

2.2 Methodology

In our first analysis, we evaluate the profitability of a standard reversal strategy for the stocks in the S&P 500. To construct the reversal portfolios, we sort all available stocks every week into mutually exclusive portfolios based on the past week returns. As the past week returns are used to form our portfolio, we will refer to this as the 'formation period'. Next, we assign equal weights to the stocks in each portfolio. Our base case reversal strategy is long (short) in the 10 stocks with the lowest (highest) returns over the past week. Portfolios are held for one week and rebalanced at a weekly frequency. We calculate and report returns for the short and long portfolio separately, as well as the returns of the long/short portfolio. The aforementioned strategy will be implemented as a trading strategy in the sense that we will analyze whether the standard short-term reversal strategy is still sizeable when adjusting for transaction costs. In order to check robustness, we will increase the number of stocks in the portfolio to 20 stocks.

In our second analysis, we evaluate the profitability of a short-term reversal strategy for the stocks in the S&P 500, conditional on overreaction. For now, we define overreaction as 20% increase in abnormal investor attention in the week before the formation period. To construct our 'overreaction' portfolio, we follow all the steps from the standard short-term reversal, except for one. Instead of going short on every stock that was a winner in the past week, we will now only go short if the stock was a winner in the previous week and if there was a significant increase in investor attention for this winner stock in the week before the formation period. Put differently, we now only go short on winners, conditional on 'overreaction'. Again, portfolios are held for one week. We will also implement this 'behavioral' strategy as a trading strategy and evaluate whether, if at all, it is still sizeable when we adjust for transaction costs. In order to check the sensitivity of our results, we will vary our base scenario of 20% overreaction to allow for lower (10%), as well as higher (30%) overreaction.

3 Empirical Results

3.1 Short-Term Price Reversals

Table 1 shows the main results of our empirical analysis. We first confirm that the standard reversal strategy is still profitable in our sample, which ranges from 2004 until 2016. Buying 10 loser stocks, and simultaneously selling 10 winning stocks, leads to a combined average weekly return of 44 basis points. Most of the return is generated by buying the losing stocks: this strategy alone accounts for 41 of the 44 basis points. If we expand our portfolios to include 20 instead of 10 stocks, the profitability of our strategy diminishes. The decrease in returns holds for both the portfolio of losing stocks (40 instead of 41 basis points), and the portfolio of winning stocks (-3 instead of 3 basis points). Combined, the profitability decreases to 38 basis points. These are numbers that do not take into account transaction costs. Indeed, implementing this strategy as a trading strategy would result in frequent transactions, and thus substantial transaction costs. As stated earlier, we follow the approach of De Groot et al (2012) in implementing transaction costs. Not surprisingly, this implementation leads to a decline in the profitability of our standard reversal strategy. After transaction costs, the profitability lowers to 13 (9) basis points for portfolios of 10 (20) stocks.

Next, we focus on the results of the strategy that tries to exploit overreaction by retail investors, as proxied by an increase in the search volume by more than 20%. Since this is only implemented for the winner portfolio, for reasons mentioned earlier, the results on the long portfolio of losing stocks do not change. However, the results on the portfolio we short are substantially different: in this base case scenario (10 stocks, 20% overreaction), the short portfolio yields a return of 19 basis points, resulting in a total return of the strategy of 60 basis points, well above the 44 basis points obtained in the standard reversal strategy. The strategy remains profitable once we consider transaction costs. Now, implementing the strategy would lead to a net return on the long/conditional short portfolio of 41 basis, as compared to 13 basis points for the standard reversal strategy. When expanding the number of stocks in portfolio to 20, the profitability of our strategy reduces to 25 basis points.

Results do change when we vary the threshold for overreaction. When we lower the criterion for overreaction, results weaken to 48 basis points without transaction costs and 26 basis points including transaction costs. The weakening of the results shouldn't surprise as we get closer to the standard reversal case. Qualitatively similar results hold for expanding the portfolio to 20 stocks. When we however harshen the inclusion criterion to an SVI increase of 30%, the results remain the same as for the 20% overreaction case, if our portfolio consists of 10 stocks. (58 basis points excluding transaction costs, 41 basis points including costs). If we allow for the inclusion of 20 stocks in our portfolio, the return on the strategy improves and now becomes 54 basis points excluding transaction costs and 35 basis points including costs. In this case, we actually observe the effect of selecting stocks with a higher amount of overreaction. In sum, this results in table 1 provide evidence that it is worthwhile to impose an overreaction criterion on the winner portfolio. This is also witnessed in Figure 1, which shows graphically the results we described above. The cumulative return on executing the conditional reversal strategy is superior to the standard reversal strategy. This holds both with and without transaction costs. This means the profitability of the reversal strategy often documented in previous literature can be augmented by conditioning the selection of the winner portfolio on the presence of overreaction.

3.2 Future Work

As this is a preliminary version of our paper, we plan on extending the analysis in several ways. Firstly, we should account for the risk of the strategy. Similar to De Groot et al. (2012), we will execute Fama French regressions to certify that the returns are not merely a compensation for risk. Next, we will vary both the size of the formation and the holding period, to see whether the profitability of the strategy varies with these periods. Finally, we wish to check whether there are periods in which the overreaction strategy is relatively less or more profitable as compared to the standard strategy.

4 Conclusion

Identifying the causes of the short-term return reversal has important implications for empirical asset pricing tests, and more generally for understanding the limits of market efficiency. In the literature of short-term reversals, two possible explanations stand out. The first explanation is based on overreaction, while the second is based on a liquidity premium. In recent years, less light has been shed on the former. This is not entirely surprising, as scholars face a substantial challenge: it is very hard to find a direct measure of overreaction. Existing measures of investor overreaction such as the number of IPOs in a year, the return on these IPOs or the monthly equity share in new issues, are indirect proxies of investor overreaction and not available on a weekly basis.

In this paper, we revisit the short-term reversal anomaly and test for the overreaction-based explanation by using a new and more direct proxy for overreaction: aggregate search frequencies from Google Trends. Our central hypothesis is that winner stocks are more likely to revert when there is overreaction in the week before the formation period. Is this the case?

To answer this question, we started off by calculating the returns of the standard short-term reversal strategies, as this is our horserace benchmark. In short, we find that the standard short-term reversal is still apparent for the data in our sample, yet is substantially reduced when we account for transaction costs. In contrast, a portfolio conditional on a significant increase in the search volume for winner stocks in the week before the formation period improves the overall returns considerably. . When combining this 'behavioral' winner portfolio with the traditional loser portfolio, the average weekly excess return for our behavioral short-term reversal strategies in our base case scenario amounts to 41 basis points, net of transaction costs. We refer to the previous section on future work in order to draw the attention of the reader to the fact that we still want to implement a number of additional tests.

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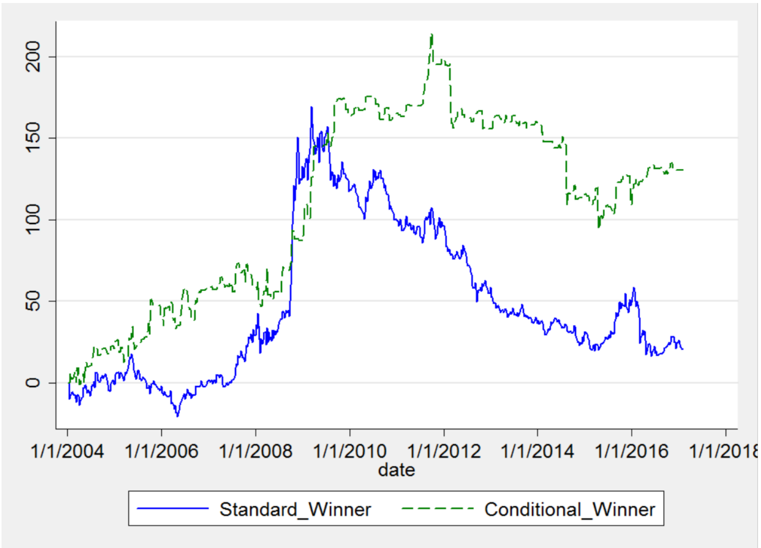
Table 1: Profitability of Reversal Investment Strategy Conditional on overreaction for the S&P500 stocks

		Long (bps)	Short (bps)	Conditional Short (bps)	Long-Short (bps)	t-stat	Long-Conditional Short (bps)	t-stat
Panel A: Gross returns standard reversal strategy and reversal strategy conditional on overreaction								
10 Stocks	10% SVI increase	41.2	3.1	7.2	44.3	2.0	48.4	1.8
	20% SVI increase	41.2	3.1	19.1	44.3	2.0	60.3	2.2
	30% SVI increase	41.2	3.1	17.3	44.3	2.0	58.4	2.2
20 Stocks	10% SVI increase	40.1	-3.0	-10.0	37.6	2.1	30.2	1.4
	20% SVI increase	40.1	-3.0	5.5	37.6	2.1	46.1	2.0
	30% SVI increase	40.1	-3.0	12.9	37.6	2.1	53.5	2.3
Panel B: Net returns standard reversal strategy and reversal strategy conditional on overreaction								
10 Stocks	10% SVI increase	29.2	-15.6	-3.1	13.6	0.6	25.9	1.0
	20% SVI increase	29.2	-15.6	12.0	13.6	0.6	41.2	1.5
	30% SVI increase	29.2	-15.6	11.8	13.6	0.6	41.0	1.5
20 Stocks	10% SVI increase	30.0	-20.9	-23.9	9.2	0.5	6.1	0.3
	20% SVI increase	30.0	-20.9	-4.5	9.2	0.5	25.6	1.1
	30% SVI increase	30.0	-20.9	5.2	9.2	0.5	35.3	1.5

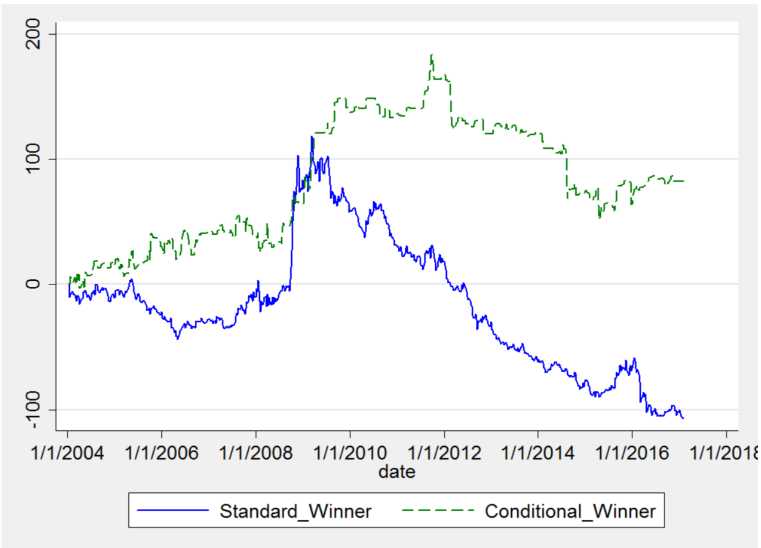
This table reports the weekly gross (panel A) and net (panel B) returns in basis points of the long portfolio, the short portfolio, the short portfolio conditional on a abnormal increase in investor attention, the standard long-short portfolio, and a long-short portfolio conditional on increased attention. Net returns are computed each week by taking the trading cost associated with the stocks size by using transaction costs porposed by De Groot et al. (2012).

Figure 1: Cumulative Retunrs of Winner Portfolio

Panel A: Gross Returns Winner Portfolio



Panel B: Net Returns Winner Portfolio



This figure shows the evolution of the cumulative returns of the standard winner portfolio, as well as the winner portfolio conditional on a 20% increase in firm level investor attention.