Are Investors Paying (for) Attention?[*]

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Abstract

I add to the understanding of how investor attention affects the pricing of assets by using a new proxy based on Google search data. In contrast to prior studies using Google data, my new proxy contains cross-sectional information in addition to time-series information. Additionally, I focus on firms that consistently receive high or low attention, rather than attention-grabbing events. I find that firms with low attention outperform firms with high attention by 8.16% annually, and after isolating the unique information in search volume and removing the impact of attention-grabbing events, the outperformance is still statistically and economically significant at 6.36% annually.

1 Introduction

Taking a classical view of finance, the amount of attention paid towards an asset should not have any effect on its returns. Rather, in the classical view, the cross-section of expected returns should be determined solely by the cross-section of priced systematic risks. Rational market agents diversify their portfolios to maximize the Sharpe ratio (Sharpe, 1966), and any irrational agents are taken advantage of by rational arbitrageurs whom trade based on fundamental value. Further, it is assumed that prices adjust to new information instantaneously.

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Over the last 30 years, much evidence has been offered in favor of behavioral view models in finance.[1] In the behavioral view, some market agents are irrational, and often in predictable ways. It is typically still assumed that there are arbitrageurs whom act (more) rationally and take advantage of mispricings. These arbitrageurs, however, are few and have limited capital, which is often provided by outside investors. If assets diverge further from fundamental value, this often requires additional capital to support the arbitrage position, causing some to reverse their positions (Shleifer and Vishny, 1997).

As not every mispricing can be completely eliminated by arbitrageurs, assets can diverge from fundamental value for extended periods of time. Even further, if some assets are more difficult to arbitrage than others, we should observe greater mispricing for those assets. Such assets include the equity of newer, smaller, more volatile, unprofitable, non-dividend paying, distressed, and extreme growth firms (Baker and Wurgler, 2006).[2]

The classical assumption that information is absorbed instantaneously into prices requires that, for any given new information, investors are paying attention to both the new information and the relevant asset. But as shown by Kahneman (1973), attention is a scarce cognitive resource, and so it is impossible for any individual to allocate attention to all assets. Even further, information in the digital age comes 24 hours a day, and we all must sleep at some point.[3]

Given limited abilities of attention, it may be rational for an investor to own and monitor fewer stocks than would be suggested in the classical framework. As described by Merton (1987), investors must pay an initial fixed "set-up" cost to evaluate a firm before they can process new incoming information. The existence of this fixed cost reduces the efficient number of assets to hold.[4] In fact, when looking at retail investor portfolios, the average retail investor holds only 4.3 stocks (Barber and Odean, 2008). Even for institutional investors, where limited attention is less of an issue owing to economies of scale, the average actively managed mutual fund has

[1] For a thorough review of behavioral asset pricing, see (Hirshleifer, 2001).

[2] In a future version of this paper, I will examine whether the return patterns are intensified within these groups of stocks.

[3] Investors in different locations around the world would be paying attention at different times, so it is plausible that information is incorporated 24 hours a day. But to the extent that fewer investors in aggregate are paying attention during the night (in the United States), information would not be incorporated into prices as quickly.

[4] This discussion considers investors that select individual stocks to hold in their portfolios. Index fund investors will not suffer from much fixed research cost as they only need to select which fund to buy. The existence of index fund investors should weaken my results, so the results would likely be stronger if funds were not an option.

only [XX] stocks [insert cite].

If we assume that each investor monitors and holds[5] only a subset of available assets, an important question is whether each asset has an equal chance of being picked. To answer this, we must think about how an investor first becomes aware of an asset. Among other possible sources, she may hear about it in the news, be exposed to its real operations (buy its products), be told about it by another individual, observe an advertisement, or discover it through aggregate data analysis. Given the ways an investor may discover an asset, there are many factors that should effect the likelihood a stock is included in an investor's information set, including firm size, growth opportunities, profitability, volatility, amount of advertising, and prevalence of news coverage.

Large firms should receive more attention as on average, their operations impact more individuals, they have more investors due to a larger market value, and they have larger advertising budgets. Growth firms should attract more attention than value firms, as they are more often developing exciting new technologies that appear in the news. Given that the small firm effect (Banz, 1981) and the value effect (Basu, 1983) go in the same direction as investor attention effects would imply, it is plausible that the small and value effects are actually driven by investor attention.[6]

If some assets are more likely to be included in investors' portfolios than others, then the demand for those assets would be greater than would be expected in the classical framework[7]. This additional demand could cause prices to increase beyond fundamental value. This increase in prices should lead to underperformance over time, if the asset approaches fundamental value.[8] Additionally, Merton (1987)'s model predicts a positive alpha for "neglected" firms, those with low investor attention.

Much of the prior literature in investor attention examines attention-grabbing events. These studies have examined news[9], extreme returns[10], unusual trading vol-

[5]Necessarily the investor must first know about the asset before purchasing it.

[6]A test of this hypothesis will be in a future version of this paper.

[7]This is only true if for a given investor and given asset, knowledge of the asset increases the likelihood of the investor buying the asset more than the likelihood of short-selling the asset. Given that only 0.29% of retail investors' portfolio positions are short-positions (Barber and Odean, 2008), this is likely true.

[8]If the asset does not approach fundamental value, we would not observe underperformance. In a world with short-sale constraints, this may be true. Any continued diversion from fundamental value would bias me against finding results, so the effect is likely stronger than the results imply.

[9]See (Barber and Odean, 2008); (Fang and Peress, 2009); (Tetlock, 2015); (Yuan, 2008)

[10]See (Barber and Odean, 2008); (Yuan, 2008)

ume[11], advertising[12], and price limits[13] as attention-grabbing events. The common result across these studies is that, on average, attention-grabbing events cause temporary buying pressure, creating a positive return,[14] followed by a return reversal. To put this in the context of Merton (1987)'s model, firms affected by attention-grabbing events are temporarily added to investors' information sets. As the firm is included in more investors' information sets, this increases demand, pushing up price.

In contrast to these prior studies, I focus on firms that consistently receive high or low attention. I do this because following the logic of Merton (1987)'s model, the attention effect should exist in equilibrium aside from attention-grabbing events. Prior studies, however, have not made an attempt to remove the temporary effect of attention-grabbing events, so they have not empirically confirmed the equilibrium effect.

Unfortunately, investor attention is not feasibly directly observable. As Barber and Odean (2008) notes, the best we could do is to have investors write down every stock they think about throughout the day. Given the difficulty of such a study, we are limited to using proxies for investor attention. Most prior studies use attention-grabbing events, and as Da et al. (2011) comments, these proxies simply assume that if there was a notable event, investors must have paid attention to it.

Da et al. (2011) advanced the literature by using a direct proxy for investor attention: the relative amount of Google searches for a company's ticker. This is an improvement because if the ticker was searched for, then someone is paying attention to it.[15] They find that an increase in Google searches predicts higher stock prices for the next two weeks, followed by a reversal, consistent with the effects being driven by attention-grabbing events. Importantly, they only had access to the *relative* number of searches for a ticker rather than the *actual* number of searches. For a given ticker, they only observe a ranking from 0 to 100 representing the percentage of the maximum search volume for that ticker. This means that they could not do any cross-sectional comparisons.

I have improved Da et al. (2011)'s proxy by obtaining the *actual* number of Google

[11]See (Barber and Odean, 2008); (Gervais et al., 2001); (Hou et al., 2009)

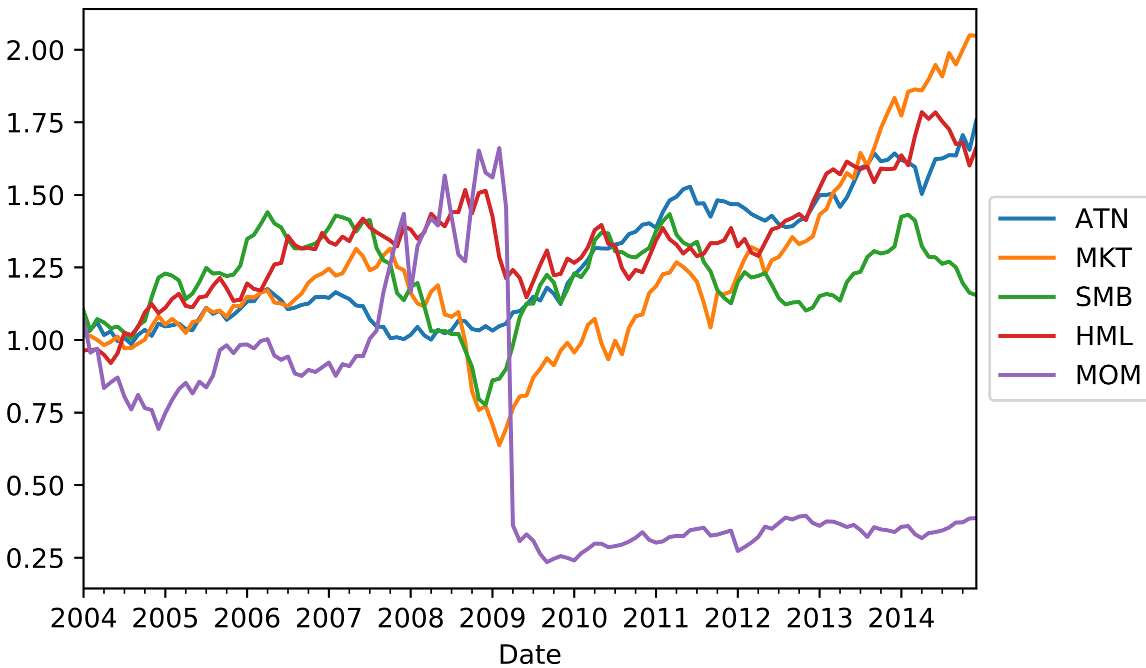
[12]See (Chemmanur and Yan, 2009)

[13]See (Seasholes and Wu, 2007).

[14]Negative returns should accompany negative events, but the effect is positive on average. The distinct characteristic which implies attention effects is the return reversal, owing to a drop-off in attention. Of course there may be other explanations for the reversal, such as investor overreaction. [insert cite]

[15]So long as the searcher intended to find information about the company and the company is included in the search results. These issues are discussed in Section 3.2.

Figure 1: Cumulative Anomaly Performance



searches for each company's ticker over time. With this proxy, I can cross-sectionally sort firms based on their level of attention, allowing a test of Merton (1987)'s model. In addition, as described in section 3.2, I improve on their method of filtering out tickers whose results are not about the firm in question.

Overall, I find evidence to support Merton (1987)'s model's predictions. Firms with low investor attention outperform firms with high investor attention by 8.16% annually. By forming a measure which separates out firm characteristics and attention-grabbing events, outperformance is still economically significant at 6.36% annually. Figure 1 shows that the attention anomaly, formed by a strategy which is long the lowest search volume firms and short the highest search volume firms, outperforms the market portfolio as well as other commonly examined pricing factors during my sample period.

The remainder of this article is organized as follows. First I form hypotheses about the effect of investor attention on stock returns in Section 2. The data and tests to be carried out are described in Section 3, followed by results in Section 4. Finally, Section 5 concludes.

2 Hypotheses

Merton (1987)'s model predicts that firms that receive less attention should outperform firms that receive more attention. But if it is possible to identify which stocks receive less attention, arbitrageurs should invest in these stocks, short-sell the high attention stocks, and make an abnormal profit. Arbitrageurs following this strategy would push prices back towards fundamental values. Their impact may be limited, however, because as discussed in Shleifer and Vishny (1997), arbitrageurs are capital-constrained and face short-sale constraints, leading to "limits" to arbitrage.

Further, if most of the neglected stocks are small firms, it may be less advantageous to execute arbitrage trades. Institutional investors are typically restricted from purchasing more than five percent of a firm's equity, and execution costs may be substantial when purchasing a large percentage of available shares. So even if the expected *rate* of return on such a strategy is high, the maximum *dollar* return may be too low to be worth the costs of executing and monitoring the strategy.

Based on uncertainty over arbitrageurs' ability to profitably execute the aforementioned strategy, I propose the following hypotheses about the effect of investor attention on stock returns:

Neglected Outperformance Hypothesis: Stocks that have low investor attention will earn higher returns than stocks with high investor attention.

Attention Indifference Hypothesis: There is no systematic difference in returns across stocks with high and low investor attention.

If the Neglected Outperformance hypothesis holds, there may be further cross-sectional implications. This hypothesis can only be true if arbitrageurs do not completely eliminate mispricing. If there is cross-sectional variation in arbitrage constraints, then we should see a greater effect for those stocks with greater constraints. Firms with greater arbitrage constraints may include those that are newer, smaller, volatile, distressed, or have extreme growth potential (Baker and Wurgler, 2006).

3 Data and Methodology

3.1 Methodology

The main goal of the study is to differentiate between the Neglected Outperformance and Attention Indifference hypotheses. To do this, first I carry out a simple sort of all the firms in my sample into decile attention portfolios from low (1) to high (10)

Table 1: Stability of Search Volume Portfolios

Portfolios are formed by sorting firms into three evenly sized groups at the end of each month based on the level of search volume. 10 represents the highest search volume portfolio, while 1 represents the lowest search volume portfolio. This table shows the probability of transition between search volume portfolios. Each entry represents the transition probabilities from the portfolio given in the row to the portfolio given in the column in percentages. Each row of values are calculated by counting each end portfolio for each month by each firm for firms in the portfolio given by the row in the prior month, summing across all months, then dividing by the total number of transitions across months for that starting portfolio.

	1	2	3
1	94.24	5.71	0.04
2	4.61	91.80	3.60
3	0.01	3.01	96.98

at the end of each month. Then I compare the average returns by year in each of the portfolios. Further, I estimate a factor model including the returns on the market portfolio, size, book-to-market, and momentum factors (Carhart, 1997).[16] Then I examine alphas by portfolio. If returns and alphas are greater for the low attention portfolio than the high attention portfolio, this offers evidence in favor of the Neglected Outperformance hypothesis. Additionally, I form an attention anomaly portfolio which is long the lowest attention assets (portfolio 1) and short the highest attention assets (portfolio 10). Then I regress returns from this anomaly on different combinations of pricing factors and anomalies reported in the prior literature. A positive, significant alpha across these regressions show that the attention effect is distinct from other anomalies, and offers more support in favor of the Neglected Outperformance hypothesis.

But even if the above evidence supports the Neglected Outperformance hypothesis, this may be due to the aggregate effects of attention-grabbing events rather than an equilibrium difference in returns. To remove the effect of attention-grabbing events, I adopt another approach. I create a new proxy, abnormal search volume, that removes the effects of attention-grabbing events and other confounding factors such as size and book-to-market, and repeat the above analysis with the new proxy.

[16] Results are robust to one- and three-factor models.

While the abnormal search volume results remove the effect of attention-grabbing events, the results with search volume may also be interpreted in a similar vein as by shown in Table 1, most firms do not switch attention portfolios each month. The highest search volume portfolio is the most stable, with 96.13% of firms remaining in the highest portfolio for the next month. The lowest search volume portfolio is still quite stable with 81.80% of firms remaining in that portfolio for the next month.

3.2 A Novel Proxy for Investor Attention

To determine the number of Google searches for each company's ticker, I combined two separate Google data sources: Google Trends and Google AdWords Keyword Planner (hereafter GAKP). Google Trends provides the relative ranking on a weekly basis starting in 2004, and is the source used in Da et al. (2011). Due to this restriction, my sample period is January 2004 through December 2014, with stock return data from February 2004 through December of 2015. GAKP provides the total number of searches over a single time period, the minimum of which is a month. For both data sources, I searched for every ticker in the CRSP database. From Google Trends I obtained weekly rankings from 0 to 100 representing the percentage of the maximum search volume for that ticker, while from GAKP I obtained the total number of searches for a single month for each ticker.

To combine the two data sources, I first made the assumption that search volume within a week is evenly distributed across the days in the week. This way I was able to convert the weekly Google Trends data to a monthly frequency. Then, knowing the actual amount of searches for a single month s, and the relative amount of searches for the entire time series, I carried out a simple interpolation to find the volume at any time t:

$$Volume_t = \frac{RelativeVolume_t}{RelativeVolume_s} Volume_s$$

I use firm tickers rather than firm names for two main reasons. First, a search for a company's ticker is more likely to be coming from an investor versus a consumer as compared to a search for the firm's name. Second, a firm's name as it would be searched may be quite different from the name in databases. These issues are discussed in more detail in Da et al. (2011).

As Da et al. (2011) point out, not all searches for tickers will return results about the company. They give as examples tickers such as "GPS," "DNA," and "BABY." To deal with this issue, they manually flag and remove such tickers.[17] But looking

[17] Their main results actually include these tickers, but they say that the results are robust to

at a list of tickers and trying to pick out those which might return other results is a very error-prone approach. This is because it is impossible for anyone to know all the possible abbreviations that may have meanings beyond the ticker. For example, “ACLS” is the ticker for Axcelis Technologies, Inc., but a Google search for “ACLS” returns results about advanced cardiac life support.

To overcome this issue, I use a standardized approach. Typically a search for a company’s ticker will return results from financial websites, such as Yahoo! Finance, Google Finance, Nasdaq, or Bloomberg. Each source has a specific URL pattern associated with a page about the company, for instance “http://finance.yahoo.com/quote/ACLS?p=ACLS.” For each ticker, I run a Google search, and collect the URLs of all results returned on the first page. If any of the URLs matches the pattern of a finance website[18] and also contains the ticker, I classify the ticker as relevant (include in the sample). This approach is much more conservative than that used in Da et al. (2011). They manually flag 7% of tickers to remove, while my approach removes 42% of tickers.[19]

Searching Google to filter the tickers creates an additional problem, however. Google tailors search results based on both your search history and your location. Therefore anyone searching the same ticker may see a different set of results. Eliminating the history issue only required using a fresh browser instance on each search with all cookies and local web storage cleared (and of course not being signed in). The location issue is more difficult, as Google uses your IP address to determine your location. A search for “FPL” in Gainesville, Florida (where this study was executed) will certainly return results for Florida Power and Light, but that may not be the case elsewhere. Removing any possible location bias required randomizing the location of the search. To do this, I used the proxy service WonderProxy[20], which, at the time of the study, had 178 different servers located around the world. For each ticker search, I select a random proxy server, and execute the search from that server.

A final timing issue exists with the Google search filtering approach. I executed all of the searches at the time of the study, when really we would want to know as of the time period of each data point, whether searching for the ticker reveal results for the company. But unfortunately I do not know any way to access historical Google searches. Regardless, this filtering method should be substantially more accurate

exclusion of these tickers.

[18]For a full list of finance websites and URL patterns considered, see the appendix.

[19]Da et al. (2011) also use a smaller sample to start with, with only active firms, while I start with a much larger list, including inactive tickers, and filter down later.

[20]Special thanks to WonderProxy for allowing me to use the service for free for research purposes.

than the method used in Da et al. (2011).

3.3 Other Data

The main outcome variable in the study is stock returns, which I obtained from the Center for Research in Security Prices (CRSP). To construct the abnormal search volume proxy, removing the effect of attention-grabbing events and other firm characteristics that would affect attention, other data was needed. Also using CRSP data, I constructed monthly idiosyncratic volatility as the standard deviation of daily abnormal[21] returns, turnover as the monthly number of shares traded divided by month end number of shares, and an extreme returns count. I define a firm-day as having an extreme return if the return for that day was either in the top or bottom 1% of returns for that firm.[22] Then the daily indicators are summed to form a monthly count.

From Compustat, I obtained sales, total assets, total book equity, net income, and capital expenditures at a quarterly frequency and advertising expense at an annual frequency.[23] From these, I constructed the advertising ratio, investment ratio, and profit margin as advertising expense, capital expenditures, and net income, respectively, divided by sales. From total book equity and market values from CRSP, I calculate book-to-market of equity.

As a measure of liquidity, I obtain monthly bid-ask spreads from Shane Corwin's website[24] (Corwin and Schultz, 2012). If there are more retail investors trading a stock, it is more likely to be affected by attention, so I constructed the institutional ownership percentage from 13-F filings provided by Thompson Reuters. For each stock in each time period, I sum the holdings of institutional investors, and divide by the number of shares outstanding.

Finally, news data comes from RavenPack News Analytics. For each news article,[25] RavenPack provides relevance, novelty, and polarity scores from 0 to 100. Novelty is a measure of how new the news is, with the first article to talk about a topic receiving a 100 and successive articles receiving lower scores. Polarity measures whether the news is positive (high score) for a firm, or negative (low score). I only keep articles with a relevance score of 100 and a novelty score of at least 75, to elim-

[21] Computed as the difference between actual returns and the returns predicted by a four-factor model.

[22] Results are robust to using the top and bottom 1% of returns for each *day* rather than each firm.

[23] Advertising expense (XAD) is not available quarterly.

[24] `http://www3.nd.edu/~scorwin/`

[25] Novelty and polarity scores are provided only when the relevance score is 100.

inate irrelevant and redundant articles. Then I divide the news into negative (under 45), neutral (45-55), and positive (over 55) groups. Lastly I sum the negative and positive news counts to get total polar news, with the intuition that neutral articles should not have a substantial impact on investor attention.

Summary statistics[26] for the variables[27] involved in the study are in Table 2, while Table 3 shows the means of the variables by search volume portfolio. On average, low attention firms have higher idiosyncratic volatility, higher bid-ask spreads, lower share turnover, less advertising, less profit, lower investment, lower institutional ownership, are much smaller, and have less news. Table 4 shows correlations between proxies for investor attention. While abnormal search volume and search volume are highly correlated, the highest magnitude correlation between search volume and another proxy is 0.34 for total assets. Therefore it seems that search volume contains unique information not captured by other proxies.

Table 2: Summary Statistics

Summary statistics are reported here. Search volume is expressed in thousands of searches per month. Total assets is in billions of dollars. Idiosyncratic volatility, bid-ask spread, share turnover, advertising ratio, profit margin, investment ratio, and institutional ownership are in percentages.

	Mean	Stdev	Min	25%	50%	75%	Max
Total Polar News	39	108	0	4	10	27	828
Search Volume	196.78	726.47	0.45	5.01	21.46	85.43	5787.88
Total Assets	13.26	43.84	0.01	0.31	1.33	5.46	324.94
Book-to-Market	0.71	1.14	-1.18	0.25	0.47	0.84	8.81
Idiosyncratic Volatility	2.28	1.67	0.50	1.17	1.78	2.79	9.84
Bid-Ask Spread	1.05	0.76	0.21	0.55	0.82	1.28	4.41
Share Turnover	20.42	19.99	0.51	7.22	14.65	26.45	113.33
Advertising Ratio	9.90	15.32	0.00	1.73	4.80	10.77	95.08
Profit Margin	0.91	31.36	-217.27	0.28	5.80	12.27	42.89
Investment Ratio	0.97	1.20	0.00	0.17	0.57	1.26	6.65
Institutional Ownership	59.93	27.85	1.13	38.87	66.61	83.08	98.95

[26]Variables as presented are winsorized at the 1% level. Winsorized variables are only used to construct the abnormal search volume proxy. Return sorts on volume are done with un-winsorized numbers.

[27]A later version of the paper will include investor sentiment as a control.

Table 3: Means by Search Volume Portfolio

Means of variables are reported within portfolios. Portfolios are formed by sorting firms into three evenly sized groups at the end of each month based on the level of search volume. 10 represents the highest search volume portfolio, while 1 represents the lowest search volume portfolio. Search volume is expressed in thousands of searches per month. Total assets is in billions of dollars. Idiosyncratic volatility, bid-ask spread, share turnover, advertising ratio, profit margin, investment ratio, and institutional ownership are in percentages.

portfolio	1	2	3
Search Volume	4.78	26.44	559.91
Total Assets	2.46	6.50	30.87
Book-to-Market	0.72	0.70	0.71
Idiosyncratic Volatility	2.56	2.28	2.00
Bid-Ask Spread	1.21	1.04	0.89
Share Turnover	15.40	22.02	23.85
Advertising Ratio	9.10	9.43	11.18
Profit Margin	-1.20	0.10	3.84
Investment Ratio	0.78	0.98	1.14
Institutional Ownership	51.97	63.42	64.42
Total Polar News	15	29	74

Table 4: Correlations Between Investor Attention Proxies

Correlations between proxies for investor attention are reported.

	Search Volume	Abnormal Search Volume	Idiosyncratic Volatility	Share Turnover	Advertising Ratio	Total Polar News	Extreme Returns Count	Total Assets	Book-to-Market
Search Volume	1.00	0.92	-0.06	0.06	0.06	0.29	-0.00	0.34	-0.00
Abnormal Search Volume	0.92	1.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	0.00
Idiosyncratic Volatility	-0.06	-0.00	1.00	0.20	0.04	-0.10	0.54	-0.15	0.15
Share Turnover	0.06	0.00	0.20	1.00	0.09	0.10	0.18	-0.01	-0.04
Advertising Ratio	0.06	-0.00	0.04	0.09	1.00	0.02	0.00	-0.03	-0.05
Total Polar News	0.29	0.00	-0.10	0.10	0.02	1.00	0.01	0.47	0.06
Extreme Returns Count	-0.00	-0.00	0.54	0.18	0.00	0.01	1.00	-0.00	0.12
Total Assets	0.34	0.00	-0.15	-0.01	-0.03	0.47	-0.00	1.00	0.20
Book-to-Market	-0.00	0.00	0.15	-0.04	-0.05	0.06	0.12	0.20	1.00

4 Results

4.1 Main Results

My findings support the Neglected Outperformance hypothesis. First, I examine the determinants of search volume estimating regression models of search volume on firm controls and attention-grabbing events (Table 5), clustering standard errors by firm. Not surprisingly, size and book-to-market explain the majority of the total explained variance when all variables are included. But even after including all of the controls, the majority of the variance of search volume remains unexplained. This shows formally that search volume reveals additional information beyond proxies used in the prior literature.

In Table 5, total assets has a significantly positive coefficient, matching the intuition that larger firms receive more attention, quantitatively, about 5,800 monthly searches per $1 billion in assets. The negative coefficient on book-to-market indicates that growth firms receive more attention than value firms. This makes sense as growth firms are often developing new technologies that are discussed frequently in the news. The positive coefficient on the investment ratio can be explained by the same reasoning. A positive coefficient on advertising implies that advertising is effective in attracting attention to the firm. An increase in turnover is associated with an increase in attention, but the causality may go in the opposite direction: additional attention leads to additional trading.

The model with all variables included is used to predict search volume. Then abnormal search volume was constructed as the difference between actual volume and predicted volume. Then I formed decile portfolios from high (10), to low (1) search volume, as described in section 3.1.

Table 5: Determinants of Search Volume

Regressions on monthly search volume are reported, using the model:

$$SearchVolume_t = \alpha + \beta X_t$$

Where X_t is a set of contemporaneous controls in month t. The final column represents the model used to create abnormal search volume. Predicted search volume is created using the coefficients from the final model. Then abnormal search volume is calculated as the difference between actual search volume and predicted search volume:

$$AbnormalSearchVolume_t = SearchVolume_t - \alpha - \beta X_t$$

Search volume is expressed in thousands of searches per month. Total assets is in billions of dollars. Idiosyncratic volatility, bid-ask spread, share turnover, advertising ratio, profit margin, investment ratio, and institutional ownership are in percentages. Standard errors are in parentheses. * represents significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)	(3)	(4)
Bid-Ask Spread			-19.8*	-8.4
			(11.3)	(12.9)
Advertising Ratio		3.0**	2.7*	2.5*
		(1.4)	(1.4)	(1.4)
Total Assets	5.8***	5.8***	5.8***	4.6***
	(1.6)	(1.6)	(1.6)	(1.7)
Book-to-Market	-46.6**	-43.2**	-42.2**	-40.2*
	(19.1)	(19.2)	(20.1)	(20.5)
Intercept	153.1***	92.5***	87.5*	65.6
	(22.7)	(22.4)	(51.3)	(53.0)
Prior Month Return			-0.2	-0.1
			(0.1)	(0.1)
Extreme Returns Count			3.3	-0.6
			(6.9)	(7.1)
Idiosyncratic Volatility			-0.1	0.6
			(7.0)	(6.9)
Institutional Ownership			-0.1	-0.2
			(0.6)	(0.6)
Investment Ratio		29.0***	23.8***	21.1**
		(9.2)	(9.0)	(8.3)
Profit Margin		0.3	0.2	0.2
		(0.4)	(0.3)	(0.3)
Total Polar News				1.1*
				(0.6)
Share Turnover			2.0***	1.5*
			(0.8)	(0.8)
N	84733	84733	84733	84733
R2	0.12	0.12	0.13	0.15
Adj-R2	0.12	0.12	0.13	0.15

Table 6: Average Monthly Raw Returns - Search Volume Portfolios

Average equally-weighted and value-weighted raw returns are computed within portfolios. The first row represents equally-weighted monthly returns while the second row represents value-weighted monthly returns. If a firm is delisted, I use the delisting return for that firm in the month of delisting. Portfolios are formed by sorting firms into three evenly sized groups at the end of each month based on the level of search volume. 10 represents the highest search volume portfolio, while 1 represents the lowest search volume portfolio.

portfolio	1	2	3	Diff (1 - 3)
cum_RET	1.12%	1.12%	1.26%	-0.13%
RET_EW	1.12%	1.12%	1.26%	-0.13%
RET_count	21431.06%	21392.42%	21367.42%	63.64%
cum_RET_wavg	1.56%	1.34%	1.10%	0.46%
RET_VW	1.56%	1.34%	1.10%	0.46%
RET_count_wavg	21431.06%	21392.42%	21367.42%	63.64%

Table 7: Four Factor Loadings - Search Volume Portfolios

Four-factor model (Carhart, 1997) loadings are computed within portfolios at a monthly frequency from February 2004 to January 2015. Portfolios are formed by sorting firms into three evenly sized groups at the end of each month based on the level of search volume. 10 represents the highest search volume portfolio, while 1 represents the lowest search volume portfolio.

portfolio	1	2	3	Diff (1 - 3)
Alpha	0.90%	0.73%	0.53%	0.37%
Beta	0.90	0.92	0.90	-0.00
SMB	0.50	0.26	-0.10	0.60
HML	0.02	-0.15	-0.03	0.05
UMD	-0.09	-0.13	-0.07	-0.02

Table 6 shows that average raw returns are higher for firms that receive low attention on a value-weighted basis. However, this relationship does not exist when examining equally-weighted returns. As the low attention portfolio is mostly populated by small firms, it is plausible that many of these firms are the same that would be targeted in a small-firm strategy. As the small-firm effect had been known for over 20 years before the start of my sample, it is plausible that many investors traded on that strategy, raising prices and lowering returns for small firms. But the large firms that receive low attention would remain mispriced, so this may be why the results exist only for value-weighted returns. Next, in Table 7, I use a four-factor model to adjust the returns within portfolios.

After adjustment, returns are substantially higher for low attention firms. On an annual basis, the low attention premium compared to high attention is 8.16% annually. Unsurprisingly, the low attention portfolio loads positively on the SMB factor while the high attention loads negatively, as the low portfolio is populated by small firms and the high by large firms. Using abnormal volume (Table 8), which should reduce size and book-to-market effects, the loadings are more even across portfolios. But even after removing the effects of attention-grabbing events by using abnormal search volume, the return difference is still 6.36% annually.

Table 8: Four Factor Loadings - Abnormal Volume Portfolios

Four-factor model (Carhart, 1997) loadings are computed within portfolios at a monthly frequency from February 2004 to January 2015. Portfolios are formed by sorting firms into three evenly sized groups at the end of each month based on the level of abnormal search volume. 10 represents the highest search volume portfolio, while 1 represents the lowest search volume portfolio. Abnormal search volume is determined by first regressing factors which should affect investor attention on search volume. Then, abnormal search volume is calculated as the difference between actual search volume and the predicted search volume from the regression.

portfolio	1	2	3	Diff (1 - 3)
Alpha	0.75%	0.73%	-0.27%	1.02%
Beta	1.09	0.98	1.01	0.08
SMB	0.61	0.85	0.57	0.05
HML	-0.00	0.00	0.14	-0.14
UMD	-0.28	-0.28	-0.23	-0.05

4.2 Relation with Known Anomalies

There may be concern that the results reported above are being driven by just a combination of size- and value-effects. It is plausible that growth firms receive more attention due to developing exciting technologies that are reported in the news, though Table 3 does not show a notable difference in book-to-market equity. Large firms receive more attention both intuitively and in the data. As small and value firms tend to outperform, and these kinds of firms may receive less attention, it is plausible that the attention effect is simply a composite small-value effect. Further, search volume could just be a proxy which captures the effects of other reported anomalies.

To address these concerns, I first look in Table 9 at the correlations between the attention anomaly and other pricing factors and anomalies reported in the prior literature.[28] The highest magnitude correlations fore the attention anomaly are with the Ohlson's O (O-SCR, -0.4) and return on assets (ROA, -0.33) anomalies. Surprisingly, there is very little correlation with the size (SMB, 0.08) and value (HML, 0.08) factors. Based on the correlations, the attention anomaly seems distinct from prior anomalies and pricing factors.

For a more formal analysis, in Table 10 I regress the monthly attention anomaly on the standard CAPM (Sharpe, 1964), three-factor (Fama and French, 1993), and four-factor (Carhart, 1997) models. Across all three models, the monthly alpha is close to 0.65% and significant at the 5% level. The loadings on HML and SMB are not significantly different from zero, showing that the attention affect is distinct from size- and value-effects. Then for each other anomaly, I regress the attention anomaly on the four-factor model plus the anomaly as a fifth factor. Across all these regressions, the alpha for the attention anomaly stays positive and significant at the 5% level or higher. Only the return on assets, asset growth (AG), Ohlson's O, and composite equity issuance (CEI) anomalies are significantly related to the attention anomaly. Across all regressions, never more than 21% of the variance of the attention anomaly is explained, so it seems reasonable to conclude that the attention anomaly is distinct from those discovered in the prior literature.

[28] See the appendix for definitions of how these anomalies are constructed. Data for other anomalies were provided by Deniz Anginer, constructed for the analysis in Anginer et al. (2016).

Table 9: Anomaly Correlations

Portfolios are formed by sorting firms into three evenly sized groups at the end of each month based on the level of search volume. 10 represents the highest search volume portfolio, while 1 represents the lowest search volume portfolio. The attention anomaly returns (ATN) are created by forming a value-weighted portfolio which is long the lowest attention portfolio and short the highest attention portfolio.

	ATN	PEAD	NOA	GP	ROA	IVA	AG	HML	NSI	O-SCR	ACC	CEI	SMB	MOM	MKT
ATN	1.00	-0.11	-0.18	-0.08	-0.45	-0.16	0.24	0.03	-0.32	-0.49	0.08	-0.34	0.34	-0.15	0.30
PEAD	-0.11	1.00	0.33	0.14	0.05	0.30	0.10	-0.08	0.16	0.19	0.05	0.12	-0.11	0.72	-0.28
NOA	-0.18	0.33	1.00	0.36	0.04	0.49	0.11	-0.24	0.33	0.12	0.01	0.30	-0.13	0.30	-0.06
GP	-0.08	0.14	0.36	1.00	0.46	0.39	0.04	-0.32	0.48	0.48	-0.01	0.46	-0.33	0.30	-0.35
ROA	-0.45	0.05	0.04	0.46	1.00	0.15	-0.33	-0.02	0.54	0.84	0.01	0.58	-0.53	0.27	-0.46
IVA	-0.16	0.30	0.49	0.39	0.15	1.00	0.34	-0.10	0.54	0.17	-0.02	0.46	-0.27	0.31	-0.26
AG	0.24	0.10	0.11	0.04	-0.33	0.34	1.00	0.20	0.16	-0.26	-0.09	-0.00	0.23	0.01	0.08
HML	0.03	-0.08	-0.24	-0.32	-0.02	-0.10	0.20	1.00	0.00	-0.03	-0.02	0.08	-0.06	-0.11	0.15
NSI	-0.32	0.16	0.33	0.48	0.54	0.54	0.16	0.00	1.00	0.53	-0.08	0.69	-0.31	0.27	-0.46
O-SCR	-0.49	0.19	0.12	0.48	0.84	0.17	-0.26	-0.03	0.53	1.00	0.04	0.52	-0.55	0.33	-0.54
ACC	0.08	0.05	0.01	-0.01	0.01	-0.02	-0.09	-0.02	-0.08	0.04	1.00	0.05	0.06	0.04	-0.07
CEI	-0.34	0.12	0.30	0.46	0.58	0.46	-0.00	0.08	0.69	0.52	0.05	1.00	-0.45	0.23	-0.49
SMB	0.34	-0.11	-0.13	-0.33	-0.53	-0.27	0.23	-0.06	-0.31	-0.55	0.06	-0.45	1.00	-0.34	0.20
MOM	-0.15	0.72	0.30	0.30	0.27	0.31	0.01	-0.11	0.27	0.33	0.04	0.23	-0.34	1.00	-0.30
MKT	0.30	-0.28	-0.06	-0.35	-0.46	-0.26	0.08	0.15	-0.46	-0.54	-0.07	-0.49	0.20	-0.30	1.00

Table 10: Anomaly Regressions

Portfolios are formed by sorting firms into three evenly sized groups at the end of each month based on the level of search volume. 10 represents the highest search volume portfolio, while 1 represents the lowest search volume portfolio. The attention anomaly returns (ATN) are created by forming a value-weighted portfolio which is long the lowest attention portfolio and short the highest attention portfolio. Each row in the table is a regression of the monthly attention anomaly (ATN) on other asset pricing factors and anomalies. The first three rows are the standard CAPM (Sharpe, 1964), three-factor (Fama and French, 1993), and four-factor (Carhart, 1997) models. The following rows add the anomaly given in the row as a fifth factor. Reported alphas are of a monthly frequency in percentage points. * represents significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Alpha	Anomaly	MKT	HML	SMB	MOM	R2	Adj-R2	N
One-Factor	0.36*		0.16***				0.09	0.08	132
Three-Factor	0.34*		0.13***	0.01	0.17***		0.17	0.15	132
Four-Factor	0.33*		0.13***	0.01	0.18***	0.01	0.17	0.15	132
PEAD	0.34*	-0.02	0.13***	0.01	0.18***	0.02	0.17	0.14	132
NOA	0.38**	-0.09*	0.14***	-0.01	0.17***	0.02	0.19	0.16	132
GP	0.28	0.09	0.15***	0.04	0.20***	0.00	0.19	0.16	132
ROA	0.42**	-0.14***	0.07	0.01	0.09*	0.01	0.23	0.20	132
IVA	0.33*	-0.01	0.13***	0.01	0.18***	0.01	0.17	0.14	132
AG	0.33*	0.12**	0.13***	-0.02	0.15***	0.00	0.20	0.17	132
NSI	0.40**	-0.12*	0.10*	0.02	0.16***	0.01	0.19	0.16	132
O-SCR	0.45**	-0.18***	0.04	0.01	0.08	0.01	0.25	0.22	132
ACC	0.31*	0.08	0.13***	0.01	0.17***	0.01	0.18	0.15	132
CEI	0.38**	-0.08	0.10*	0.02	0.15***	0.01	0.19	0.15	132

5 Conclusion

Overall, I find support for the Neglected Outperformance hypothesis: firms that receive a low amount of investor attention outperform those that receive a high level of investor attention. This effect persists even after removing the effects of attention-grabbing events, which have previously been shown to produce temporary price effects which revert on a short-term basis. Even without removing those effects, it seems the main results are driven by equilibrium mispricing rather than short-term effects, as attention portfolios tend to be stable.

Few papers provide compelling evidence to confirm Merton (1987)'s hypothesis, as most papers focusing on investor attention use attention-grabbing events as their measures. Under Merton (1987)'s model, the outperformance of neglected firms should persist beyond attention-grabbing events. This paper is among the few which confirm his hypothesis, and arguably with the most accurate proxy for investor attention.

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