INVESTOR ATTENTION AND RETURN ANOMALIES

COMPARING DIRECT AND INDIRECT PROXIES OF INVESTOR ATTENTION AND THEIR EFFECT ON THE SWEDISH STOCK MARKET

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Abstract:

We compare two proxies for investor attention, media coverage, measured as the number of articles written about a firm, and relative Google Search Volume Index (SVI), and investigate their role in explaining return anomalies on the Swedish stock market. Using a media-based zero-investment trading strategy we find significant abnormal returns, unexplained by known risk factors and robust to common return anomalies. This effect, driven by excess returns of no-media coverage stocks, is more pronounced among stocks of firms with large market capitalization, growth stocks and stocks with a high past 12-month momentum. In contrast, an SVI-based strategy does not exhibit any significant abnormal returns.

Keywords:

Return anomalies, investor attention, media coverage, Google SVI, informational frictions, illiquidity

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I. Introduction

Merton (1987) proposed the idea of investor awareness as an explanation for abnormal returns through his investor recognition hypothesis (IRH). The model assumes that investors are not aware of all securities, and that different investors are aware of different subsets of stocks. An implication of this is that investors build their optimal portfolios with the securities they are aware of, leading to undiversified positions in the market. These investors require a return premium as compensation for holding an increased amount of idiosyncratic risk. Merton finds that less well-known stocks generally show larger expected returns, which is in line with the IRH hypothesis. As higher expected returns also imply an increased cost of capital for firms, it is also in their interest to achieve and maintain a high level of investor recognition. Measures proposed by Merton (1987) to grab investor attention include mass media coverage and public relations.

While Merton (1987) constructed a model testing for investors sub-optimal security portfolios, we will build upon this hypothesis and test it empirically. Multi-factor asset pricing models assume that all available information is incorporated into asset prices. A prerequisite for this assumption is that investors pay attention to the said security. We add to this area of research by comparing two sources from where investors find company specific information, which are different in nature, and investigate the impact of these on abnormal returns. Recipients of news communicated by media channels are passive and can choose which parts of the conveyed information they direct their attention to. Therefore, media is an indirect proxy for investor attention. On the other hand, Google searches are a direct reflection of an investors interest. An investor is already aware of the security if they are searching for information on a search engine. Thus, we investigate whether SVIs are a direct proxy for investor attention. By applying both proxies to the same methodology we not only compare these to each other, but also investigate whether an investment strategy based on either of the two measures can explain abnormal return originating from a lack of investor attention.

We find that an investment strategy which longs stocks with a no media coverage and shorts stocks with high media coverage generates abnormal returns unexplained by established risk factors. The strategy yields a minimum alpha of 62 basis points per month when estimated from the Fama-French-Carhart Four Factor model. This result is robust to well documented return anomalies including IPO underperformance, delisting bias and bid-ask bounce. We confirm that the driver of the abnormal returns stem from stocks lacking coverage in a separate analysis of the long- and short legs of the portfolio formed on the investment strategy. We cannot confirm that an SVI-based investment strategy yields any positive abnormal returns when applying the same methodology. An SVI-based approach neither generates positive average monthly return nor abnormal returns when estimated from both single and multifactor risk models.

The abnormal returns are the strongest among stocks with large market capitalization, contrary to the normal notion that small capitalization stocks are drivers of abnormal returns. Additionally, the effect is pronounced among growth stocks and stocks experiencing a strong past 12-month momentum. Analysis of the underlying explanations to the media-based no-attention premium show conflicting evidence. Whereas we rule out return continuations and reversals as driving factors of our abnormal returns, we find it harder to draw definite conclusions on illiquidity and investor recognition. In robustness checks we find indications that the return anomalies come from illiquid low-priced stocks. However, when sorting our sample into subsamples on liquidity measures, we find conflicting results, with low average past month price as the only supporting factor. Similar issues arise when we test for the investor recognition hypothesis. We find a strong effect in a subsample of stocks with a high fraction of individual ownership, as is expected. However, the effect in the low idiosyncratic volatility and low analyst coverage subsamples is weak or non-existent compared to the subsamples of high idiosyncratic volatility and analyst coverage respectively. This speaks against Merton's (1987) hypothesis that stocks with a low degree of investor recognition exhibit larger returns. Nonetheless, the outperformance of no-media coverage stocks compared to stocks with high media coverage is in its nature consistent with his investor recognition hypothesis.

The paper proceeds as follows. Section II reviews the literature on investor attention and abnormal returns. In Section III we present our hypotheses and the underlying theory. Our research design is explained in detail in Section IV whereas the data collecting and descriptives are explained in Section V. Results of our tests are reported in Section VI and discussed in Section VII. Section VIII concludes.

II. Literature Review

A. Proxies for Investor Attention and the Stock Market

Our study builds upon the findings of Fang and Peress (2009) investigation of the cross-section of media and stock returns. They observe significant abnormal returns on American stocks with no media coverage, what they call a "no-media" premium. This is particularly large among small stocks, stocks with low analyst coverage, stocks with high idiosyncratic volatility, and stocks primarily owned by individual investors. Fang and Peress (2009) use the number of articles written on publicly listed firms as a proxy for media coverage while controlling for well-documented return anomalies. Their sample consists of articles from four influential daily American newspapers: New York Times, USA Today, Wall Street Journal, and The Washington Post. Their stock sample consists of all companies listed on the NYSE and 500 randomly selected companies on Nasdaq between January 1, 1993 and December 31, 2002.

Other related studies using media as a proxy for investor attention are Barber and Odean (2008) who find that individual investors are net buyers of attention-grabbing stocks, such as stocks in the news, stocks with high abnormal trading volume and stocks with extreme one-day returns. A suggested explanation to this is that individual investors lack the capacity to evaluate all available stocks and thus favor attention grabbing stocks. In another study, Fang et al. (2014) investigate the relation between mutual fund traders and mass media coverage of stocks. They find that funds with the highest propensity to buy media-covered stocks underperform the funds with the lowest propensity by 1.1% to 2.8% per year. They suggest that professional investors are also subject to limited attention. Lastly, Hillert et al. (2014) use 2.2 million articles from forty-five U.S. newspapers and find that firms particularly covered by media exhibit, all things equal, stronger momentum. They suggest that media coverage can exacerbate investor biases, leading return predictability to be strongest for firms in the spotlight of public attention.

We also refer to two studies which proxy investor attention using Google SVI. Da et al. (2011) propose search frequency on Google as a direct measure of investor attention, namely the Search Volume Index (SVI). They find that an increase in SVIs, based on searches of stock ticker symbols, outperform of more than 30 basis points other stocks during the subsequent two weeks. They find this to be a timelier measure and likely measures the attention of retail investors. Similarly, Bank et al. (2011) also investigate the influence of search volume on Google on German stocks. They find that an increase in search queries is associated with a rise in trading activity and stock liquidity. They put forward that the improved liquidity is due to a reduction in asymmetric information costs, but assess, however, that the search volume primarily measures attention from uninformed investors. Lastly, they suggest that increase in search volume is associated with temporarily higher future returns.

Media, in different forms, is one type of the proxy for investor attention and studies with this as a focus point are nearest related to ours. However, investor attention can be proxied in other ways, which we give examples of below. It is relevant to acknowledge these other methods and their findings in order to distinguish an effect on stock returns originating from other investor recognition proxies than media. Grullon et al. (2004) use advertising expenditure as a proxy for investor attention and build upon the area which hypothesizes that people bias their investment portfolios in favor of familiar stocks. They conclude that a higher expenditure leads to a larger number of both individual and institutional investors, and better liquidity of their common stock. Thus, an investor's degree of familiarity with a firm may affect its cost of capital and consequently its value. On a similar note, Arbel et al. (1983) find that certain securities neglected by analysts, often due to unfulfilled investment requirements, earn a superior performance over shares held by institutions, what they call a "neglected firm effect". This anomaly persists over size effect as it is found in both small- and medium-sized firms. Lastly, Frieder and Subrahmanyam (2003) find that there's a negative and significant cross-sectional relation between institutional holdings and brand visibility, consistent with the notion that individual investors prefer to invest in stocks with easily recognized products. They put forward that that institutional holdings are positively related to firm size and beta, which supports the notion that institutional investors neglect small firms, whereas individuals prefer holding stocks with high recognition, and greater information.

B. The Relationship Between News and Information, and Stocks

Other related papers which look at the general effect of news and information on the stock market include the following studies. Klibanoff et al. (1998) who investigate whether dramatic news reported on the front page of New York Times affects the pricing of closed-end funds. Their findings conclude that during weeks when news appear on the front page, price movements are more interconnected to fundamental value, i.e. informational asymmetries are minimized. They argue that this is consistent with the hypothesis that news events increase the rate of reaction in some investors. Tetlock (2007) uses the linguistic content of Wall Street Journal to measure the interaction between the media and the stock market. He concludes that high pessimism predicts downward pressure on market prices, followed by a reversal to fundamentals. Furthermore, unusually high or low pessimism predicts a high market trading volume. Chan (2003) compares monthly returns for companies who are mentioned in the headlines of news with those who are not. This is closely related that of Fang and Peress (2009), with the differences that Chan (2003) focuses on news, not media coverage, and observes the effect on the market. The findings show a strong drift after bad news, with a slow investor reaction and reversal after extreme price movements unaccompanied by public news. The effect is mainly observed in smaller, more illiquid stocks. Chan (2003) also finds that the number of no-news stocks which are winners is almost always less in his sample than no-news losers, meaning that there are proportionately more negative no-news shocks. Lastly, no-news winners do not outperform losers over a three-year period and do not seem to have higher expected returns. This speaks against the findings of Fang and Peress (2009). Barry and Brown (1984) investigate an explanation for the size effect, arguing that less information available on a security than a comparable may lead to a perception of increased risk. They hypothesize, similarly to Fang and Peress, that investors require a premium to hold such securities. They conclude that there's an association between their proxy, the period of listing, and security returns which cannot be accounted for by firm size.

C. Other Determinants of Stock Returns

Research which investigates other determinants of stock returns are also related to our paper. Two papers related to ours follow. Diether et al. (2002) investigate dispersion in analysts' earnings forecast and find that stocks with a higher dispersion earn lower future returns. This is more pronounced in small stocks and stocks with poor past year performance. They suggest that dispersion can proxy for differences of opinion among investors and thus relax assumptions of homogenous expectations. Their findings support Miller's (1977) prediction that market prices reflect the optimistic valuation, meaning that a greater dispersion yields a discrepancy in market price from the actual value. Another related paper by Ang et al. (2006) find that stocks with high idiosyncratic volatility have low average returns, a finding which is at odds with the notion of efficient markets which state that there's no interrelation between idiosyncratic volatility and expected returns. Boehme et al. (2009) find strong support for Mertons model of cross-sectional stock returns being positively related to idiosyncratic risk, but specifically for stocks with low levels of investor recognition.

III. Hypothesis and Theoretical Background

Hypothesis: *Firms with no attention among investors, proxied by either media coverage and/or Google SVI, yield abnormal returns unexplained by commonly known risk factors and return anomalies.*

Fundamental Portfolio Theory

Portfolio theory aims to explain how investors can maximize their expected returns given a certain level of market risk. These theories hold up under specified assumptions regarding the asset markets and investors. When investors or markets go against these assumptions, we can expect to find abnormal returns, namely the part of returns which these established models cannot explain. Below we present the models which we use to investigate our no-attention premium hypothesis.

The Capital Asset Pricing Model (CAPM) is the first model which aims to explain the relationship between systematic risk and expected return. Firstly, the model assumes that investors are risk averse and only hold the efficient portfolio (maximizes the tradeoff between expected returns and volatility). Secondly, capital markets are perfect, meaning that investors can buy and sell securities without transactional costs or taxes, and can borrow at the risk-free rate. Thirdly, information is costless and available to everyone. Fourthly, investors have homogenous expectations regarding volatilities, correlations and expected returns of securities. If these assumptions hold, all investors should identify the same efficient portfolio with the highest Sharpe ratio, modifying only the amount of riskless securities in order to obtain risk in line with their individual risk tolerance.

When the underlying assumptions of CAPM fail investors have the possibility to "beat the market", i.e. earn positive alphas, which should otherwise not be possible in the equilibrium state of CAPM. If investors, irrationally but systematically, choose to hold an inefficient or undiversified portfolio due to, for example, a preference for attention stocks (Barber and Odean, 2008), a familiarity bias (Huberman, 2001) or because they choose from a subsample of stocks (Merton, 1987), then the consequence of this is that the market portfolio becomes inefficient.

Banz (1981) empirically observes that small stocks earn higher average returns than the market portfolio, even after controlling for their higher beta (associated with their higher risk). This empirical result is called the size effect. Fama and French (1992) propose an extension of CAPM, which captures the size effect, by constructing factors based on firm characteristics. The Fama and French Three-Factor-Model adds two factors to CAPM's existing market risk factor. The first factor, small-minus-big (SMB), is formed by sorting firms based on their market capitalization, where low market capitalizations stocks (which are observed to yield positive alphas) are bought and high market capitalization stocks are shorted. The second factor, high-minus-low (HML), is formed by sorting by book-to-market ratio, where high book-to-market ratio stocks are bought, i.e. value stocks, and low book-to-market ratio stocks, growth stocks, are shorted.

Jegadeesh and Titman (1993) identified that past stock returns can predict future returns, another deviation from CAPM. Carhart (1997) expands on Fama and French's Three-Factor Model by adding a factor which captures this momentum anomaly. By ranking stocks based on their past year return, buying stocks with the top 30% return and shorting the 30% lowest performing stocks, a one-year momentum portfolio (MOM) is created, also called Carhart momentum factor.

IV. Research Design

In this paper we carry out a cross-sectional analysis of investor attention and stock returns. We expand on the research of Fang and Peress (2009) by taking the indirect measure of investor attention, media coverage, in their study and comparing it to the direct measure Google Search Volume Index (SVI) in our analysis. We analyze raw returns in univariate analysis and examine excess returns in relation to various risk factors in multivariate analysis. The method mirrors that of Fang and Peress (2009) in order to obtain comparable results.

A. Univariate Tests: Average Returns of Portfolios Sorted by Media Coverage and Relative Google SVI Scores.

We first investigate monthly raw returns yielded from portfolios consisting of stocks grouped on level of media coverage. Stocks are sorted into three portfolios with increasing media coverage. Stock with no coverage are identified first and sorted into the first, no-media portfolio. For the remaining stocks, the median number of articles is used to sort stocks into the second, low coverage portfolio, and third, high coverage portfolio, respectively. Any ties with the median number of articles are sorted into the low coverage portfolio.

The same, albeit slightly adapted, sort methodology is used for the relative SVI scores. Due to the index nature of the SVI, instead of sorting stocks with a relative SVI of zero into the first portfolio, we divide stocks into even tertiles. Thus, the first portfolio consists of the lowest tertile, and the third portfolio consists of the highest tertile, based on the stocks' relative SVI score.

In further analysis, we double sort stocks, firstly on firm characteristics and secondly on media coverage and relative SVI score. This double sorting helps us identify in which subsets of stocks any potential return premium can be observed. Unlike Fang and Peress (2009), who sort into three groups based on characteristics, we only sort into two evenly large characteristics groups, in order to maintain adequate sample sizes, as our stock sample is much smaller.

Our portfolios are equally weighted and resorted on a monthly basis, meaning they are held for one month only. Portfolio returns are thus calculated over the month following formation. We present the average monthly returns for the simple- and double-sorted portfolios in Table III in Section VI. Additionally, we carry out paired t-tests on the monthly returns of the no-media coverage and high media coverage portfolios, alternatively the lowest SVI tertile and highest SVI tertile portfolios.

B. Multivariate Tests: Profitability of a Trading Strategy Based on Media Coverage and Relative Google SVI Scores

Next, we investigate the profitability of two zero-investment trading strategies based on our two measures for investor attention, media coverage and relative SVI scores, respectively. We carry out the same monthly simple and double sorting procedure as in our univariate analysis. Thereafter, we long the no-media coverage portfolios and short the high media coverage portfolios, alternatively long the low SVI portfolios and short the high SVI portfolios. As before, the portfolios are equally weighted and likewise are the both legs of our zero-investment portfolio. Portfolios are again held for one month before being resorted and returns are calculated over the month following formation.

The time series of returns for our zero-investment portfolios are regressed against risk factors, proven to affect cross-section stock returns. If the risk factor models can fully explain the zero-investment portfolio returns, the resulting alphas, or intercepts of the equations, will be insignificantly different from zero. Deviations from this, however, suggest there are additional risk factors not accounted for, one of which could be the no-attention premium. We provide the regression equations below:

1. The Capital Asset Pricing Model (CAPM): The dependent variable is the excess return of the zero-investment portfolio, regressed against the excess market returns.

$$R_{pt} - R_{ft} = \alpha_p + \beta_p^{Mkt}\left(R_{Mkt} - R_{ft}\right) + \varepsilon_{pt}$$

2. The Fama-French Three-Factor Model: The dependent variable is the excess return of the zero-investment portfolio, regressed against the independent variables excess market return, small-minus-big (SMB) and high-minus-low (HML).

$$R_{pt} - R_{ft} = \alpha_p + \beta_p^{Mkt}\left(R_{Mkt} - R_{ft}\right) + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + \varepsilon_{pt}$$

3. The Carhart Four-Factor Model: The dependent variable is the excess return of the zero-investment portfolio, regressed against the independent variables excess market returns, small-minus-big (SMB), high-minus-low (HML) and one-year momentum (MOM).

$$R_{pt} - R_{ft} = \alpha_p + \beta_p^{Mkt}\left(R_{Mkt} - R_{ft}\right) + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + \beta_p^{MOM} MOM_t + \varepsilon_{pt}$$

V. Data and Descriptive Statistics

Our sample consists of 279 stocks of companies listed on Nasdaq Stockholm on the Large, Mid and Small Cap lists, between January 1, 2013 and December 31, 2016. We use the company lists for both currently listed and delisted companies on Modular Finance Holdings as of December 31, 2018 as our starting point in order to only include stocks with available ownership data. It is worth noting that Holdings only contains data on companies delisted from around 2015 onwards, and companies delisted from the exchange prior to that are naturally excluded from our sample. Companies not listed on the Large, Mid and Small Cap lists during our sample period are excluded. As are companies not domiciled in Sweden and companies that for other reasons lack complete ownership data on Holdings for the entirety of their listing that overlaps our sample period. New listing and delisting data are obtained from Nasdaq Nordic's yearly reported changes to the Nasdaq Stockholm list. For companies with multiple share classes, we select one and favor the share with higher trading volume and more available data.

Stock closing price, closing bid and ask price, market capitalization, price-to-book ratio and trading volume data are collected on trading day level from Thomson Reuters Datastream. Analyst coverage data, such as number of earnings estimates, their mean and standard deviation are obtained on monthly and yearly basis from Datastream as well. Variable construction and definitions of used variables are reported in Appendix Table AI.

For measuring media coverage, we follow the method of Fang and Peress (2009) and use the number of newspaper articles mentioning the stock as a proxy for the exposure. This is our indirect measure of investor attention. We get information regarding news coverage on our sample companies from the database Retriever Mediearkivet. We focus our search on the five largest Swedish newspapers: Svenska Dagbladet (SvD), Dagens Nyheter (DN), Dagens industri (Di), Göteborgs-Posten (GP) and Sydsvenskan (SydSv) with a combined daily circulation of 908.500 copies in 2011 (Nya Lundstedt dagstidningar, 2020). This makes up 30% of the total daily newspaper circulation in Sweden 2011.[1] We use the circulation data for 2011, as this is the last year DN and Di are included in the newspaper circulation report TS-upplaga and we require comparable circulation data across the newspapers. For the search, we manually create the search terms for each company. We allow for certain variations in spelling, based on company-specific analysis of article output in search trial runs, as well as company name changes as announced by Nasdaq Nordic's yearly reports. In order to exclude irrelevant results, we search for the companies only in the headline and the lead paragraph of articles.

Our direct proxy for investor attention is based on the Google Search Volume Index (SVI) and manually extracted from Google Trends. Google SVI scores are weighted indexes. Thus, we keep one search term, a company from our sample, constant while extracting the SVIs individually for each company. This ensures that the indexes are anchored to the same baseline and enables us to average them and calculate relative SVI scores over all firms. Original SVI scores below one are replaced with 1, in order to make the calculation of relative SVI possible. Google provides SVIs for a given search either as a *topic*, which is narrower and our preferred choice, or as a *search term*, which has more breadth in the underlying searches it includes. For most stocks, we can specify that the search is referring to the *topic* (company) in question. However, for a handful of the stocks in our sample we only had the option of using the more general *search term*. The terms we use are as close as possible to the ones we use for Retriever, but we allow for deviations, e.g. when it results in a *topic* tied to the correct company. We also note that the SVI is better at incorporating variations in spelling in the underlying searches, as compared to our media coverage data, suggesting we do not need to specify common erroneous spelling mistakes in the terms we use.

Quarterly ownership data, as well as static industry information, is retrieved from Modular Finance Holdings. Stocks owned through an endowment insurance are presented as owned by the insurance company (Modular Finance AB, 2020), but we assess this to have little influence on our aggregated data. The fraction of institutional ownership as reported per the last day of each quarter is used to estimate the same fraction for the subsequent quarter.

We obtain the daily, weekly and monthly Fama and French factors for the Swedish market from the Research Data Center at Swedish House of Finance. The factors are further defined in Appendix Table AI.

The time period for our study is restricted by the availability of data. Nasdaq Nordic reports detailed corporate changes to the Nasdaq Stockholm list from 2013 onwards, which sets the starting boundary for our study. Furthermore, the Fama and French factors for the Swedish market used in our analysis are available only up to the end of 2016, limiting any further extension of our

[1] The total daily newspaper circulation in Sweden was 3 059 600 copies in 2011. Confirmed by Jens Borgström at Kantar Sifo, who gives out the yearly circulation report TS-upplaga, per e-mail on April 14, 2020. The data reported by Nya Lundstedt dagstidningar is built directly on the TS-upplaga report.

sample period. Thus, we form portfolios in a total of 47 months, starting in January 2013, with the last portfolio being formed in November 2016, for which we calculate returns in December 2016.

In Table I we present unconditional and conditional statistics for the number of articles, as well as conditional statistics for SVI scores, on an annual basis. The unconditional statistics show the fraction of firms, listed at the year-end, covered by each newspaper during the year. The conditional statistics cover the number of newspaper articles and the relative SVI score for each company in a given year. The last row presents the average values for our sample years.

Table I

Summary Statistics of Newspaper Coverage and Google SVI

This table presents summary statistics for the newspaper coverage and Google Search Volume Indices (SVI) of our sample firms. Unconditional statistics for media coverage are presented as percentage of firms receiving coverage in newspapers and conditional statistics as the number of articles written on the firm conditioned on coverage. Unconditional statistics for Google SVI show the relative SVI per firm. The column All Papers refers to all five newspapers in our sample: Dagens Nyheter (DN), Dagens Industri (Di), Göterborgs-Posten (GP), Svenska Dagbladet (SvD) and Sydsvenskan (SydSv). The row All Years presents the average for each source.

	Unconditional Coverage Statistics Fraction of Stocks Covered by						Conditional Statistics No. of Articles		Unconditional Statistics Google SVI	
Year	All Papers	DN	Di	GP	SvD	SydSv	Mean	Median	Mean	Median
2013	0.95	0.87	0.90	0.40	0.79	0.59	64	17	191	11
2014	0.94	0.86	0.93	0.34	0.88	0.47	57	17	187	11
2015	0.96	0.50	0.87	0.32	0.90	0.36	46	10	183	12
2016	0.95	0.34	0.85	0.32	0.84	0.32	41	8	159	11
All Years	0.95	0.64	0.89	0.34	0.85	0.44	51	12	180	12

We observe that the media coverage is high in our sample. On average, 95% of all stocks are mentioned in the media at least once a year. This is not surprising as our sample consists of stocks listed on the Large, Mid and Small Cap lists on Nasdaq Stockholm, which is the largest stock exchange in Sweden, but also holds a relatively small number of listed companies, 333 as of the year-end 2018[2], which makes it easy to cover a large part of the companies.

There is a great difference between the fraction of stocks covered by the different newspapers. GP and SydSv cover, on average, 34% and 44% respectively, in comparison to Di and SvD who, on average, cover 89% and 85% respectively of all companies whose stocks are included in our sample. A possible explanation to this pattern is that GP and SydSv both are more regionally oriented and less focused on the business sector than Di and SvD.

Business-oriented Di has the broadest coverage of our sample over the years. The four other newspapers together add a maximum of 10% points to Di's yearly coverage of roughly 90%. This suggests that there is a large overlap in companies covered by the newspapers in our sample. The conditional statistics in Table I indicate that media coverage is not only decreasing over the years, but also skewed. The average number of articles stock is mentioned in in a given year is 51, while

[2] As reported in Nasdaq Nordics yearly statistics 2018.

the median number of articles is 12. This indicates that some firms have a much greater presence in media than the majority of firms. Since all companies are listed it should not be driven by public disclosures such as earnings announcements.

The skewness can also be noticed in the conditional statistics for Google SVI, indicating that a few companies in our sample have extremely high relative scores. The outliers of the relative SVI scores, however, are likely to be driven by searches on companies that cater to consumer needs. This view is supported by Figure 1, presenting the sector distribution of our attention measures, as we can see that companies in the sectors Trading and Goods (4), Discretionaries (10) and Telecom and Media (11) are overly represented in the highest relative SVI tertile, as compared to companies in other sectors.

The left histogram of Figure 1 shows the sector distribution of media coverage. Looking at the black stacks, we see that the across all industries, the average fraction of companies without media coverage on a monthly basis is roughly 40-60%, whereas the fraction of companies with high coverage is around 10% to 40%. The one exception to this are the companies in sector 11, Telecom and Media. Virtually every company in this sector receive high media coverage on a monthly basis. Apart from this we propose that media coverage is relatively unbiased between sectors.

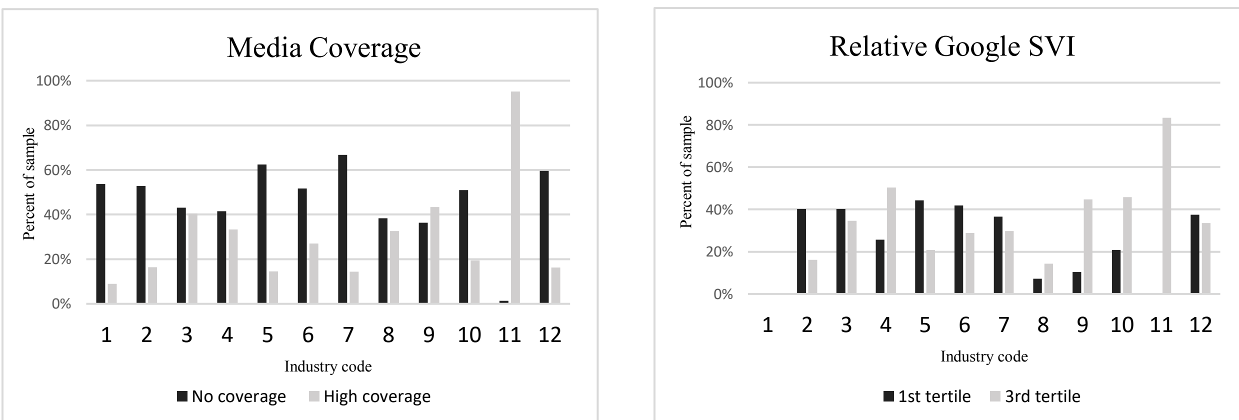

Figure 1: Sector distribution of media coverage and SVI. The histogram shows the industry distribution of stocks with no and high media coverage respectively (to the left) and the industry distribution of stocks in the lowest and highest relative SVI tertiles (to the right) based on monthly sortings. The industries, as defined by Modular Finance Holdings are as follows – 1: energy and environment; 2: real estate; 3: finance; 4: trading and goods; 5: health care; 6: industry; 7: information technology; 8: materials; 9: mining and metals; 10: discretionaries; 11: telecom and media; 12: services.

In Table II we present the determinants of media coverage and relative SVI, respectively. We regress the dependent variables *total-circulation-weighted number of articles* and *relative Google SVI* against independent variables defined in Table AI. We use the Fama-Macbeth (1973) two step regression method, correcting the standard errors for autocorrelation using the Newey-West (1987) procedure with one lag.

Table II
Determinants of Media Coverage and Google Search Volume Index (SVI)

This table reports the determinants of Media Coverage and Relative Google Search Volume Index (SVI) resulting from two Fama-Macbeth (1973) regressions. The first dependent variable is the circulation-weighted number of articles published about a stock in a given year. The second dependent variable is the relative SVI for a firm, averaged over a given year. Independent variables are defined in Table AI. t-statistics, presented in parentheses, are based on standard errors adjusted for autocorrelation using the Newey-West (1987) procedure with one lag. ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: Weighted Number of Articles		Dependent Variable: Relative Google SVI	
Size	2.4857	2.5225	117.1407	122.7222
	(16.86)***	(15.22)***	(3.55)**	(3.69)**
Book-to-Market	2.5116	2.5294	100.9684	98.9568
	(3.85)**	(3.90)**	(7.50)***	(11.06)***
Analyst Coverage	0.9799	0.9403	140.8885	129.8818
	(2.11)	(1.87)	(1.89)	(1.79)
Fraction of individual ownership	3.3491	3.4004	447.3175	436.0459
	(1.63)	(1.62)	(4.15)**	(4.50)**
Analyst dispersion	0.0454	0.0619	-57.8740	-53.8913
	(0.11)	(0.14)	(-5.59)**	(-4.53)**
Idiosyncratic volatility	10.9128	12.3183	699.7553	789.645
	(2.82)*	(3.28)**	(4.34)**	(3.32)**
Past year absolute return		-1.2995		-87.3504
		(-3.03)*		(-1.36)
Past year return	-0.6442		-13.0359	
	(-2.36)*		(-0.21)	
Constant	-38.7440	-39.3745	-2097.714	-2163.937
	(-16.34)***	(-14.81)***	(-4.66)**	(-4.55)**
Observations	488	488	488	488
R^2	0.2800	0.2819	0.1583	0.1596

We observe that firm size has the strongest correlation to media coverage. Large firms in our sample are much more likely to have news articles written about them. Similarly, we also find that firms with large book-to-market ratios, i.e. value stocks, are more likely to be covered by the media. These findings suggest that of the companies listed on Nasdaq Stockholm, it is the established large cap stocks that receives the most attention. Furthermore, we can observe a significant relationship between idiosyncratic volatility and media coverage, where stocks with high idiosyncratic volatility are featured more often in the media. We do not see any significant relationship between individual ownership, analyst coverage and dispersion and media coverage.

Thus, we cannot speculate in whether the media caters their news coverage to a particular group. Past year absolute returns are significant on the 10%-level, while past year returns are not. This is an indication, albeit a weak one, that historical extreme returns are likely to be a driver of media coverage, independent of them being positive or negative.

We also check for fixed time effects in our sample, reported in Table AII of Appendix. We find significant decreases in media coverage for years 2015 and 2016, which coincides with the radical decrease in DN's coverage of companies, as seen in the unconditional statistics of Table I. In this regression, we note that the positive correlation between media coverage and idiosyncratic volatility has a higher significance. The interpretation of large cap companies as receivers of media coverage remains supported. Lastly, the results in Table II suggest significant correlations between relative SVI and all our independent variables, except for analyst coverage and past year absolute and signed returns. However, when including time fixed effects, see Table AII, the regression disqualifies the correlations between our independent variables and relative SVI and find a negative correlation with year 2016. Therefore, we find it difficult to draw any conclusions on the relationship between firm characteristics and the relative SVI of a company.

VI. Hypotheses Tests and Results

A. Univariate Analysis

Table III A tabulates the average returns of stocks, single-sorted first and double-sorted by firm characteristics and media coverage. We observe, in the first row of Table III A, the average monthly returns for the simple-sorted no-, low and high media coverage portfolios which are 1.93%, 1.72% and 0.92%, respectively. The reported t-Statistic for the return difference between the no- and high media coverage group is statistically significant on a 1%-level. It is also an economically meaningful monthly return difference of 1%. This indicates that sorting stocks on media coverage generates a significant raw return, which is in line with our hypothesized abnormal return on stocks with low investor recognition. We observe the same trend throughout the conditional tests in Panels A-G. The portfolios, double-sorted on firm characteristics, support the unconditional result. When controlling for firm characteristics, one-by-one, we see a significance level of our t-test at least 5% for all portfolios, except book-to-market. The return difference between the no- and high media coverage portfolios is positive and thus also economically significant. The portfolio sorted by size seems to experience the strongest return difference between no- and high-media coverage where we find a 1%-level significance across both groups, which suggests the return difference is not driven by small stocks versus large stocks. The panels sorted by individual ownership and analyst coverage, respectively, show that highest significance is found for stocks with high individual ownership and stocks with low analyst coverage. We investigate this relationship later. Furthermore, stocks with a high past month return experience a significant return difference the month following portfolio formation, while the portfolio return difference is more significant for stocks which experience a low return in the current month. The positive return difference between no- and high media coverage groups throughout the panels supports the hypothesis of a no-media coverage premium, even when controlling for certain characteristics.

Table III A
Media Coverage and Stock Returns: Univariate Comparisons

This table presents average monthly returns in percentages for stocks with no, low, and high media coverage. Each month, we first divide our sample of stocks in two, evenly large, subsamples based on firm characteristics: size, book-to-market, past and current month returns, price, individual ownership and analyst coverage (defined in Table AI). Thereafter, we split the subsamples into three media-coverage portfolios: no coverage, low coverage, and high coverage. The media-coverage portfolio is determined by the number of newspaper articles written about the company in the month of portfolio formation. Firms with no coverage are identified first and assigned to the first media-coverage portfolio. The median number of articles for the remaining companies is used to divide into low and high coverage portfolios. Ties are assigned to the low coverage portfolio. We then compute the equal-weighted average return for each portfolio using individual stock returns in the month following formation. ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Average Monthly Return					Average No. of Stocks		
	Media Coverage				t-Statistics for	Media coverage		
	No	Low	High	No - High	No - High	No	Low	High
All stocks	1.93	1.72	0.92	1.01	(3.50)***	120.1	70.0	57.0
				Panel A: By Size				
1	1.62	1.35	-0.70	2.32	(3.15)***	80.0	36.3	11.0
2	2.59	2.11	1.19	1.39	(3.83)***	41.0	36.0	47.2
				Panel B: By Book-to-Market				
1	2.31	1.72	0.95	1.36	(3.33)***	58.7	35.6	30.8
2	1.62	1.76	0.94	0.69	(1.59)*	61.9	35.1	27.0
				Panel C: By Past Month Return				
1	1.64	1.81	0.81	0.82	(2.13)**	61.6	34.5	29.1
2	2.22	1.64	0.99	1.23	(3.70)***	59.2	36.2	29.2
				Panel D: By Current Month Return				
1	2.06	1.98	0.72	1.34	(3.42)***	62.1	33.8	28.2
2	1.85	1.51	1.02	0.83	(2.20)**	59.0	37.3	30.3
				Panel E: By Price				
1	2.11	1.88	0.81	1.30	(2.87)***	72.3	36.1	16.6
2	1.65	1.55	0.97	0.68	(1.95)**	48.2	34.8	41.2
				Panel F: By Individual Ownership				
1	1.66	1.44	0.99	0.68	(1.72)**	49.2	35.0	39.7
2	2.11	1.95	0.82	1.29	(2.70)**	71.4	36.1	18.2
				Panel G: By Analyst Coverage				
1	1.96	1.17	0.68	1.28	(3.24)***	68.5	37.9	19.2
2	1.93	2.23	1.07	0.86	(2.36)**	52.2	33.5	38.6

Table III B
Google SVIs and Stock Returns: Univariate Comparisons

This table presents average monthly returns in percentages for stocks with low, medium and high relative Google Search Volume Index (SVI). Each month, we first divide our sample of stocks in two, evenly large, subsamples based on firm characteristics: size, book-to-market, past and current month returns, price, individual ownership and analyst coverage (defined in Table AI). Thereafter, we split the subsamples into relative SVI tertile portfolios. The relative SVI of a company is the sample-weighted average SVI in the month of portfolio formation. We then compute the equal-weighted average return for each portfolio using individual stock returns in the month following formation.∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Average Monthly Return					Average No. of Stocks		
	Google SVI				t-Statistics for	Google SVI		
	Low	Medium	High	No - High	No - High	Low	Medium	High
All stocks	1.51	2.03	1.41	0.10	(0.33)	80.0	79.0	79.1
Panel A: By Size								
1	1.65	1.67	1.85	-0.206	(-0.42)	40.7	39.0	39.2
2	1.95	1.58	1.18	0.77	(2.57)***	40.1	39.8	39.5
Panel B: By Book-to-Market								
1	1.92	2.04	1.54	0.37	(0.96)	40.0	39.5	39.3
2	1.38	1.58	1.43	-0.05	(-0.12)	40.6	39.3	39.5
Panel C: By Past Month Return								
1	1.50	1.84	1.19	0.31	(0.85)	40.1	39.4	39.3
2	1.64	2.09	1.61	0.03	(0.08)	40.1	39.7	39.5
Panel D: By Current Month Return								
1	1.77	2.02	1.51	0.26	(0.59)	40.1	39.4	39.3
2	1.30	1.72	1.57	-0.27	(-0.81)	40.3	39.5	39.5
Panel E: By Price								
1	1.63	1.96	2.05	-0.42	(-0.89)	40.5	39.2	39.3
2	1.66	1.55	1.05	0.60	(2.06)**	40.1	39.7	39.5
Panel F: Individual Ownership								
1	1.40	1.68	1.20	0.20	(0.54)	40.0	39.5	39.3
2	1.98	1.89	1.71	0.27	(0.66)	40.6	39.3	39.4
Panel G: Analyst Coverage								
1	1.70	1.39	1.52	0.17	(0.40)	40.2	39.4	39.2
2	1.72	2.31	1.24	0.48	(1.18)	40.2	39.6	39.5

We also present the average number of stocks in each portfolio. Due to the portfolio formation procedure, the number of companies in each portfolio differs across the firm characteristics subgroups. We note that the portfolios generally include a sufficient number of stocks, relatively evenly distributed across the media coverage groups. In general, the no media coverage group contains the highest number of stocks, whereas the high media coverage group contains the fewest, due to the tie rule when sorting on the median. The portfolio for small stocks with high media coverage is the smallest portfolio with an average of only 11 stocks.

Table III B shows the results of the univariate return comparison, single-sorted on relative SVI first and then double-sorted on firm characteristics and the relative SVI in the panels. Unlike in Table III A, we do not find significance in the raw return difference between stocks with a low relative SVI and those with a high relative SVI. We find a significant return difference in only two of the firm characteristics subsample – in the large size group and high price group. This indicates there is a return premium only among ignored stocks among those who have a large market capitalization and high stock price. The return difference is negative for some of the characteristic groups, however we cannot conclude that this difference is different from zero as they are insignificant. We report the average portfolio sizes, but note that they are very even, as they should be due to the tertile sorting on relative SVI score.

B. Multivariate Analysis

We proceed to examine the no-attention premium hypothesis by controlling for known risk factors. We form two types of zero-investment portfolios. The first one longs stocks with no-media coverage and shorts stocks with high media coverage. The second type longs stocks with low relative SVI scores and shorts stocks with high relative SVI scores. Portfolio formation is further defined in Section IV. The results from the regressions are tabulated in Table IV.

We regress our portfolio returns against both equal- and value-weighted risk factors, of which we consistently present the results from the regressions against equal-weighted factors in the main text. Corresponding regressions to the ones reported in Table IV and V run against value-weighted risk factors are presented in Appendix, Table AIV and AVII, and show essentially the same results. The favoring of equal-weighted risk factors is based on an overall evaluation of the weighting schemes and the characteristics of our own portfolios, which are equally weighted, resulting in more weight on stocks with small capitalization.

Table IV presents the baseline results of the excess returns from our trading strategies regressed on three factor models. We observe significant positive alphas for our media-based zero-investment portfolio when regressed against CAPM and Fama-French Three-Factor model. The estimated alphas measure to 98 basis points in the CAPM, 77 basis points in the Fama-French Three-Factor model and 62 basis points in the Carhart Four-Factor model. The alpha yielded from the regression against Carhart Four-Factor model is significant, however only at the 10% level. We can conclude that our media-related trading strategy is earning abnormal positive returns above what can be explained by the established models. There is an incremental absorption of the alpha as we progress from CAPM to the Four-Factor model. Part of the estimated alpha of CAPM is absorbed by the Fama-French Three-Factor model, but even Carhart's Four-Factor model leaves

Table IV
Media- and SVI-Based Trading Profits: Baseline Multivariate Results

This table examines the profitability of two separate, zero-investment trading strategies. The first one longs a portfolio of stocks with no media coverage and shorts a portfolio of stocks with high media coverage. The long portfolio consists of stock with no media coverage in the month of portfolio formation and the short portfolio of stocks above the median number of articles of the remaining stocks. The second strategy longs a portfolio of stocks belonging to the lowest relative SVI tertile and shorts a portfolio of stocks belonging to the highest relative SVI tertile. The relative SVI of a company is the sample-weighted average SVI in the month of portfolio formation. The zero-investment portfolio, as well as the long and short legs of it, are all equally weighted. The portfolio is held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the zero-investment portfolio are regressed on established risk factors, equally weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM		Model 2: FF Three-Factor		Model 3: Carhart Four Factor	
	Media	SVI	Media	SVI	Media	SVI
Panel A: Long No-Attention Stocks, Short High-Attention Stocks						
Mkt-rf	-0.0534	-0.0287	0.0384	-0.0162	0.0980	0.0175
	(0.524)	(0.739)	(0.665)	(0.865)	(0.295)	(0.864)
SMB	-	-	0.1377	0.1051	0.2302**	0.1575
			(0.101)	(0.241)	(0.021)	(0.144)
HML	-	-	-0.1925*	0.0728	-0.1449	0.0998
			(0.089)	(0.544)	(0.200)	(0.422)
MOM	-	-	-	-	0.1945*	0.1101
					(0.084)	(0.370)
Intercept	0.0098***	0.0010	0.0077**	0.0002	0.0062*	-0.0007
	(0.003)	(0.754)	(0.017)	(0.963)	(0.057)	(0.840)
Observations	47	47	47	47	47	47
R^2	0.0091	0.0025	0.1300	0.0415	0.1904	0.0599
Panel B: Alphas for No-Attention Stocks						
Intercept	0.0089**	0.0048	0.0072*	0.0040	0.0052	0.0028
	(0.022)	(0.166)	(0.072)	(0.282)	(0.195)	(0.458)
Panel C: Alphas for High-Attention Stocks						
Intercept	0.0013	-0.0035	0.0007	-0.0036	0.0012	-0.0033
	(0.559)	(0.178)	(0.745)	(0.203)	(0.620)	(0.262)

two-thirds of the alpha estimated by CAPM left unexplained. Thus, there are positive abnormal returns in our media-based trading strategy that cannot be explained by these established risk factors.

We see weak correlations between the independent variables in the factor models and the return of our media-based zero-investment portfolio. The SMB-factor exhibits a stronger correlation in the Carhart Four-Factor model than in the Three-Factor model, nevertheless it may indicate that a part of the absorbed abnormal return is due to a size effect in our sample. As the SMB-coefficient is positively signed it indicates that our trading strategy has a positive exposure to small stocks.

The remaining factors, Mkt-rf, HML and MOM do not significantly correlate with the trading strategy. The coefficients for the HML-factor, however, are negatively signed and from the weak significance in the Three-Factor model we can suspect that our zero-investment portfolio also has an increased exposure to growth stocks.

A closer look at the regression results on our excess returns of the long and short portfolios of our media-based trading strategy, reported in Table AIII, shows that the alphas in the zero-investment portfolio originate from positive abnormal returns in the long position, rather than from underperforming stocks in the short position. Thus, the media effect is unlikely to be driven by individual investors habit of buying attention grabbing stocks, which subsequently tend to underperform, as described by Barber and Odean (2008). If it were the case, then the alpha in the zero-investment portfolio should be driven by the High-Attention portfolio. The alphas in the long portfolio are significant for the CAPM and Three-Factor model and decrease with the addition of risk factors, as is expected. The legs are oppositely correlated to the market portfolio, indicating that both follow the market movements.

The SVI-based trading strategy estimates alphas insignificantly different from zero. We therefore conclude that this strategy does not earn any abnormal returns. Neither do we find any significant correlations between the portfolio return and the risk factors.

We also investigate the excess returns of our SVI-based zero-investment portfolio legs, the long and short portfolios, in separate regressions, reported in Table AV. We find that both the long and short portfolios are correlated with excess market returns at a 1% significance level with coefficients and alphas of the same magnitude, however the coefficients have opposite signs. This indicates that both the long and short portfolios of our SVI-based trading strategy follow the market, and as a result, the effects of this are erased when combining them into our zero-investment portfolio. Thus, the sorting on relative SVI score does not seem to add any value to our zero-investment trading strategy.

There is a concern that the weak results reported for our SVI-based trading strategy are accentuated by extreme relative SVI scores of companies in certain consumer-facing sectors. In Figure 1, we note that sectors Trading and Goods (4), Mining and Metals (9), Discretionaries (10) and Telecommunication and Services (11) are overly represented in the highest relative SVI tertile when forming portfolios and the reason to this is likely to be non-investor consumption behavior (with the exception of sector 9). We exclude said sectors, repeat the portfolio sorting and run the regression again, reported in Table AVI, but our conclusion on the inadequacy of the SVI-based trading strategy remains unchanged.

As we cannot find any indication that the SVI-based trading strategy yields significant alphas, we do not to investigate this any further. Instead, we continue to investigate the media-based trading strategy by forming subsamples of stocks based on firm and stock characteristics and carrying out the same regression as in Table IV. We report these alphas in Table V. Results from regressions on value-weighted factors are reported in AVII and support the results we present below.

Table V
Media-Based Trading Profits by Firm Characteristics

This table examines the profitability of a media-based zero-investment trading strategy, sorted on firm characteristics. Each month, we first divide our sample of stocks in two, evenly large, subsamples based on firm characteristics: size, book-to-market and 12-month momentum. Then the stocks are sorted into two legs. The first leg longs a portfolio of stocks with no media coverage and the second one shorts a portfolio of stocks with high media coverage. The long portfolio consists of stocks with no media coverage in the month of portfolio formation and the short portfolio of stocks above the median number of articles of the remaining stocks. The zero-investment portfolio, as well as the long and short legs of it, are all equally weighted. The portfolio is held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the zero-investment portfolio are regressed on established risk factors, equally weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM	Model 2: FF Three-Factor	Model 3: Carhart Four-Factor
		Panel A: By Firm Size	
		Small	
Intercept	0.0135	0.0127	0.0118
	(0.132)	(0.186)	(0.240)
		Large	
Intercept	0.0108***	0.0099**	0.0085**
	(0.006)	(0.015)	(0.042)
		Panel B: By Book-to-Market	
		Low	
Intercept	0.0121***	0.0087**	0.0066
	(0.007)	(0.043)	(0.126)
		High	
Intercept	0.0089*	0.0077	0.0068
	(0.051)	(0.113)	(0.180)
		Panel C: By Past 12-Month Momentum	
		Low	
Intercept	0.0019	-0.0009	-0.0019
	(0.593)	(0.802)	(0.592)
		High	
Intercept	0.0156***	0.0142***	0.0113***
	(0.000)	(0.001)	(0.007)

In Panel A of Table V, we observe that the alphas are greater in the subsample of smaller stocks than in that of larger stocks, however, the alphas are significant only for our larger subsample sorted on size. This provides an interesting find as many return anomalies are more common among small, illiquid stocks. The fact that we instead find it among large cap stocks, of similar size, strengthens our hypothesis of a no-attention premium, driven by media coverage. Additionally, the attention effect is both larger and more significant among low book-to-market stocks, i.e. growth stocks. We find a strong attention effect among stocks with greater past 12-month momentum, i.e. stocks that have performed strongly over the past 12 months. In comparison, the effect is completely absent among loser stocks.

C. Robustness Checks

We carry out robustness checks on the baseline multivariate results reported in Table IV. We check for common causes of return anomalies, such as bid-ask bounce, IPO underperformance, delisting bias and illiquidity among low priced stocks. In Table VI we see a statistical significance in almost all alphas generated by our trading strategy, implying that the trading strategy is robust to several anomalies which could be underlying drivers of the return premium. The exception is Panels E and F, where we exclude large parts of our stock sample based on cut-off prices, which voices the concern that our results are driven by illiquid small stocks.

Our baseline results in Table IV build upon portfolio returns calculated on monthly closing prices. We repeat the regression but calculate the returns on the monthly closing bid-ask midpoints instead. In Table VI Panel A we observe an improvement in significance compared to our baseline results which leads us to conclude that excess returns are indeed not driven by a bid-ask bounce.

As our stock sample includes both IPO listings and delistings during our sample period, there is a concern that our baseline results are affected by media coverage in combination with abnormal returns due to either IPO underperformance or delisting bias. From Panels B through D, we conclude that this is not the case and our results remain robust when we exclude affected stocks for the entirety of our sample period, both separately and simultaneously.

Lastly, we exclude stocks that are traded for under 25 SEK and 50 SEK respectively on any day during our sample period, due to illiquidity concerns. This results in the exclusion of a large part of our sample, 124 and 197 stocks respectively. By excluding stocks traded under 25 SEK, we lose significance for all factor models, except CAPM. The same pattern, quite naturally, is repeated when excluding stocks traded under 50 SEK. We check the average number of stocks in the portfolios, in order to rule out any skewness in the distribution of stocks across the media coverage portfolios. Given the large decrease in the sample, we fear, for example, that the no-media coverage portfolio could be wiped out. However, we find that the portfolios remain balanced with an average of 52.2 stocks in the no-media coverage and 34.2 in the high media coverage portfolios in Panel E, and average number of stocks of 19.7 and 21.3 for the corresponding portfolios in Panel F.

In unreported analysis, we regress against value-weighted factors instead of the equal-weighted factors reported in Table VI. These regressions estimate positive alphas above 1%, significant on the 10% level, for both cut-off prices. It is not impossible, that the value-weighting scheme provides a better fit for the portfolios in Panels E and F, as it is likely that large capitalization stocks are overly represented in the remaining sample. Nevertheless, these findings motivate further testing on illiquidity as a driver of our baseline results.

Table VI
Robustness Checks

This table examines the robustness of the profitability of a zero-investment trading strategy. We check an alternative to returns calculated on prices, i.e returns based on bid-ask midpoints. Additionally, we test the reults by excluding IPO stocks, delisted stocks and stocks traded for less than 25 SEK and 50 SEK, respectively. The long portfolio consists of stocks with no media coverage in the month of portfolio formation and the short portfolio of stocks above the median number of articles of the remaining stocks. The zero-investment portfolio, as well as the long and short legs of it, are all equally weighted. The portfolio is held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the zero-investment portfolio are regressed on established risk factors, equally weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM	Model 2: FF Three-Factor	Model 3: Carhart Four-Factor
	Panel A: Returns Based on Bid-Ask Midpoints		
Intercept	0.0105***	0.0084***	0.0069**
	(0.001)	(0.007)	(0.026)
	Panel B: Excluding IPO Stocks		
Intercept	0.0107***	0.0089***	0.0071**
	(0.001)	(0.007)	(0.029)
	Panel C: Excluding Delisted Stocks		
Intercept	0.0111***	0.0092***	0.0075**
	(0.001)	(0.005)	(0.020)
	Panel D: Excluding both IPO and Delisted Stocks		
Intercept	0.0109***	0.0093***	0.0072**
	(0.001)	(0.006)	(0.029)
	Panel E: Excluding Stocks Traded for Less Than 25 SEK		
Intercept	0.0120*	0.0051	0.0029
	(0.066)	(0.188)	(0.442)
	Panel F: Excluding Stocks Traded for Less Than 50 SEK		
Intercept	0.0116*	0.0061	0.0043
	(0.061)	(0.235)	(0.418)

VII. Discussion

We evaluate three possible explanations to the attention effect we observe in our sample, namely return continuations and reversals, illiquidity and informational frictions. Fang and Peress (2009) assess the feasibility of these explanations to their no-media return premia and we compare our results to theirs.

If the excess returns from our media-based trading strategy stems from return continuations or reversals, we should be able to identify this in our results. Chan (2003) finds that stocks experience a strong drift if they experience low returns in conjunction to headlines in the news. However, the abnormal returns we observe with our media-based trading strategy are unlikely to be caused by negative return drifts, as these would have to be found among our high media coverage stocks. In Panels A and B of Table IV, we note that the alphas originate in the long leg of our zero-investment portfolio, whereas the other leg, shorting high media coverage stocks, show alphas insignificantly different from zero. This is the same observation which Fang and Peress (2009) make in their analysis of this explanation. For return reversals to be the driver of our alphas, they would have to appear among the no-media stocks. This is a finding documented by Chan in the aforementioned study. We find highly significant positive alphas for our trading strategy among stocks with a high past 12-month momentum in Table V. Long term loser stocks, on the other hand, do not contribute to our trading strategy at all. In the univariate analysis in Table III A, we find that past month loser stocks with no media coverage on average yield higher raw returns than their peers with high media coverage. However, this return difference is even greater and the significance level higher among past month winners. Thus, we rule out reversal effects as an explanatory factor for our abnormal returns. In comparison, Fang and Peress (2009) do not confirm the stronger return difference in their univariate analysis of past month winners. Rather, they dismiss the return reversal theory by looking at longer holding periods.

Our findings in Table V are different both from what we expect and from what Fang and Peress (2009) find. We note that the abnormal return stems from the large size portfolio indicating a reversed size effect. As previously stated, this is surprising as small stocks are usually drivers of abnormal returns as documented by Barry (1984) and found in the Fama-French Three-Factor model. In Panel B we find that growth stocks are drivers of abnormal returns, unexpected by theory, but in line with what Fang and Peress (2009) document. Lastly, from Panel C we find a strong attention effect among stocks with higher past 12-month momentum. In comparison, the effect is completely absent among loser stocks. The results suggest that among high momentum stocks, no news is good news. We speculate that this may relate to the findings of Tetlock (2007), but applied to specific stocks rather than overall market movements. The qualitative properties of the media coverage become interesting, if it could prove whether the excess returns of the high media coverage portfolio are pushed down by a high degree of negative media coverage, resulting in the observed success of our media-based zero-investment trading strategy in that specific subsample. Furthermore, our findings are contradictory to Hillert et al. (2014) who observe the opposite, a momentum effect among stocks with high coverage. If this were the case in our sample, we would find significance in our low rather than high momentum portfolio.

Our robustness checks raise the issue of illiquidity influencing our results. In Table VII we therefore repeat the double-sorting procedure of Table V, but this time on liquidity measures.

Table VII
Illiquidity and the Media Effect

This table examines the profitability of a media-based zero-investment trading strategy, sorted on illiquidity measures. Each month, we first divide our sample of stocks in two, evenly large, subsamples based on illiquidity measures: Amihud's (2002) illiquidity ratio, bid-ask spread, KSEK trading volume and price. Then the stocks are sorted into two legs. The first leg longs a portfolio of stocks with no media coverage and the second one shorts a portfolio of stocks with high media coverage. The long portfolio consists of stocks with no media coverage in the month of portfolio formation and the short portfolio of stocks above the median number of articles of the remaining stocks. The zero-investment portfolio, as well as the long and short legs of it, are all equally weighted. The portfolio is held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the zero-investment portfolio are regressed on established risk factors, equally weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM	Model 2: FF Three-Factor	Model 3: Carhart Four-Factor
	Panel A: By Amihud's (2002) Illiquidity Ratio		
		Low	
Intercept	0.0098***	0.0084**	0.0064*
	(0.009)	(0.029)	(0.094)
		High	
Intercept	0.0170*	0.0167*	0.0162
	(0.068)	(0.093)	(0.122)
	Panel B: By Bid-Ask Spread		
		Low	
Intercept	0.0083**	0.0061*	0.0042
	(0.017)	(0.077)	(0.221)
		High	
Intercept	0.0155*	0.0145	0.0164*
	(0.065)	(0.106)	(0.080)
	Panel C: By KSEK Trading Volume		
		Low	
Intercept	0.0137	0.0133	0.0148
	(0.121)	(0.157)	(0.133)
		High	
Intercept	0.0096**	0.0072*	0.0051
	(0.020)	(0.074)	(0.203)
	Panel D: By Price		
		Low	
Intercept	0.0130***	0.0104**	0.0104**
	(0.009)	(0.039)	(0.049)
		High	
Intercept	0.0061	0.005	0.0024
	(0.109)	(0.214)	(0.542)

We hypothesize that, if our results are driven by illiquidity, we will find stronger effects in the more illiquid subsamples. Contrary to our expectations, our media-based trading strategy result in relatively large and more significant alphas among stocks with a low Amihud illiquidity ratio, as seen in Panel A of Table VIII. The estimated alphas of stocks with a high illiquidity ratio are in comparison larger, but so are the p-values. Likewise, it is difficult to draw any conclusions from the bid-ask spread and trading volume sortings, as both convey conflicting results. If illiquidity is the explanation to our findings, we should find stronger effects among stocks with a high bid-ask spread and stocks with lower trading volume. Table VII, however, does not provide any strong evidence for this illiquidity hypothesis. The only sorting that gives clear support for illiquidity as an explaining factor is the sorting on price. High-priced stocks do not demonstrate significant alphas, as opposed to the low-priced stocks. Since we already excluded roughly half of our sample in the robustness checks with cut-off prices, the results for above-median priced stocks are in line with previous results.

A third potential explanation to a media-based attention effect build on a stock's overall level of recognition. Fang and Peress (2009) find support for Merton's (1987) investor recognition hypothesis (IRH). Their findings support the hypothesis that a stronger media premium should be found among stocks which have a low recognition by other measures, such as analyst coverage, individual ownership and idiosyncratic volatility. Our analogous analysis of this hypothesis speaks both in favor of and against these findings. Firstly, from Table II we do not observe any significant relationship between these above-mentioned measures and media coverage in our sample. Fang and Peress find that media coverage is negatively related to analyst coverage, which they conclude indicates that these are substitutes rather than complements. They also find that media coverage is positively related to analyst dispersion, fraction of individual ownership and idiosyncratic volatility. Based on these relationships and further analysis, Fang and Peress conclude that the media effect is stronger among stocks with low analyst coverage and a high fraction of individual ownership, where a media effect plays a large incremental role in leveling informational asymmetries. Our analysis only yields corresponding results observed in Panel A of Table VIII. Among stocks with high individual ownership the attention effect yields significant abnormal returns. In other words, these stocks see a lower fraction of institutional investors, which in turn could indicate that these are small or unknown firms, perhaps with concentrated ownership. Whether this is due to frictions caused regulatory restrictions as proposed by Merton (1987) or a significant relationship as reported by Frieder et al. (2003) cannot be concluded.

Our results observed in Panel B and C, on the other hand, speak against Fang and Peress (2009) and Merton (1987). Panel B shows inconclusive patterns regarding an attention premium stemming from stocks with high idiosyncratic volatility. We expect to find abnormal returns from the portfolio filtered on high idiosyncratic volatility for our results to be in line with Merton. This would also be in line with the findings of panel A where we suspect that the ownership base of these stocks may be imperfectly diversified. Instead the results yield significant abnormal returns in both the low and high idiosyncratic subsamples. We postulate that this indicates either that idiosyncratic volatility is not a sufficient measure of attention or that the abnormal returns depend on some other factor. The fact that our investment strategy yields abnormal returns within both the high and low subsamples in Panel B of Table VIII, is not only inconclusive in terms of Merton's theory, but also goes against Ang et al. (2006). They document that stocks with high idiosyncratic volatility earn low future returns, a finding we cannot confirm in our analysis. Lastly, in Panel C we find that the portfolio with high analyst coverage yields abnormal returns, a contradiction to Merton's IRH and the findings of Arbel et al. (1983) who observe that securities neglected by analysts earn a superior performance. Reasonably, these stocks already have investor attention if they have a high degree of analyst coverage. Yet, we only observe significant abnormal returns in the high subsample and not the low. We find indications of a positive relationship between idiosyncratic volatility and media coverage in Table II. In Table AII this relationship is significant at the 1%-level. A further and separate analysis of the short and long legs of our investment strategy

Table VIII
Investor Recognition and the Media Effect

This table examines the profitability of a media-based zero-investment trading strategy, sorted on proxies for investor attention. Each month, we first divide our sample of stocks in two, evenly large, subsamples based on attention proxies: fraction of individual ownership, idiosyncratic volatility and analyst coverage. Then the stocks are sorted into two legs. The first leg longs a portfolio of stocks with no media coverage and the second one shorts a portfolio of stocks with high media coverage. The long portfolio consists of stocks with no media coverage in the month of portfolio formation and the short portfolio of stocks above the median number of articles of the remaining stocks. The zero-investment portfolio, as well as the long and short legs of it, are all equally weighted. The portfolio is held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the zero-investment portfolio are regressed on established risk factors, equally weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM	Model 2: FF Three-Factor	Model 3: Carhart Four-Factor
	Panel A: By the Fraction of Individual Ownership		
		Low	
Intercept	0.0061	0.0049	0.0035
	(0.145)	(0.263)	(0.443)
		High	
Intercept	0.0142***	0.0120**	0.0102*
	(0.0142)	(0.021)	(0.055)
	Panel B: By Monthly Idiosyncratic Volatility		
		Low	
Intercept	0.0094***	0.0086**	0.0072*
	(0.008)	(0.021)	(0.060)
		High	
Intercept	0.0142***	0.0106*	0.0083
	(0.009)	(0.051)	(0.134)
	Panel C: By Analyst Coverage		
		Low	
Intercept	0.0057	0.0048	0.0034
	(0.171)	(0.281)	(0.455)
		High	
Intercept	0.0145***	0.0123**	0.0106*
	(0.005)	(0.021)	(0.052)

could reveal whether the significant abnormal returns are driven by no- or high media coverage stocks, or if there is no conclusive relationship. We conclude that our results yield inconclusive evidence to whether the attention premium stems from the investor recognition hypothesis.

The comparison between our indirect and direct measure of attention show that our proxies are not interchangeable. We find similar results to Fang and Peress (2009) when repeating their methodology with a media-based trading strategy. However, when we apply the same methodology on an alternative, direct measure for attention, we fail to reproduce the results. We suspect the poor performance of a trading strategy based on Google SVI roots in a poor fit between the methodology and the features of the data we use. The publicly available version of Google's

SVI tool is not optimized for comparisons on large cross-sections, rather it is better for time-series estimations on individual securities. Additionally, the use of company names, as Bank et al. (2011), rather than company tickers, as Da et al. (2009), is likely to skew the relative SVIs, due to the inclusion of more general searches, especially on consumer-facing companies. Alternatively, it could be that the no-media premium Fang and Peress (2009) find and claim stem from a lack of investor attention has explanations beyond investor recognition. This could explain why the positive abnormal returns from our media-based trading strategy fail to translate into corresponding alphas in our SVI-based trading strategy.

Although our findings overlap with previous research, we are humble to the fact that our sample is restricted to a relatively small number of stocks. Despite including the large majority of stocks listed on Nasdaq Stockholm during our sample period, our sample only makes up a fraction of that of Fang and Peress (2009). In order to maintain adequate sizes of our subsamples, we therefore do our characteristics-sortings in two groups, rather than three. Consequently, it is not impossible that effects they notice in their subsamples are subsumed in our more general sorting.

VIII. Conclusion

We compare two proxies of investor attention and investigate their relation in the cross-section of stock returns. In line with Fang and Peress (2009) we study the effect of media coverage and observe a no-media premium on the Swedish stock market. The same effect cannot be observed when applying their methodology to a direct proxy, Google Search Volume Index (SVI).

A media-based trading strategy generates significant monthly abnormal returns, estimated to 0.62% using the Carhart Four-Factor model, and the effect is the most pronounced among stocks with a large market capitalization, growth stocks and stocks with a strong past 12-month momentum. These results are robust to common return anomalies, such as bid-ask bounce, IPO underperformance and delisting bias. We investigate three possible explanations to these abnormal returns. We find that abnormal returns are not driven by return continuations or reversals. However, the results are conflicting when it comes to the role of illiquidity and investor recognition as underlying drivers in our sample.

We conclude that stocks with no media coverage yield significantly higher returns than their peers with high media coverage, suggesting that stockholders of firms with no media coverage are compensated for additional risk in owning these stocks. Although our findings in some senses oppose Merton's (1987) investor recognition hypothesis, they support his idea that media coverage can indeed play a role in determining firms' cost of capital. This provides an interesting find for companies seeking to lower their cost of capital, as it shows that increased media exposure can be an efficient tool in the process.

References

ANG, A., HODRICK, R.J., XING, Y. and ZHANG, X., 2006. The Cross-Section of Volatility and Expected Returns. *The Journal of Finance,* 61(1), pp. 259-299.

ARBEL, A., CARVELL, S., & STREBEL, P., 1983. Giraffes, institutions and neglected firms. Financial Analysts Journal, 39(3), pp.57-63.

BANK, M., LARCH, M. and PETER, G., 2011. Google search volume and its influence on liquidity and returns of German stocks. *Financial Markets and Portfolio Management,* 25(3), pp. 239-264.

BANZ, R.W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics,* 9(1), pp. 3-18.

BARBER, BRAD M. AND ODEAN, TERRANCE, 2008, *All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors*, Review of Financial Studies, 21(2), pp. 785-818.

BORGSTRÖM, J. (April 14, 2020). TS-upplaga för 2011. Kantar Sifo Media Audit.

CHRISTOPHER B. BARRY, STEPHEN J. BROWN,1984, Differential information and the small firm effect, *Journal of Financial Economics*, 13(2), pp. 283-294.

BOEHME, R.D., DANIELSEN, B.R., KUMAR, P. and SORESCU, S.M., 2009. Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets Miller (1977), *Journal of Financial Markets*, 12(3), pp.438-468

CARHART, M.M., 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance,* 52(1), pp. 57-82.

CHAN, W.S., 2003. Stock price reaction to news and no-news: Drift and reversal after headlines. *Journal of Financial Economics,* 70(2), pp. 223-260.

DA, Z., ENGELBERG, J. and GAO, P., 2011. In Search of Attention. *Journal of Finance,* 66(5), pp. 1461-1499.

DIETHER, K.B., MALLOY, C.J. and SCHERBINA, A., 2002. Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance,* 57(5), pp. 2113-2141.

FAMA, E.F. and FRENCH, K.R., 1992. The Cross-Section of Expected Stock Returns. *The Journal of Finance,* 47(2), pp. 427-465.

FANG, L. and PERESS, J., 2009. Media coverage and the cross-section of stock returns*, The Journal of Finance,* 64(5), pp. 2023-2052

FANG, L.H., PERESS, J. and ZHENG, L., 2014. Does Media Coverage of Stocks Affect Mutual Funds' Trading and Performance? *Review of Financial Studies,* 27(12), pp. 3441-3466,

FRIEDER, L. and SUBRAHMANYAM, A., 2003. Brand Perceptions and the Market for Common Stock. *Journal of Financial and Quantitative Analysis*, 40(1), pp. 57-85

GRULLON, G., KANATAS, G. and WESTON, J.P., 2004. Advertising, breadth of ownership, and liquidity. *Review of Financial Studies,* 17(2), pp. 439-461

HILLERT, A., JACOBS, H. and MÜLLER, S., 2014. Media makes momentum. *Review of Financial Studies,* 27(12), pp. 3467-3501.

HUBERMAN, G., 2001. Familiarity Breeds Investment. *The Review of Financial Studies,* 14(3), pp. 659-680.

JEGADEESH, N. and TITMAN, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance,* 48(1), pp. 65-91

KLIBANOFF, P., LAMONT, O. and WIZMAN, T.A., 1998. Investor Reaction to Salient News in Closed-End Country Funds. *The Journal of Finance,* 53(2), pp. 673-699.

MERTON, ROBERT, 1987, A Simple Model of Capital Market Equilibrium with Incomplete Information, *Journal of Finance,* 42(3), pp. 483-510,

MILLER, EDWARD M, 1977, Risk, Uncertainty, and Divergence of Opinion, *Journal of Finance*, 32(4), pp. 1151-68,

MODULAR FINANCE AB. (March 26, 2020). *Modular Finance Holdings FAQ*. Retrieved from Modular Finance Holdings: https://www.holdings.se/app/#/faq

NYA LUNDSTEDT DAGSTIDNINGAR. (April 9, 2020). Sökformulär för Nya Lundstedt dagstidningar. Retrieved April 2020, from Nya Lundstedt dagstidningar: http://tidning.kb.se/nld/nld/main?tidnId=&katId=39&PFD=2011-01-01&PTD=2011-12-31&titel=&fritext=&fritext2=&sortering=info&sok=Sök

TETLOCK, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance,* 62(3), pp. 1139-1168.

Appendix

Table AI
Variable's Definitions

	Stock Characteristics
Amihud's (2002) illiquidity ratio	Absolute return divided by the KSEK trading volume, scaled with 10^3.
Analyst coverage	The natural logarithm of, 1 plus the number of analyst estimates in the time period.
Analyst dispersion	Natural logarithm of, 1 plus the standard deviation of mean analyst estimate, divided by the absolute mean estimate.
Bid-ask midpoint	Closing bid price minus closing ask price, divided by 2.
Bid-ask spread	Closing bid price minus closing ask price, divided by the bid-ask midpoint.
Book-to-market	Natural logarithm of the inverse of the price-to-book ratio by the previous year-end.
Current month return	Closing price of current month divided by closing price of previous month, minus 1.
Fraction of individual ownership	The estimated percentage of individuals owning the share. Estimated as 1 minus the fraction of institutional ownership of the company as of the previous quarter-end.
Yearly (monthly) idiosyncratic volatility	Standard deviation of residuals from regressing daily returns on equally weighted Fama-French factors, scaled by $250^{1/2}$ ($21^{1/2}$).
KSEK trading volume	Closing price times daily trading volume.
Past 12-month momentum	The product of 1 plus the monthly return for the past 12 months, minus 1.
Past year (month) absolute return	Absolute value of closing price of previous year (month) divided by closing price of the year (month) prior to that, minus 1.
Past year (month) return	Closing price of previous year (month) divided by closing price of the of the year (month) prior to that, minus 1.
Price	Average closing price during the previous month.
Size	Natural logarithm of the total market capitalization of the company in KSEK, calculated as the closing price of stocks by the previous year-end, times common shares outstanding.
	Factors
Mkt-rf	Market return in excess of risk-free rate (1 month Swedish T-Bill)
SMB	Small-Minus-Big, the return of a portfolio of small stocks, minus the return of a portfolio of large stocks.
HML	High-Minus-Low, the return of a portfolio of stocks with high book-to-market ratio, minus the return on a portfolio of stocks with low book-to-market.
MOM	Winners-Minus-Losers, the return of a portfolio of stocks with a high past 12-month return, minus the return on a portfolio of stocks with a low past 12-month return.

Table AII

Determinants of Media Coverage and Google Search Volume Index (SVI) – Time Fixed Effects

This table reports the determinants of Media Coverage and Relative Google Search Volume Index (SVI) resulting from time fixed effects linear estimations. The first dependent variable is the circulation-weighted number of articles published about a stock in a given year. The second dependent variable the relative SVI for a firm, averaged over a given year. Independent variables are defined in Table AI. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

		Dependent Variable: Weighted Number of Articles		Dependent Variable: Relative Google SVI	
Size		1.7054	1.6405	41.8292	46.3901
		(2.48)**	(2.41)**	(1.47)	(1.65)*
Book-to-Market		0.6231	0.6770	18.63	16.2921
		(0.93)	(1.02)	(0.67)	(0.59)
Analyst Coverage		-0.6051	-0.5767	14.7280	11.0007
		(-0.91)	(-0.86)	(0.53)	(0.40)
Fraction of individual ownership		-1.0808	-0.6962	-329.5922	-337.4017
		(-0.18)	(-0.12)	(-1.34)	(-1.38)
Analyst dispersion		-0.0447	-0.0545	-6.9979	-6.1829
		(-0.15)	(-0.18)	(-0.57)	(-0.50)
Idiosyncratic volatility		4.2664	4.4184	-88.5816	-84.6007
		(2.72)***	(2.81)***	(-1.37)	(-1.30)
Past year absolute return			-0.2012		-10.0520
			-(0.54)		(-0.66)
Past year return		-0.2680		0.0179	
		(0.79)		(0.00)	
Year					
	2014	-0.3436	-0.3432	-10.8091	-10.6542
		(-1.08)	(-1.08)	(-0.82)	(-0.81)
	2015	-1.3644	-1.3185	-12.3465	-14.8327
		(-3.73)***	(-3.69)***	(-0.82)	(-1.00)
	2016	-2.0375	-1.9833	-41.0378	-43.7903
		(-4.82)***	(-4.81)***	(-2.35)**	(-2.57)**
Constant		-21.7171	-20.8351	-317.1769	-378.3378
		(-2.13)**	(-2.07)**	(-0.75)	(-0.91)
Observations		488	488	488	488
R^2		0.1455	0.1471	0.0904	0.0886

Table AIII
Media- and SVI-Based Trading Profits: Extended Baseline Multivariate Results

This table expands on Table IV in our multivariate analysis of the profitability of the two trading strategies that longs stocks with no media coverage (or low SVI) and shorts stocks with high media coverage (or high SVI). Here we show the complete results of the regressions against established risk factors of the long och short portfolio separately. The long portfolio consists of stocks with no media coverage in the month of portfolio formation (lowest relative SVI tertile) and the short portfolio of stocks above the median number of articles of the remaining stocks (highest relative SVI tertile). The relative SVI of a company is the sample-weighted average SVI in the month of portfolio formation. . The long and short portfolios are both equally weighted. The portfolios are held for 1 month after portfolio formation and rebalanced monthly.The resulting time series returns of the long and short portfolios are regressed on established risk factors, equally weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM		Model 2: FF Three-Factor		Model 3: Carhart Four Factor	
	Media	SVI	Media	SVI	Media	SVI
			Panel A: Long No-Attention Stocks Portfolio			
Mkt-rf	0.8689***	0.8499***	0.9417***	0.8730***	1.0193***	0.9177***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	-	-	0.1039	0.0828	0.2244**	0.1522
			(0.321)	(0.397)	(0.069)	(0.194)
HML	-	-	-0.01585	0.0068	-0.0966	0.0425
			(0.262)	(0.959)	(0.494)	(0.753)
MOM	-	-	-	-	0.2534*	0.1458
					(0.074)	(0.277)
Intercept	0.0089**	0.0048	0.0072*	0.0040	0.00521	0.0028
	(0.022)	(0.166)	(0.072)	(0.282)	(0.195)	(0.458)
Observations	47	47	47	47	47	47
R^2	0.6223	0.6514	0.6419	0.6572	0.6685	0.6669
			Panel B: Short High-Attention Stocks Portfolio			
Mkt-rf	-0.9213***	-0.8776***	-0.9010***	-0.8870***	-0.9186***	-0.8974***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	-	-	0.0363	0.0248	0.0092	0.0087
			(0.551)	(0.736)	(0.900)	(0.922)
HML	-	-	-0.0354	0.0645	-0.0494	0.0562
			(0.666)	(0.516)	(0.562)	(0.586)
MOM	-	-	-	-	-0.0571	-0.0338
					(0.498)	(0.740)
Intercept	0.0013	-0.0035	0.0007	-0.0036	0.0012	-0.0033
	(0.559)	(0.178)	(0.745)	(0.203)	(0.620)	(0.262)
Observations	47	47	47	47	47	47
R^2	0.8497	0.7786	0.8516	0.7813	0.8533	0.7819

Table AIV

Media- and SVI-Based Trading Profits: Baseline Multivariate Results – Value-Weighted Factors

This table examines the profitability of two separate, zero-investment trading strategies. The first one longs a portfolio of stocks with no media coverage and shorts a portfolio of stocks with high media coverage. The long portfolio consists of stocks with no media coverage in the month of portfolio formation and the short portfolio of stocks above the median number of articles of the remaining stocks. The second strategy longs a portfolio of stocks belonging to the lowest relative SVI tertile and shorts a portfolio of stocks belonging to the highest relative SVI tertile. The relative SVI of a company is the sample-weighted average SVI in the month of portfolio formation. The zero-investment portfolio, as well as the long and short legs of it, are all equally weighted. The portfolio is held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the zero-investment portfolio are regressed on established risk factors, value-weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM		Model 2: FF Three-Factor		Model 3: Carhart Four Factor	
	Media	SVI	Media	SVI	Media	SVI
Panel A: Long No-Attention Stocks, Short High-Attention Stocks						
Mkt-rf	-0.0534	-0.0287	0.1527	0.1145	0.1459	0.0971
	(0.524)	(0.739)	(0.115)	(0.264)	(0.137)	(0.341)
SMB	-	-	0.3844***	0.3250***	0.3835***	0.3228***
			(0.001)	(0.007)	(0.001)	(0.007)
HML	-	-	0.0588	0.2027*	0.0768	0.2489
			(0.578)	(0.077)	(0.490)	(0.037)
MOM	-	-	-	-	0.0623	0.1596
					(0.572)	(0.171)
Intercept	0.0098***	0.0010	0.0070	-0.0015	0.0072**	-0.0011
	(0.003)	(0.754)	(0.019)	(0.632)	(0.018)	(0.728)
Observations	47	47	47	47	47	47
R^2	0.0091	0.0025	0.2385	0.1751	0.2444	0.2115
Panel B: Alphas for No-Attention Stocks						
Intercept	0.0089**	0.0048	0.0051	0.0011	0.0054	0.0014
	(0.022)	(0.166)	(0.140)	(0.717)	(0.121)	(0.643)
Panel C: Alphas for High-Attention Stocks						
Intercept	0.0013	-0.0035	0.0022	-0.0023	0.0021	-0.0022
	(0.559)	(0.178)	(0.319)	(0.391)	(0.356)	(0.419)

Table AV
Media- and SVI-Based Trading Profits: Extended Baseline Multivariate Results – Value-Weighted Factors

This table expands on Table IV in our multivariate analysis of the profitability of the two trading strategies that longs stocks with no media coverage (or low SVI) and shorts stocks with high media coverage (or high SVI). Here we show the complete results of the regressions against established risk factors of the long och short portfolio separately. The long portfolio consists of stocks with no media coverage in the month of portfolio formation (lowest relative SVI tertile) and the short portfolio of stocks above the median number of articles of the remaining stocks (highest relative SVI tertile). The relative SVI of a company is the sample-weighted average SVI in the month of portfolio formation. The long and short portfolios are both equally weighted. The portfolios are held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the long and short portfolios are regressed on established risk factors, value-weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM		Model 2: FF Three-Factor		Model 3: Carhart Four Factor	
	Media	SVI	Media	SVI	Media	SVI
Panel A: Long No-Attention Stocks Portfolio						
Mkt-rf	0.8689***	0.8499***	1.1442***	1.0872***	1.1315***	1.0740***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	-	-	0.5170***	0.4951***	0.5154**	0.4934***
			(0.000)	(0.000)	(0.000)	(0.000)
HML	-	-	0.0885	0.2141**	0.1223	0.2491**
			(0.475)	(0.060)	(0.346)	(0.036)
MOM	-	-	-	-	0.1169	0.1211
					(0.364)	(0.295)
Intercept	0.0089**	0.0048	0.0051	0.0011	0.0054	0.0014
	(0.022)	(0.166)	(0.140)	(0.717)	(0.121)	(0.643)
Observations	47	47	47	47	47	47
R^2	0.6223	0.6514	0.7293	0.7595	0.7346	0.7658
Panel B: Short High-Attention Stocks Portfolio						
Mkt-rf	-0.9213***	-0.8776***	-0.9896***	-0.9708***	-0.9836***	-0.9750***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	-	-	-0.1315	-0.1689	-0.1307	-0.1694
			(0.121)	(0.098)	(0.126)	(0.100)
HML	-	-	-0.0310	-0.0126	-0.0468	-0.0016
			(0.703)	(0.897)	(0.584)	(0.988)
MOM	-	-	-	-	-0.0549	0.0381
					(0.517)	(0.708)
Intercept	0.0013	-0.0035	0.0022	-0.0023	0.0021	-0.0022
	(0.559)	(0.178)	(0.319)	(0.391)	(0.356)	(0.419)
Observations	47	47	47	47	47	47
R^2	0.8497	0.7786	0.8580	0.7932	0.8594	0.7939

Table AVI
SVI-Based Trading Profits: Multivariate Results (Excluded Sectors)

This table examines the profitability of a zero-investment trading strategy. The strategy longs a portfolio of stocks belonging to the lowest relative SVI tertile and shorts a portfolio of stocks belonging to the highest relative SVI tertile. We exclude stocks belonging to firms in sectors 4, 9, 10 and 11 as defined in Figure 1. The relative SVI of a company is the sample-weighted average SVI in the month of portfolio formation. The zero-investment portfolio, as well as the long and short legs of it, are all equally weighted. The portfolio is held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the zero-investment portfolio are regressed on established risk factors, equally weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM	Model 2: FF Three-Factor	Model 3: Carhart Four-Factor
Panel A: Long No-Attention Stocks, Short High-Attention Stocks			
Mkt-rf	-0.0983	-0.1218	-0.1108
	(0.234)	(0.183)	(0.263)
SMB	-	0.0517	0.0687
		(0.541)	(0.500)
HML	-	0.1490	0.1578
		(0.194)	(0.187)
MOM	-	-	0.0359
			(0.759)
Intercept	-0.0005	-0.0005	-0.007
	(0.882)	(0.887)	(0.827)
Observations	47	47	47
R^2	0.0314	0.0761	0.0782
Panel B: Alphas for No-Attention Stocks			
Intercept	0.0048	0.0040	0.0028
	(0.166)	(0.282)	(0.458)
Panel C: Alphas for High-Attention Stocks			
Intercept	-0.0050	-0.0042	-0.0033
	(0.114)	(0.208)	(0.334)

Table AVII

Media-Based Trading Profits by Firm Characteristics – Value-Weighted Factors

This table examines the profitability of a media-based zero-investment trading strategy, sorted on firm characteristics. Each month, we first divide our sample of stocks in two, evenly large, subsamples based on firm characteristics: size, book-to-market and 12-month momentum.. Then the stocks are sorted into two legs. The first leg longs a portfolio of stocks with no media coverage and the second one shorts a portfolio of stocks with high media coverage. The long portfolio consists of stocks with no media coverage in the month of portfolio formation and the short portfolio of stocks above the median number of articles of the remaining stocks. The zero-investment portfolio, as well as the long and short legs of it, are all equally weighted. The portfolio is held for 1 month after portfolio formation and rebalanced monthly. The resulting time series returns of the zero-investment portfolio are regressed on established risk factors, value-weighted and further defined in Table AI, and results presented below. p-values are given in parentheses, whereas $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Model 1: CAPM	Model 2: FF Three-Factor	Model 3: Carhart Four-Factor
		Panel A: By Firm Size	
		Small	
Intercept	0.0135	0.0134	0.0126
	(0.132)	(0.152)	(0.180)
		Large	
Intercept	0.0108***	0.0101**	0.0105***
	(0.006)	(0.013)	(0.010)
		Panel B: By Book-to-Market	
		Low	
Intercept	0.0121	0.0104**	0.0108**
	(0.007)***	(0.023)	(0.020)
		High	
Intercept	0.0089**	0.0051	0.0051
	(0.051)*	(0.236)	(0.247)
		Panel C: By Past 12-Month Momentum	
		Low	
Intercept	0.0019	-0.0007	-0.0007
	(0.593)	(0.850)	(0.832)
		High	
Intercept	0.0156***	0.0135***	0.0140***
	(0.000)	(0.002)	(0.001)